University of Miskolc

FACULTY OF MECHANICAL ENGINEERING AND INFORMATICS

OPTIMIZATION OF LOGISTIC SYSTEMS IN INDUSTRY 4.0 ENVIRONMENT

PHD THESES

Prepared by
Mohammad Zaher Akkad
Mechanical Engineering (BSc),
Mechanical Engineering (MSc)

József Hatvany Doctoral School
of Information Science, Engineering and Technology

Research field of Material flow systems and logistics

Head of Doctoral School
Prof. Dr. Jenő Szigeti

Head of Research Field
Prof. Dr. Béla Illés

Supervisor
Prof. Dr. Tamás Bányai

Miskolc
2024

CONTENTS

CONTENTS I

SUPERVISOR'S RECOMMENDATIONS III

DECLARATION OF AUTHORSHIP AND AUTHOR'S DECLARATION IV

ACKNOWLEDGMENT V

LIST OF ABBREVIATIONS AND SYMBOLS VI

LIST OF FIGURES IX

LIST OF TABLES XI

1. THEORETICAL BACKGROUND 1

1.1. INTRODUCTION 1
1.2. APPLIED METHODOLOGY IN LITERATURE 3
1.3. DATA ANALYZING 6
1.4. SYSTEMIC LITERATURE REVIEW 8
1.5. THEORETICAL BACKGROUND OUTCOMES AND AIMED SCIENTIFIC GAPS 13

2. OPTIMIZATION ALGORITHMS 15

2.1. INTRODUCTION 15
2.2. HEURISTIC OPTIMIZATION ALGORITHMS 16
2.2.1 Genetic algorithm 17
2.2.2. Particle swarm algorithm 17
2.2.3. Simulated annealing 18
2.2.4. Ant colony optimization 19
2.3. OPTIMIZATION ALGORITHMS BENCHMARKS 19

3. WASTE MANAGEMENT SYSTEM OPTIMIZATION 22

3.1. INTRODUCTION 22
3.2. PROPOSED CYBER-PHYSICAL WASTE COLLECTION SYSTEM 24
3.3. EVALUATION OF A CONVENTIONAL CITY LOGISTICS SOLUTION 27
3.4. MULTI-ECHELON COLLECTION AND DISTRIBUTION OPTIMIZATION SYSTEM 30
3.5. CPS FOR WASTE MANAGEMENT FOCUSING ON ENERGY EFFICIENCY AND SUSTAINABILITY 33
3.5.1. Introduction 33
3.5.2. Developed mathematical modeling 35
3.6. VIII DISTRICT BUDAPEST CASE STUDY 37
3.6.1. First scenario of thirty smart bins in Budapest 38
3.6.2. Second scenario of twenty smart bins in Budapest 42

4. ENERGY EFFICIENCY OPTIMIZATION OF LAST MILE SUPPLY SYSTEM 44

4.1. MISKOLC CASE-STUDY FOR VEHICLE ROUTING PROBLEM 44
4.2. KOSICE CASE-STUDY FOR CAPACITIVE COLLECTION SYSTEM 48
4.3. LAST MILE SUPPLY OPTIMIZATION SYSTEM WITH RL CONSIDERATION 52
4.4. DEVELOPED SYSTEM'S MATHEMATICAL MODELLING 54
4.5. VII DISTRICT BUDAPEST CASE STUDY 55
4.5.1. First scenario of diesel trucks 56
4.5.2. Second scenario of electric trucks 57

4.6. DISCUSSION AND OUTCOMES 58

5. IN-PLANT COMPLEX PRODUCTION SYSTEM OPTIMIZATION........ 60

5.1. INVESTIGATION OF THE INDUSTRY 4.0 TECHNOLOGIES ADOPTION EFFECT ON CE........ 60
5.1.1. Theoretical background........ 61
5.1.2. Methodology and data........ 63
5.1.3. Hypotheses building........ 65
5.2. RESULTS AND DISCUSSION........ 67
5.2.1. Relations investigation of the research model 1........ 67
5.2.2. Relations investigation of the research model 2........ 70
5.3. DISCUSSION OF THE RESULTS........ 72
5.4. ENERGY CONSUMPTION OPTIMIZATION OF MILK-RUN-BASED IN-PLANT SUPPLY SOLUTION 75
5.4.1. Introduction........ 75
5.4.2. Structure of Industry 4.0-based in-plant supply 76
5.5. MATHEMATICAL MODEL OF INDUSTRY 4.0 SUPPORTED IN-PLANT SUPPLY OPTIMIZATION 78
5.5.1. Conventional milk-run-based in-plant supply optimization........ 79
5.5.2. Real-time milk-run-based in-plant supply optimization........ 81
5.5.3. Optimization numerical analysis........ 83
5.5.4. Conventional milk-run-based in-plant supply optimization........ 85
5.5.5. Real-time milk-run-based in-plant supply optimization........ 90
5.6. RESULTS DISCUSSION AND CONCLUSIONS........ 94

6. THESES OF THE DISSERTATION........ 97

LIST OF AUTHOR'S PUBLICATION IN THE SAME RESEARCH FIELD 99

REFERENCES 100

SUPERVISOR'S RECOMMENDATIONS

As the supervisor and professor at the Institute of Logistics at the University of Miskolc, I am writing this letter in support of Mr. Mohammad Zaher Akkad's application for the PhD scientific degree at the University of Miskolc.

It is with genuine enthusiasm that I am providing a reference for Mohammad Zaher Akkad. I have known Mohammad Zaher Akkad for a few years now: I initially came to know him during his postgraduate coursework studies in Mechanical Engineering at the University of Miskolc, in which I was the supervisor of his TDK essay. This TDK essay was presented at the Local Conference of Student Research Societies. I was his PhD supervisor, and this enabled me to gain, professionally and personally, a very thorough impression of Mohammad Zaher Akkad.

It is so easy to provide a reference for a person of Mr. Akkad's caliber. One only needs to glimpse at his professional qualifications to be convinced that he is one of those rare individuals who are never satisfied with what they have achieved and who are continuously striving for excellence. He can be described as a perfectionist, in the best possible sense of this notion. The works that he submitted were always very thoroughly researched and immaculately presented, demonstrating a remarkable capacity to think analytically and to provide a balanced, penetrating, and persuasive argument. The same is even more obvious in his PhD thesis, which is undeniable the most highly literate and well-written dissertation that I have supervised in the whole of my academic career. One of the finest achievements of his thesis is the presentation of novel models and methods in the optimization of logistics systems in Industry 4.0 era.

His excellent scientific results can be validated by his excellent publications. As the MTMT publication and citation summary shows, Mohammad Zaher Akkad has 21 scientific publications: 13 scientific journal articles 6 conference papers and 2 other scientific works. The Hirsch-index of his publications is 2 and they have 28 independent citations. The total impact factor of his publications is 11.351, while his weighted impact factor is 4.909.

In light of the above I am completely convinced that a person of Mr. Mohammad Zaher Akkad's accomplishment and talent is capable of carrying out independent scientific research work. Please do not hesitate to contact me for further information if required.

Miskolc, 24/06/2024

Tamás Bányai
professor in logistics
Supervisor

DECLARATION OF AUTHORSHIP AND AUTHOR'S DECLARATION

The author hereby declares that this dissertation has not been submitted, either in the same or in a different form, to this or to any other university for obtaining a PhD degree. The author confirms that the submitted work is his own and the appropriate credit has been given where reference has been addressed to the work of others.

I, the undersigned, Mohammad Zaher Akkad, declare that I have prepared this doctoral dissertation and have used only the sources provided. All parts that I have taken from another source, either directly or in the same content but paraphrased, are clearly marked with the source.

Miskolc, 24/06/2024

Mohammad Zaher Akkad

ACKNOWLEDGMENT

First and foremost, I praise and thank God, the Almighty, for the showers of blessings throughout my research work, enabling me to complete my dissertation successfully.

I would like to express my deep and sincere gratitude to my mentor, role model, and supervisor, Prof. Dr. Tamás Bányai, for his impeccable guidance, encouragement, and advice throughout this journey. This work would not have been possible without his excellent supervision. I also extend my heartfelt thanks to all the members of the Institute of Logistics at the University of Miskolc for their unwavering support.

I dedicate this work to the soul of my mother, Sabah, whose memory continues to inspire and guide me every day. Her love, wisdom, and strength have left an indelible mark on my life, and her spirit has been a constant source of motivation throughout my journey. Though she is no longer with us, her presence is felt in every step I take, and I strive to honor her legacy through my achievements.

To my father, Zoheir, whose unwavering support and belief in me have been the bedrock of my success. His dedication, hard work, and sacrifices have provided me with the opportunities to pursue my dreams. His encouragement has given me the confidence to overcome challenges and persist in the face of adversity.

To my soulmate, İrem, for standing by my side always. Your love, patience, and unwavering belief in me have been my anchor throughout this journey. You have been my confidant, my partner, and my greatest source of comfort. Your support has been invaluable, and I am deeply thankful for your presence in my life.

To my brothers, Abd Ulkader and Fateh, and my sisters, Ghenwa and Zahra, I am deeply grateful for your endless care and support. Your encouragement and understanding have been a source of strength for me, and I cherish the bond we share. Your constant presence in my life has provided me with the confidence to pursue my dreams.

To my friends and colleagues, who have become my family in Hungary. Your camaraderie, support, and encouragement have made this journey not only bearable but enjoyable. The bonds we have formed and the experiences we have shared have enriched my life profoundly. Your friendship has been a source of joy and comfort, and I am grateful for each one of you.

To Hungary, my home, where I cannot see my future anywhere else. Your rich culture, vibrant community, and enduring spirit have profoundly influenced my journey, and I am proud to call you, my home. Also, I acknowledge the financial support of the Tempus Public Foundation. This support has been instrumental in enabling me to pursue my academic goals and dreams.

Last but not least, sincere thanks to all the members of the University of Miskolc. Your collective efforts, guidance, and support have made a significant impact on my academic journey, and I am deeply grateful for the enriching environment you have provided.

LIST OF ABBREVIATIONS AND SYMBOLS

List and explanation of abbreviations

Abbreviation	Explanation
IoT	Internet Of Things
CPS	Cyber-Physical Systems
CE	Circular Economy
DSC	Digital Supply Chains
GA	Genetic Algorithm
RL	Reverse Logistics
MES	Manufacturing Execution System
SI	Swarm Intelligence
ACO	Ant Colony Optimization
PSO	Particle Swarm Optimization
VRP	Vehicle Routing Problem
NRP	Node Routing Problem
ARP	Arc Routing Problem
CVRP	Capacitated Vehicle Routing Problem
TE	Total Energy Consumption
TSP	Travelling Salesman Problem
EMS	European Manufacturing Survey
BDA	Big Data and Analytics
AM	Additive Manufacturing
NPI	New Or Improved Product Development
IEI	Improved Environmental Impact
GHG	Greenhouse gases

List of used notations

Notation	Description
n	Visited locations overall number
m	Trucks overall number
K	The indices group represents trucks
I	The indices group represents visited locations
$i, j \in I$	Two arbitrary indices denote a visited location
$k \in K$	An arbitrary index of a truck
q_i	A value representing the goods weight of location i
q_{ijk}	Non-negative amount represents the goods' weight in truck k while moving from location i to j
C	The truck's maximum capacity of goods
T_{max}	The specified maximum time to finish the entire process
t_k	The time that is taken by truck k to finish its route and go back to the start location
q_{max}	The maximum goods' capacity in each location is to be tackled
X_{ijk}	A decision variable that is 1 if vehicle k proceeds from location i to location j otherwise, it is 0
Y_{ik}	A decision variable that is 1 if location i is part of vehicle k route, otherwise, it is 0
TE	Total optimized energy consumption
c_{ijk}^T	The specific fuel consumption for truck k when moving from location i
c_{kmin}^T	Specific fuel consumption's lower bound
c_{kmax}^T	Specific fuel consumption's upper bound
Q	The maximum waste loading capacity of the truck
E_T	The energy consumption of all transportation processes
E_{MH}	The energy consumption of all waste loading operations
$c_{i,k}^{FT}$	The specific fuel consumption of the transportation process for truck k after moving from bin i
$c_{i,k}^{FMH}$	The specific fuel consumption of material handling operations for truck k at bin i
c_{kmin}^{FMH}	The lower bound for the specific fuel consumption of material handling operations
c_{kmax}^{FMH}	The upper bound for the specific fuel consumption of material handling operations
c_{kmin}^{FT}	The lower bound for the specific fuel consumption of the transportation process
c_{kmax}^{FT}	The upper bound for the specific fuel consumption of the transportation process
L	The total length of the transportation routes within the time span of optimization
α	The number of delivery trucks
β_{max}^{α}	The number of pick-up and delivery points assigned to collection route α
$x_{\alpha.\beta}^*$	The ID number of pick-up and delivery task assigned to route α as pick-up or delivery task β
$y_{x_{\alpha.\beta}^*}$	The ID of pick-up or delivery point
$p_{y_{x_{\alpha.\beta}^*}}$	The position of pick-up or delivery point assigned to route α as pick-up or delivery task β
l	The length of transportation route as a function of positions of pick-up and delivery points
C_T^{FUEL}	Fuel consumption of whole transportation process without material handling (loading and unloading)
$c_{\alpha.\beta}^{FT}$	The specific fuel consumption of transportation
C_{MH}^{FUEL}	The fuel consumption of material handling operations at the pick-up and delivery points
$c_{\alpha.\beta}^{FMH}$	The specific fuel consumption regarding material handling operations
v	The average speed of the truck
$q_{x_{\alpha.\beta}}$	The pick-up or delivery volume assigned to route α as pick-up or delivery task β
$c_{\alpha.min}^{FT}\ c_{\alpha.max}^{FT}$	Lower and upper limit of fuel consumption of transportation depending on the weight of loading
$q_{\alpha max}^{TRANS}$	The upper limit of the loading weight
$c_{\alpha.min}^{FMH}\ c_{\alpha.max}^{FMH}$	Lower and upper limit of fuel consumption of material handling depending on the weight of loading
$q_{\alpha max}^{MH}$	The upper limit of the material handling weight
E^r	Total emission in the time span of the optimization for emission type r (CO_2. NO_x. CO. HC. PM. SO_2)
$x_{\alpha.\beta}$	The decision variable of the optimization problem
C^{eFUEL}	The energy consumption of e-trucks and micro-mobility vehicles in kWh
$c_{\alpha.\beta}^{eFT}$	The specific energy consumption of e-trucks and micro-mobility vehicles
Q_{α}^{Tmax}	The loading capacity of vehicle α
Q_{α}^{Lmax}	The capacity of the available loading resource of transportation device α
$C_{\alpha.\beta_{max}^{\alpha}}^{eFUEL}$	The energy consumption of e-truck α passing the last pick-up or delivery point assigned to route α
$C_{\alpha}^{eFUELmax}$	The available energy of e-truck α
η_{α}	The utilization of the e-truck
$\bar{\eta}$	The average utilization of e-vehicles
$s_{k.\alpha}$	The suitability parameter
$x_{\alpha.\beta}^*$	ID number of pick-up and delivery task assigned to route α as pick-up or delivery task β
$y_{x_{\alpha.\beta}^*}$	the ID of pick-up or delivery point

$x_{\alpha.\beta}$	Assignment matrix as a decision variable of the optimization problem in scenario 2
C_{EC}	Energy consumption of milk-run-based in-plant supply solution within time frame of analysis
$l_{i,0,x_{i,1}}$	Length of the route scheduled between the milk-run trolley depot and the first station of the in-plant supply in the case of route *i*
$q_{i,0,x_{i,1}}$	Weight of the loading of the milk-run trolley between the milk-run trolley depot and the first station of the in-plant supply in the case of route *i*
$l_{i,x_{i,i_{max}},0}$	Length of the route scheduled between the last station and the milk-run trolley depot of the in-plant supply in the case of route *i*
$q_{,x_{i,i_{max}},0}$	Weight of the loading of the milk-run trolley between the last station and the milk-run trolley depot of the in-plant supply in the case of route *i*
$l_{i,x_{i,j},x_{i,j+1}}$	Length of the route scheduled between station *j* and station *j+1* in the case of the milk-run route *i.*
$q_{i,x_{i,j},x_{i,j+1}}$	Weight of the loading of the milk-run trolley between station *j* and station *j+1* in the case of the milk-run route *i*
e	Specific energy consumption of the milk-run trolley depending on the weight of the loading of the milk-run trolleys
i_{max}	Number of stations assigned to route *i*
$x_{\alpha,\beta}$	Assignment matrix
e^{MH}	Specific energy consumption of material handling operations
$\Delta q_{i,j}$	Loaded/unloaded products weight at station *j* of route *i* (difference of weight before and after station *j*)
$\tau_{i,x_{i,1}}^{min}$	Lower limit of the arrival time of the milk-run trolley to the first station of the scheduled route *i*
$\tau_{i,x_{i,1}}^{max}$	Upper limit of the arrival time of the milk-run trolley to the first station of the scheduled route *i*
$v(q_{i,0,x_{i,1}})$	Velocity of the milk-run trolley depending on the loading between the milk-run trolley depot and the first station of route *i*
j_i^*	Station between the first station and the depot of the milk-run trolley
$v\left(q_{i,x_{i,j},x_{i,j+1}}\right)$	Velocity of the milk-run trolley depending on the loading between station *j* and *j+1*
σ	Number of routes after adding new milk-runs based on the real-time in-plant supply demand
ξ	Number of supply demands generated by the supervisory level
σ_{max}	Number of milk-run routed after adding new milk-runs to the MES-based scheduled routes
$r_{i,j}$	Succeeded station
bc_i	Available capacity of the battery in the case of MES data-based routing
bc_σ	Available capacity of the battery in the case of conventional integrated routing of MES data-based and real-time in-plant supply optimization
$x_{\alpha,\beta}^*$	Assignment matrix
i_{max}^*	Number of stations added to route *i* including both MES-based and supervisory level-based in-plant supply demands
$\tau_{i,x_{i,1}^*}^{min}$	Lower limit of the arrival time of the milk-run trolley to the first station of the scheduled route *i* after adding all real-time supply-demand generated by the supervisory level
$\tau_{i,x_{i,1}^*}^{max}$	Upper limit of the arrival time of the milk-run trolley to the first station of the scheduled route *i* after adding all real-time supply-demand generated by the supervisory level
$v\left(q_{i,0,x_{i,1}^*}\right)$	Velocity of the milk-run trolley depending on the loading between milk-run trolley depot and the first station of route *i* after adding all real-time supply-demand generated by the supervisory level
j_i^{**}	Station between the first station and the depot of the milk-run trolley after adding the real-time in-plant supply demands to the scheduled milk-run

LIST OF FIGURES

FIGURE 1: A LOGISTICS-ORIENTED INDUSTRY 4.0 APPLICATION MODEL [11] 2
FIGURE 2: FIRST SEARCH IN THE WEB OF SCIENCE DATABASE 3
FIGURE 3: SECOND SEARCH IN THE WEB OF SCIENCE DATABASE 4
FIGURE 4: THIRD SEARCH IN THE WEB OF SCIENCE DATABASE 4
FIGURE 5: FOURTH SEARCH IN THE WEB OF SCIENCE DATABASE 5
FIGURE 6: SIXTH SEARCH IN THE WEB OF SCIENCE DATABASE 6
FIGURE 7: DISTRIBUTION OF ARTICLES BY RESEARCH AREA 6
FIGURE 8: DISTRIBUTION OF ARTICLES BY CATEGORIES 7
FIGURE 9: FIVE MOST CITED ARTICLES IN THE FOUND SEARCH SCIENCE 7
FIGURE 10: CPS WASTE COLLECTION SYSTEM SCHEME 25
FIGURE 11: CONVENTIONAL CITY LOGISTICS SOLUTION 27
FIGURE 12: TOTAL TRANSPORTATION TIME AND ENERGY CONSUMPTION OF ROUTE 1 29
FIGURE 13: EMISSION OF GARBAGE COLLECTION TRUCK IN SCENARIO 1 30
FIGURE 14: MODEL OF MULTI-ECHELON COLLECTION AND DISTRIBUTION SYSTEM IN DOWNTOWN AREAS 31
FIGURE 15: CYBER-PHYSICAL WASTE MANAGEMENT SYSTEM SCHEME 34
FIGURE 16: INFORMATION AND WASTE FLOW 35
FIGURE 17: TOTAL ENERGY CONSUMED BY THE THREE TRUCKS (GA) 39
FIGURE 18: TOTAL ENERGY CONSUMED BY THE THREE TRUCKS (PSO) 39
FIGURE 19: TOTAL ENERGY CONSUMED BY THE THREE TRUCKS (SA) 39
FIGURE 20: ACTUAL ROUTES WHEN USING GA 40
FIGURE 21: ACTUAL ROUTES WHEN USING PSO 40
FIGURE 22: ACTUAL ROUTES WHEN USING SA 41
FIGURE 23: TOTAL ENERGY AND EMISSIONS OF THE CASE OF THIRTY BINS 41
FIGURE 24: ACTUAL ROUTES WHEN USING A RANDOM SOLUTION 41
FIGURE 25: TOTAL ENERGY AND EMISSIONS OF THE CASE OF TWENTY BINS 42
FIGURE26 : ACTUAL ROUTE MAP FOR GA OPTIMIZATION 45
FIGURE27 : ACTUAL ROUTE MAP FOR PSO OPTIMIZATION 45
FIGURE28 : ACTUAL ROUTE MAP FOR SA OPTIMIZATION 46
FIGURE29 : ACTUAL ROUTE MAP FOR RANDOM ROUTE 46
FIGURE30 : GA OPTIMIZATION CURVE FOR DISTANCE AND ITERATIONS 47
FIGURE31 : PSO OPTIMIZATION CURVE FOR DISTANCE AND ITERATIONS 47
FIGURE32 : SA OPTIMIZATION CURVE FOR DISTANCE AND ITERATIONS 47
FIGURE 33: USED MODEL IN THE CASE STUDY 49
FIGURE34 : ALGORITHMS' RESULTS COMPARISON 50
FIGURE 35: FIRST APPLICATION-OPTIMIZED ROUTE BY NN 50
FIGURE36 : FIRST APPLICATION-OPTIMIZED ROUTE BY GA 51
FIGURE 37: SECOND APPLICATION-OPTIMIZED ROUTE BY NN 51
FIGURE38 : SECOND APPLICATION-OPTIMIZED ROUTE BY GA 52
FIGURE 39: LAST MILE SUPPLY SYSTEM SCHEME 53
FIGURE 40: GA OPTIMIZATION METHODOLOGY 53
FIGURE41 : OPTIMIZED SOLUTION FOR THE FIRST SCENARIO (DIESEL) 56
FIGURE42 : RANDOM SOLUTION FOR THE FIRST SCENARIO (DIESEL) 57
FIGURE 43: OPTIMIZED SOLUTION FOR THE SECOND SCENARIO (ELECTRIC) 57
FIGURE 44: RANDOM SOLUTION FOR THE SECOND SCENARIO (ELECTRIC) 58
FIGURE 45: CALCULATED TOTAL ENERGY 58
FIGURE 46: CALCULATED TOTAL DISTANCE 58
FIGURE 47: USED TECHNOLOGIES AND PRODUCT INNOVATION (VARIABLES) WITH ABRIDGMENTS 65
FIGURE 48: RESEARCH MODEL 1 FOR TESTING H1A AND H1B 66
FIGURE 49: RESEARCH MODEL 2 FOR TESTING H2A AND H2B 66
FIGURE 50: COMPARISON OF COMPANIES' PERCENTAGES THAT USE INDUSTRY 4.0 OR NON-INDUSTRY 4.0 TECHNOLOGY. 68
FIGURE 51: COMPARISON OF COMPANIES' PERCENTAGES THAT USE I4.0, NON-I4.0, OR CE TECHNOLOGY 71
FIGURE 52: STRUCTURE OF INDUSTRY 4.0 TECHNOLOGIES SUPPORTED BY MILK-RUN-BASED IN-PLANT SUPPLY 77
FIGURE 53: INDUSTRY 4.0 TECHNOLOGIES SUPPORTED REAL-TIME MILK-RUN-BASED IN-PLANT SUPPLY OPTIMIZATION MODEL 82

FIGURE 54: FIRST ROUTE OF THE CONVENTIONAL MILK-RUN-BASED IN-PLANT SUPPLY INCLUDES MES DATA-BASED SUPPLY DEMANDS 85
FIGURE 55: SECOND ROUTE OF THE CONVENTIONAL MILK-RUN-BASED IN-PLANT SUPPLY 86
FIGURE 56: THIRD ROUTE OF THE CONVENTIONAL MILK-RUN-BASED IN-PLANT SUPPLY INCLUDES MES DATA-BASED SUPPLY DEMANDS 87
FIGURE 57: THE OPTIMIZED LOADING CAPACITY OF THE THREE MILK-RUN TROLLEYS 88
FIGURE 58: CUMULATIVE ENERGY CONSUMPTION OF THE THREE MILK-RUN ROUTES IN THE CONVENTIONAL REAL-TIME CASE 88
FIGURE 59: THE FIRST ROUTE OF THE CONVENTIONAL MILK-RUN-BASED IN-PLANT SUPPLY INCLUDES REAL-TIME SUPPLY DEMAND 89
FIGURE 60: THE SECOND ROUTE OF THE CONVENTIONAL MILK-RUN-BASED IN-PLANT SUPPLY INCLUDES REAL-TIME SUPPLY DEMAND 89
FIGURE 61: THE THIRD ROUTE OF THE CONVENTIONAL MILK-RUN-BASED IN-PLANT SUPPLY INCLUDES REAL-TIME SUPPLY DEMAND 90
FIGURE 62: THE MODIFIED FIRST ROUTE 91
FIGURE 63: THE MODIFIED SECOND ROUTE 92
FIGURE 64: THE MODIFIED THIRD ROUTE 93
FIGURE 65: THE OPTIMIZED LOADING CAPACITY OF THE THREE MILK-RUN TROLLEYS 93
FIGURE 66: THE OPTIMIZED LOADING CAPACITY OF THE THREE MILK-RUN TROLLEYS 94

LIST OF TABLES

TABLE 1: BENCHMARK FUNCTIONS BOUNDARIES 20
TABLE 2: BENCHMARK COST/AVERAGE COST RESULTS 20
TABLE 3: BENCHMARK EXECUTION TIME RESULTS 20
TABLE 4: POSITIONS OF PICK-UP AND DELIVERY POINTS (TEST DATA) 28
TABLE 5: WEIGHT OF GOODS TO PICK-UP OR DELIVERY (TEST DATA) 29
TABLE 6: REFERENCE PARAMETERS WERE CALCULATED IN SCENARIO 1 30
TABLE 7: SUITABILITY OF VEHICLES TO PERFORM PICK-UP AND DELIVERY TASKS 32
TABLE 8: ENERGY CONSUMPTION AND CAPACITY PARAMETERS OF E-VEHICLES 33
TABLE 9: EU VI EMISSION STANDARDS FOR HEAVY-DUTY AND TRANSIT TESTING IN G/KWH 37
TABLE 10: TRUCK SPECIFICATIONS 37
TABLE 11: BINS' LOCATIONS AND WASTE AMOUNTS 37
TABLE 12: EXECUTION RESULTS OF THE CASE OF THIRTY BINS 38
TABLE 13: ESTIMATED ACCRUED EMISSIONS IN G OF THE CASE OF THIRTY BINS 42
TABLE 14: EXECUTION RESULTS 42
TABLE 15: ESTIMATED ACCRUED EMISSIONS IN G OF THE CASE OF TWENTY BINS 42
TABLE 16: MISKOLC CASE STUDY LOCATIONS 44
TABLE 17: MISKOLC CASE STUDY RESULTS 44
TABLE 18: USED LOCATIONS IN KOSICE CITY CENTER 49
TABLE 19: FIRST CASE STUDY APPLICATION RESULTS 49
TABLE 20: SECOND CASE STUDY APPLICATION RESULTS 50
TABLE 21: USED TRUCK SPECIFICATIONS 55
TABLE 22: THE GOODS' WEIGHT AND THEIR LOCATIONS 55
TABLE 23 :RESULTS OF DIESEL TRUCKS SCENARIO 56
TABLE 24 :RESULTS OF ELECTRIC TRUCKS SCENARIO 57
TABLE 25: COMPARISON OF COMPANIES THAT USE INDUSTRY 4.0/NON-INDUSTRY 4.0 TECHNOLOGIES 67
TABLE 26: RESULTS OF LOGISTIC REGRESSION (RESEARCH MODEL 1, DEPENDENT VARIABLE – REW) 69
TABLE 27: RESULTS OF LOGISTIC REGRESSION (RESEARCH MODEL 1, DEPENDENT VARIABLE – REE) 69
TABLE 28: COMPARISON OF COMPANIES THAT USE THE INDUSTRY 4.0 OR NON-INDUSTRY 4.0 TECHNOLOGY 70
TABLE 29: RESULTS OF LOGISTIC REGRESSION (RESEARCH MODEL 2, DEPENDENT VARIABLE – NPI) 72
TABLE 30: RESULTS OF LOGISTIC REGRESSION (RESEARCH MODEL 2, DEPENDENT VARIABLE – IEI) 72
TABLE 31: MES DATA-BASED SUPPLY DEMANDS OF THE IN-PLANT SUPPLY OPTIMIZATION PROBLEM 84
TABLE 32: REAL-TIME GENERATED SUPPLY DEMANDS OF THE IN-PLANT SUPPLY OPTIMIZATION PROBLEM 85
TABLE 33: NUMERICAL RESULTS OF PREDEFINED IN-PLANT MATERIAL SUPPLY OPERATIONS WITHIN ROUTE 1 85
TABLE 34: NUMERICAL RESULTS OF PREDEFINED IN-PLANT MATERIAL SUPPLY OPERATIONS WITHIN ROUTE 2 86
TABLE 35: NUMERICAL RESULTS OF THE SCHEDULING OF PREDEFINED IN-PLANT MATERIAL SUPPLY OPERATIONS PERFORMED BY THE MILK-RUN TROLLEY WITHIN ROUTE 3 87
TABLE 36: NUMERICAL RESULTS OF THE CONVENTIONAL OPTIMIZATION OF REAL-TIME SUPPLY DEMANDS WITHIN THE ADDITIONAL ROUTE 4 89
TABLE 37: NUMERICAL RESULTS OF THE CONVENTIONAL OPTIMIZATION OF REAL-TIME SUPPLY DEMANDS WITHIN ADDITIONAL ROUTE 5 89
TABLE 38: NUMERICAL RESULTS OF THE CONVENTIONAL OPTIMIZATION OF REAL-TIME SUPPLY DEMANDS WITHIN ADDITIONAL ROUTE 6 90
TABLE 39: NUMERICAL RESULTS OF REAL-TIME GENERATED SPECIFIC IN-PLANT MATERIAL SUPPLY OPERATIONS WITHIN ROUTE 1 91
TABLE 40: NUMERICAL RESULTS OF REAL-TIME GENERATED SPECIFIC IN-PLANT MATERIAL SUPPLY OPERATIONS WITHIN ROUTE 2 92
TABLE 41: NUMERICAL RESULTS OF REAL-TIME GENERATED SPECIFIC IN-PLANT MATERIAL SUPPLY OPERATIONS WITHIN ROUTE 3 93
TABLE 42: COMPARISON OF THE COMPUTATIONAL RESULTS 94

1. THEORETICAL BACKGROUND

1.1. Introduction

The concept of digitizing everything is becoming a reality in various fields including manufacturing and logistics. Automation of manufacturing and logistics operations and processes, application of artificial intelligence and machine learning, the appearance of the Internet of Things (IoT), and other advanced technologies, like digital twinning offer a wide range of applicable tools and solutions. Also, industrial revolutions are the transitions of the manufacturing process and have fundamentally changed the economy and society. The phrase 'Industrial Revolution' symbolizes a significant industrial leap. This means the increase of quality, quantity, or both by implementing innovative industrial methods via new tools and technologies [1]. Until recently, three industrial revolutions were identified. We are now amid the Fourth Industrial Revolution, briefly called "Industry 4.0", which is now being developed and dominated by the different industrial sectors comprehensively [2]. While the Fifth Industrial Revolution (Industry 5.0) is mentioned [3], especially in central European countries, Industry 4.0 is dominating the industrial areas. The most prominent feature of Industry 4.0 is the adoption of intelligent technologies that rely on the IoT and remove the lines that separate the physical, digital, and biological areas [4]. Industry 4.0 applications include the most recent technology, especially in telecommunications, the internet, and nanotechnology, which allow us to use small devices with great efficiency [4,5]. This combination of advanced technologies has given us the scope to obtain various applications that have revolutionized the world of industry and changed the traditional concept of communication between machine and human into having the concept of communication between machine and machine [6]. It is easy to observe the rapid pace of development of the industry, which makes it imperative for us to follow up on the new applications of Industry 4.0 eagerly so we can keep abreast of this development and benefit from it in our field of specialization. These applications have moved the logistics field to a new level [7]. The pace of industrial development is constantly increasing. The results of the technological revolution that we are living, in addition to the intelligent technologies built on the internet and resulting from Industry 4.0 make it imperative to pursue these techniques in different fields from CAD modeling [8] to digital twinning solutions [9].

This started with the first industrial revolution that set the stage for industrial production. The introduction of mechanical production facilities using steam occurred at the end of the eighteenth century. Entering the twentieth century, the second industrial revolution was based on electricity, in conjunction with mass production techniques and the introduction of conveyor belts. It popularized mass production and gradually gave rise to assembly lines. This, in turn, gave birth to industrial engineering [10]. The third industrial revolution was a digital revolution, characterized by the rise of computers and automation in industrial control. Throughout the last half of the twentieth century, widespread applications of electronics and information systems further automated production. This enabled different manufacturers to reprogram manufacturing equipment and restructure processes to perform different tasks in a short period. While mechanical/electrical/digital innovations triggered the prior industrial revolutions, Industry 4.0 was triggered by the advent of the internet and its facilitation of communication between machines and humans in the cyber-physical system (CPS). The benefits and opportunities that are anticipated to have with Industry 4.0 appear to be various. For instance, resulting in highly flexible mass production, real-time coordination and optimization of value chains, reduction of complexity costs, or the emergence of entirely new services and business models [11].

Industry 4.0 technologies make it possible to build interconnected logistic solutions, where the objective of increasing efficiency, availability, reliability, and cost efficiency while decreasing energy consumption and economic footprint is targeted at the global level. Human activities are constantly changing and evolving in response to changes in technology, economics, industry, environment, and climate. These transformations pave the way for a modern era in the manufacturing industry, characterized by a shift towards organizing production processes based on technology and devices capable of independent communication throughout the value chain. These developed solutions entail organizing production processes around technology and devices capable of autonomous communication throughout the value chain. This involves the development of suitable information systems, physical infrastructure, and various logistics systems to meet future demands while leveraging newly developed technologies (Additive Manufacturing, Advanced Robotics, Artificial Intelligence, Autonomous Vehicles, Drones, IoT, etc.) that are contained under one umbrella, which is called Industry 4.0. As an outcome, there is a need for new paradigms of the way freight is moved, stored, realized, and supplied throughout the world. One of the proposed solutions is CPS, the concept of an open global logistics system, which completely redefines current supply chain configuration, value-creation patterns, and business models. This transformation encompasses the automation of manufacturing and logistics operations, incorporating artificial intelligence, machine learning, IoT, and other advanced technologies like digital twinning. These technological advancements offer a multitude of applicable tools and solutions. Industry 4.0 technologies facilitate the development of interconnected logistic solutions, focusing on enhancing efficiency, availability, reliability, and cost-effectiveness, while concurrently reducing energy consumption and economic impact on a global scale.

Based on a described logistics-oriented Industry 4.0 application model [11] (Figure 1), two dimensions were included. The first dimension is the supply chain which can be an autonomous and self-controlled logistics subsystem that interacts with each other like transport (via autonomous trucks), turnover handling (via trailer unloading or piece-picking robots), or order processing. The second dimension is the digital data value chain. Machine and sensor data are collected at the physical level along the entire physical end-to-end supply chain. Through a connectivity layer, the gathered data is provided for any kind of analytics, possibly resulting in potential value-added business services.

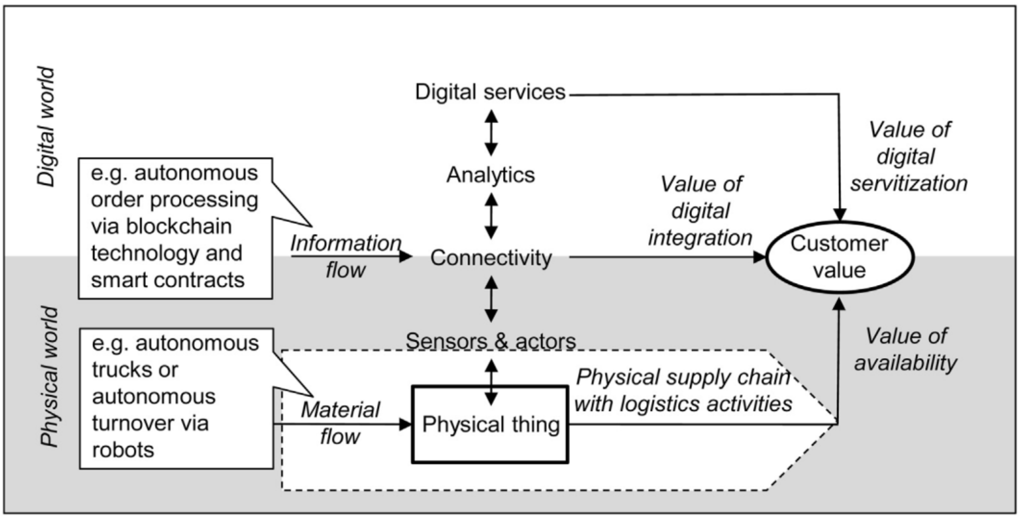

Figure 1: A logistics-oriented Industry 4.0 application model [11]

As an aspect of the logistics in the waste area, nowadays, about 54% of the world's population lives in urban areas. This proportion is expected to increase to 66% by 2050 [12]. This intensive increase in the world's population results in increased waste production. The waste management systems can be divided into two main parts: the technological part and logistics. There is a wide range of waste treatment technologies, including anaerobic digestion, gasification [13], dumping, land farming, composting, pyrolysis [14], sewage treatment [15], incineration [16], and reuse, but some of them have a huge environmental impact and they can cause serious environmental pollution [17]. Taking the benefits of Industry 4.0 technologies to make it possible to transfer conventional manufacturing and service systems into CPSs with remote management.

1.2. Applied methodology in literature

It is crucial to describe the main scientific results so far, identify the main tackled topics, and define the scientific gaps in the aimed research area to start drawing the main research directions and create a valuable scientific contribution. For that, a combined approach of two ways was used in this dissertation to create an inclusive literature review. While a systematic literature review that is based on defined steps [18] was used to cover a full-time span with analysis tools, a personal search for the related research articles was added to make the literature more inclusive. The outcomes and found scientific gaps are discussed at the end of this chapter. Moreover, as this dissertation investigates more than one direction, further specified literature is to be discussed in each chapter when it is needed.

Regarding the applied systematic literature review, the following points were used [18]. 1. Defining the research terms (keywords) to use. 2. Selecting which sources of data to be used in the search. 3. Analyzing the resulting articles. 4. Describing the main scientific results, identifying the main topics, and defining the scientific gaps and bottlenecks.

The keywords, which were identified to cover this research area are "Industry 4.0" and "logistic systems". To have a better perspective of the existing data, diverse ways of searching were applied with these keywords. The results of these ways will briefly be listed before giving details for the selected way. The entire search was done within the Web of Science database, and it was conducted in October 2023; therefore, new articles may have been published since then.

First, only TITLE: ("Industry 4.0") was used. Initially, 3877 articles were identified. This list was reduced to 3424 articles by selecting English articles and review articles. The classification of these articles depending on the publishing year is elaborated in Figure 2.

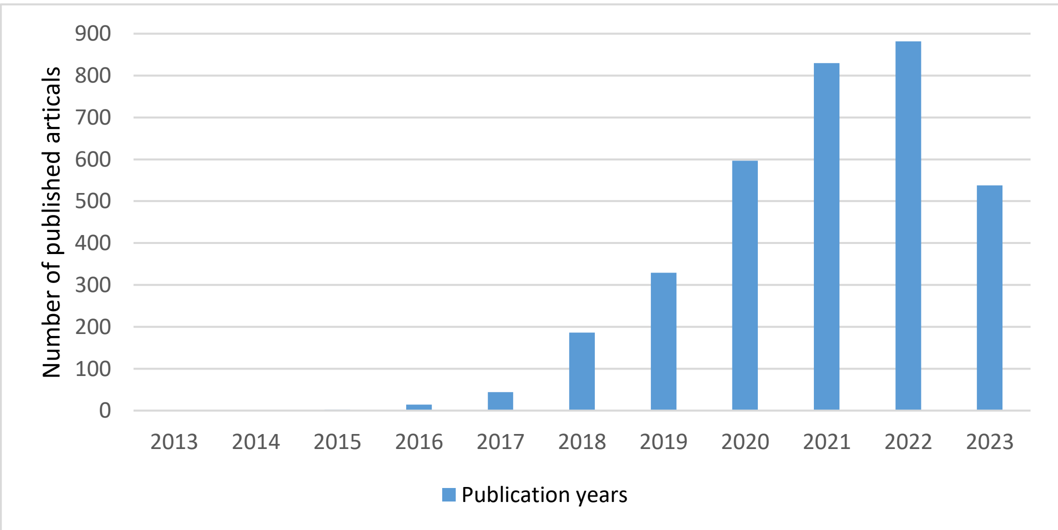

Figure 2: First search in the Web of Science database

In this search, the first article was in 2013. 2016 was the first year where more than two articles were published (14 articles). A gradual increase is obvious in the article numbers until it reached 882 articles in 2022 and 538 articles in 2023 (still going). This reflects the growing interest in and importance of Industry 4.0 within the last few years.
Second, only TITLE: (“logistic systems”) was used. Initially, 1682 articles were identified. This list was reduced to 1510 articles by selecting English articles and review articles. The classification of these articles depending on the publishing year is elaborated in Figure 3. The first year when these resulting articles were published was 1975. To simplify the figure, the published article totals were taken in groups until 2000.
In this search, we can notice an increase in articles dealing with logistics over time. Even a few years are less than the previous ones but that does not change the total increase.

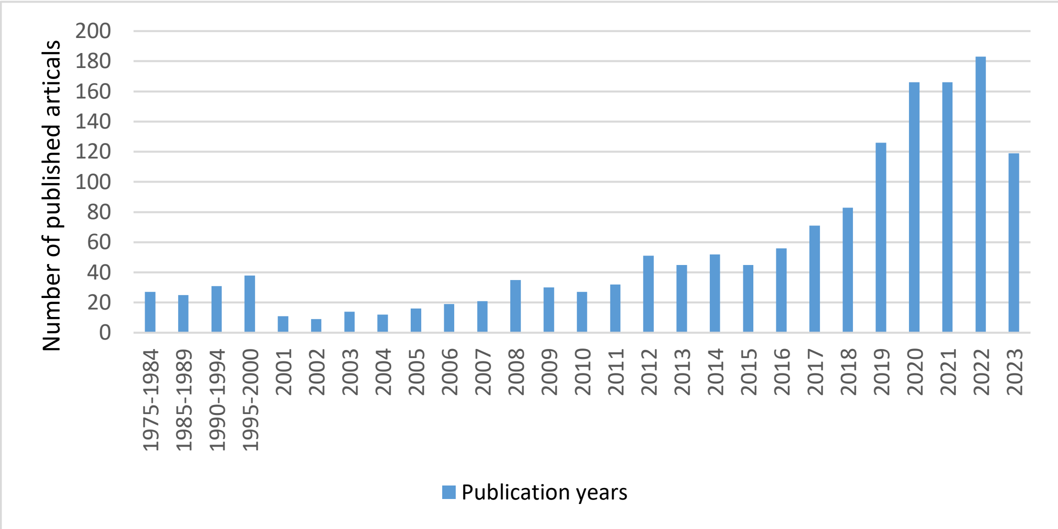

Figure 3: Second search in the Web of Science database

Third, TITLE: (“Industry 4.0”) and TOPIC: (“logistic systems”) were used together. Initially, 152 articles were identified. This list was reduced to 149 articles by selecting English articles and review articles. The classification of these articles depending on the publishing year is elaborated in Figure 4. The first articles in this result were published in 2017.

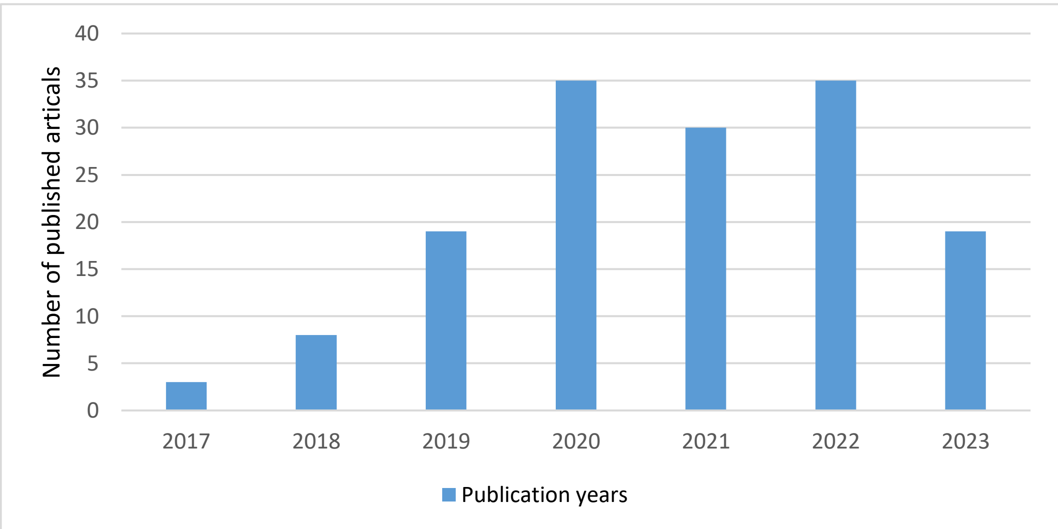

Figure 4: Third search in the Web of Science database

Fourth, TOPIC: (“Industry 4.0”) and TITLE: (“logistic systems”) were used together. Initially, 23 articles were identified. This list was reduced to 22 articles by selecting articles and reviewing articles. The classification of these articles depending on the publishing year is elaborated in Figure 5. The first article in this result was published in 2018.

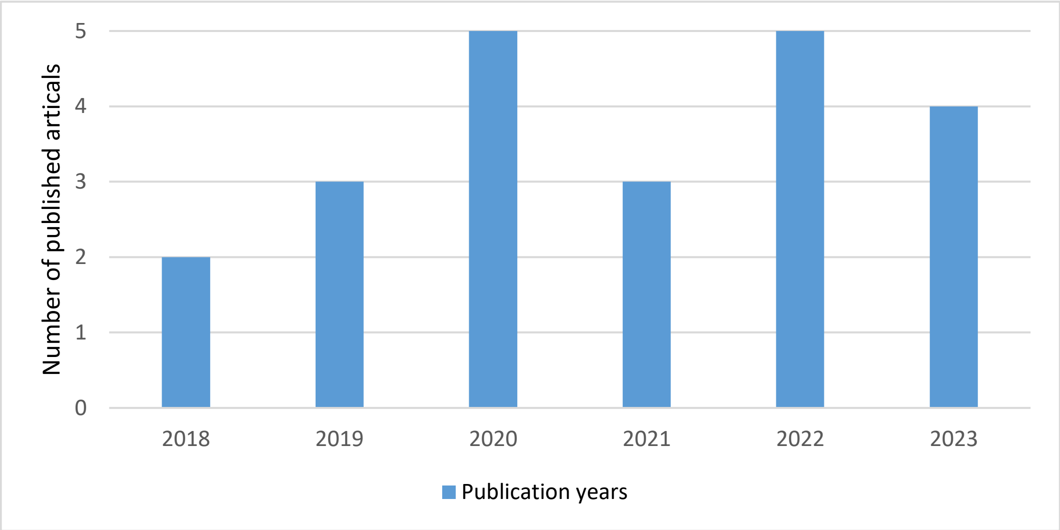

Figure 5: Fourth search in the Web of Science database

Fifth, TITLE: (“Industry 4.0” and “logistic systems”) were used together. Initially, 5 articles were identified. One in 2018, one in 2020, two in 2021, and one in 2022.
Sixth, TOPIC: (“Industry 4.0” and “logistic systems”) were used together. Initially, 479 articles were identified. This list was reduced to 468 articles by selecting English articles and review articles. The classification of these articles by the publishing year is elaborated in Figure 6.
The first article on this result was published in 2006 [19] titled "Assessment of a Personal Computer and its Effective Recycling Rate". Its objective was to study the environmental impact throughout the life cycle of personal computers (PCs) and ascertain an optimal recycling rate for PCs at the end of their usage. An analysis using a Life Cycle Assessment was conducted on a PC, considering various recycling scenarios. The results indicated that the recycling methods in use during that period were insufficient in mitigating the environmental impacts related to ozone depletion and ecotoxicity. It emphasized the importance of efficient reverse logistics (RL) for the collection and transportation of end-of-life PCs to improve recycling outcomes. The second article was published in 2015 [20] and titled “Cloud-assisted industrial cyber-physical systems: An insight”. It described the development and character of industrial CPS and its role in manufacturing, sales, and logistics. Then it presented a service-oriented industrial CPS model then talked about key enabling technologies and some challenges of industrial CPS implementation.

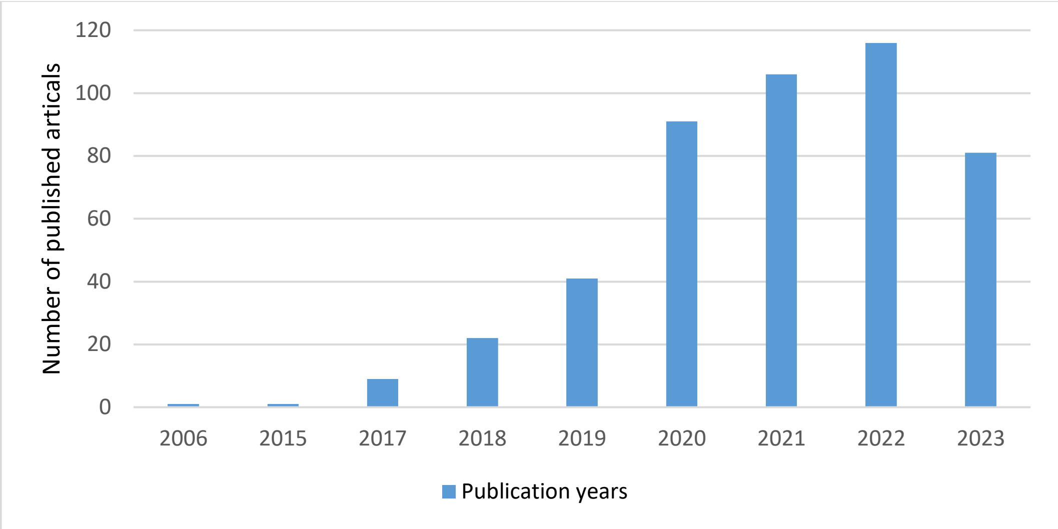

Figure 6: Sixth search in the Web of Science database

After the six different searches, we can realize the mounting role of Industry 4.0, the importance of logistic systems in scientific research, and the increasing amount of research that combines them. For the next step, which is analyzing the articles, the sixth search was chosen that used both "Industry 4.0" and "logistics" as a TOPIC. The eighty-nine articles that resulted from this search will be read, analyzed, and defined depending on the topic and type then making literature review for them to find out the research gaps and bottlenecks.

1.3. Data analyzing

The reached 468 articles were classified depending on the research area. Figure 7 shows the distribution of these articles while considering twenty subject areas. This distribution shows that most of the published articles are in engineering, economics, and computer sciences. Engineering and economics areas reflect the effect of these topics on the industry, while the computer sciences and operational research management areas define the importance of computational methods that are involved within Industry 4.0 research and applications.

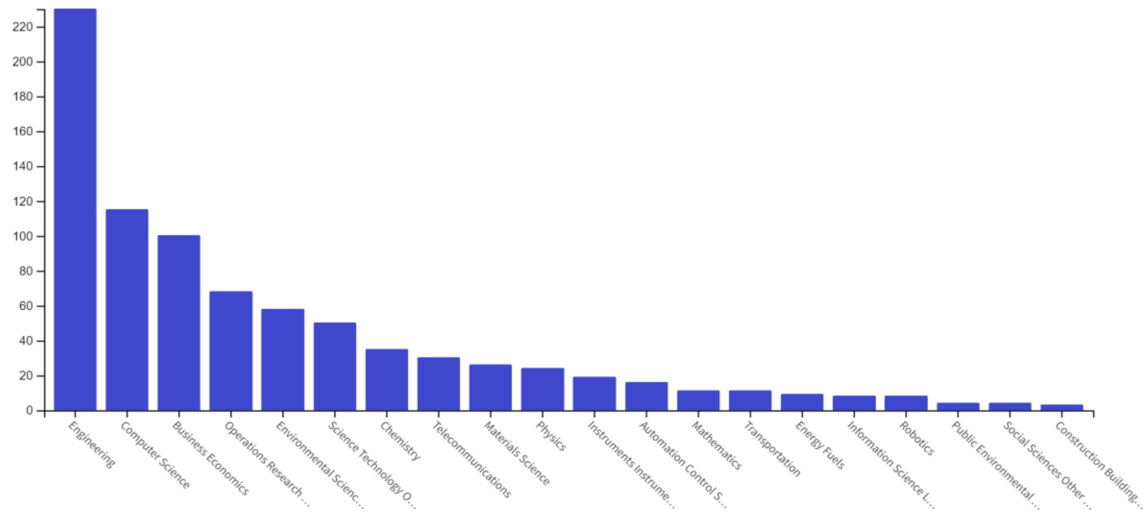

Figure 7: Distribution of articles by research area

By analyzing the published articles from the Web of Science categories point of view and by choosing the biggest twenty categories, Figure 8, it is found the most common categories are within engineering areas in both manufacturing and industry then in management, operation research, and computer science next to other areas like environment and automation. These categories variety show the importance of Industry 4.0 in logistics and its effect on various aspects of sciences. Figure 6 elaborates this effect has been increasing rapidly during the last few years.

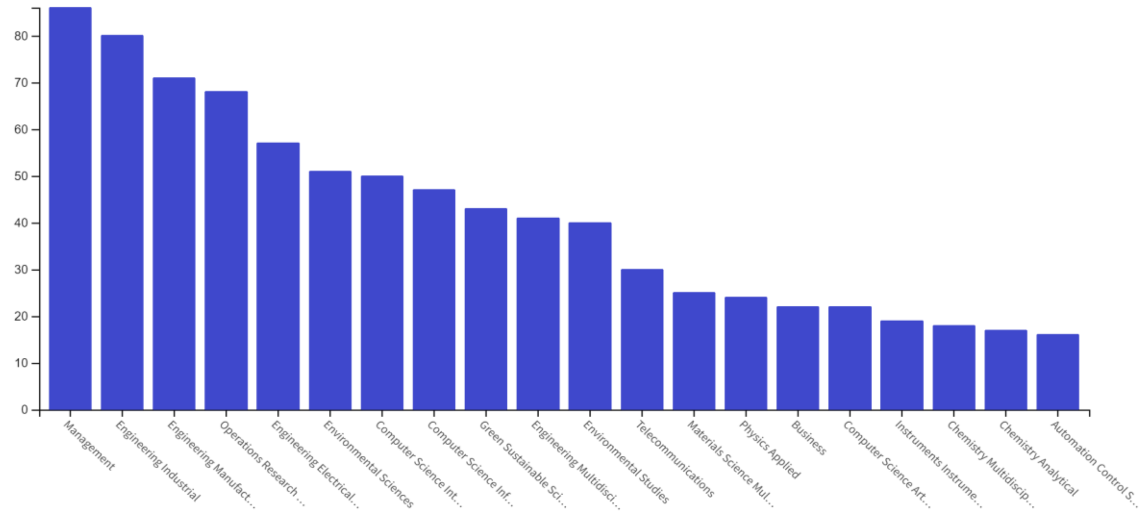

Figure 8: Distribution of articles by categories

As citation reflects the strong impact of the research, the highest five cited articles in the found search are highlighted [11] [21] [22] [23] [24]. Figure 9 shows them with their number of citations.

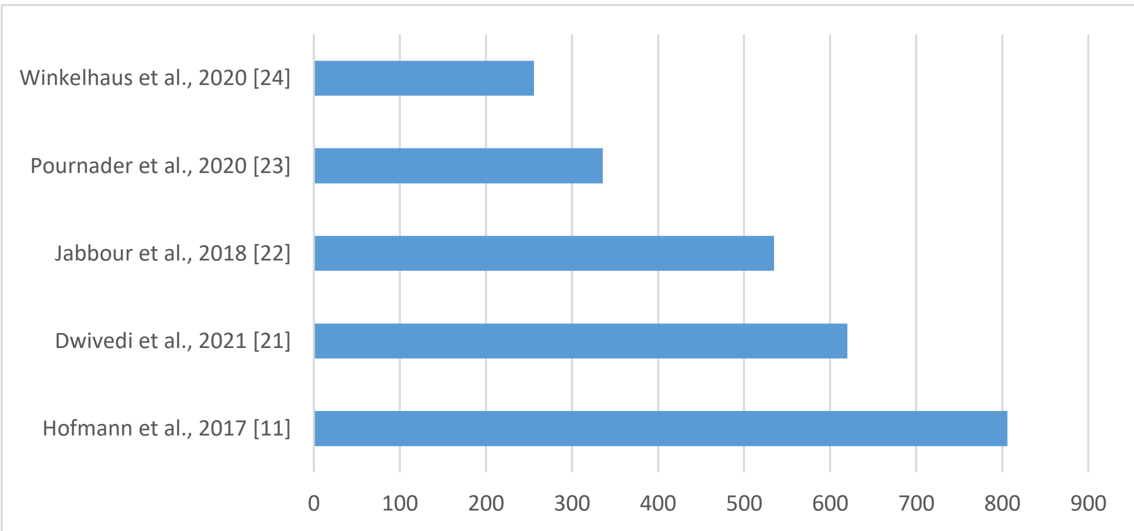

Figure 9: Five most cited articles in the found search Science

The most cited article is "Industry 4.0 and the Current Status as well as prospects on Logistics" [11] in 2017, which was cited 806 times. The discussed prospect within this paper sought to discuss the opportunities of Industry 4.0 in the context of logistics management since implications are expected in this field. The authors pursued the goal of shedding light on the young and mostly undiscovered topic of Industry 4.0 in the context of logistics management, thus following a conceptual research approach.

1.4. Systemic literature review

After reviewing the selected articles and excluding the irrelevant ones, a systematic literature review is presented. The second article in the previous search results was published in 2016 [25] titled “Industry 4.0 Implies Lean Manufacturing: Research Activities in Industry 4.0 Function as Enablers for Lean Manufacturing”. This paper analyzed the incompletely perceived link between Industry 4.0 and lean manufacturing and investigated whether Industry 4.0 can implement lean manufacturing. It provided an insight into manufacturers' dilemma as to whether they could commit to Industry 4.0 considering the investment required and unperceived benefits. In 2016, Kovacs et al [26] introduced the logistical tendencies and challenges with reasons and driving forces. Tendencies in the changes of customer demands, production requirements, formation of supply chains, inventory strategies, transportation activities, and activity of the logistics service sector are analyzed. The Industry 4.0 concept was also introduced, which was considered that would change the production and logistical processes drastically. Prause [27] addressed his research with the question of how the e-residency concept might facilitate the development and implementation of Industry 4.0 and how entrepreneurs may benefit more from new Industry 4.0-related business models by using the e-residency platform of Estonia. Weinberger et al [28] introduced the concept of high-resolution management where IoT enables the collection of high-resolution data for the physical world where, as in the digital world, every aspect of business operations can be measured in real-time. The capability facilitates high-resolution management, such as short optimization cycles in industrial production, logistics, and equipment efficiency, comparable to methods like A/B-testing or search engine optimization, which are state-of-the-art in digital business. Jurenoks [29] described the modification of network routing protocols for energy balancing in nodes, using the mobility of the coordinator node, which provided dynamic network reconfiguration possibilities. Trappey et al [30] concentrated on examining technology roadmaps for the integration of IoT technologies within smart logistic services. Case studies were conducted to pinpoint the correlation between IoT-centric technologies and the implementation of advanced logistic services. Logistic operations were categorized into an ontology schema based on a four-tier service framework. The study proposed a roadmap approach to visualize the allocation and evolution of patents corresponding to logistic services across each tier. Utilizing the roadmap methodology, the study analyzed IoT-enabled smart logistics to discern technology-related business strengths and strategies. Choi et al [31] investigated issues of a CPS application in manufacturing enterprises and introduced a CPS development case based on the IoT platform. Erkollar et al [32] investigated the deployment of novel logistics and smart city applications within the EU, along with a detailed discussion of their developed methodology. A model was devised to determine the optimal method for application implementation, taking into account time and cost limitations. Chaberek-Karwacka [33] Chaberek-Karwacka focused on addressing how newly adopted information technologies in logistics processes influence the dynamics of resource mobility in urban environments, and how they contribute to alleviating congestion issues. The study's primary premise was that information flows could partly substitute physical flows, leading to the central thesis that modern technologies facilitating streamlined information exchanges in both business-to-business and business-to-consumer interactions can mitigate the demand for goods and human movement within cities. The optimization resulted in shifts in the structure of resource demand and consequently altered the requirements for their mobility. Szozda [34] utilized findings from social research where a survey was conducted among 122 supply chains employing applied research techniques. From the gathered data and research findings, it could be inferred that the concept of Industry 4.0 is familiar to modern enterprises and significantly impacts the structuring of both physical and information flows within supply chains. Managers demonstrated awareness of the evolving nature of production, procurement, and distribution processes throughout the supply chain. Chen et al [35] reviewed the current practices of ubiquitous manufacturing, discussed the challenges faced by researchers and practitioners, and determined potential opportunities. It concluded that the success of ubiquitous manufacturing depends on the quality of the manufacturing services deployed and that ubiquitous manufacturing is a realizable target for Industry 4.0. Prause et al [36] investigated the relationship between networking, organizational development, structural frame conditions, and sustainability in the context of Industry 4.0. The research was empirically validated by using data samples from a business-reengineering project in an internationally operating high-tech manufacturing enterprise located in Estonia. The empiric analysis was based on semi-structured expert interviews and secondary data together with a case study approach. Hofmann et al [11] worked on discussing the opportunities of Industry 4.0 in the context of logistics management since implications were expected in this field. The aim was to explore the relatively new and underexplored domain of Industry 4.0 within the realm of logistics management, employing a conceptual research methodology. Initially, a model focusing on Industry 4.0 applications in logistics, along with its fundamental components, was introduced. Various logistics scenarios were then examined to elucidate potential practical implications and were deliberated upon with input from industry experts. The study revealed opportunities in terms of decentralization, self-regulation, and efficiency. Strandhagen et al [37] aimed to pinpoint and examine Industry 4.0 technologies relevant to manufacturing logistics, while also exploring how the manufacturing environment influences the adoption of these technologies. This was accomplished through a case study involving four Norwegian manufacturing firms. The study's outcomes revealed that the feasibility of integrating Industry 4.0 into manufacturing logistics hinged upon the specific production environment. Companies characterized by low production repetitiveness exhibited less enthusiasm for applying Industry 4.0 technologies in manufacturing logistics, whereas those with highly repetitive production processes displayed a greater propensity for adoption. Strandhagen et al [38] presented what so-called Logistics 4.0 is, highlighting its key components such as instantaneous data exchange, automated processes, and real-time big data analysis, which serve as catalysts for emerging business models. Additionally, presented a model aimed at comprehending and interconnecting various facets of business operations. Karia [39] investigated the role of knowledge resources as a crucial factor in the relationship between technology resources and the competitive advantage of logistics service providers. Survey data of 122 logistics service providers in Malaysia was used to analyze the proposed relationship. The results confirmed that knowledge resources positively affected cost advantages and significantly mediated the relationship between technology resources and cost advantages. Banyai et al [40] proposed an integrated delivery supply model. A mathematical model was introduced to formulate the problem of real-time smart scheduling of delivery. The integrated model included the assignment of first mile and last mile delivery tasks to the available resources and the optimization of operations costs, while constraints like capacity, time window, and availability were taken into consideration. A black hole optimization-based algorithm dealing with a multi-objective supply chain model was presented. The sensitivity of the enhanced algorithm was tested with benchmark functions. Numerical results with different datasets demonstrated the efficiency of the proposed model and validated the usage of Industry 4.0 inventions in delivery. Lee et al [41] proposed an IoT-based warehouse management system with an advanced data analytical approach using computational intelligence techniques to enable Industry 4.0 smart logistics. Based on the data collected from a company case study, the proposed IoT-based warehouse management system showed that the warehouse productivity, picking accuracy, and efficiency could be improved, and it was robust to order variability. Oeser et al [42] worked on finding a general holistic view of the implications of the growing and highly relevant customer segment of elder consumers for the food demand chain (food retail, production, logistics, and business informatics) in Germany. They also stated within their results that Industry 4.0 could facilitate the efficient and effective supply of food. Bressanelli et al [43] focused on the IoT, big data and analytics (BDA). Eight functionalities enabled by such technologies were identified (improving product design, attracting target customers, monitoring, and tracking product activity, providing technical support, providing preventive and predictive maintenance, optimizing the product usage, upgrading the product, enhancing renovation and end-of-life activities). By investigating how these functionalities affected three Circular Economy (CE) value drivers (increasing resource efficiency, extending lifespan, and closing the loop), the conceptual framework was developed about the role of digital technologies as an enabler of the CE within usage-focused business models. This showed how digital technologies help to overcome the drawbacks of usage-focused business models for the adoption of CE. Banyai [44] described a real-time scheduling optimization model focusing on the energy efficiency of the operation by using Industry 4.0 technologies. A mathematical model of last-mile delivery problems was introduced including scheduling and assignment problems. The objective of the model was to determine the optimal assignment and scheduling for each order to minimize energy consumption, which allows for improved energy efficiency. Lin et al [45] investigated the deployment of an intelligent computing system consisting of a cloud center, gateways, fog devices, edge devices, and sensors attached to facilities in a logistics center. It used an integer programming model for deploying gateways, fog devices, and edge devices in their respective potential sites so that the total installation cost was minimized, under the constraints of maximal demand capacity, maximal latency time, coverage, and maximal capacity of devices. It also solved an NP-hard facility location problem by a metaheuristic algorithm that incorporates a discrete monkey algorithm to search for superior-quality solutions and a genetic algorithm (GA) to increase computational efficiency. A simulation verified the high performance of the proposed algorithm in the deployment of intelligent computing systems in moderate-scale instances of intelligent logistics centers. Jabboure et al [22] contributed to unveiling how different Industry 4.0 technologies could underpin CE strategies and organizations by addressing those technologies as a basis for sustainable operations management decision-making. Gong et al [46] presented a simulation platform of automobile mixed flow assembly built based on Industry 4.0, which operated and managed automobile assembly, logistics warehouse, and CPS effectively. Flex Sim software was adopted to establish the auto-mixed assembly model that finds out the bottleneck of the auto-mixed assembly problem. Using parameter adjustment, rearrangement, and merger of processes, the whole assembly time of the 500 automobiles dropped by 33 hours, the equipment utilization rate increased by 20.19%, and the average blocked rate decreased by 21.19%. The optimized results showed that the proposed model could increase manufacturing efficiency by applying Industry 4.0 technologies. Sell et al [47] presented a concept for the integration of self-driving vehicles into Industry 4.0 by a last-mile automated shuttle bus designed and built in Estonia for short-range transportation. Tsai [48] proposed a green activity-based costing production planning model under Industry 4.0. Three models with five possible scenarios were suggested: normal and material cost fluctuation, material cost discount, and carbon tax with the related cost function. The aluminum-alloy wheel industry was chosen as the illustrative industry to present the results. The model provided a way to deal with the cost problem under Industry 4.0 as well and to be able to handle the environmental issues in making production decisions. Banyai et al [17] introduced waste collection process of downtowns as a CPS. A mathematical model of that waste collection process was described, which incorporated routing, assignment, and scheduling problems. The objectives of the model were: (1) optimal assignment of waste sources to garbage trucks; (2) scheduling of the waste collection through routing of each garbage truck to minimize the total operation cost, increase reliability while comprehensive environmental indicators that have great impact on public health are to be taken into consideration. Moreover, a binary bat algorithm was described, whose performance was validated with different benchmark functions. Sicari et al [49] introduced a new flow-based programming tool for the IoT through a detailed case study focusing on smart transportation and logistics. Banyai et al [50] introduced a structure of matrix production as a CPS focusing on logistics aspects. A mathematical model of this in-plant supply process was described including extended and real-time optimization from routing, assignment, and scheduling points of view. The optimization problem described in the model was an NP-hard problem. Heuristics were used to find a suitable solution. Moreover, a sequential black hole-floral pollination heuristic algorithm was described. Liu et al [51] introduced architectural concepts and business model analyses for an innovative intelligent facial mask production model, comprising three modules: in-store service, intelligent logistics, and smart manufacturing. The in-store service module utilized artificial intelligence to enhance customer experience. The intelligent logistics module employed CPS for cloud processing of traffic data, aiming to optimize the transport of facial mask products, reducing both time and costs. The entire process was characterized by high efficiency and full automation, offering customers personalized facial mask production and services. Neal et al [52] showed how returnable transit items can become an integral part of the Industry 4.0 vision as an intelligent container that can interact with components, machines, and other cyber-physical manufacturing services. It discussed a CPS reference architecture for the integration of intelligent containers and presented a hardware and software proof of concept solution suitable for industrial deployments. Lee et al [53] proposed a CPS model for the smart robotic warehouse to implement workflow data collection and procedure monitoring. A decoupled method was presented to find a conflict-free path for the mobile vehicles in the warehouses, after distributing destinations to mobile robots to minimize the total travel distance. Zhang et al [54] systematically analyzed the production management requirements of a large-scale production system in terms of both hardware (production equipment) and software (application system), which was oriented to dynamic production demands, and then proposed a production service system enabled by cloud-based smart resource hierarchy. Bougdira et al [55] introduced the main design features of traceability and its model in Industry 4.0. The study advocated that traceability should not only allow trace and tracking but also ensure product safety and quality. Accordingly, the proposal included an intelligent traceability description, ontology-based modeling, and a cloud-based application. Garrido-Hidalgo et al [56] proposed an end-to-end solution for reverse supply chain management based on cooperation between different IoT communication standards, enabling cloud-based inventory monitoring of electrical and electronic equipment waste through embedded sensors. A case study was deployed using IoT devices and sensors, carrying out a set of experimental tests focused on wireless communications to evaluate its performance. The network configuration adopted overcomes the near real-time challenge and provides sufficient coverage to interconnect industrial areas such as warehouses or shop floors. The results pointed to different communication bottlenecks that needed to be addressed to enhance the reliability of large-scale industrial IoT networks. Queiroz et al [57] identified seven basic capabilities that shape the digital supply chain framework and six main enabler technologies, derived from 13 propositions. The proposed framework could bring valuable insights for future research development. Garay-Rondero et al [58] presented a conceptual model that defines the essential components influencing the evolution of digital supply chains through the implementation and acceleration of Industry 4.0. This shows the diversity of disciplines that were affected by Industry 4.0 with a variety of applications that can be implemented and innovated. However, Industry 4.0 is still in continuous development and the opportunities of using its technology and applications are still a wide-open space.

Moreover, a proposed model of the master production scheduling process of a group of small and medium enterprises was presented as a starting point toward digitalization to find a guide for the digital transformation of manufacturing in the medium-term production planning process [59]. It was identified that the Industry 4.0 technologies could improve medium-term planning and integrate them into a standardized master production schedule process model. Another article [60] presented a multi-objective evolutionary approach based on decomposition for efficiently addressing the multi-objective flow shop problem, which showed the competitiveness of the proposed approach compared with other baseline metaheuristics. Scheduling optimization within in-plant supplying was tackled within different aspects such as the graduation-inspired synchronization framework [61] that showed superiority compared to the others on average and displays minor variations in statistics regarding cost-efficiency, punctuality, and simultaneity measures, indicating that it was more effective, stable, and resilient in stochastic environments, or by a proposed system [62] that presented two-phased solution provided to improve the communication within data heterogeneous networks achieving maximum network throughput. Also, less delay was demonstrated by using a simulation that showed that digital twins and IoT devices could communicate seamlessly in Industry 4.0 networks. Also, smart manufacturing scheduling was identified to set up a conceptual and structured relationship framework to raise the effectiveness of the scheduling process towards better flexibility, through enhanced rescheduling ability, and towards autonomous operation, mainly supported by the use of machine learning technology based on several reviewed contributions [63] from the Industry 4.0 perspective or even Industry 5.0 solutions [3] that served as a starting point for research and development projects and algorithms' developments, which are needed in the field of multi-agent, multistage and inverse optimizations. Also, Industry 4.0 technologies were adopted into optimization models in another application where the new system and mathematical model were described and showed a big advantage. On the other side, a study showed that the benefit of using integrated real-time in the designed models in the scheduling process depended on the proper choice of both the scheduling approach and the solution procedures, and in a few scenarios, this usage was even counterproductive [64], which encourages for further research regarding the design of approaches and solution procedures that allow fully exploiting the technological advances of Industry 4.0 for decision-making in scheduling.

Among the production planning and scheduling, milk-run solution in the logistics field shows a possible approach to achieve more benefits and higher efficiency. This solution was tackled from various perspectives in the research field as it was found in literature. It was discussed as a tool to improve logistics flows processed next to lean production tools in a case study [65]. Among the mentioned conclusions, they reached that manufacturers could become more agile and increase customer service levels while reducing the cost of custom manufacturing by using a milk-run approach. In another study in Turkey [66], an optimization model was presented to minimize the transportation cost by minimizing the travel distance and maximizing vehicle capacities while it tackled a milk-run situation. It was also considered [67] as a solution to minimize carbon emissions and reduce the distribution cost of logistics enterprises, and it was described as a win-win situation for social and economic aspects. In another consideration for forward and reverse milk-run vehicle routing and scheduling, constraints imposed by an in-plant distribution network were modeled [68]. It was used to determine the number and time of transport trips, and the proposed model met the need for alternative and repeated formulation of successive forward and reverse decision problems. Also, in a German automotive component manufacturer [69], a milk-run solution was applied for the collected goods from several suppliers to be transported to an individual customer and the collected goods from a distinct supplier to be delivered to a diverse group of customers. It aimed for a probable opportunity to minimize the procurement cost of the raw materials because the number of trucks used for the transportation of goods was reduced, which reduced the operating cost by saving fuel and time which means increasing the company's profit margin by reducing production costs.

Also, The city logistics area is a rich topic to tackle and research regarding its diverse implementations, especially during recent years because of the numerous innovations in both transportation and Industry 4.0 areas. Renewable energy evolutions in transport vehicles like e-cars create a wide scope to adopt them in the city logistics applications considering the relatively shorter distances in the city logistics area compared to the outside cities. Moreover, Industry 4.0 applications, which depend on the IoT and artificial intelligence support innovating smart solutions to shorten the required time and road distance while collecting and analyzing information at the same time, giving the capacity to examine them. On the other hand, sustainability is a critical topic that is represented in the Sustainable Development Goals such as the 11^{th} goal "sustainable cities and communities" [70], which gives it a priority to be tackled in research. The investigation of reducing the spent power, emissions, and contamination aspects was advised to be researched for its positive influence on the climate and environment. Studying these novel solutions has significantly raised in many aspects showing the importance of applying them. Last-mile logistics is the latest stage of the supply chain, and it involves a particular share of the overall delivery cost and energy. Industry 4.0 applications allowed the possibility of reducing the time of the order execution within the real-time handling of open tasks in the package delivery service providers' network. Therefore, the last mile logistics optimization shows significant potential for researchers, and it creates a challenge for them [71].

Depending on the energy efficiency significance of last mile services that are represented by package delivery service providers, it is expressed that this research area is very valuable. The rising value of resources, cost, and power in supply chain applications and the purpose of detecting design and operation strategies enforced in real-time are strong motivations for researching this area [44]. Real-time intelligent scheduling in the last mile delivery was also presented [40] as a developed methodological approach based on the Industry 4.0 applications. Depending on a systemic literature review [44] that was based on 231 articles, more attention and research were required in the last mile supply area, especially with considering the metaheuristic algorithms for the energy efficiency aspect. The GA was presented as an effective metaheuristic algorithm in many fields [72] such as operation management, scheduling, and inventory control. An important aspect of last mile transportation is RL that is one of its definitions is [73] “the process of planning, application, control of the operation, cost, and flow of raw materials, the inventory process, finished products, the information related, from the point of consumption to the point of origin, to recover or create value or proper disposal”. RL has distinct characteristics, for example, critical uncertainties of time, quality, and quantity supply next to the operations' complexities. A framework founded on the reverse stream of distribution starting from the producer until the user and backward to the producer was proposed [74]. It defined the motivation types mainly as the economic amount, governance legislation, and ecological image while disposal kinds were defined as reuse, repair, recycling, and re-manufacturing. Another framework for RL defined five directions: (1) return causes; (2) reception body; (3) product types and their characteristics; (4) recovery operations and settings, and (5) involved actors and their roles [S1]. To clarify the RL problems and develop solutions, modeling techniques were used [75], but the prime problem is the need for a high number of variables considered. In a study [76], five strategic operators were considered significant for the RL that are environmental concerns, quality, costs, customer service, and political/legal considerations. Also, RL was researched [77] within the composed framework of environmental operators (regulation and environment respect) and business operators (customer satisfaction and returns) [78]. However, a need for further research on the aspects of strategic and organizational frameworks of RL was confirmed [79], which includes integrating the RL in the designed supply system for instance. Considering RL for sustainability aspect was confirmed [S1] as one of the main factors in the city logistics area, particularly from an Industry 4.0 technologies point of view.

1.5. Theoretical background outcomes and aimed scientific gaps

As a summary of the presented literature review, the following points are mentioned:

- The number of articles regarding city logistics has dramatically increased in the last few years. Energy efficiency is becoming more and more important in the field of city logistics, while sustainability aspects are also taken into consideration. Multi-echelon solutions are expected to improve energy efficiency and sustainability of supply chains and city logistics.
- Industry 4.0 technologies are expected to contribute directly to digitalization, full product life analysis, dynamic feedback, and other tools that could achieve more deep and inclusive analysis to reach higher optimization in the investigated systems. Also, last-mile transportation operations are a rich area to research considering its various applications and tools to be adopted especially considering the innovative Industry 4.0 technologies and applications.
- The literature stated various applications of the developed Industry 4.0 technologies in the manufacturing and in-plant supply areas with a high potential of raising the efficiency of energy consumption. This reflects the grand expectations of achieving a positive impact through the adoption of these technologies.
- Using metaheuristic optimization is considered an effective method to optimize the last-mile transportation processes. The GA showed strong optimization results in many areas including the logistics area. Also using the direct lines (not real) distances between the locations was a common way to be used in previous studies.

- While RL takes a primary share of the transportation applications in city logistics, it still requires more research to investigate its results and effects. Also, electric vehicles show promising leverage for raising energy efficiency. However, further research on this adoption and its effects is required to find out deep outcomes.
- The articles that addressed the city logistics from a sustainable point of view focus on conventional supply chain solutions. Few of the articles have aimed to provide an approach or to optimize the design of logistics networks within urban areas while considering energy efficiency.
- Waste management is considered a complex problem with direct and indirect impacts on various aspects such as transportation, environment, economy, social life, urban area planning, and waste treatment, which influence many stakeholders. Also, one of the promising solutions for raising sustainability in waste management is electric vehicles. However, various operational operators, such as limited capacity and distances alongside battery power, pose significant challenges in adopting this solution.
- Waste management optimization research focused mainly on vehicle routing to minimize the total route distance, while energy efficiency and environmental aspects were less commonly tackled. This expresses a research gap to cover, especially with the various available Industry 4.0 tools. Additionally, most articles utilized the distance matrix to calculate the distances, which means that the results cannot be considered realistic.

The identified research gaps to be covered include the following directions:

1. While many studies worked on finding and presenting the benefits of Industry 4.0 technologies in manufacturing and in-plant supply, further research focus and details are expected to be done. Especially, some studies showed contradictory results to what was expected with no clear/direct correlation. Therefore, presenting new models and modeling take a positive part in this direction.
2. There is a need for designing and implementing comprehensive CPS based on Industry 4.0 technologies in city logistics. Mainly in two specific areas. First, waste management system (collection). Second, last mile system (distribution). Also, combined systems that include RL as the applications of logistics systems in city logistics can vary widely.
3. Creation and validation of mathematical modeling that describes and evaluates the logistic systems are needed. Further validation has special importance as well, and this can be done through numerical cases and/or real cases.
4. In-plant logistic supply systems need further investigation regarding the Industry 4.0 technologies adoption effect. Based on such investigation results, further implementation of a comprehensive system is needed to include effective Industry 4.0 technologies in this manner.
5. A scientific gap regarding the actual impact of Industry 4.0 technologies on in-plant supply systems does exist, especially regarding real-time optimization. While the potential positive impact claimed to be shown, validating this impact was limited to specific situations without general studies that showed a full description of the system's structure and mathematical modeling.
6. A scientific gap was found to identify the problem of functional integration for the Manufacturing Execution System (MES) data-based and real-time generated supply demands even though it showed the potential to decrease energy consumption and Greenhouse gases (GHG) emissions.
7. The optimization algorithms witnessed extensive development until reaching the heuristic and meta-heuristic algorithms. However, this development needs deeper analysis and scrutiny.
8. All the mentioned research gap directions are recommended to be analyzed in connection with their impact on sustainability and energy efficiency.

2. OPTIMIZATION ALGORITHMS

Optimization refers to finding the optimal value or best possible option with the given constraints. With optimization, resource utilization can be planned to be the most effective and cost-efficient, especially in the logistics sector where cost and time are both important factors. However, when dealing with complex systems, finding the best solution is considered almost impossible due to the time and resources consumed. Therefore, optimization algorithms are used to find an optimum solution as much as possible within a relatively short time. Optimization algorithms evolved from conventional mathematical approaches to modern developed methods that use heuristic and metaheuristic approaches.
This chapter discusses the optimization algorithms development and differences as they take an essential role in solving complex problems. After an introduction that contains a brief literature review, four of the most used heuristic algorithms are presented in detail. Then, benchmark tests are used to compare their performances. The achieved results of this chapter were published mainly in three articles [S3, S4, S5].

2.1. Introduction

As in life generally and in engineering especially, finding the optimum results is the target, and it is the goal in almost every application, particularly in problem-solving designs where it is attempted to reach the best value. For instance, minimizing energy consumption and cost or maximizing performance, profit, and efficiency. Time, resources, and money make essential limits for the vehicles and transportation area; therefore, optimization is fundamental to be applied in reality [80,81]. Therefore, the appropriate utilization of available assets of any kind requires a paradigm change in logical thinking and designing inventions. Mathematical optimization started with traditional approaches, for instance, linear programming, sequential quadratic programming, Newton-Raphson, interior-point methods, fractional programming, and LaGrange duality. Subsequently, modern approaches were invented that are mainly going to be evolutionary or bioinspired. Some examples of modern approaches contain evolutionary algorithms, swarm intelligence (SI), artificial neural networks, and cellular signaling pathways that are mainly classified as heuristic and metaheuristic algorithms. For instance, GA and SI are being used in many applications [82]. Nevertheless, the logistics area has different direct and indirect applications that aim to optimize target solutions in a short time, mainly by using modern digital technologies, such as CPSs and the IoT that are involved in the newly developed models and these applications gain ground in industrial transformation rapidly in the last few years [83]. Alongside Industry 4.0, other technologically founded industrial processes that aim to improve the industrial process are used, for instance, lean operations, six-sigma, CE, and other smart manufacturing tools and systems [S1]. Those tools and processes are addressed in the context of improving sustainable supply chains, including collaboration, transparency, flexibility, innovation, and capabilities [84]. Optimum results detection is the main objective in the vehicles sector, particularly in problem-solving designs where it is attempted to reach the best value, such as minimizing energy consumption and cost or maximizing the performance, profit, and efficiency [85]. Scientific research in the logistics area has complex and multi-objective cases that are defined as NP-hardness (non-deterministic polynomial-time hardness). These cases are very hard or even impossible to solve in the conventional methods, i.e., the optimization of vehicle routing problems [86] with multi-echelon systems. Heuristic and metaheuristic algorithms (modern algorithms) are becoming more widely used to reach the best optimization results in the shortest time. Furthermore, hybrid algorithms that combine more than one type are also used for the same purposes since they might achieve better results.

As a brief literature review about the optimization algorithms, Shoja et al. [87] presented a hybrid algorithm of the GA and particle swarm optimization (PSO) algorithm for supply chain network design problems with the possibility of direct shipment, and the used algorithm showed superior results. Masood et al. [88] worked on a two-stage heuristic algorithm to enable a cost-efficient delivery for optimizing the material supply to mixed-model assembly lines that contribute to the overall production cost efficiency with reasonable solutions. Another study [89] used a GA to optimize service selection and schedule load balancing. Also, an upgraded firefly algorithm [90] was presented to enhance the performance in solving constrained engineering optimization problems. Bányai et al. [91] presented a mathematical model of just-in-sequence supply and a flower pollination algorithm-based heuristic was used to determine the optimal assignment and schedule for each sequence to minimize the total purchasing cost, which supports improving cost efficiency, and its performance to increase cost-efficiency in just-in-sequence solutions was validated. Inventory control of RL for shipping electronic commerce was presented [92] based on an improved multi-objective particle swarm algorithm, and it showed effective results. Another work [93] presented an algorithm to minimize the traveling distance of the handling machines when moving the cargo from an inbound truck to an outbound truck. This problem that was discussed is known as the cross-dock door assignment problem, and the solution was represented by a modified classical mathematical model.

It is noticed that a few optimization algorithms were used several times within the analyzed articles. To mention three of them; the first one is the ant colony optimization algorithm (ACO), used as a hybrid algorithm. In an article in 2018, a hybrid algorithm of the ant colony optimization metaheuristic and the Floyd-Warshall algorithm was used [94] to minimize pickers' travel distance in manual warehouses. In 2016, a hybrid ACO was used for a closed-loop location-inventory-routing problem [95]. It considered the quality defect returns and the non-deficit returns in the e-commerce supply chain system to minimize the total cost of both forward and RL networks. The second one is swarm optimization. In 2019, a heuristic swarm optimization was used [96] in a low-carbon economy perspective, and it was based on the analysis of the need for optimizing the distribution path of cold chain logistics of agricultural products. This algorithm was improved from a convergence factor, inertia weight, learning factor, and population size. The results showed that the improved algorithm could effectively optimize the distribution path of cold chain logistics of agricultural products. Even though the dolphin swarm algorithm has proved its simplicity and effectiveness, it was falling into local optimization points with high-dimensional function optimization problems [97]. Therefore, chaotic mapping was proposed for the dolphin swarm algorithm, and the chaotic dolphin swarm algorithm was presented to successfully solve high-dimensional function optimization problems. The third one, the GA, was also used in hybrid systems. A study in 2019 [98] provided a comparative analysis of hybrid optimization intelligence models that combined different metaheuristic algorithms like GA, particle swarm optimization, shuffled frog leaping algorithm, and imperialist competitive algorithm. In another research [99], a three-stage supply chain network problem including suppliers, plants, distribution centers, and customers was investigated. This problem as it is a multi-echelon supply chain network, is considered an NP-hard problem, and a metaheuristic based on GA and invasive weed optimization was designed to find the problem solution. The results showed a high efficiency of that proposed approach.

2.2. Heuristic optimization algorithms

Scientific research in the vehicles and transportation area has complex and multi-objective cases that are defined as NP-hardness (non-deterministic polynomial-time hardness). These cases are very hard or even impossible to solve in the conventional methods, i.e., the optimization of vehicle routing problems [86], especially when it uses the multi-echelon system. Heuristic and metaheuristic algorithms (modern algorithms) are becoming more widely used to reach the best optimization results within a brief time. Other developments such as using real distances between the locations were researched [S2]. Furthermore, hybrid algorithms that combine more than one type are also used for the same purposes since they may achieve better results. In an analytical review of modern optimization algorithms [S3], accelerated progress in using the heuristic and metaheuristic algorithms was found in various applications. Based on that, four optimization algorithms: genetic, particle swarm, simulated annealing, and ant colony are to be presented in detail.

2.2.1 Genetic algorithm

The GA is a metaheuristic inspired by the evolution operation and belongs to the major class of evolutionary algorithms in informatics and computational mathematics [100]. These algorithms are used to make high-quality solutions by optimization by focusing on bio-inspired operators such as selection, convergence, or mutations [101]. Starting with John Holland who developed the GA in 1988 based on Darwin's evolutionary theory [102]. Afterward, in 1992, the GA was extended by him as well [103]. This algorithm is considered under the address of evolutionary algorithms, which are utilized to solve problems that are not already efficiently solved. This approach is used widely to solve logistics and supply chain optimization problems (scheduling, shortest path, etc.) that are considered NP problems, and in modeling and simulation, that heuristic approach is used [104]. Every possible solution has a group of characteristics (the phenotype or genes) that are evolved and changed; typically, solutions are encoded in the binary digits as strings of 0s and 1s, however, another codec is also possible. Evolution, in general, begins starting from a collection of random individuals as the consideration of an iterative process for finding the population in each reproduction. For each generation, the fitness of all the individual solutions in the population is measured. Then, with the fitness value, the objective feature is solved [105]. Afterward, the individuals’ fits are chosen sufficiently in a probability way from the existing population, and the gene is modified to make a new generation cycle for all (recombined and randomly with mutated potential). A newer generation of viable solutions would be reached in the next generation of the process. The algorithm usually stops and considers the reached generation as the optimized solution when either a maximum number of generations has been generated or satisfaction has been met [106]. For that reason, every successive generation should be a more suitable solution within the population.

```
GA ():
  Initialize the population.
  Evaluate the initial population fitness.
  while (termination criteria are not satisfied) do
    Select parents from the current population.
    Perform crossover between parents with a probability of pc
  Mutate the new population with a probability pm
  Evaluate the fitness of the new population.
  Find the fittest (best) individual.
end while
```

2.2.2. Particle swarm algorithm

PSO is a metaheuristic algorithm and one of swarm intelligence (SI) optimization algorithms, which use the power of collaboration to solve complex problems [107]. It is easy to implement, good with multi-objective problems, has few parameters for tuning, and is one of the best algorithms to find the maximum or minimum of the function. It is originally attributed to Kennedy and Eberhart in 1995 [108] where the inspiration often comes from nature, it mimics the behavior of biological systems like fishes or a flock of birds. The social interaction concept is used to solve problems. Several particles (agents) constitute a swarm that moves around in search space, looking for the global best solution within the possible solutions in the search space g_{best}. These particles communicate with one another using search directions (gradients) and each particle represents a potential solution to the problem and can remember the best position (solution) it has reached p_{best} [109]. The swarm of particles updates its velocity and position from iteration to iteration, based on equations (1) and (2):

$$v_i(t+1) = \omega v_i(t) + c_1 r_1\big(p_{best} - x_i(t)\big) + c_2 r_2\big(g_{best} - x_i(t)\big) \tag{1}$$

$$x_i(\mathrm{t}+1) = x_i(\mathrm{t}) + v_i(t+1) \tag{2}$$

Where v is the velocity vector, $x(t)$ is the current position of the particle, and $x(t+1)$ is the new position in the next iteration, p_{best} is the best solution this particle has reached; g_{best} is the global best solution of all the particles. ω is a constant (inertia weight), c_1 and c_2 are two constants' weights, and r_1 and r_2 are two random variables (acceleration coefficients) [110].

PSO ():
- Initialize process:
  - Initialize the swarm position "x" and velocity "v" for each particle.
  - Initialize the current best p_{best} and global best g_{best}
- Repeat While (t < Max Iteration)
  - For each particle i:
    - Update its velocity v_i and position x_i by (1), (2)
    - Evaluate the objective function $f(x_i(\mathrm{t}+1))$
    - $p_{best_i} \leftarrow x_i(\mathrm{t}+1)$ If $f(p_{best_i}) > f(x_i(\mathrm{t}+1))$
    - $g_{best} \leftarrow x_i(\mathrm{t}+1)$ If $f(g_{best}) > f(x_i(\mathrm{t}+1))$

2.2.3. Simulated annealing

SA algorithm is one of the oldest and preferred meta-heuristics methods for solving optimization problems. Specifically, for approximating the global optimization in a large search space and avoiding local minima [111]. It is inspired by the annealing of solids, which refers to a concept in physics describing the cooling of a solid until reaching minimal energy. The algorithm starts from a higher initial temperature. When the temperature gradually decreases, the solution tends to be stable [112]. The annealing concept was first developed in statistical mechanics, inspired by the behavior of physical systems in a heat bath [113]. Starting with Kirkpatrick et al. in 1983 [114] and Cerny in 1985 [115], the concept of a general solution approach for optimization problems was introduced. In General, the algorithm starts with an initial solution x, then generates a candidate solution y randomly or using some rule from the neighborhood of x. To decide whether the solution y is accepted or not, the Metropolis acceptance criterion is used, which shows how a thermodynamic system moves from an old state to another new state to minimize the energy [116]. The temperature cooling rate is defined as α, and the acceptance probability is given by the following:

$$p = \begin{cases} 1 & if\ f(x_{new}) < f(x_{old}) \\ exp\left(-\frac{f(x_{new})-f(x_{old})}{T}\right) & if\ f(x_{new}) \geq f(x_{old}) \end{cases} \tag{3}$$

and the temperature cooling schedule is defined as follows:

$$T_{i+1} = \alpha\, T_i \tag{4}$$

SA ():
- Generate an initial solution x_0
- $x_{best} \leftarrow x_0$
- Compute the value of the objective function $f(x_0)$ and $f(x_{best})$
- $T_i \leftarrow T_0$
- while $T_i > T_{min}$ do
  - $X_{new} \leftarrow$ Generate a neighbor candidate.
  - $\Delta f \leftarrow f(x_{new})$ - $f(x_{best})$
  - if Δf < 0 then
    - $x_{best} \leftarrow x_{new}$

        else
                Calculate acceptance probability p by (3)
                if random [0, 1] < p then
                        $x_{best} \leftarrow x_{new}$
                end if
        end if
        Update temperature T by (4)
        $i \leftarrow i + 1$
end while
Return x_{best}

2.2.4. Ant colony optimization

ACO has an easy-to-use context to find rough solutions to difficult optimization problems in the graph such as the shortest path problem. ACO is a stochastic-based metaheuristic method inspired by the foraging behavior of social ants in a colony [117]. Artificial ants are used to reach solutions to combinatorial optimization problems [118]. The ACO's principal idea is for ants to detect shorter routes between their nests and the locations of their food. A chemical substance that is called pheromone is released by the ants to allow communication with each other. While an ant travels, it deposits a specific pheromone amount, so the other ants are possible to follow. Each ant travels on a slightly random route until it enters a pheromone trail where it should decide to follow it or not. If this ant decides to follow this reached trail, the pheromone of this ant reinforces the existing trail. Therefore, the rise of the pheromone increases the probability of another ant selecting this path to follow as well. This leads to the idea that with the higher number of ants that travel on a specific route, attracting other ants to select this route is raised as well. Moreover, an ant that uses a shorter route to reach the food's location would return to the nest faster. With this consideration, further ants would finish the shorter route which means the pheromone would accumulate faster on shorter paths compared to the longer paths that would be less reinforced [119]. Pheromone's evaporation also participates in making the less desirable routes to be more difficult to detect by ants, which means further decreasing their usage in general.

2.3. Optimization Algorithms Benchmarks

The performance of the chosen algorithms "GA, PSO, SA, and ACO" is compared by conducting experiments on five benchmark functions; Python is used for implementing algorithms. The used benchmarks' functions are as follows where D is the number of dimensions.

Ackley function, its formula:

$$f(x) = -20 \exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right) - \exp\left(-\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\right) \tag{5}$$

Non-Continuous Rastrigin function, its formula:

$$f(x) = \sum_{i=1}^{D}(y_i^2 - 10\cos(2\pi y_i) + 10) \tag{6}$$

$$y_i = \begin{cases} x_i & if\ |x_i| < 0.5 \\ \frac{round(2x_i)}{2} & else\ |x_i| \geq 0.5 \end{cases} \tag{7}$$

Alpine function, its formula:

$$f(x) = \sum_{i=1}^{D-1}|x_i \sin(x_i) + 0.1x_i| \tag{8}$$

Griewank function, its formula:

$$f(x) = \frac{1}{4000}\sum_{i=1}^{D} x_i^2 - \prod_{i=1}^{D}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \tag{9}$$

Schwefel 2.22 function, its formula:

$$f(x) = \sum_{i=1}^{D}|x_i| + \prod_{i=1}^{D}|x_i| \tag{10}$$

The comparison is on two bases; the optimized cost considering the average cost that was achieved by the algorithms and the average consumed time for code execution. The global minimum values of the benchmark functions, the corresponding x vectors as well as the lower and upper boundaries of the search space are presented in Table 1.

Table 1: Benchmark functions boundaries

Function name	$x_{i_{min}}$	$x_{i_{max}}$	x^*	$f(x^*)$
Ackley	-32	32	(0, 0, …, 0)	0
Non-Continuous Rastrigin	-5.12	5.12	(0, 0, …, 0)	0
Alpine	-10	10	(0, 0, …, 0)	0
Griewank	-600	600	(0, 0, …, 0)	0
Schwefel 2.22	-10	10	(0, 0, …, 0)	0

The four algorithms were run 20 times on each benchmark. The results of the evaluations were averaged, and the minimum evaluation value was also considered. Generally, the search space x* for any benchmark is continuous (belongs to the set of Real numbers), hence few adjustments had to be made to each algorithm. In the case of GA, both mutation operators and crossover operators had to be replaced. For PSO, no changes had to be applied since its default implementation complies with the search space. For SA, the method for generating the neighbor candidate was altered to conform to the continuous search space. The parameters for the four applied algorithms are as follows:

- GA. Number of iterations: 4000. Population size: 100. Elite size: 30. Mutation probability: 0.01 (1%). Crossover probability: 1.0 (100%). Crossover method: Simulated Binary Cross Over (SBX). Mutation method: Gaussian Mutation. Selection method: Fitness Proportionate Selection.
- PSO. Number of iterations: 3000. Number of particles (agents) in a swarm: 100. Cognitive constant c1: 0.5. Social constant c2: 0.2. Velocity inertia w: 0.98.
- SA. Number of iterations: 20000. Starting temperature: 1000. Stopping temperature: 10-14. Temperature cooling rate α: 0.997.
- ACO. Number of iterations: 500. Number of ants (agents): 50. Pheromone evaporation rate (ρ): 0.5. (β) a parameter for controlling the relative importance of the heuristic (distance) factor on the probability of selection: 2.0. (α) a parameter for controlling the relative importance of pheromones on the probability of selection: 1.0.

Table 2 shows the results of the benchmarks regarding the best cost and average cost of the 20 runs. Table 3 shows the results of the benchmarks regarding the average execution time.

Table 2: Benchmark cost/average cost results

Function name	Best Cost/Average Cost			
	GA	PSO	SA	ACO
Ackley	0.05435/ 0.07113	0.005506/0.03243	5.28125/12.156907	9.0755 E-10 /4.6073 E-09
Non-Continuous Rastrigin	16.25899/20.1494	29.2752/57.0901	212.4601/267.4628	128.9573/191.2994
Alpine	0.19723/0.45004	0.0095/0.80053	26.83422/39.64438	4.1060E-11 /6.9742E-08
Griewank	0.0081/0.06693	0.00202/0.04938	0.82798/0.89061	0/0.02913
Schwefel 2.22	0.2993/0.36172	0.02221/0.1611	28.67485/14655.573	1.47808E-12 /2.06256E-11

Table 3: Benchmark execution time results

Function name	Average execution time (s)			
	GA	PSO	SA	ACO
Ackley	30.8668	21.1457	6.2626	25.5904
Non-Continuous Rastrigin	39.2308	36.8104	4.1272	26.2430
Alpine	31.0246	17.3847	6.246006	25.8337
Griewank	32.1173	24.835	6.2817	25.8969
Schwefel 2.22	29.5942	14.7014	6.2413	24.6301

Based on that, the ACO algorithm achieved the best minimization results across all benchmarks, except for Non-Continuous Rastrigin, where GA had prevailed. On the other hand, a comparison between PSO and GA on the rest of the benchmarks (Ackley, Alpine, Griewank, and Shwefel2.22) shows that PSO attained better minimization results. Considering time efficiency, SA had the fastest average execution time among all algorithms and GA showed the longest average execution time. PSO was the second fastest in all benchmarks except for Non-Continuous Rastrigin, where ACO was the second fastest. The benchmarks revealed that ACO is the best in most optimization benchmarks followed by GA and PSO. However, when it comes to average execution speed across all benchmarks, SA was the fastest. The SA algorithm's efficiency can be attributed to the simplicity of its implementation. Next to the previous point, this could help a lot in the algorithm selection process depending on every case priority. While SA showed unstable results with big differences between the best and average costs, this can be solved by applying repeated runs for SA and selecting the best results when it is in use. These results could be highly effective for selecting the applied algorithm in the applications.

This chapter included the main contribution to Thesis 1. (Chapters 1 and 4 contributed as well).

Thesis 1: Building a comprehensive systematic literature review that presented, analyzed, and summarized the impact of Industry 4.0 in logistics systems in the light of sustainability and green environment. The literature was based on a developed mixed systemic methodology. The presented literature tackled the development and differences of optimization algorithms as they take an essential role in solving complex problems. Therefore, benchmark tests were used to compare and analyze the most used four algorithms' performance. The comparison was on two bases; the optimized average cost achieved by the algorithms and the average consumed time for code execution. Also, an upgrade for GA was presented with an explanation of the used coding system. Furthermore, a case study was solved using the described upgraded GA. [S1, S3, S4, S5, S10, S12].

3. WASTE MANAGEMENT SYSTEM OPTIMIZATION

This chapter discusses and shows the research direction of waste management system optimization as follows. An introduction to waste management that included real data on waste management in Hungary and Europe. Then a proposed CPS for waste collection with its parts and processes. Then, multi-echelon CPS in the city logistics is designed and described. To have a reference, a conventional city logistics solution is presented and described with its mathematical modeling. Then, the mathematical modeling of the multi-echelon collection and distribution optimization system is described and detailed. A numerical analysis is used to compare the two systems and clarify their effectiveness. After that, a further step with CPS for waste management focusing on energy efficiency and sustainability is discussed. The developed mathematical modeling is described. In the end, a VIII district Budapest case study is used to validate the system, for two scenarios of thirty and twenty smart bins. The achieved results of this chapter were published mainly in six articles [S2, S4, S6, S7, S8, S9].

3.1. Introduction

Waste production is an indispensable human process that happens daily in all communities. With the population increase and the industry developments, the waste amounts are growing, and their treating processes are taking a bigger share of the transportation and handling tasks in the city logistics. These waste collection, transportation, and treatment are described as waste management, and it has been investigated and developed, especially with the various applications, solutions, and developments in the logistics, transportation, and industrial areas. Also, with the higher attention to the environmental impact in the different areas, the green aspect of waste management takes more importance, particularly in city logistics where congestion occurs regularly.

The European Union repeatedly formulated aims, plans, and recommendations concerning waste management [120]. A common EU aim is to recycle 65% of municipal waste and 75% of packaging waste by 2030 [121]. The document “General Union Environment Action Program to 2020; Living well, within the limits of our planet” described a waste management hierarchy according to environmental aspects [120–122]:

- prevention,
- reduce waste. To avoid any extra amount of waste,
- reuse. It requires relatively little or no processing where the material can be used again without any structural changes,
- recycling, and waste treatment. It means creating usable raw materials from the waste,
- incineration with energy recovery. The released gases and heat are used for power generating. By the end of this process, the gases are released after purification from any contaminated substances,
- disposal. This method remains the worst option that should be avoided for its long-term affect.

It is possible to describe waste management as the collective process of monitoring, collecting, transporting, treating, recycling, or disposing of waste. This process takes its importance to lighten the negative effects of waste on the health, environment, and public appearance. Waste can be defined as any excess undesirable material, and it can mean rubbish or trash. Waste collection is a main part of the waste management process. It is the process of transferring the waste to the treatment or landfill facility. Waste treatment refers to the needed processes to ensure that waste has the least possible effect on the environment. The waste treatment methods may vary from one country to another [S8]. On the one hand, waste management may be considered as a necessary cost that should be paid to reach a clean environment that is not harmful to the health of inhabitants. On the other hand, other authorities give significant importance to waste management because it saves raw materials resources. Many developed countries implemented successfully waste treatment projects to get benefits from waste like recycling.

Regarding analysis the waste management development, It is observed that there is a shift towards a more holistic approach in the analysis of waste management [123], and reducing environmental impact is the priority for future generations. Waste minimization mechanisms should be implemented as well, taking into consideration the sustainable development principles [122]. Also, sustainable development implementation mustn't cause long-term business disadvantages for companies [124]. Numerous European cities have been using sustainable systems in waste management for a few years, working on optimizing the generated and collected amounts of waste to a minimum. However, the dominant method of waste disposal is landfilling in Hungary [120]. The waste minimization techniques can be used in the waste reduction of municipal waste treatment, but the waste management problem in the European Union is classified by [125]:

- the increase in industrialization and urbanization,
- the increase in the generated waste amount per capita,
- they maintain need of a high level of infrastructure investment (incinerators, landfills, recycling facilities),
- institutional barriers,
- the diversity of interest groups next to the political and legal changes in the field of waste management.

Different waste collection solutions are analyzed in the literature focusing on various aspects of evaluation, like technology, logistics, human resources, policies, and social aspects [17]. The optimal structure of the waste collection system influences the performance of waste collection processes. A Portugal case study shows that strategic expansion plans of waste management companies can be supported by complex mathematical models and heuristic optimization algorithms [126]. The importance of multi-level solutions is highlighted with a three-phase hierarchical approach in the Spanish region of Galicia [127] and Ankara [128]. The authors focused on routing problems and facility location. Waste collection systems show a broad range of uncertainties, for instance, the design of appropriate infrastructure difficulties for waste collection and recycling were described in a Hong Kong case study [129]. Other case studies from Denmark [130], Kampala City [131], Italy [132], and Taiwan [133] demonstrated the importance of new technologies in municipal waste collection systems.

By using the Eurostat Statistics, the statistical office of the European Union, two data imported to be analyzed: the municipal waste management operations [134] and the recycling rate of municipal waste [135]. It should be considered that the collected dataset was based on municipal waste which is produced by households next to other waste sources like commerce, offices, and public institutions. The generated municipal waste amount data includes the collected waste by or on behalf of municipal authorities and disposed of through the responsible waste management system. The municipal waste recycling rate gives a useful indication of the overall waste management system quality. The recycling rate indicator measures the share of recycled municipal waste in the total municipal waste generation. Recycling includes material recycling, composting, and anaerobic digestion. The ratio is expressed in percent (%) as both terms are measured in the same unit, namely tons. The following definitions were introduced within the collected data:

- Incineration expresses thermal treatment of waste in an incineration plant,
- Energy recovery is defined as the incineration that fulfills the energy efficiency criteria,

- Recycling means any recovery operation in which waste materials are reprocessed into products, materials, or substances whether for the original or other purposes,
- Composting and anaerobic digestion are processes of biological decomposition of biodegradable waste under controlled aerobic (composting) or anaerobic conditions,
- Landfill is defined as the deposit of waste into or onto land; it includes specially engineered landfills and temporary storage of over one year on permanent sites.

Based on the presented table [S7] for the annual municipal for 37 European countries from 2014 to 2020. The waste amount in Hungary is relatively the same except for 2020 where it is 6.5% less than the average of 2014-2019. Also, for the annual municipal waste generated in kilograms per capita for the same 37 European countries [S7], it would be easier to compare the numbers in this case. In 2014, Hungary was 24th in the order, while it is 33rd in 2018, which means a waste amount decrease, and that is harmonious with the previous table. On the other hand, the recycling rate of municipal waste as a percentage data was available for only 36 European countries [S7]. Based on the presented table, Hungary had a very slight rise in the recycling rate between 2014 and 2020 taking into consideration that the maximum rate was in 2018. The data showed that Hungary does not have a noticeable increase in the recycling rate in the last few years, which reflects a possibility and need for further research and developments in this area.

3.2. Proposed cyber-physical waste collection system

The collection of household waste is performed in a wide geographical area which means that collection represents a significant part of the whole costs. Waste management systems need up-to-date technical, technological, and logistics solutions to increase efficiency, reliability, and flexibility. The application of Industry 4.0 technologies offers a good opportunity to transfer conventional waste collection and processing systems into a CPS. For that, a new municipal waste collection system based on Industry 4.0 technologies is to be presented. Municipal waste means all kinds of garbage, which results in normal life in residential communities such as houses, apartments, and villas, or places attached to population groups such as supermarkets, shops, grocery stores, and similar places. In another expression, all solid waste related to humans if it has no chemical, biological, or potentially hazardous effects on humans is considered municipal waste. The waste that results from the demolition and construction process, is also municipal waste, but it is not included in this system because it does not exist in inhabited communities, or it only exists as temporary work and the resulting waste should be transferred by special trucks directly to the landfill. This system includes dealing with the waste starting from the source points until the waste treatment facilities. Figure 10 shows the scheme of this proposed system. The system management cloud is connected directly to all the system's parts. As the purpose of this system is to present an initial scheme to show the general concept and possible acquired benefits, the mentioned numbers and techniques were anticipated while the tackled parts are detailed later in the chapter.

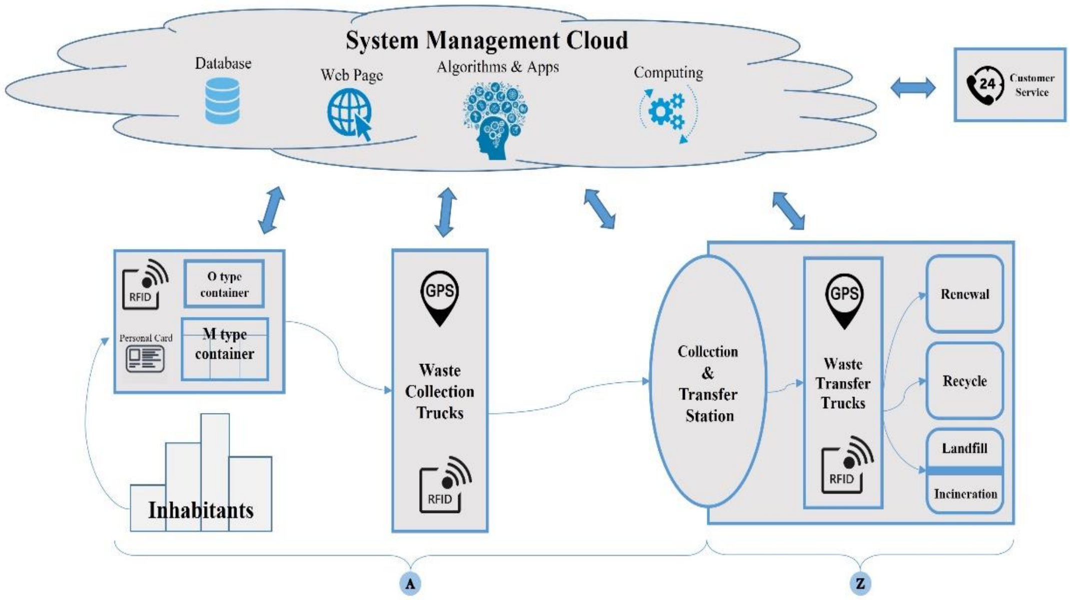

Figure 10: CPS waste collection system scheme

This system can be divided into five parts: containers, treatment facilities, collection and transfer station, trucks, and system management cloud.

1. Containers. Two types of containers are used.

O type, which is used for organic waste. There should be a container for each building with a different capacity depending on the size of the building. This container has a sensor to measure the size of the waste inside it. This sensor can give three different colors as notifications, depending on the amount of waste inside the container. A yellow notification, which means it contains at least 50%, an orange notification, which means it contains at least 75%, and a red notification, which means it contains more than 90%.

M type, which is used for inorganic waste (mixed). There should be a container of this type for each group of buildings where the citizens can throw the inorganic waste directly at them without the need to separate them. The person who wants to throw the waste needs to use his specific ID card. Each user's data is stored on the system's server automatically with the amount of trash he/she has thrown out and the time. Therefore, people who do not have an ID card cannot use this container, to avoid any damage that may result from the dumping of organic garbage or stones for example.

The M container has two parts. The first part is above the ground, which is used by the people to throw the waste inside it directly after using the ID card. The second part is divided into three sections. The first one is for paper and cartons, the second one is for glass and the third one is for electronics and other waste types. After throwing the waste into the first part, the waste is sorted automatically into the suitable section in the second part. Weight measuring, size measuring, and X-rays are possible to be used in the sorting process. The second part is underground and cannot be reached without using a special work ID by the workers, so the container is emptied into the waste collection vehicle by using hydraulic lifting equipment. As O type container, each section in the second part has a sensor to measure the size of the waste inside it. This sensor can give three different colors as notifications, depending on the amount of waste inside the container. A yellow notification indicates at least 50% full, an orange notification indicates at least 75% full, and a red notification indicates more than 90% full.

Both types of containers have active Radio frequency Identification (RFID) to send their information continuously to the system. A notification is also sent to the system every time the containers are emptied, by using the worker’s ID card.

2. Treatment facilities. They are the final stage where the waste is transported to be treated or used in the best manner. These facilities are divided according to the type of waste they deal with into four sections.
Firstly, renewal. In this section, waste is reused or disassembled for useful parts. The most targeted waste here is clothes, electrical, and mechanical equipment. After completion of the dismantling and evaluation phase, any excess material is transferred to one of the other sections when there is enough to fill a full transport truck.
Secondly, recycle. In this section, the raw materials are obtained for recycling, which means reducing the waste amount that needs to be disposed of. The main possible waste here is paper and glass.
Thirdly, incineration. In this section, unusable and non-recyclable materials are collected to be burned; the obtained heat is used to produce energy.
Fourthly, landfill. In this section, the remaining waste is buried after treatment to have faster biodegradation. The gases produced by the biodegradation of organic waste after burying can be collected and utilized.
3. Collection and transfer station. Waste, which comes from containers, is collected at this station depending on the type. Additional sorting is done within this station to avoid any mistake in the type of waste that might happen in the containers. Possible to collect information from gentelligent technology devices in this station.
This station is close to the city to speed up the process of transporting waste and there is no need to be a very large area because the amount of transported waste can be optimized to not exceed a specific percentage based on coming collected waste from the containers and transferred waste to the treatment facilities. The purpose of this station is to organize waste sorting and transport operations. On the other hand, large trucks are used to transport the waste to the treatment facilities as they are relatively far from the city.
4. Trucks. These trucks are dedicated to transport waste and handle loading & unloading waste easily. Two types of trucks are used in this system. Waste collection trucks, to move the waste from the containers to the collection and transfer station. The size of these trucks is suitable to be used for containers unloading and for moving within the city. And waste transfer trucks to move the waste from the collection and transfer station to the treatment facilities. Their size is bigger than the first type to be suitable for transporting waste outside the city faster.
5. System management cloud. All the above-mentioned parts are directly connected to the system management using the internet. Cloud computing is used to store data and deal directly with all the system parts. It also allows administrators to access their accounts for monitoring and guidance, according to their permissions. All data about the transportation, delivery of waste, collection trucks and waste quantities in each part of the system, as well as the records of surveillance cameras are saved. Programs with special algorithms are used to create routes of waste collection trucks according to the waste type and quantities within the containers. In addition, there is available customer service for complaints and remarks at any time, connected to system management.
This was an overview of a cyber-physical municipal waste collection system that optimally serves humanity while preserving time & effort and reducing environmental damage. It is a clear example of applying modern technologies in the field of waste management logistics. The system's structure offers the possibility to modify this system and suit the size of the city. In large cities, more than one system can be applied to suit the required size, such as making more than one collection and transfer station or dividing the city into two, three, or more sections with individually responsible systems that are connected to the management level only. This means centralized and decentralized management simultaneously to achieve greater flexibility. Further details were mentioned about the system mechanism in this article [S8].

3.3. Evaluation of a conventional city logistics solution

In the case of conventional city logistics solutions, the supply of pick-up, and delivery points (households, supermarkets, shops, etc.) is processed directly (Figure 11). However, more and more e-vehicles are adopted in supply chain solutions, but most of the cargo trucks are conventional diesel trucks. Their processes are optimized by the agents of each service provider, but the separated optimization without any cooperation leads to increased fuel consumption and emission. Therefore, an evaluation methodology is shown, which makes it possible to evaluate existing conventional city logistics solutions to define reference parameters for further comparison with the optimized system. Without any cooperation of large service providers and self-employed truck drivers, it is not possible to optimize this conventional solution. The optimization of each service provider is great from their point of view, but it has no significant impact on the emission reduction target. Meeting the targets of zero-emission in urban centers by 2030 [S9] the below-described methodology makes it possible to find the bottlenecks of the system, which can have a great impact on the emission of the urban area.

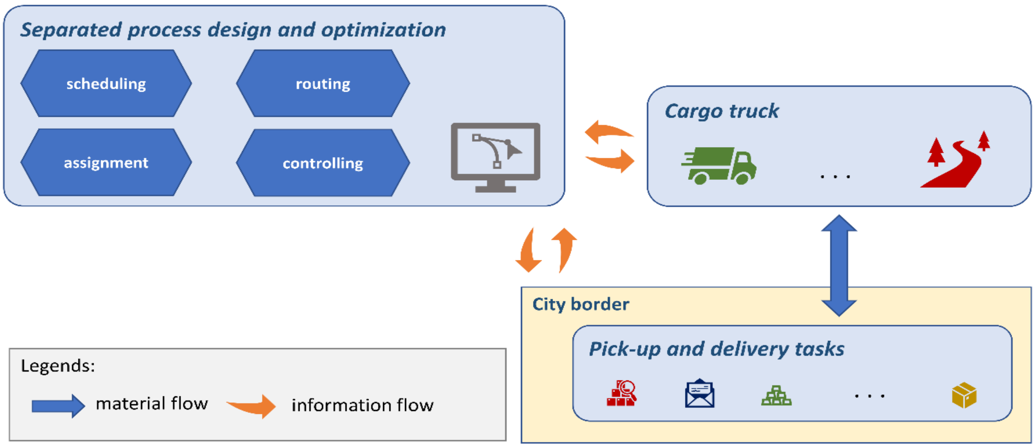

Figure 11: Conventional city logistics solution

The evaluation methodology focuses on time, fuel- and emission-related objective functions, while no capacity, energy, availability, and time-related constraints are taken into consideration because the system is in this case only evaluated and not optimized.

The first parameter of the evaluation is the total length of transportation routes within the period of analysis. The transportation is performed with conventional trucks and no logistics center is taken into consideration for pick-up and delivery operations; all pick-up and delivery are performed by the trucks as direct supply. The parameter of the evaluation, in this case, can be written as follows:

$$L = \sum_{\alpha=1}^{\alpha_{max}} \sum_{\beta=1}^{\beta_{max}^{\alpha}-1} l\left(p_{y_{x^*_{\alpha,\beta}}}, p_{y_{x^*_{\alpha,\beta+1}}}\right) \tag{11}$$

where L is the total length of the transportation routes within the time span of optimization, α is the number of delivery trucks, β_{max}^{α} is the number of pick-up and delivery points assigned to collection route α, $x^*_{\alpha,\beta}$ is the ID number of pick-up and delivery task assigned to route α as pick-up or delivery task β, $y_{x^*_{\alpha,\beta}}$ defines the ID of pick-up or delivery point, $p_{y_{x^*_{\alpha,\beta}}}$ is the position of pick-up or delivery point assigned to route α as pick-up or delivery task β and l is the length of transportation route as a function of positions of pick-up and delivery points.

The second parameter of the evaluation is the fuel consumption, which can be calculated depending on the length of transportation routes, required material handling operations (loading and unloading), and the specific fuel consumption rate:

$$C^{FUEL} = C_T^{FUEL}\left(l, v, c_{\alpha,\beta}^{FT}\right) + C_{MH}^{FUEL}\left(c_{\alpha,\beta}^{FMH}\right) \tag{12}$$

where C_T^{FUEL} is the fuel consumption of the whole transportation process without material handling (loading and unloading), $c_{\alpha,\beta}^{FT}$ is the specific fuel consumption of transportation, C_{MH}^{FUEL} is the fuel consumption of material handling operations at the pick-up and delivery points, $c_{\alpha,\beta}^{FMH}$ is the specific fuel consumption regarding material handling operations and v is the average speed of the truck.
The fuel consumption of the transportation process can be expressed as

$$C_T^{FUEL} = \sum_{\alpha=1}^{\alpha_{max}} \sum_{\beta=1}^{\beta_{max}^{\alpha}-1} l\left(p_{y_{x^*_{\alpha,\beta}}}, p_{y_{x^*_{\alpha,\beta+1}}}\right) \cdot q_{x^*_{\alpha,\beta}} \cdot c_{\alpha,\beta}^{FT}(q_{x^*_{\alpha,\beta}}) \tag{13}$$

where $q_{x_{\alpha,\beta}}$ is the pick-up or delivery volume assigned to route α as pick-up or delivery task β.
The specific fuel consumption of the transportation process can be calculated as follows:

$$c_{\alpha,\beta^*}^{FT} = c_{\alpha,min}^{FT} + \frac{c_{\alpha,max}^{FT} - c_{\alpha,min}^{FT}}{c_{\alpha,max}^{FT}} \cdot (q_{\alpha max}^{TRANS} - \sum_{\beta=1}^{\beta^*} q_{x^*_{\alpha,\beta}}) \tag{14}$$

where $c_{\alpha,min}^{FT}$ and $c_{\alpha,max}^{FT}$ are the lower and upper limit of fuel consumption of transportation depending on the weight of loading and $q_{\alpha max}^{TRANS}$ is the upper limit of the loading weight.
The fuel consumption of the loading and unloading operations performed by the truck mounted crane can be given by

$$C_{MH}^{FUEL} = \sum_{\alpha=1}^{\alpha_{max}} \sum_{\beta=1}^{\beta_{max}^{\alpha}} c_{\alpha,\beta}^{FMH}(q_{x^*_{\alpha,\beta}}) \tag{15}$$

The specific fuel consumption of material handling processes can be calculated as follows:

$$c_{\alpha,\beta}^{FMH} = c_{\alpha,min}^{FMH} + \frac{c_{\alpha,max}^{FMH} - c_{\alpha,min}^{FMH}}{c_{\alpha,max}^{FMH}} \cdot (q_{\alpha max}^{MH} - q_{x^*_{\alpha,\beta}}) \tag{16}$$

where $c_{\alpha,min}^{FMH}$ and $c_{\alpha,max}^{FMH}$ are the lower and upper limit of fuel consumption of material handling depending on the weight of loading and $q_{\alpha max}^{MH}$ is the upper limit of the material handling weight.
The third parameter of the evaluation is the emission, which can be calculated depending on the fuel consumption:

$$E^r = E_{TRANS}^r\left(l, v, c_{\alpha,\beta}^{FT}\right) + E_{MH}^r\left(c_{\alpha,\beta}^{FMH}\right) \tag{17}$$

where E^r is the total emission in the time span of the optimization for emission type r (CO2, NOx, CO, HC, PM, SO2).
The emission of the transportation and material handling process can be described by Equations (18-19):

$$E_{TRANS}^r = \sum_{\alpha=1}^{\alpha_{max}} \sum_{\beta=1}^{\beta_{max}^{\alpha}-1} l\left(p_{y_{x^*_{\alpha,\beta}}}, p_{y_{x^*_{\alpha,\beta+1}}}\right) \cdot c_{\alpha,\beta}^{FT} \cdot e_{\alpha,\beta}^r(c_{\alpha,\beta}^{FT}) \tag{18}$$

$$E_{MH}^r = \sum_{\alpha=1}^{\alpha_{max}} \sum_{\beta=1}^{\beta_{max}^{\alpha}} c_{\alpha,\beta}^{FMH}(q_{x^*_{\alpha,\beta}}) \cdot e_{\alpha,\beta}^r(c_{\alpha,\beta}^{FMH}) \tag{19}$$

For the mentioned system, the following conventional city logistics problem is analyzed and evaluated. There are 25 pick-up and delivery points in the downtown area, where five delivery trucks collect and distribute various types of goods (e.g., package delivery, waste collection). The positions of the delivery points, the weight and loading/unloading time of goods at each pick-up and delivery points are known (see Table 4 and Table 5).

Table 4: Positions of pick-up and delivery points (test data)

PID	Coordinates		PID	Coordinates		PID	Coordinates		PID	Coordinates	
ID[1]	x	y	ID[1]	x	y	ID[1]	x	y	ID[1]	x	y
1	3.745	5.905	2	4.444	5.629	3	5.052	5.187	4	5.532	4.608
5	5.852	3.928	6	5.993	3.191	7	5.947	2.441	8	5.715	1.725
9	5.313	1.091	10	4.766	0.575	11	4.108	0.212	12	3.381	0.024
13	2.628	0.023	14	1.901	0.208	15	1.241	0.569	16	0.692	1.083
17	0.288	1.716	18	0.054	2.431	19	0.005	3.181	20	0.144	3.919

21	0.462	4.601	22	0.941	5.181	23	1.547	5.624	24	2.245	5.903
25	2.991	5.999	REF[2]	5.800	6.200	-	-	-	-	-	-

[1]PID ID = Pick-up or delivery point identification number. [2]REF = Reference point, from where the supply chain process is evaluated.

There are 5 delivery routes within the time span of analysis, the capacity of each delivery truck is 400 LU (loading unit). Each delivery route includes six pick-up or delivery points excluding reference points. The fuel consumption of the trucks is between 41 and 52 L/km depending on the weight of the load, while I am calculating with an average speed of 25 km/h in the downtown area. Loading and unloading operations are processed by truck-mounted cranes, which have an energy consumption between 25 and 37 L/loading per hour depending on the weight of loading.

Table 5: Weight of goods to pick-up or delivery (test data)

PID ID[1]	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Weight[2]	-13	-23	-43	-26	-65	-38	51	31	12	-31	-12	24	42	-23	62
LUT[3]	1.2	1.8	1.8	3.0	2.4	2.4	1.2	3.0	2.1	2.4	3.6	1.5	2.4	6.0	3.6
PID ID[1]	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Weight[2]	27	45	6	56	-42	32	34	55	-21	20	43	92	34	10	12
LUT[3]	2.4	3.0	2.1	1.8	3.0	2.4	1.2	12	18	6.0	3.0	2.4	2.4	2.1	18

[1]PID ID = Pick-up or delivery point identification number. [2]Positive values represent delivery points, negative values represent pick-up points. [3]Loading/unloading time.

The pick-up and delivery routes are optimized by each service provider without any cooperation. It means that within the frame of this scenario, there is no further optimization performed, the results of the analysis of this scenario are used as reference parameters for the later optimization.
As an example, the calculated parameters regarding transportation time, fuel consumption, and emission of route 1 are shown in Figure 12 and Figure 13. The first service provider is a municipal waste collection provider using a garbage collection truck. It means that its route is a simple collection route with pick-up points. Its collection route is 19.04 km, the total collection time is 0.97 hours, while the energy consumption is 12.48 L fuel (see Figure 12).

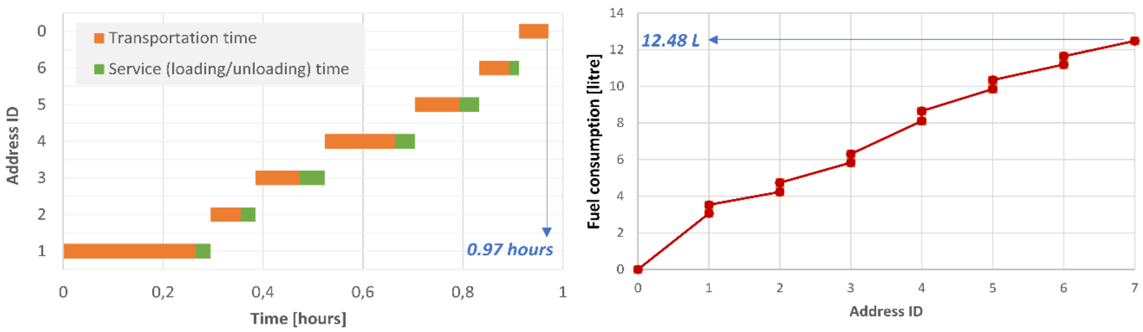

Figure 12: Total transportation time and energy consumption of route 1

The emission of diesel consumption can be calculated by [136]. In the case of the first collection route, the CO2 emission is 33624 g, the NOx emission is 148 g, the CO emission is 37.5 g, the HC emission is 14.9 g, the PM emission is 1.25 g, and the SO2 emission is 0.99 g.

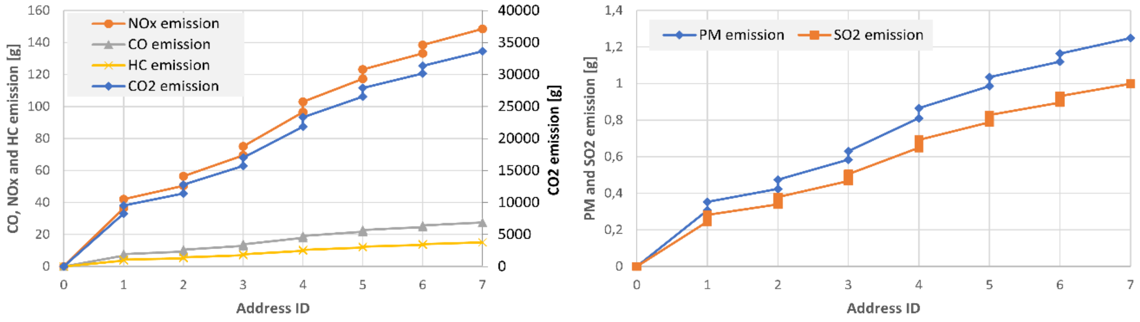

Figure 13: Emission of garbage collection truck in scenario 1

The values of the parameters calculated for the other 4 routes (route 2-5) and the summarized values for scenario 1 are shown in Table 6.

Table 6: Reference parameters were calculated in scenario 1

Route ID	Time			DIS[3]	Fuel consumption			Emission[4]					
	TR[1]	M[2]	Total		TR[1]	M[2]	Total	CO_2	NO_x	CO	HC	PM	SO_2
1	0.76	0.21	0.97	19.04	9.56	2.92	12.48	33624	148	37.5	14.9	1.25	0.99
2	0.75	0.23	0.98	18.92	9.03	2,35	11.38	30656	135	25.0	13.6	1.13	0.91
3	0.77	0.33	1.10	19.41	9.82	2.18	12.00	32354	143	26.4	14.4	1.20	0.96
4	0.77	0.64	1.41	19.41	9.84	2.27	12.11	32637	144	26.6	14.5	1.21	0.96
5	0.83	0.56	1.39	20.87	10.68	2.08	12.76	34382	152	28.1	15.3	1.27	1.02
Total	3.88	1.97	5.85	97.65	48.93	11.80	60.73	163653	722	143.6	72.7	6.06	4.84

[1]TR = Transportation time [hours]. [2]M = Materials handling time [hours] (loading/unloading). [3]DIS = Distance [km]. [4]Emission [g].

3.4. Multi-echelon collection and distribution optimization system

An optimization methodology for a multi-echelon city logistics solution is described. The external logistics service providers are transporting goods to/from logistics centers located outside of the urban area (city border). The collection and distribution of goods to/from pick-up and delivery points are processed from this intermediate storage directly by e-trucks and micro-mobility e-vehicles (Figure 14). The optimization of the whole process is centralized. It means that in this case there is strong cooperation among transportation resources and not only the fuel consumption but also the emission of various greenhouse gases can be reduced. The intelligent agent optimizes scheduling, assignment, routing layout design, and controlling tasks that focus on time, distance, energy consumption, and emission-related objective functions, while capacity, availability, suitability, time-window, energy, and service level related constraints can limit the optimal solution. This scenario focuses on an e-vehicle-based solution, where the efficiency of the whole system can be increased by using existing Industry 4.0 technologies, like smart devices, radiofrequency identification, digital twin solutions, and cloud and fog computing to solve big data problems of a large-scale system including a wide range of users, transportation resources and goods.

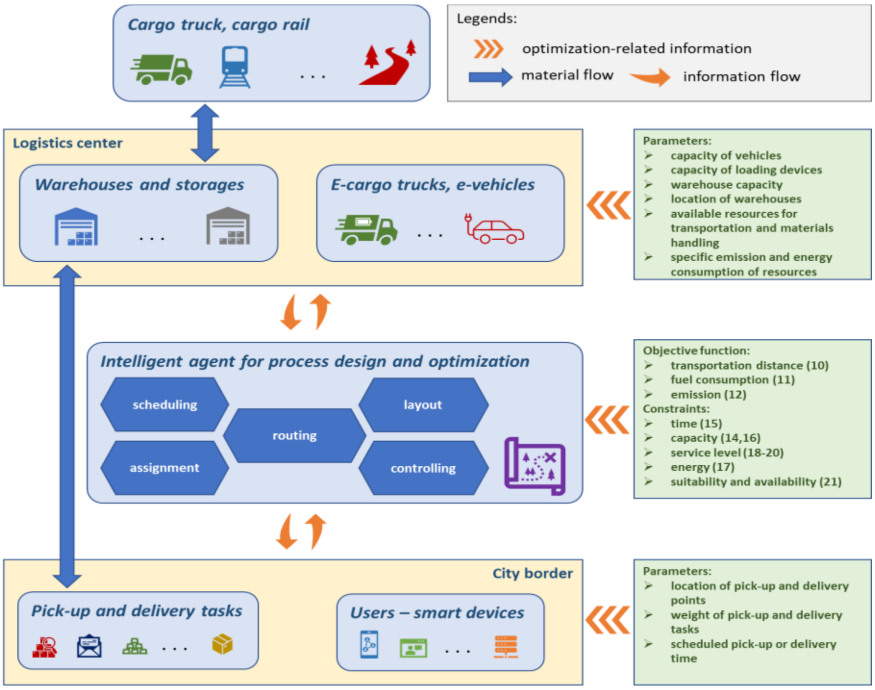

Figure 14: Model of multi-echelon collection and distribution system in downtown areas

The following parameters are taken into consideration as input parameters of the optimization task regarding the city area, including locations and tasks: location of pick-up and delivery points, the weight of pick-up and delivery tasks, upper- and lower-time limits for pick-up and delivery tasks. The following input parameters are linked to the logistics center: the capacity of loading devices, warehouse capacity, location of warehouses, available resources for transportation and materials handling, specific emission, and energy consumption of resources. These parameters are extensively discussed after the equations.

The first objective function is the minimization of the total length of transportation routes which can be based on Equation (10):

$$L = \sum_{\alpha=1}^{\alpha_{max}} \sum_{\beta=1}^{\beta_{max}^{\alpha}-1} l\left(p_{y_{x_{\alpha,\beta}}}, p_{y_{x_{\alpha,\beta+1}}}\right) \to min. \tag{20}$$

where $x_{\alpha,\beta}$ is the decision variable of the optimization problem.

The second objective function is the minimization of the fuel consumption, which can be given like Equation (2) by

$$C^{eFUEL} = \sum_{\alpha=1}^{\alpha_{max}} \sum_{\beta=1}^{\beta_{max}^{\alpha}-1} l\left(p_{y_{x_{\alpha,\beta}}}, p_{y_{x_{\alpha,\beta+1}}}\right) \cdot q_{x_{\alpha,\beta}} \cdot c_{\alpha,\beta}^{eFT}(q_{x_{\alpha,\beta}}) + \sum_{\alpha=1}^{\alpha_{max}} \sum_{\beta=1}^{\beta_{max}^{\alpha}} c_{\alpha,\beta}^{eFMH}(q_{x_{\alpha,\beta}}) \to min. \tag{21}$$

where C^{eFUEL} is the energy consumption of e-trucks and micro-mobility vehicles in kWh.

The specific fuel consumption can be calculated by Equation (12) and Equation (16). The third objective function is the minimization of CO2, NOx, CO, HC, PM, and SO2 emission, which can be written like Equation (17):

$$E^{r} = \sum_{\alpha=1}^{\alpha_{max}} \sum_{\beta=1}^{\beta_{max}^{\alpha}-1} l\left(p_{y_{x_{\alpha,\beta}}}, p_{y_{x_{\alpha,\beta+1}}}\right) \cdot c_{\alpha,\beta}^{eFT} \cdot e_{\alpha,\beta}^{r} + \sum_{\alpha=1}^{\alpha_{max}} \sum_{\beta=1}^{\beta_{max}^{\alpha}} c_{\alpha,\beta}^{eFMH}(q_{x_{\alpha,\beta}}) \cdot e_{\alpha,\beta}^{r} \to min. \tag{22}$$

where $c_{\alpha,\beta}^{eFT}$ is the specific energy consumption of e-trucks and micro-mobility vehicles in kWh/LUkm (LUkm = loading unit kilometer) and the emissions depends on the e-fuel consumption:

$$e_{\alpha,\beta}^{r} = e_{\alpha,\beta}^{r}(c_{\alpha,\beta}^{eFT}) \text{ and } e_{\alpha,\beta}^{r} = e_{\alpha,\beta}^{r}(c_{\alpha,\beta}^{eFMH}) \tag{23}$$

The above-mentioned optimization problem is limited by some constraints. The first constraint is a capacity-related constraint, which defines that it is not allowed to exceed the loading capacity of the available e-trucks and micro-mobility vehicles (e-cargo bikes, e-cargo scooters, or cargo drones):

$$\forall \alpha\colon \max\left(q_{x_{\alpha,1}}, \sum_{\beta=1}^{2} q_{x_{\alpha,\beta}}, \sum_{\beta=1}^{3} q_{x_{\alpha,\beta}}, \cdots \sum_{\beta=1}^{\beta_{max}^{\alpha}} q_{x_{\alpha,\beta}}\right) \leq Q_{\alpha}^{Tmax} \tag{24}$$

where Q_{α}^{Tmax} is the loading capacity of vehicle α.

The second constraint defines that all pick-up and delivery operations must be performed within a given time span:

$$\forall k\colon (\exists \alpha, \beta) \rightarrow x_{\alpha,\beta+1} = k \tag{25}$$

The third constraint defines that it is not allowed to exceed the capacity of the available loading resource (mounted loading crane or human resource):

$$\forall \alpha, \beta\colon x_{\alpha,\beta} > 0 \rightarrow q_{x_{\alpha,\beta}} \leq Q_{\alpha}^{Lmax} \tag{26}$$

where Q_{α}^{Lmax} is the capacity of the available loading resource of transportation device α.

The fourth constraint defines that it is not allowed to exceed the available energy of e-truck and micro-mobility vehicles:

$$\forall \alpha\colon C_{\alpha,\beta_{max}^{\alpha}}^{eFUEL} \leq C_{\alpha}^{eFUELmax} \tag{27}$$

where $C_{\alpha,\beta_{max}^{\alpha}}^{eFUEL}$ is the energy consumption of e-truck α passing the last pick-up or delivery point assigned to route α and $C_{\alpha}^{eFUELmax}$ is the available energy of e-truck α.

The fifth constraint defines that the utilization of available e-trucks and micro-mobility vehicles must be as equal as possible to increase the flexibility of the system:

$$\sum_{\alpha=1}^{\alpha_{max}} |\bar{\eta} - \eta_{\alpha}| \rightarrow min. \tag{28}$$

where η_{α} is the utilization of the e-truck, which can be written as follows:

$$\forall \alpha\colon \eta_{\alpha} = \frac{1}{Q_{\alpha}^{Tmax}} \cdot \max\left(q_{x_{\alpha,1}}, \sum_{\beta=1}^{2} q_{x_{\alpha,\beta}}, \sum_{\beta=1}^{3} q_{x_{\alpha,\beta}}, \cdots \sum_{\beta=1}^{\beta_{max}^{\alpha}} q_{x_{\alpha,\beta}}\right) \tag{29}$$

and $\bar{\eta}$ is the average utilization of e-vehicles, which can be calculated by

$$\bar{\eta} = \frac{1}{\alpha_{max}} \cdot \sum_{\alpha=1}^{\alpha_{max}} \eta_{\alpha} \tag{30}$$

The sixth constraint defines that the pick-up and delivery tasks can be processed only with suitable vehicles:

$$\forall k\colon s_{k,\alpha} = 0 \rightarrow x_{\alpha,\beta} = 0 \text{ otherwise } x_{\alpha,\beta} \in (0,1) \tag{31}$$

where $s_{k,\alpha}$ is the suitability parameter; if $s_{k,\alpha} = 1$ then e-vehicle α is suitable to process pick-up or delivery task k, otherwise not.

Next, the following multi-echelon city logistics problem is analyzed and evaluated. There is a logistics center outside the city border and e-vehicles are available to perform pick-up and delivery tasks. The 25 pick-up and delivery points in the downtown area and the 30 pick-up and delivery tasks are the same as in a conventional solution. The positions of the delivery points, the weight and loading/unloading time of goods at each pick-up and delivery points are known (see Table 4 and Table 5). Table 7 shows the suitability matrix, which is an assignment matrix among e-vehicles and pick-up or delivery tasks.

Table 7: Suitability of vehicles to perform pick-up and delivery tasks

PID ID[1]	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
GT[2]	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
e-T A[3]	0	0	0	0	0	0	1	0	1	1	1	0	0	1	1
e-t B[3]	0	0	0	0	0	0	1	1	0	0	0	0	1	0	1
e-t C[3]	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0
PID ID[1]	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
GT[2]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

e-T A[3]	1	1	0	0	1	1	0	0	0	1	0	1	1	0	0
e-t B[3]	1	0	1	1	0	1	1	1	1	0	0	0	0	1	1
e-t C[3]	0	0	1	1	1	0	1	1	1	1	1	0	1	1	1

[1]PID ID = Pick-up or delivery point identification number. [2]GT = garbage truck. [2]e-T = e-truck for general transportation purposes.

Other input parameters of the optimization problem regarding the e-vehicles, like capacity, specific energy consumption, are shown in Table 8.

Table 8: Energy consumption and capacity parameters of e-vehicles

Vehicle	Energy consumption Transportation [kWh]		Energy consumption Loading/unloading [kWh]		Capacity [LU]	
	min	max	min	max	TRANS[1]	MH[2]
GT[3]	20	41	14	22	300	80
e-T A[4]	11	18	12	17	350	100
e-t B[4]	12	19	11	16	380	70
e-t C[4]	9	18	10	15	240	60

[1]TRANS = Transportation. [2]MH = material handling, loading, unloading. [3]GT = garbage truck. [4]e-T = e-truck for general transportation purposes.

The mentioned results next to further details mentioned in [S9] show that by using oil-based energy generation sources, 88% emission reduction can be reached. These reduced rates in the case of the same scenario taking other energy generation sources, like coal, photovoltaic, wind, or water into account. Therefore, adoption of e-vehicles in city logistics solutions appears to be progressing faster than expected. City logistics processes based on e-vehicles lead to decreased fuel consumption and emission, while the availability and flexibility can be increased. Energy efficiency, sustainability, and emission reduction have been extensively researched in all fields of logistics. Also, the transformation of conventional city logistics solutions into an e-vehicle based multi-echelon supply chain significantly decreases energy consumption and emission, while service level and flexibility are likely to be increased. Depending on the source of electric energy generation, different emission reductions can be realized.

As a managerial impact, the application of the above-described methodology can support managerial decisions regarding the logistics center, the adoption of various e-vehicles, and micro-mobility vehicles, or the operation strategy of the whole supply chain. I can summarize the conclusions and research implications as follows:

The development of new city logistics solutions must be based on the performance evaluation of available conventional systems. A new methodology was developed for the evaluation of conventional city logistics solutions to calculate time-, distance-, energy consumption-, and emission-related performance parameters.

Designing and operating sustainable city logistics systems are great challenges for researchers because of the complexity of city logistics solutions, especially in the case of CPSs led to NP-hard optimization problems, where the application of heuristic and metaheuristic solutions is unavoidable. A mathematical model was developed to support the design and optimization of a multi-echelon city logistics solution. The model takes capacity, timeliness, suitability, availability, and energy-related constraints into consideration.

The comparison and the computational results of conventional and multi-echelon e-vehicle-based city logistics solutions show that the multi-level supply chain and the application of e-vehicles have a great impact on costs, energy efficiency, emission, and service level. The emission rates are based on well-to-wheel analysis, where the production and transportation of primary fuel, production and transportation, and road fuel are taken into consideration [S9].

3.5. CPS for waste management focusing on energy efficiency and sustainability

3.5.1. Introduction

Using a multi-echelon system in city logistics creates an advantage by raising the efficiency of distribution tasks [S8]. A further step is taken for a two-echelon cyber-physical waste collection system as illustrated in Figure 15. The collection and transfer station is the connection point between the two echelons. The first echelon starts from the smart waste bins that provide real-time waste amounts using the IoT to the collection and transfer station where the waste is stored, organized, and/or separated. This station gives the system the required flexibility by identifying its task and location depending on the situation being tackled. The smart bin's sensor is represented by the colors green, orange, and red depending on the waste percentage. Green means the percentage is higher than 50%, orange means the percentage is higher than 70%, and red means the percentage is higher than 90%. The second echelon starts from the collection and transfer station to the treatment facility, where the waste is processed. The treatment facility varies from landfilling to other types such as recycling, dismantling, or incineration. The system components for waste collection, transportation, and treatment are directly connected to cyber management, where data is stored, and computing processes are executed.

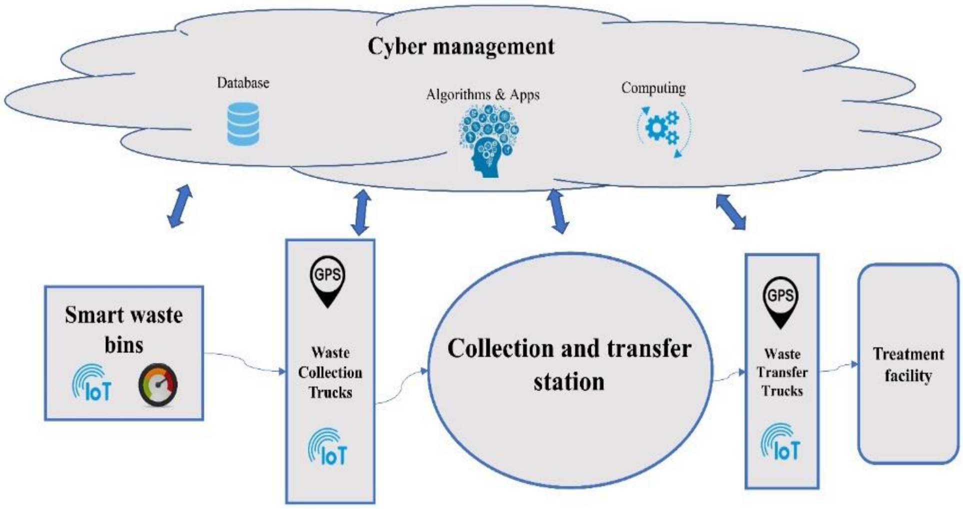

Figure 15: Cyber-physical waste management system scheme

Many collection and transfer stations may exist in the system depending on the urban area as each station covers a relatively small area. In a small urban area, it is possible to have one collection and transfer station. Each station's location and tasks are adjustable based on the specific case. For instance, waste trucks can park in that station, so it would be their start-off location. Figure 17 shows the information and waste flow in the designed system.

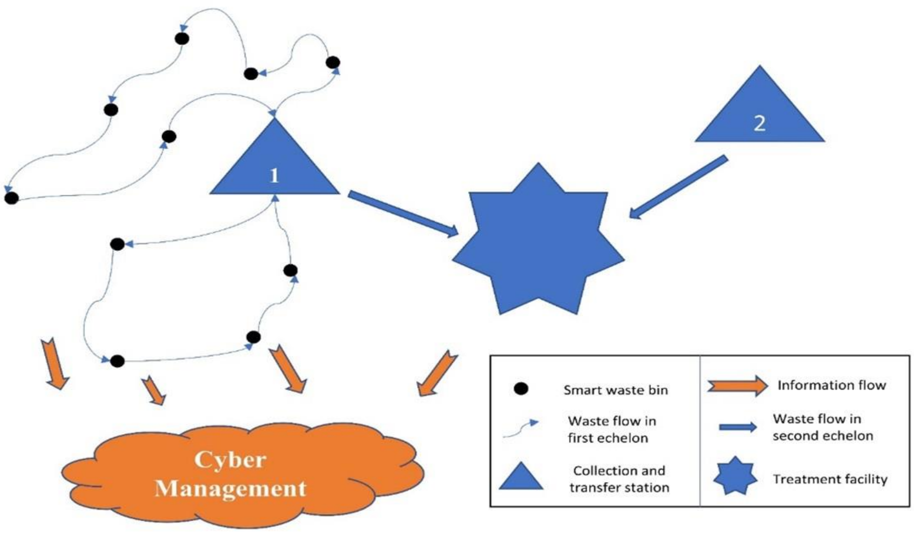

Figure 16: Information and waste flow

The collection and transfer station's tasks vary from waste storage to waste separation and/or dismantling, which reflects higher flexibility and potential. For instance, it is possible to ignore some of the stations depending on the smart waste bins' percentages and locations when it is more effective to do so or due to operational needs. This first echelon is tackled in detail within with the implementation of collecting waste up to the collection and transfer station. All bins with a waste percentage of less than 50% were ignored. The waste collection process was also carried out in a specific time span. The routes and time taken were calculated using Open Route Service, which was developed by HeiGIT gGmbH [137]. It gives the required real distances and time in which vehicles move between given locations.

3.5.2. Developed mathematical modeling

The vehicle routing problem (VRP) addresses the operation of serving a set of customers in reduced travel distance routes by starting in and returning to the same location [138]. The VRP is also known as the node routing problem (NRP), and it has been the focus of much research attention in many applications, including but not limited to waste collection. However, some researchers consider the waste collection problem to be an arc routing problem (ARP). The main difference is that in the arc routing problem, the focus is on the routes instead of nodes because the vehicle/vehicles carry out the service while traversing the routes. In other words, in the waste collection problem, from an arc point of view, the customers are located along the routes, not at the nodes [139]. However, this was not the case here, since there was a specific set of smart bins with known locations that should have been serviced/emptied; hence, the VRP model was chosen. Moreover, in certain cases, the density of the points along a street is so large that the natural way to approach the corresponding routing problem is to adopt the ARP instead of the VRP [140]. Such cases did not apply here, where the locations of the bins were sparsely scattered around the city.

The capacitated vehicle routing problem (CVRP) is an extension of the VRP with capacity constraints. The CVRP in solid waste collection is defined as collecting waste from a set of bins by a homogeneous or heterogeneous fleet of trucks with fixed capacities that cannot be violated; each of them starts from and returns to the same point [141]. The CVRP model is explained below, where n is the number of smart bins and m is the number of trucks, with the set of homogeneous trucks defined as $K = \{1, 2, \dots, m\}$, each of which is initially stationed at the collection and transfer station. The index set $I = \{1,2, \dots, n\}$ corresponds to the smart bins, where $i, j \in I$, and $i = 0$ corresponds to the start point location. Each smart bin contains a non-negative waste quantity q_i, and a non-negative value D_{ij} represents the real distance from bin i to bin j, where $i \neq j$.

The CVRP model considered both the capacity of the trucks and the smart bins, where:

- C represents the maximum waste capacity that each of the trucks can transport along their specified routes.
- Q represents the maximum waste capacity that can be carried by the truck's mounted crane during material handling operations.
- q_{max} refers to the maximum capacity that each smart bin can hold.
- Additionally, the model also imposes a time limit, where:
- T_{max} represents the maximum allocated time for the whole waste collection process.
- t_k corresponds to the time taken by truck k to complete its assigned route and return to the collection and transfer station.

The objective function is to minimize the total energy consumption (TE) of the used trucks in kWh during the waste collection and transportation, which is calculated depending on the route length, required material handling operations (waste loading), and specific fuel consumption rate [S9]. The model includes two decision variables. First, X_{ijk} is defined as 1 if vehicle k moves from bin i to bin j; otherwise, it is 0. Second, Y_{ik} is defined as 1 if bin i belongs to the route of vehicle k; otherwise, it is 0.

The total energy function is expressed as follows:

$$\mathrm{TE} = E_T + E_{MH} \tag{32}$$

where E_T is the energy consumption of the transportation process and E_{MH} is the energy consumption of material handling (waste loading) operations at the bins' locations. The energy consumption of the transportation process is:

$$E_T = \sum_{i=0}^{n} \sum_{j=1}^{n} \sum_{k=1}^{m} D_{ij}\, X_{ijk}\, c_{i,k}^{FT} \tag{33}$$

where $c_{i,k}^{FT}$ is the specific fuel consumption of the transportation process that is calculated as:

$$c_{i,k}^{FT} = c_{kmin}^{FT} + ((c_{kmax}^{FT} - c_{kmin}^{FT})/c_{kmax}^{FT})q_{ik}/((q_{ik}/c_{kmax}^{FT}) + C - q_{ik}) \tag{34}$$

where c_{kmin}^{FT} and c_{kmax}^{FT} are the lower and upper bounds of the specific fuel consumption of transportation depending on the loading waste weight, and q_{ik} represents truck k waste load after moving from bin i.

The energy consumption of the waste loading operations performed by the truck's mounted crane is given by:

$$E_{MH} = \sum_{i=1}^{n} \sum_{k=1}^{m} c_{i,k}^{FMH} \tag{35}$$

where $c_{i,k}^{FMH}$ is the specific fuel consumption of material handling operations that is calculated as:

$$c_{i,k}^{FMH} = c_{kmin}^{FMH} + ((c_{kmax}^{FMH} - c_{kmin}^{FMH})/c_{kmax}^{FMH})q_i/((q_i/c_{kmax}^{FMH}) + Q - q_i) \tag{36}$$

where c_{kmin}^{FMH} and c_{kmax}^{FMH} are the lower and upper bounds of the specific fuel consumption of material handling operations depending on the loading waste weight, and q_i is the waste quantity of bin i.

The optimization model, which aims to minimize the total energy consumption, is described in Equation (37) and is formulated as follows:

$$minimize\ (E_T + E_{MH}) \tag{37}$$

Subject to the following constraints:

$$\sum_{j=1}^{n} \sum_{k=1}^{m} X_{0jk} = 1 \tag{38}$$

$$\sum_{j=1}^{n} q_{0jk} = 0 \ \ \forall k \in K \tag{39}$$

$$\sum_{i=0}^{n} \sum_{k=1}^{m} X_{ijk} = 1 \ \ \forall j \in \mathrm{I}. \tag{40}$$

$$\sum_{j=1}^{n} X_{ijk} = \sum_{j=1}^{n} X_{jik} = Y_{ik} \ \ \forall i \in I;\ k \in K. \tag{41}$$

$$\sum_{i=0}^{n} \sum_{k=1}^{m} q_{jik} - \sum_{i=0}^{n} \sum_{k=1}^{m} q_{ijk} = c_j \ \ \forall j \in I. \tag{42}$$

$$\sum_{i=1}^{n} c_i X_{ijk} \le C \ \ \forall j \in I;\ k \in K. \tag{43}$$

$$\sum_{i=1}^{n} \sum_{k=1}^{m} X_{i0k} = 1. \tag{44}$$

$$\sum_{i=1}^{n} q_i \le 0.9 \sum_{k=1}^{m} C_k. \tag{45}$$

$$max(t_1, t_2, \dots t_m) < T_{max}. \tag{46}$$

$$100\, q_i/q_{max} \ge 50\ \forall\ i \in I. \tag{47}$$

where q_{ijk} represents the waste load amount picked up by truck k when moving from bin i to bin j. Equations (38) and (39) specify that truck k starts the tour from the start point carrying no load. Equation (40) states that each bin is visited by only one vehicle. Equation (41) ensures the continuity condition. Equation (42) ensures that the vehicle empties the visited bins. Equation (43) shows that the total collected waste from all visited bins in a tour must not exceed the vehicle capacity. After the tour, the truck returns to the depot according to Equation (44). Equation (45) states that the total waste amount of the aimed smart bins is less than the total capacity of the used trucks. Equation (46) ensures that the time taken by all trucks does not exceed the total time span allocated for the waste collection process. Equation (47) states that all the considered bins for waste collection have a waste amount equal to or larger than 50%.

3.6. VIII district Budapest case study

This case study has two scenarios of thirty and twenty smart bins in the VIII District in Budapest were considered to validate the mathematical model. The optimized energy consumption of the total used vehicles was calculated based on actual routes in kWh. The optimized solutions were calculated using three metaheuristic algorithms: GA, PSO, and SA. The solutions are compared with a random solution to outline their effectiveness. Assumed the used trucks complied with Euro VI European emission standards. The used values are mentioned in Table 9 to calculate the accrued emissions of CO, NMHC, CH4, NOx, and PM for Euro VI under the WHSC test for heavy-duty and transit testing [142] in g/kWh depending on energy consumption.

Table 9: EU VI emission standards for heavy-duty and transit testing in g/kWh

CO	**NMHC**	**CH_4**	**NOx**	**PM**
4	0.16	0.5	0.46	0.01

The lower and upper bounds are considered of the specific fuel consumption of transportation and the lower and upper bounds of specific material handling, for an average speed of 25 km/h. The values are shown in Table 10. Each bin's capacity was 100 kg. The maximum allocated time span T_{max} = 3 hours.

Table 10: Truck specifications

c_{kmin}^{FT}	c_{kmax}^{FT}	c_{kmin}^{FMH}	c_{kmax}^{FMH}	Q
41 kWh/km	52 kWh/km	25 kWh	37 kWh	200 kg

To obtain the smart bins' location data, two geographical locations were chosen. These two locations served as geographical boundaries for the generation of location data within the area of study in Budapest. The distance between those two locations, which would be the diameter, was calculated using the Haversine formula. Additionally, the central location along the segment between the two boundaries was also calculated; hence, a circle/ellipse was formed. The locations were then randomly generated within the circle boundary. The random locations were generated from a uniform distribution. All the locations were checked on the map to ensure that they represented convenient locations, and some of them were manually adjusted. The waste values for each smart bin were also randomly generated following a uniform distribution. Smart bins' locations and waste amounts are shown in Table 11.

Table 11: Bins' locations and waste amounts

ID	**Latitude**	**Longitude**	**Waste Amount**
0	47.487448	19.105228	-
1	47.483984	19.085934	98 kg
2	47.492993	19.078542	75 kg
3	47.497693	19.072976	66 kg
4	47.48618	19.092511	70 kg
5	47.491468	19.087551	99 kg

6	47.493208	19.085197	79 kg
7	47.488254	19.080151	67 kg
8	47.49816	19.077611	97 kg
9	47.489349	19.087007	73 kg
10	47.485646	19.08784	66 kg
11	47.496471	19.072441	94 kg
12	47.49282	19.085386	78 kg
13	47.490987	19.085437	72 kg
14	47.482154	19.09956	75 kg
15	47.488997	19.084106	54 kg
16	47.483539	19.077086	65 kg
17	47.494968	19.071751	69 kg
18	47.486889	19.080102	89 kg
19	47.487093	19.088391	91 kg
20	47.496417	19.072926	90 kg
21	47.478491	19.091825	56 kg
22	47.479669	19.088727	83 kg
23	47.495945	19.08181	68 kg
24	47.487821	19.075307	96 kg
25	47.486882	19.071569	92 kg
26	47.485501	19.072039	93 kg
27	47.488094	19.084196	57 kg
28	47.489819	19.082287	64 kg
29	47.494475	19.071527	66 kg
30	47.48275	19.07939	90 kg

Regarding the parameters used for the implementation of the algorithms, in the case of GA optimization, the number of iterations was 600, cross over probability pc was 1, mutation probability pm was 0.08, population size was 300, elite size was 40, and the selection methods were fitness proportionate selection, the reverse sequence mutation method, and the ordered cross over method. In the case of PSO, the number of iterations was 500, the number of particles was 400, c2 was 0.1, and c1 was 0.9. In the case of SA, the number of iterations was 3000, the starting temperature was 140, the stopping temperature was 10−12, and the temperature cooling rate α was 0.991.

3.6.1. First scenario of thirty smart bins in Budapest

The execution time, the total consumed energy, and the total distances for this case are summarized in Table 12. The results were calculated using the three algorithms next to a random solution "RS" without optimization.

Table 12: Execution results of the case of thirty bins

	Execution Time (s)	**Total Energy (kWh)**	**Total Distance (km)**
GA	17.5616664	1766.8860	24.19838
PSO	25.9850608	1765.9722	24.16504
SA	0.7237922	1958.02908	28.75177
RS	−	3176.2595	58.3101

Figures 17, 18, 19 show the total energy consumed by the three trucks for each iteration.

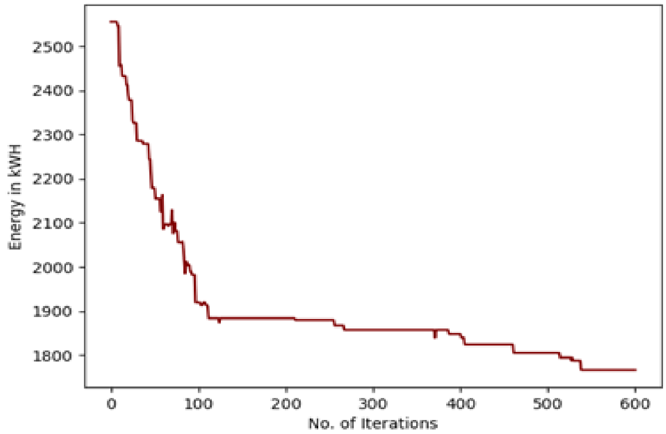

Figure 17: Total energy consumed by the three trucks (GA)

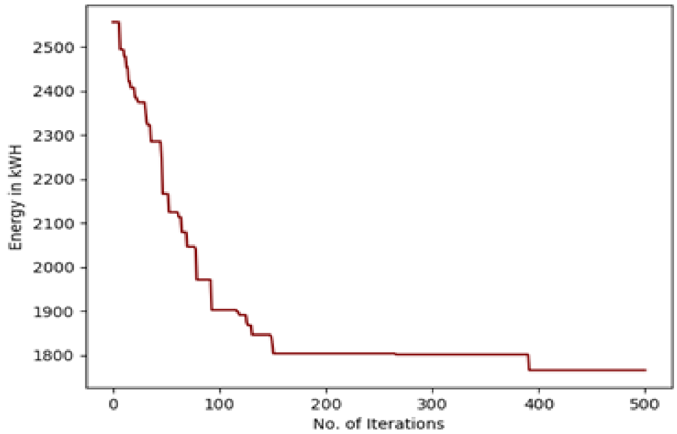

Figure 18: Total energy consumed by the three trucks (PSO)

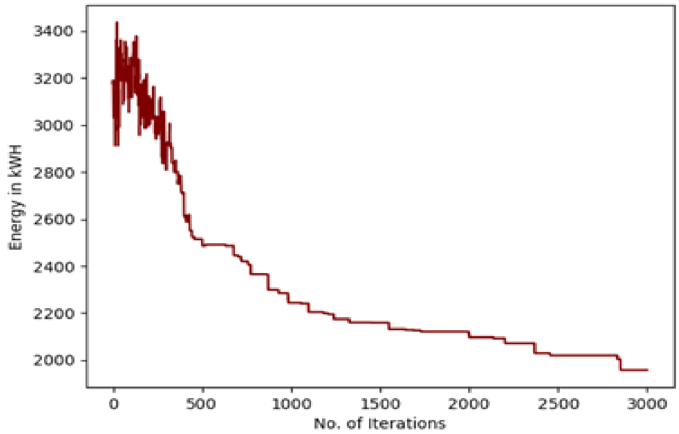

Figure 19: Total energy consumed by the three trucks (SA)

Figures 20, 21, 22 show the actual routes taken by the three trucks when using the three algorithms next to a random solution without optimization. The black location represents the collection and transfer location. Green, orange, and red locations represent the smart bins with the waste percentage. The three trucks' lines are represented by blue, red, and black colors.

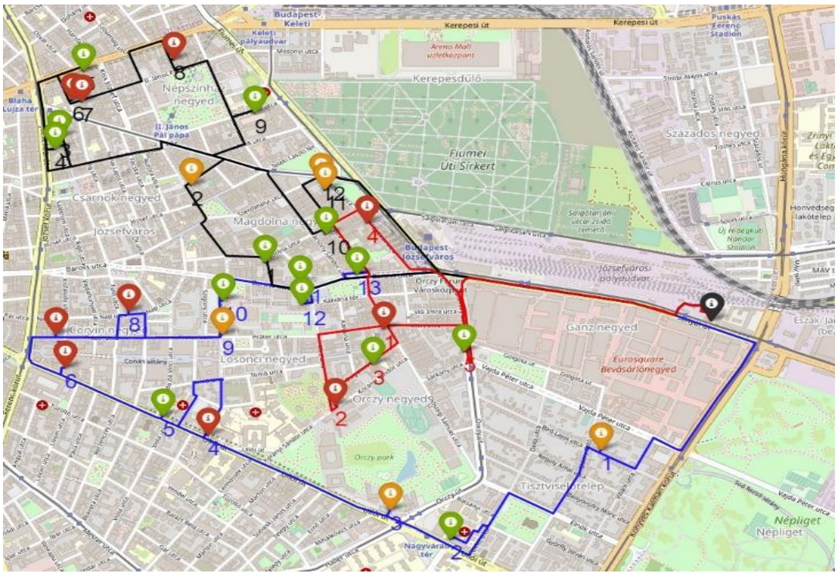

Figure 20: Actual routes when using GA

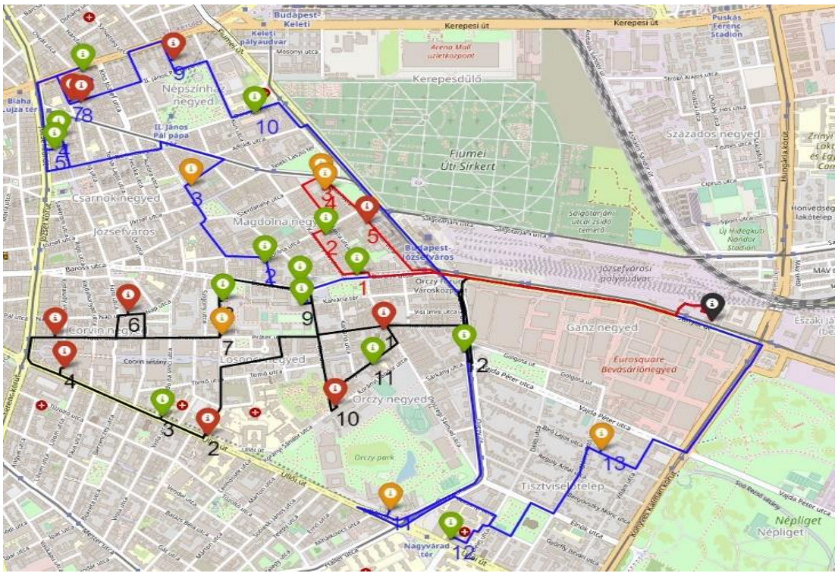

Figure 21: Actual routes when using PSO

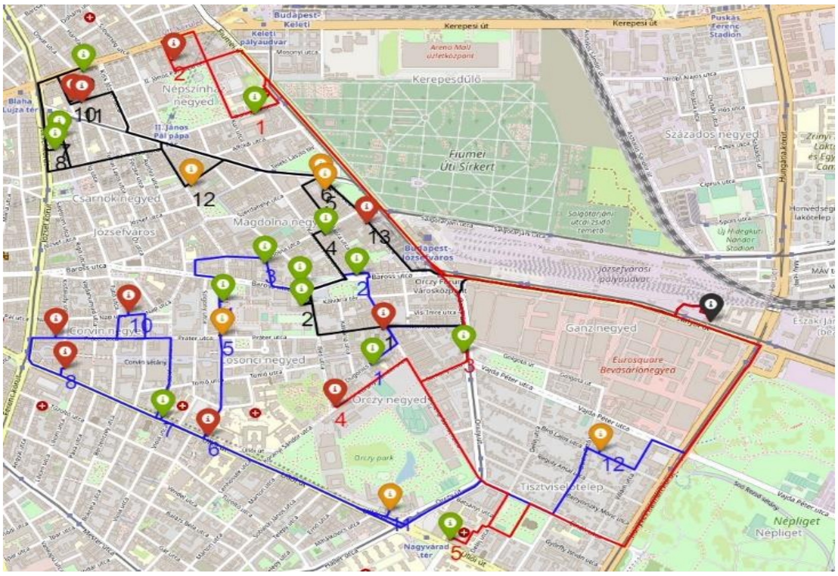

Figure 22: Actual routes when using SA

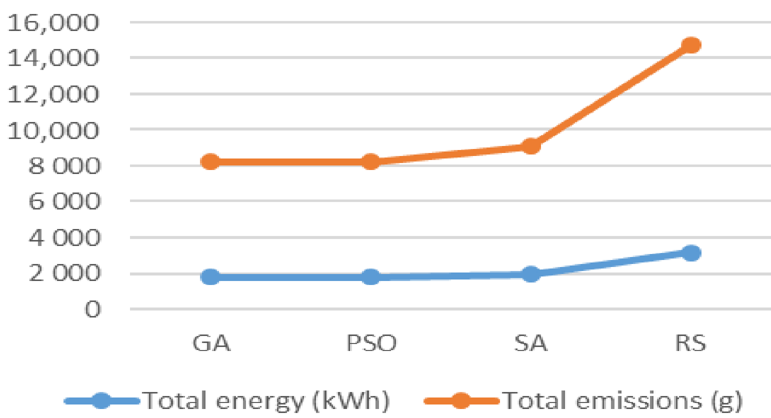

Figure 23: Total energy and emissions of the case of thirty bins

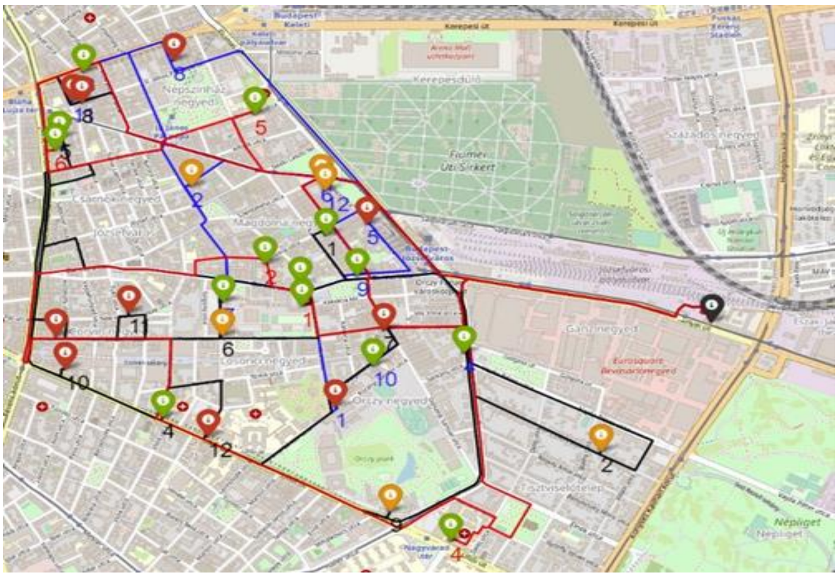

Figure 24: Actual routes when using a random solution

Table 13: Estimated accrued emissions in g of the case of thirty bins

	CO	NMHC	CH_4	NOx	PM	Total
GA	7067.5	282.70	282.70	282.70	282.70	8198.4
PSO	7063.9	282.56	282.56	282.56	282.56	8194.1
SA	7832.1	313.28	313.28	313.28	313.28	9085.2
RS	12705	508.20	508.20	508.20	508.20	14738

The random solution in Figure 24 shows many overlaps in the routes, which reflects the causes of its increase in results compared to the optimized results. Table 13 shows the estimated accrued emissions. Additionally, Figure 23 shows the total energy and emissions of the three optimized results and the random solution. Among the three algorithms, GA demonstrated the best results. It achieved a 44.4% reduction in total consumed energy and emissions and a 58.5% decrease in the total distance compared to the random solution. PSO showed a similar reduction of 44.4% of total consumed energy and emissions and a 58.7% decrease in the total distance compared to the random solution. Although both GA and PSO achieved a similar reduction in consumed energy and emissions, GA was computationally faster; it saved a third of the total execution time. SA demonstrated a 38.4% reduction in total consumed energy and emissions and a 50.7% decrease in the total distance compared to the random solution. However, SA was much faster than both GA and PSO. In conclusion, GA achieved the best results, while SA achieved less optimized results with the shortest execution time.

3.6.2. Second scenario of twenty smart bins in Budapest

The execution time, the total consumed energy, and the total distances for this case are summarized in Table 14. Also, Table 15 shows the estimated accrued emissions.

Table 14: Execution results

	Ex. Time (s)	Total Energy (kWh)	Total Distance (Km)
GA	14.4321162	1188.3266	16.4887
PSO	6.459	1190.7251	16.5891
SA	0.2832	1311.2013	19.4575
RS	–	1974.3287	35.5153

Table 15: Estimated accrued emissions in g of the case of twenty bins

	CO	NMHC	CH_4	NOx	PM	Total
GA	4753.3	190.1	594.2	546.6	11.88	6096.1
PSO	4762.9	190.5	595.4	547.7	11.91	6108.4
SA	5244.8	209.8	655.6	603.2	13.11	6726.5
RS	7897.3	315.9	987.2	908.2	19.74	10128

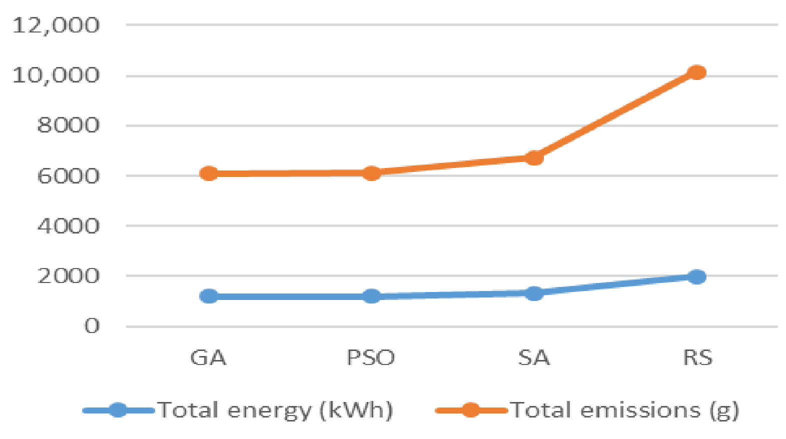

Figure 25: Total energy and emissions of the case of twenty bins

Figure 25 shows the total energy and emissions results. Like the first scenario, both GA and PSO achieved the best results in minimizing the total energy and emissions, with 39.8% and 39.7% decreases in total consumed energy and emissions compared to the random solution, respectively. Additionally, 53.6% and 53.3% decreases in total distance were shown compared to the random solution. SA showed a decrease of 33.59% in total consumed energy and emissions compared to the random solution and a decrease of 45.2% in total distance compared to the random solution. Moreover, SA was much faster in terms of execution time than both PSO and GA.

While the three algorithms showed great results in optimizing energy efficiency and raising sustainability, there was evident variation in the execution time in favor of SA. Therefore, SA is recommended to be used in situations where time efficiency is essential. Its speed of execution can be attributed to its simplicity. GA and PSO showed more optimized results than SA. The execution time was the longest in PSO in the first case, while it was the longest in GA in the second case. This difference may be explained due to the case's data size. It is important to consider this, because it is possible to have a huge increase in the execution time for PSO in cases with big data sizes.

The designed system encompassed the following aspects: the IoT, smart bins with multi-percentage sensors, data and information analysis, vehicles' actual routes, energy and emissions optimization, multi-echelon system, time windows, and flexibility. The system's flexibility was demonstrated through the dynamic nature of the collection and transfer station's tasks based on the given situation. For instance, this station can be used as a waste separation center. Using the actual routes made the results more realistic and factual than the traditional direct lines. However, using case studies with a bigger number of smart bins seems promising to gain more reliable results. For instance, there was a big difference in the PSO execution time between the two cases.

This chapter included the main contribution to Theses 2 and 3.

Thesis 2: After an analysis was done based on real data for waste management in Europe generally and Hungary specifically, a proposed CPS for waste collection was presented with details about its parts and processes from the logistics point of view. As there is no available one found, a conventional city logistics solution was presented and described with its mathematical modeling to have it as a reference baseline. Then, a multi-echelon collection and distribution optimization system was described and detailed. A numerical analysis was used to compare the two systems and clarify their effectiveness. The optimization aimed at scheduling, assignment, routing layout design, and controlling tasks that focus on time, distance, energy consumption, and emission-related objective functions. Also, it focused on an e-vehicle-based solution, where the efficiency of the whole system could be increased by using existing Industry 4.0 technologies, like smart devices, radiofrequency identification, digital twin solutions, and cloud and fog computing to solve big data problems of large-scale system including a wide range of users, transportation resources and goods. [S7, S8, S9].

Thesis 3: CPS for waste management focusing on energy efficiency and sustainability was presented and discussed. The developed mathematical modeling was described. Also, a case study in the VIII district in Budapest was used to validate the system for two scenarios of thirty and twenty smart bins. The designed system encompassed the following aspects: IoT, smart bins with multi-percentage sensors, data and information analysis, vehicles' actual routes, energy and emissions optimization, multi-echelon system, time windows, and flexibility. The system's flexibility was demonstrated through the dynamic nature of the collection and transfer station's tasks based on the given situation. [S2, S4, S6].

4. ENERGY EFFICIENCY OPTIMIZATION OF LAST MILE SUPPLY SYSTEM

This chapter discusses and shows the research direction of last mile supply system with RL consideration. This research started with a case study in Miskolc city center where VRP problem was optimized by three algorithms next to a random route that is used as a comparison reference. Then, a second case study in Kosice city center to validate a capacitive collection system using five algorithms. After that, as a next step, a last mile supply optimization system with RL consideration is presented and described. The developed system's mathematical modelling is detailed. A case study in VII District in Budapest is used to validate the model. GA was used for the optimization with upgrade that was described. The achieved results of this chapter were published mainly in three articles [S4, S5, S10].

4.1. Miskolc case-study for vehicle routing problem

As a case study application to solve a TSP problem by the mentioned algorithms, twenty locations in Miskolc city center were used for finding the shortest route to visit all of them while starting and ending in a specific location. Three algorithms are used to find the optimized results next to a random route that is used as a comparison reference. The real routes are calculated by using the Open Route Service that was developed by HeiGIT gGmbH [137]. It gives the required real distances for vehicles to move among given locations. Table 16 states the used location in Miskolc city center where the ID 0 states the route start- and endpoint.

Table 16: Miskolc case study locations

ID	Latitude	Longitude	ID	Latitude	Longitude
0	48.104500	20.792322	11	48.100542	20.789675
1	48.102439	20.788955	12	48.102063	20.789383
2	48.101865	20.787420	13	48.102104	20.790459
3	48.101852	20.786693	14	48.103304	20.791231
4	48.101265	20.786310	15	48.103188	20.793006
5	48.100182	20.787304	16	48.104120	20.794390
6	48.098837	20.786294	17	48.105830	20.793720
7	48.098384	20.786947	18	48.105156	20.785587
8	48.098272	20.788453	19	48.106049	20.787717
9	48.100108	20.788731	20	48.105392	20.786827
10	48.100719	20.788667	—	—	—

The results of the optimization are mentioned in Table 17. PSO achieved the shortest route then GA with a very near result to PSO than SA as a less optimized result among the three algorithms. PSO achieved a 69.3% save of the random route, GA achieved a 68.4% save, and SA achieved a 57.9% save. The results reflect the importance of using optimization for its effectiveness in reducing the required route. Moreover, the results are compatible with the obtained benchmarks in chapter 2.

Table 17: Miskolc case study results

	GA	PSO	SA	Random route
Shortest route (km)	6.14917	5.97373	8.20097	19.46269
Shortest route time (min)	17.33216	16.91766	22.8899	49.6466
Code Exec. time (s)	5.0876	4.09234	0.28272	—
% Saved route	68.4 %	69.3 %	57.9 %	—

The following Figures 26, 27, 28, 29 show the real route maps for the three algorithms next to a random route. Also, Figures 30, 31, 32 show the optimization curve for distance with the iteration progress for three algorithms.

Figure26 : Actual route map for GA optimization

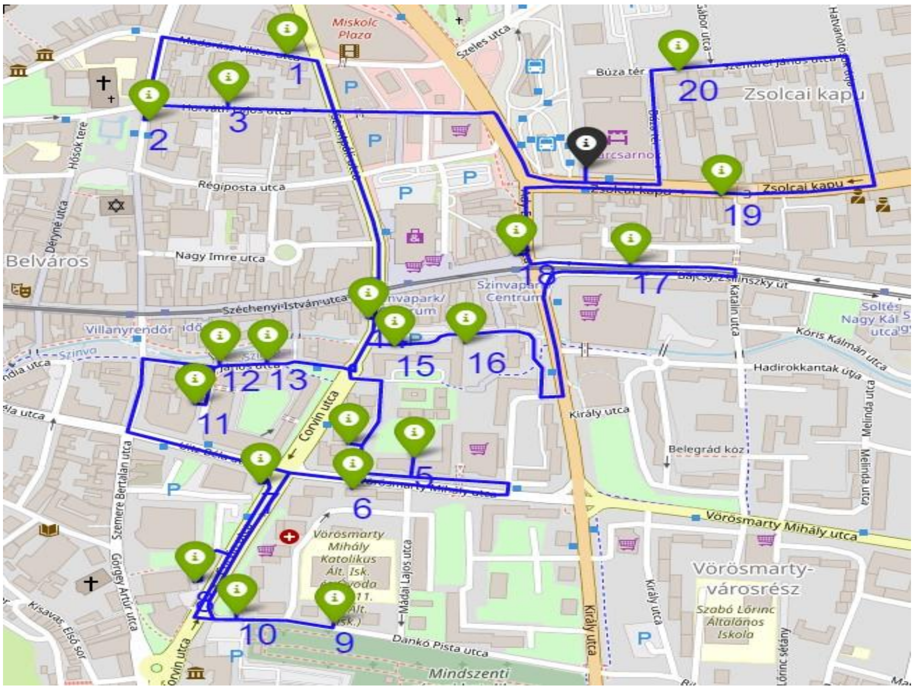

Figure27 : Actual route map for PSO optimization

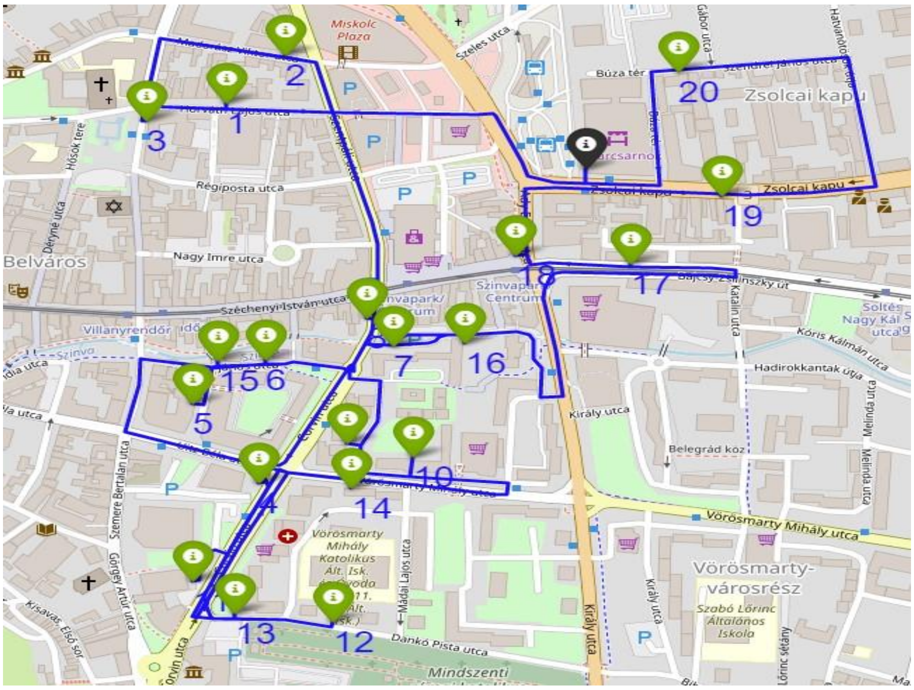

Figure28 : Actual route map for SA optimization

Figure29 : Actual route map for random route

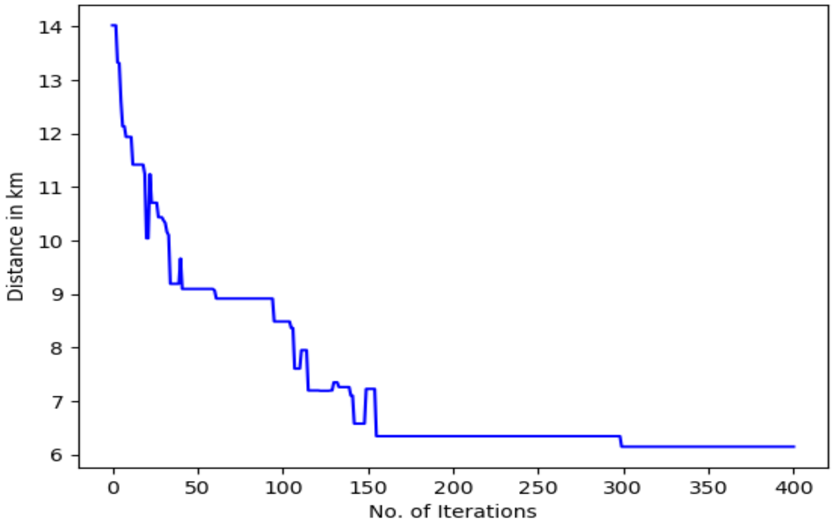

Figure30 : GA optimization curve for distance and iterations

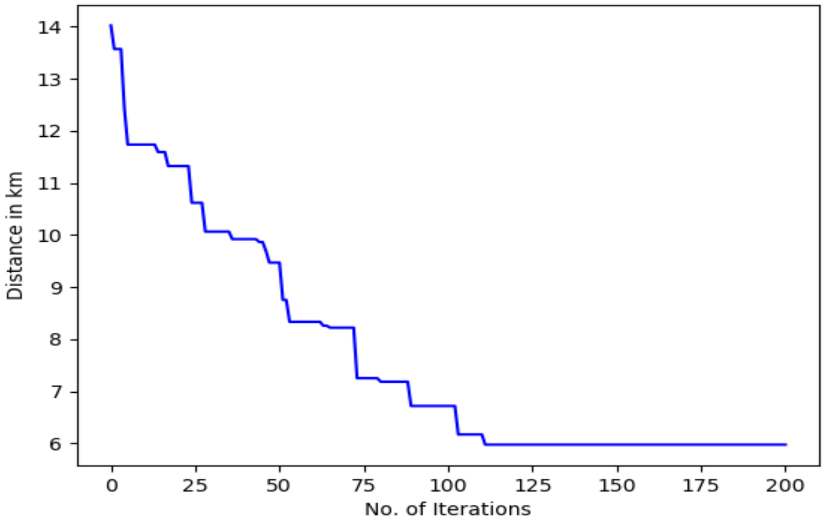

Figure31 : PSO optimization curve for distance and iterations

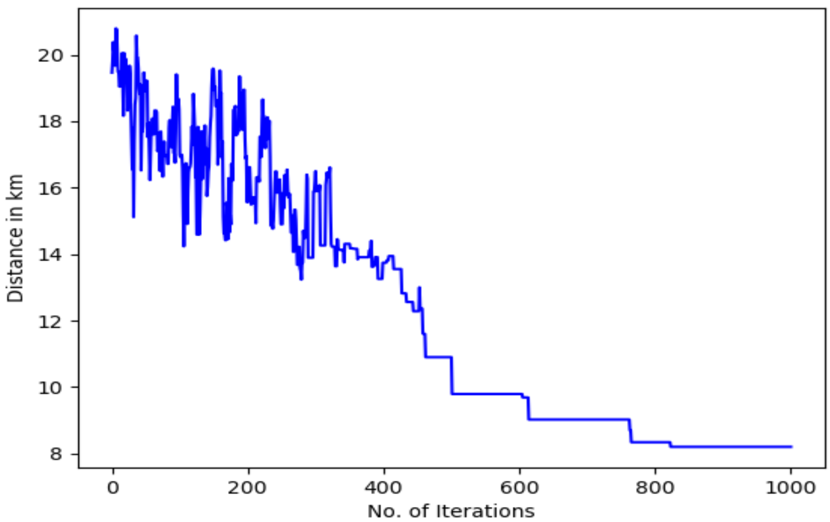

Figure32 : SA optimization curve for distance and iterations

The presented case in Miskolc city center where twenty locations should be visited as a TSP explained, in numbers, the three algorithms' effectiveness. By comparing them with the random route, long distances were saved up to 68.4%. Especially in the current energy crisis, the results gain an important effect on distance and energy savings. The distance optimization progress for every iteration was presented as a curve for the three algorithms. GA reached the optimized result in iteration number 300 while PSO reached it in iteration number 110 approximately. SA needed more than 800 iterations to reach the best result with a noticeable vibration curve in its first third, which is explained by the nature of the SA algorithm. PSO showed the best results then GA with relatively near values then SA. The results reflect the importance of using optimization algorithms because of their effectiveness in reducing the required distance and energy. On the other hand, SA was the fastest in the average execution time then PSO then GA. In conclusion, this confirms the optimization algorithms' importance and effeteness within a relatively short time.

4.2. Kosice case-study for capacitive collection system

To address the mentioned applications using optimization methods, as a case study, thirty locations were picked randomly in the city center of Kosice to find the shortest route to traverse all of them with a constraint to start and end at the same location, taking into consideration selecting the locations in the residential areas or with a population activity and not an industrial area, which mimics real delivery points. NN algorithm serves as the baseline reference algorithm to compare the results of the four algorithms against it. The real routes are calculated by utilizing the Open Route Service that was developed by HeiGIT gGmbH [137]. It gives the best real path between two required locations by vehicles to traverse depending on the real directions of the streets if they are in one or two directions, travel speeds are dynamic, which are changed based country specific speed limits, different way types, and surfaces of the road to consider reduced speeds in residential areas, or when entering a roundabout. Table 18 lists the used locations in Kosice city center where the ID 0 states the location where the truck starts from and ends after finishing its route. The mentioned weight for each location that is used for the second application where three trucks are used with a capacity limit. The weight defines a constraint that cannot be exceeded by each truck for the total weight of the visited locations. In addition, there is a weight limit, which represents the maximum weight available per order at each location.

Figure 33 shows the adopted model for a goods' supply system that uses several trucks referred to as i that visit the locations and go back to the start point. The trucks distribute the goods to the locations. The utilized IoT tools in the trucks allow the information flow into the cyber management that deals with data to find the best routes. The following constraints are considered: truck maximum limit of goods, total collected goods for each truck, trucks' flexibility (fewer differences in the total carried goods between the trucks), one/two ways consideration, and real routes' distances calculation instead of the traditional way of calculating direct lines between the locations**.**

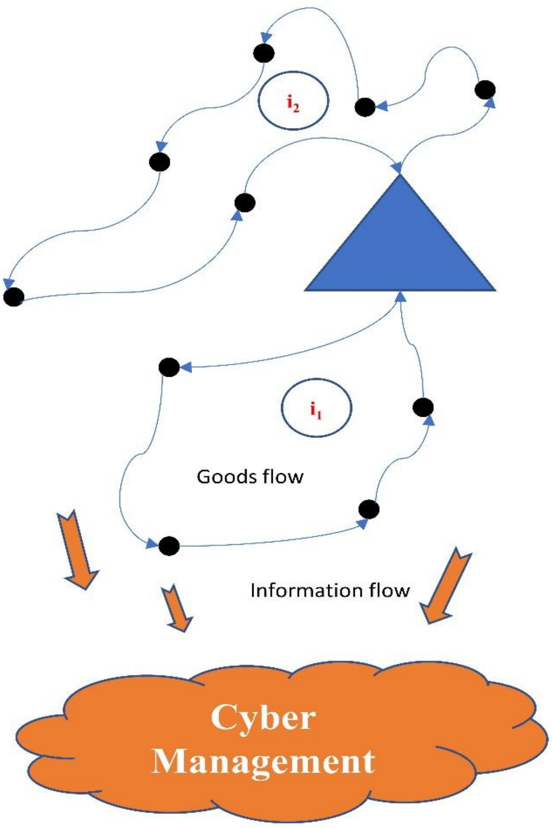

Figure 33: Used model in the case study

Table 18: used locations in Kosice city center

ID	Latitude	Longitude	weight	ID	Latitude	Longitude	Weight
0	48.688953	21.223432	-	16	48.68028510240033	21.274614769106996	6
1	48.73099254232587	21.225416574853625	52	17	48.67249541221792	21.269268186388043	44
2	48.726430241598855	21.223333614224675	46	18	48.66964229942875	21.270384851937244	10
3	48.712236438645114	21.205961538692634	43	19	48.72618966091185	21.26371791656911	33
4	48.708578969436836	21.222205381898544	21	20	48.72608570392025	21.2545644458204	11
5	48.67896714440343	21.271184198394813	18	21	48.72963336750223	21.24843739224237	28
6	48.68280129899581	21.283325920238244	5	22	48.73758588813169	21.25215327136872	34
7	48.72645173037964	21.278077576394676	70	23	48.73781050486706	21.259699675371184	87
8	48.72809459393173	21.278314107283933	45	24	48.73928005290904	21.263319365903175	51
9	48.7347425760872	21.270281177615896	29	25	48.706544326779955	21.25400114199683	5
10	48.73696701680051	21.265850915239092	58	26	48.71294314930677	21.25312922256893	53
11	48.75220261409178	21.272692097785423	7	27	48.71359894495363	21.247729090533333	9
12	48.72892199502447	21.23470474502146	59	28	48.70495193565775	21.250230913210387	48
13	48.71963042569478	21.24769334276912	48	29	48.70179290123074	21.259369323956705	51
14	48.70814938151528	21.262052881190222	75	30	48.72520773942602	21.230843983322842	36
15	48.70276649110591	21.25961425715763	54	Total	-	-	1136

GA, PSO, ACO, and SA algorithms with the NN algorithm are used to determine the optimization outcomes for the two TSP and MTSP applications that were addressed. Table 19 shows the outcomes of the first application, which employed one vehicle with no capacity restrictions. The outcomes of the second application are presented in Table 20, which used three trucks and had a capacity limit of 400 (units) per truck.

Table 19: First case study application results

	SA	PSO	GA	ACO	NN
Execution time (s)	1.2876	29.98697	13.22961	18.6166	0.0002548
Distance (km)	64.032	67.03403	63.19393	63.2252	68.0736

Table 20: Second case study application results

	SA	PSO	GA	ACO	NN
Execution time (s)	1.4088	37.28983	22.01450	17.9311	0.0004077
Total distance (km)	93.425	93.09157	88.29585	93.8455	100.0768

Figure 34 illustrates a comparison of the calculated distances in the two applications by the used four algorithms next to the NN.

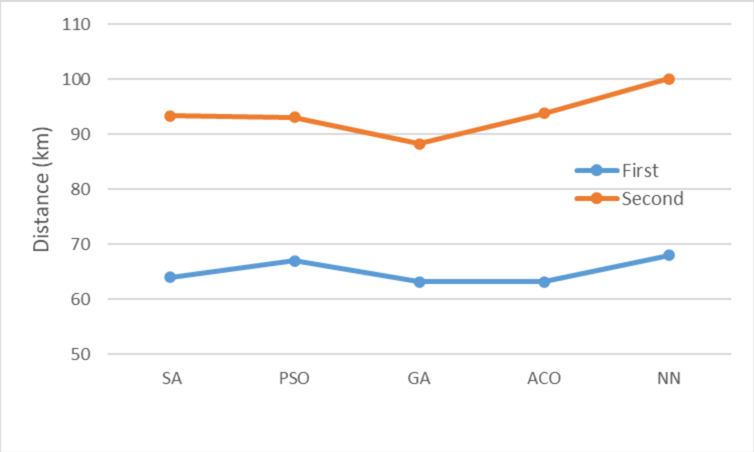

Figure 34 : Algorithms' results comparison

While NN showed the longest distance in the two applications, it was the fastest in execution time. Among the other 4 applied algorithms, in the first application, GA showed the shortest distance, then ACO with very near result, then SA and PSO. The results were near in general, and this is expected since this first application shows a simple case of one truck without capacity constraints. In the second application, where more constraints were applied, GA showed the shortest distance then the other three algorithms ACO, SA, and PSO with very near results.

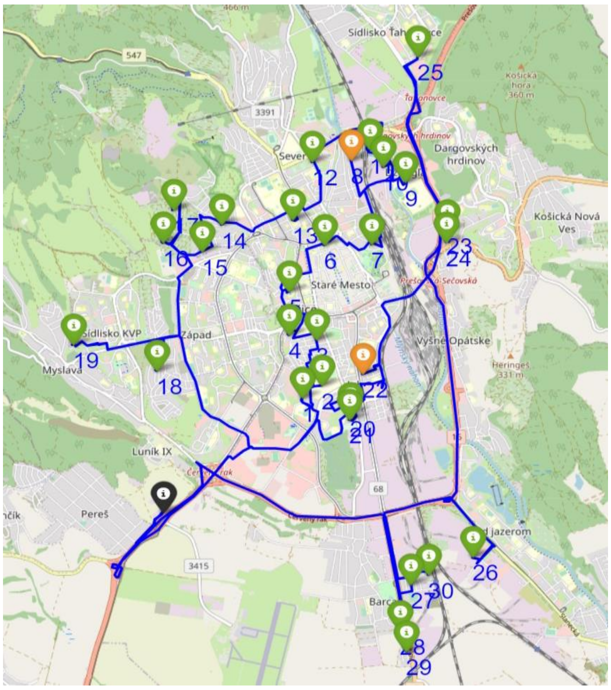

Figure 35: First application-optimized route by NN

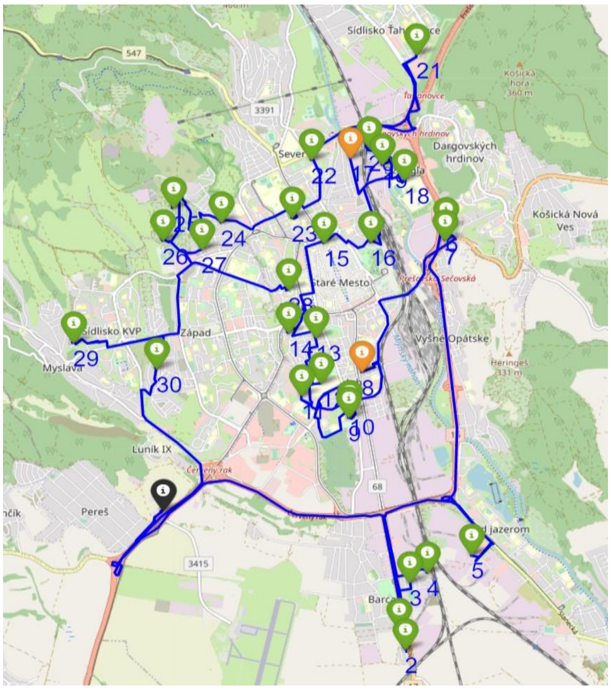

Figure36 : First application-optimized route by GA

Figures 35 and 36 depict the optimized routes by NN and GA algorithms over the 30 locations in the first application. The maps show the real routes at the city center of Kosice city. The black location represents location 0 where the truck starts from and ends after finishing its trip. Also, Figures 37, 38 depict the optimized routes by NN and GA algorithms over the 30 locations in the second application. Blue, black, and red colors represent the three truck routes while the black location represents location 0.

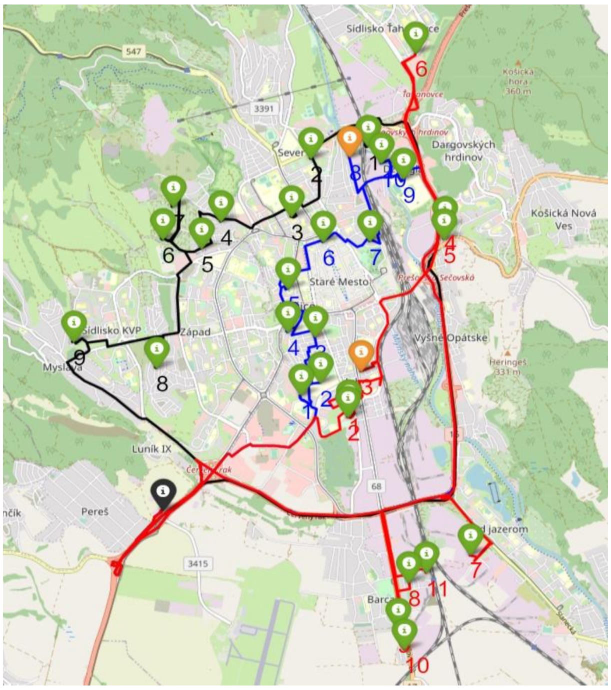

Figure 37: Second application-optimized route by NN

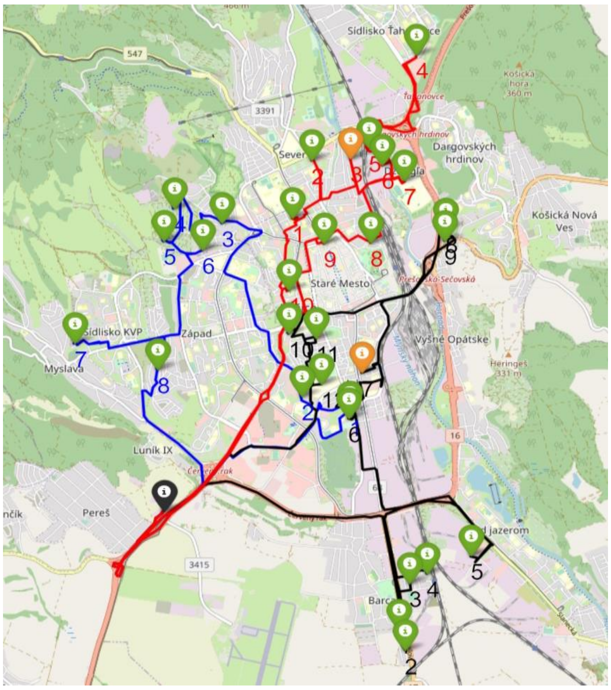

Figure38 : Second application-optimized route by GA

This case study shows that all chosen algorithms achieved better results than the standard NN algorithm. GA achieved the shortest route distance compared to ACO, PSO, and SA in both applications. However, the best execution time among the four algorithms in total was in SA. The results reflect the importance of using metaheuristic optimization due to its effectiveness in reducing the total distance for the required route in a short time. Moreover, the results are somewhat compatible with the benchmarks obtained in the last chapter. One may argue that the optimization findings are not very significant because the distance in GA indicated a 13% and 10% saving over NN, in the two applications respectively. However, the optimization's goal and the definition of the application should determine the desired benefit of which algorithm to use. Therefore, the two used applications show how making the application more complicated may reflect on the optimization results. The adopted IoT tools allowed applying the constraints of vehicle maximum limit of goods, total collected goods for each vehicle, vehicles' flexibility, one/two ways consideration, and real routes' distances calculation. According to the results, GA is the advised algorithm to use, because it showed stable optimization effectiveness in both applications in contrast to the other algorithms.

4.3. Last mile supply optimization system with RL consideration

The last mile transportation system expresses the operations that take place under the city logistics aspect. While the goods storage station represents the last echelon of where the goods are to be delivered to the specified locations, RL also happens to be collected from specified locations to be moved to the goods storage station. This system is represented as a scheme in Figure 39. Routes and consumed time are calculated depending on Open Route Service, which gives real distances and time. This service was developed by HeiGIT gGmbH [137].

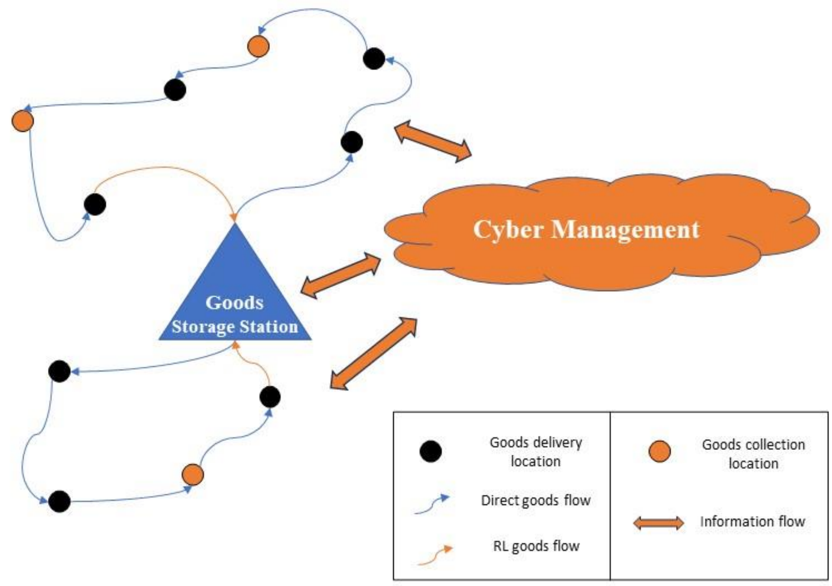

Figure 39: Last mile supply system scheme

The locations express both types of goods' delivery and collection. It shows how RL operations were integrated into the supply system. Cyber management expresses the cloud system where the data is stored, analyzed, and calculated. Therefore, information flow is considered between the cyber management and IoT tools within the system parts such as the trucks and goods storage station. GA is used in this system to calculate the optimized energy efficiency solutions for doing the goods' delivery/collection. Also, an upgrade step is used regarding the iteration number. Instead of raising the iteration number to reach better results, three runs are done, and the best value will be selected as the optimized result. The optimization is represented in Figure 40 next to the used locations’ order coding for 2 trucks case that is applied in the coming case study. After the separation of the two trucks' location orders, the locations will be reordered separately considering that location 0 is the start and end location for both trucks. Therefore, the last location is transferred into 0 after separating the two locations' orders. This process is illustrated in Figure 40, which is more detailed in the coming mathematical modeling.

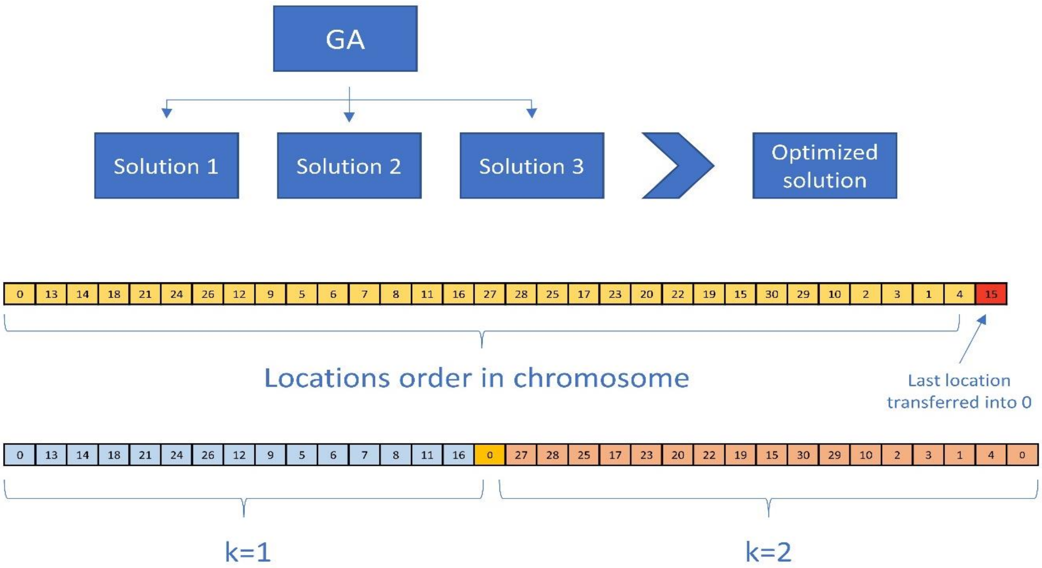

Figure 40: GA optimization methodology

4.4. Developed system's mathematical modelling

In the VRP, it is worked on finding the shortest travel distance roads with starting in and returning to the same place for serving a group of customers [138]. The VRP has been applied in various applications, including but not bounded to city logistics goods' delivery and collection. The used model is explained below, where n is the visited locations' number and m is the used trucks' number by homogeneous trucks that are defined as $K = \{1, 2, \dots, m\}$, the mentioned trucks are stationed at the goods storage station at the beginning. The index set $I = \{0,1,2, \dots, n\}$ refers to the locations, where $i, j \in I$. $i = 0$ refers to the goods storage station location. For each location, there is q_i goods' quantity that should be delivered/collected. The positive value refers to the delivery task while the negative value refers to the collection task. D_{ij} refers to the real road distance from location i to location j, where $i \neq j$, and it should non-negative value.

The following model considers the capacity of both the trucks and the goods, where:

- C refers to the maximum goods' amount that is possible for the trucks to transport.
- q_{max} refers to the maximum goods' amount in each location that is possible to be tackled. Additionally, the model presents a time limit as well, where:
- T_{max} refers to the maximum specified time for the whole process.
- t_k refers to the time that is taken by truck k to finish its route and go back to the start location.

The total energy consumption (TE) is the defined objective function where it aims to be minimized. It refers to the spent kWh by the used trucks during the goods delivery/collection system, which is found depending on the distance length, and specific fuel consumption rate [S9]. The following mathematical modeling is developed to tackle the described system (Figure 39) based on previous chapter [S2] that tackled a waste management system. This modeling has two decision variables. X_{ijk} that is 1 if vehicle k proceeds from location i to location j; otherwise, it is 0. Y_{ik} that is 1 if location i is part of the vehicle k route; otherwise, it is 0.

The objective function is described as:

$$\mathrm{TE} = \sum_{k=1}^{m} \sum_{i=0}^{n} \sum_{j=1}^{n} X_{ijk}.Dij.c_{ijk}^{T} \rightarrow min \tag{48}$$

where D_{ij} is the real distance from location i to location j, X_{ijk} is the decision variable, k is the number of trucks, and c_{ijk}^{T} refers to the specific fuel consumption that is defined as

$$c_{i,j,k}^{T} = c_{kmin}^{T} + ((c_{kmax}^{T} - c_{kmin}^{T})/c_{kmax}^{T})q_{ijk}/((q_{ijk}/c_{kmax}^{T}) + C - q_{ijk}) \tag{49}$$

where c_{kmin}^{T} and c_{kmax}^{T} refer to the lower and upper bounds within the specific fuel consumption depending on the weight of the goods, and q_{ijk} represents the weight of the goods picked up by truck k when moving from location i to location j.

Subject to the following constraints:

$$\textstyle\sum_{i=0}^{n} \sum_{k=1}^{m} X_{ijk} = 1 \;\; \forall j \in \mathrm{I} \tag{50}$$

$$\textstyle\sum_{j=1}^{n} X_{ijk} = \sum_{j=1}^{n} X_{jik} = Y_{ik} \;\; \forall i \in I;\; k \in K \tag{51}$$

$$\textstyle\sum_{i=0}^{n} \sum_{k=1}^{m} q_{jik} - \sum_{i=0}^{n} \sum_{k=1}^{m} q_{ijk} = c_j \;\; \forall j \in I \tag{52}$$

$$\textstyle\sum_{i=1}^{n} c_i X_{ijk} \leq C \;\; \forall j \in I;\; k \in K \tag{53}$$

$$\textstyle\sum_{i=1}^{n} \sum_{k=1}^{m} X_{i0k} = 1 \tag{54}$$

$$\textstyle\sum_{i=1}^{n} q_i \leq \sum_{k=1}^{m} C_k \tag{55}$$

$$max(t_1, t_2, \dots t_m) < T_{max} \tag{56}$$

Equation (50) ensures that only one vehicle visits every location. Equation (51) states the condition of continuity. Equation (52) states that the truck does deliver/collect the goods at the visited location. Equation (53) states that the carried goods within the tour should not overrun the capacity of the vehicle. After the last location is visited, the truck returns to the goods storage station according to equation (54). Equation (55) ensures that the total goods' weight for the allocated locations is less than the overall capacity of used trucks. Equation (56) states that the taken time by each truck does not exceed the allocated time for the process.

4.5. VII District Budapest case study

For validating the presented mathematical model, a case study that consists of thirty locations in the VII District in Budapest is described and analyzed. The actual real routes are used to find the total optimized energy consumption of the used trucks in kWh by using the GA metaheuristic algorithm. The solutions are to be compared against a random solution for each case to outline the optimization efficiency. Within this case, the lower and upper bounds of specific fuel consumption are considered the same as the previous ones [S9] while assuming an average speed of 25 km/h in the city center. The time window is an essential consideration since there is interaction with customers, moreover, electric trucks have limited operational time depending on their battery capacity. Used truck specifications are presented in Table 21.

Table 21: Used truck specifications

	c_{kmin}^{T}	c_{kmax}^{T}	q_{max}	C	T_{max}
Diesel	20 kWh/km	41 kWh/km	100 kg	600 kg	3 hours
Electrical	11 kWh/km	18 kWh/km	100 kg	500 kg	2 hours

For obtaining the locations' data, a generating method was used [S2]. Two geographical locations were chosen as geographical boundaries to find the locations' data in the VII District in Budapest. The Haversine formula was used to calculate the diameter depending on the distance between those two selected locations. Additionally, a circle was shaped depending on the calculation of the centric location over the segment amidst the two boundaries. Then, the locations were generated in the circle boundary in a random way using a uniform distribution. After that, the generated locations were ensured that they represent convenient locations on the map, and a few of them were manually adjusted. The goods' weight in every location was generated following a uniform distribution in a random way as well. Table 22 shows the goods' weight and their locations.

Table 22: The goods' weight and their locations

ID	Latitude	Longitude	Goods' weight (kg)
0	47.501374	19.093158	-
1	47.497593	19.055899	33
2	47.498133	19.057511	-9
3	47.497602	19.058477	74
4	47.496396	19.059368	88
5	47.497686	19.060825	-68
6	47.498425	19.061217	67
7	47.500001	19.059982	71
8	47.499277	19.064749	-17
9	47.497431	19.067606	1
10	47.49691	19.068347	20
11	47.498606	19.069738	52
12	47.498354	19.073727	-40
13	47.499479	19.074273	29
14	47.500382	19.073401	-18
15	47.504214	19.074972	19
16	47.502627	19.080453	8
17	47.502982	19.081409	-40
18	47.505488	19.082116	61
19	47.507706	19.081259	37
20	47.509121	19.081838	-17
21	47.508908	19.083005	81
22	47.508367	19.083632	52
23	47.50606	19.084608	76
24	47.504937	19.085591	-14
25	47.503217	19.08456	43
26	47.50247	19.08532	50
27	47.504233	19.087563	-39
28	47.503577	19.088435	39
29	47.501554	19.065602	-40
30	47.50562	19.069682	40

For implementing the GA, the following parameters were considered: population size is 100, the crossover probability is 40%, mutation probability is 20%, the number of iterations is 100, and the selection method is tournament selection.

4.5.1. First scenario of diesel trucks

In this scenario, two trucks were needed. Total consumed energy, total distance, needed time for the process, and initial weights for each truck, in this case, are summarized in Table 23. Execution of the whole code is 14.62 seconds. Also, the total energy and distance for a random solution are mentioned.

Table 23 :Results of diesel trucks scenario

	Total energy (kWh)	Total distance (km)	Time (min)	Initial weight (Truck 1)	Initial weight (Truck 2)
Solution 1	606.17698	29.24704	50.06	105	197
Solution 2	**534.2343**	**25.94166**	**39.331**	**152**	**150**
Solution 3	548.88179	26.33791	43.3312	157	145
Optimized solution	**534.2343**	**25.94166**	**39.331**	**152**	**150**
Random solution	1429.40629	66.1656	-	-	-

Figures 41, 42 show the actual routes for the optimized solution and random solution of this case. Red and blue colors are used to distinguish each truck's route.

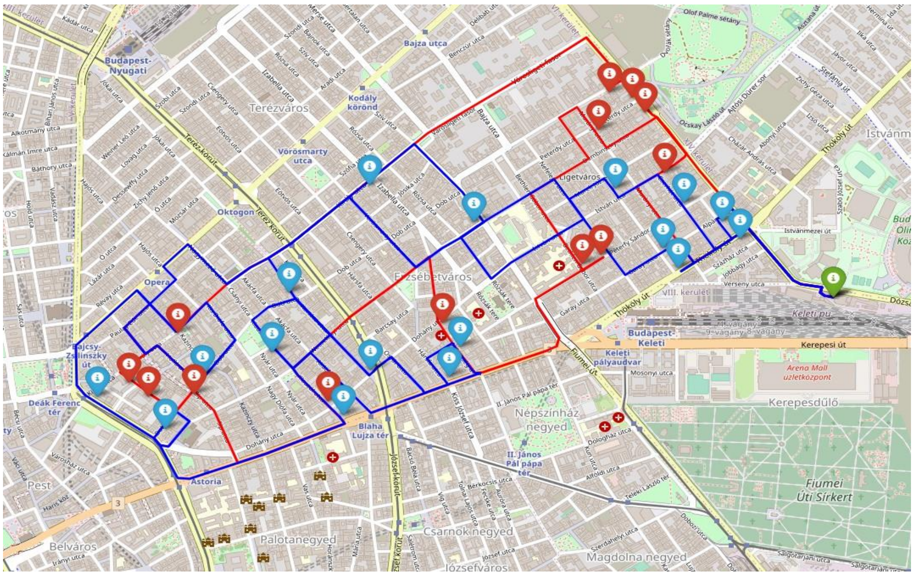

Figure41 : Optimized solution for the first scenario (diesel)

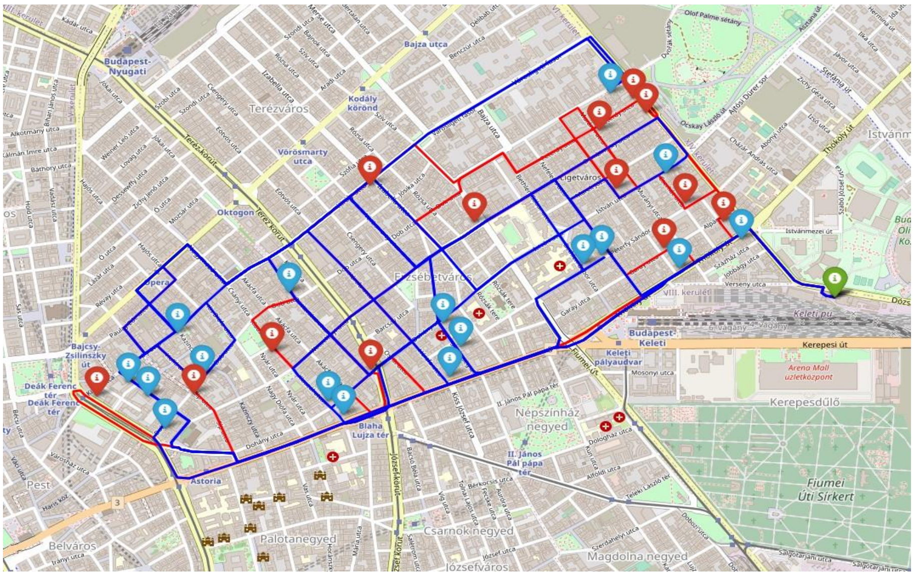

Figure42 : Random solution for the first scenario (diesel)

4.5.2. Second scenario of electric trucks

In this scenario, two trucks were needed as well. Total consumed energy, total distance, needed time for the process, and initial weights for each truck are presented in Table 24. The execution of the whole code is 13.95 seconds. Also, the total energy and distance for a random solution are mentioned. Figures 43, 44 show the actual routes for the optimized solution and random solution of this case. Red and blue colors are used to distinguish each truck's route.

Table 24 :Results of electric trucks scenario

	Total energy (kWh)	Total distance (km)	Time (min)	Initial weight (Truck 1)	Initial weight (Truck 2)
Solution 1	**289.8513**	**24.7695**	**45.7**	**217**	**85**
Solution 2	326.82914	28.42226	42.4	187	115
Solution 3	298.91565	25.31579	39.8	208	94
Optimized solution	**289.8513**	**24.7695**	**45.7**	**217**	**85**
Random solution	707.68439	59.83013	-	-	-

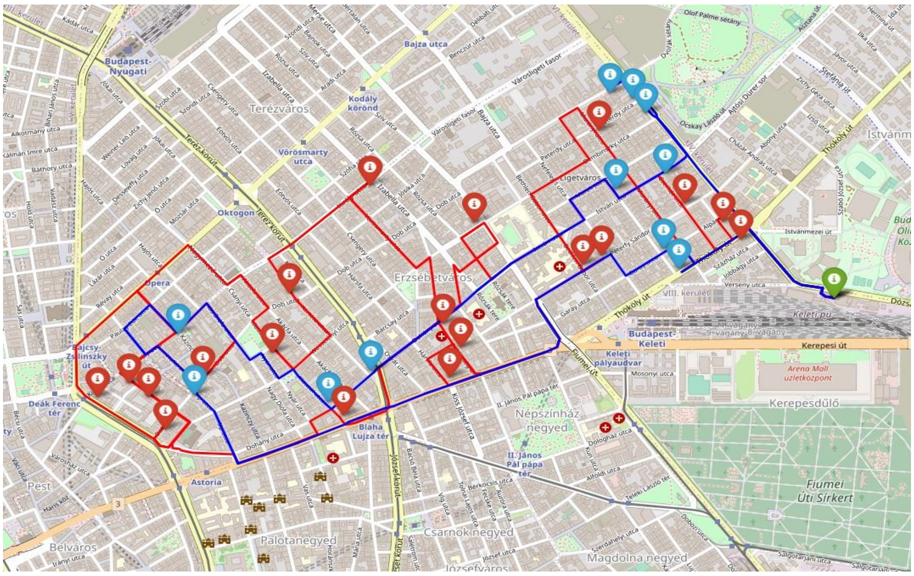

Figure 43: Optimized solution for the second scenario (electric)

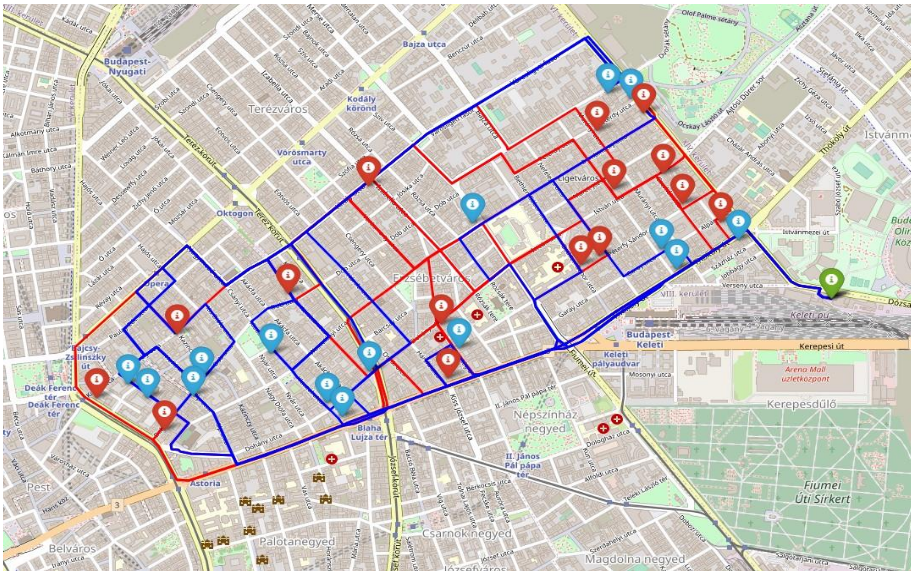

Figure 44: Random solution for the second scenario (electric)

4.6. Discussion and outcomes

The results showed a big difference between the optimized and random solutions. The random solutions in Figures 42 and 44 showed numerous overlaps in the selected routes, which explains why there is a raise in their results compared with the optimized solutions. Figures 45 and 46 express the differences for calculated total energy and distance where OS refers to the optimized solution and RS refers to the random solution.

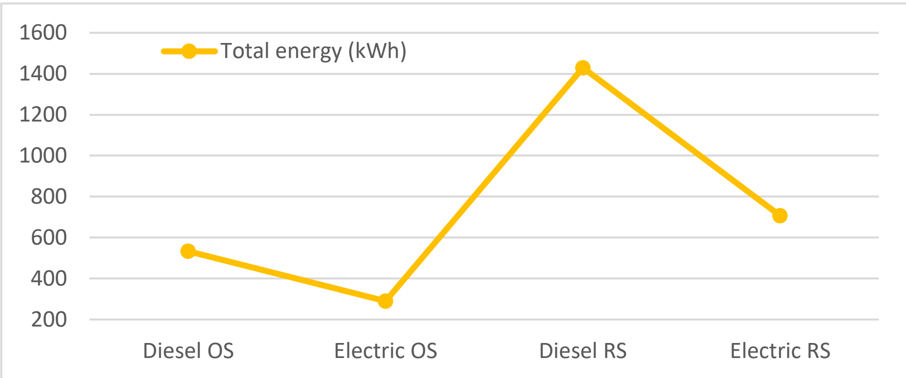

Figure 45: Calculated total energy

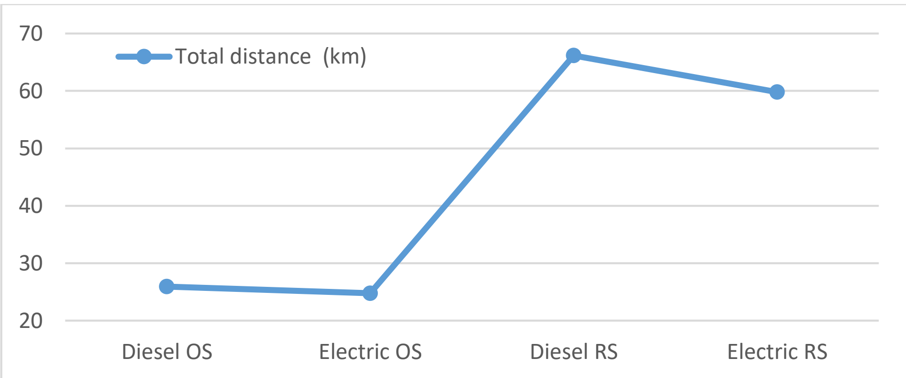

Figure 46: Calculated total distance

The results express two aspects to be compared. First, the optimization efficiency of GA with the random solution comparison. The results expressed minimizing the total energy as 37.3% and 40.95 % compared to the random solution for diesel and electric cases respectively. Also, the results expressed minimizing the total distance as 39.2% and 41.4 % compared to the random solution for diesel and electric cases respectively. Second, comparing the diesel and electric cases efficiency. The results expressed minimizing the total energy as 54.26% in the electric case compared to the diesel one. However, in the total distance, the results were very similar. The GA algorithm showed highly efficient results in the optimization of this case, especially considering the applied upgrade where three solutions were done at the beginning to have a higher chance to exclude any possible local minimum points. The execution time is relatively acceptable. However, even with conceding real-time updates, new runs to calculate updated routes are possible considering that it takes about around 15 seconds to reach the results for 30 location cases. The electric trucks showed a very positive impact on energy reduction, which supports adopting them widely in reality. However, possible challenges to this adoption may happen, therefore, analyzing real-life cases of electric truck use is interesting to find out the accrued trouble. Depending on the achieved results, the adoption of electric trucks in the city center is recommended for their positive impact on the environment by saving spent energy. Also, raising the efficiency of the used optimization method next to widen the tackled data like including RL in the tackled system is highly recommended.

From an alternative perspective, the selection of battery chargers entails significant considerations. Mainly, three levels of battery chargers are used [143]. Level 1 chargers represent the most rudimentary category and are typically included with the vehicle at the time of purchase, boasting an amperage rating of approximately 12 amps. Characterized by their relatively slow charging speeds, Level 1 chargers are best suited for overnight charging purposes. In contrast, level 2 chargers offer accelerated charging speeds, with amperage ratings typically ranging from 16 to 80 amps. Frequently installed at residences or within public charging stations, level 2 chargers cater to daily charging requirements adeptly. Lastly, level 3 chargers use direct current power and deliver the swiftest charging rates. Boasting high amperage ratings, often surpassing 100 amps, level 3 chargers are commonly situated at public charging stations, along thoroughfares, and within commercial establishments. This represents a further research direction to include the charger type selection in the optimization model depending on cost, charging speed, battery duration and size, and available infrastructure.

This chapter included the main contribution to Thesis 4.

Thesis 4: Presenting three case studies. The first one was in the Miskolc city center where the VRP problem was optimized by three algorithms next to a random route that is used as a comparison reference. The second one was in Kosice city center to validate a capacitive collection system using five algorithms. The adopted IoT tools allowed applying the constraints of vehicle maximum limit of goods, total collected goods for each vehicle, vehicles' flexibility, one/two ways consideration, and real routes' distances calculation. According to the results, GA is the advised algorithm to use, because it showed stable optimization effectiveness in both applications in contrast to the other algorithms. Furthermore, a last-mile supply optimization system within urban areas focusing on RL consideration was presented and described. The designed system incorporated cloud computing, real routes of vehicles, analysis of collected data, energy consumption optimization, and time windows. Also, a mathematical model was developed to optimize the total energy consumption. Real thirty locations in Budapest in the VII district were described and used for the third case study for finding the solutions of the optimized routes and energy consumption by GA for both diesel and electric trucks. The results were analyzed and compared against a random solution to clarify the presented optimization's effectiveness. [S4, S5, S10].

5. IN-PLANT COMPLEX PRODUCTION SYSTEM OPTIMIZATION

This chapter discusses and shows the research direction of in-plant complex production system optimization. It starts with an investigation of the Industry 4.0 technologies' adoption effect on CE. Next to theoretical analysis for this possible impact, a research collaboration with the Technical University of Kosice facilitated access an important data from the European Manufacturing Survey (EMS) project. An innovative way is used to analyze and discuss this impact by using many tools including statistical ones. The applied methodology and outcomes are detailed. After that, energy consumption optimization of milk-run-based in-plant supply solution is presented. The found system is described and detailed. The mathematical model for both conventional and real-time milk-run-based in-plant supply optimization is detailed. An optimization numerical analysis is used to compare the results and validate the model. The achieved results of this chapter were published mainly in three articles [S11, S12, S13].

5.1. Investigation of the Industry 4.0 technologies adoption effect on CE

Industry 4.0 represents several applications and technologies that provide various possible positive impacts on the industrial and logistics areas through supporting various practices that include CE [S1]. Despite the promising potential of Industry 4.0 technologies, there is a need to understand their effects on the manufacturing companies' outcomes in action. A study aimed to understand the patterns of Industry 4.0 technologies' adoption in manufacturing firms [144] showed that companies that have an advanced implementation level of Industry 4.0 tend to use most of the front-end technologies rather than a specific subset. Also, the Industry 4.0 framework was applied to raise the efficiency of energy and maintenance in a chemical plant where significant reductions (around 50%) in energy consumption and needed inspections for maintenance, next to less replacement time for the used pieces were achieved with a rational cost [145]. Management systems for energy and maintenance were integrated into the supply chain management system and the overall company management systems. Collected information by these management systems supported the process of decision-making. For the aspect of reuse and disassembly, a scientific gap in researching those two actions was mentioned [146].

Based on the resulting literature [146], CPSs, IoT, BDA, additive manufacturing (AM), and simulation were specified as prime Industry 4.0 technologies attached to the CE. On the other hand, the only found paper by a systematic literature review that focused on reuse strategies considered AM the main solution for raising reuse efficiency [147]. In that case, reusing was intended for the terms of facilitating the textiles disassembly and reassembly. In the conclusion of that analytical work, AM and the IoT were the most mentioned as digital enablers for the CE. CPSs were taken as valid assisting tools to develop innovative lifecycle and product management strategies as well [146]. In a study in 2021 [148] that used a survey that aimed 120 project managers, and 27 projects about the Industry 4.0 technologies effects on the CE, AM showed one of the greatest influences on CE, as an assumption, because it was more difficult to estimate the other Industry 4.0 technologies' impact to determine that contribution as a value. It also mentioned the necessity of developing other quantitative studies that embrace the industrial companies that use Industry 4.0 technologies as a combination in their processes and that have a synergistic impact on CE. Because although a few technologies appear to have a greater positive impact than others on individual bases, it appears important to consider the combined effect to measure the real influence on CE, however, the complexity of such multiple cases can limit its results. The results showed the existence of various effects that Industry 4.0 technologies bring to companies that contribute to circularity. The developments are mainly concerned with reducing the consumed material and energy, waste, and emissions generation. However, each technology showed noticeable different potential impacts. Especially, AM and robots that showed a higher positive impact. [148].

This investigation brings new light to this discussion of whether Industry 4.0 technologies have a potential influence on the use of CE technologies in manufacturing companies. It also reveals if the use of these Industry 4.0 technologies has a relation (potential influence) to the new product development, especially when the improved environmental impact of the product is the case. Moreover, the used data provided the possibility of including non-Industry 4.0 technologies to conduct a comparison of whether Industry 4.0 or non-Industry 4.0 technologies have a bigger potential to influence the adoption of CE technologies in manufacturing companies.

5.1.1. Theoretical background

This part presents a theoretical background related to this investigation. Mainly, the CE concept and the Industry 4.0 technologies related to CE are to be discussed.

CE represents a business mindset to assist companies and communities in moving toward sustainability [149]. It provides an alternative viewpoint on the operational and formal frameworks of producing and consuming that is focused on re-establishing the estimation of used assets. CE suggests using a roundabout path to treat the materials that are possible to provide financial, sustainable, and social advantages [150] to organizations and replacing the conventional style of ‘take, make, use and dispose’, which is recognized as the linear economy. However, applying CE concepts and standards in companies and manufacturing practices may face obstructions that cause more limitations than the fully expected results [151]. For instance, in a study of the CE implementation in China [152], the following challenges to a successful implementation of the CE were identified: a shortage of credible information, lack of state-of-art technology, weak legislation enforced, low economic rewards, weak leadership and management, and shortage of public awareness.

Regarding materials utilization [153], CE is a growing paradigm that aims to achieve sustainable utilization of natural resources [149]. It concentrates on increasing the resources' circularity within manufacturing systems, because raw resources are limited, and the waste even at the end of its life, can hold a value [154]. CE is primarily based on two cycles that are technical and biological [155]. The technical cycle emphasizes the growth of a product's life anticipation by a fast order of circular systems that include reusing, repairing, refurbishment, remanufacturing, and recycling [156]; this cycle is also looking to convert what is identified waste into inputs for other forming frameworks. The biological cycle supports the environment by reducing the gross extraction of raw assets, using the materials in a sustainable way, and adopting anaerobic assimilation methods in waste management [157,158]. CE can be represented with three principles as well. These three principles are protecting regular raw capital for achieving a balance for usage amongst sustainable and non-renewable assets, increasing the expected life for the assets by both natural and specialized ways, and reducing the unfavorable effects of production substructures [S1]. The following six business actions that are referred to by the ReSOLVE framework were presented by Ellen MacArthur Foundation [155]. ReSOLVE refers to Regenerate, Share, Optimize, Loop, Virtualize, and Exchange, which are used to direct organizations through the fulfillment of the CE principles. As a classification of Industry 4.0, nine technologies were the major blocks of Industry 4.0 [159]: BDA, autonomous robots and vehicles, AM, simulation, augmented and virtual reality, horizontal/vertical system integration, the IoT, cloud, fog, and edge technologies, and blockchain and cyber-security. Considering the expected influence of Industry 4.0 technologies on CE, six commonly identified Industry 4.0 technologies in the literature are to be presented in more detail in various industrial aspects. Even other technologies were mentioned but no more relevant studies found that support more details about their possible impact on CE.

Additive manufacturing. Thirty articles identified AM as a reference element for the relationships between Industry 4.0 and CE [146]. It mainly described how AM can help to manage the products' lifecycle and processes while only a few considerations were mentioned for other connections. Also, few researchers discussed AM use to improve existing recycling processes by new sustainable networks using and manufacturing process digitalizing, for instance, through a new type of process [160] or managerial strategies [161]. Others proposed AM utilization concept for supporting the products or components remanufacturing [162] [163], circular business model development that centered on recycled materials [164], and the reuse of products/materials [147].

Internet of Things. IoT is regarded as a very important technology that can facilitate the transmission into CE [146]. Away from the papers that focused on a general potential description for the IoT to extend the product life cycle, there was a mutual realization that IoT extends its potential influence on a broad number of areas related to CE. One of the options was to adopt the IoT for smart cities strategies in innovative waste management [165]. Another option was to improve the metallurgical processes' circularity level [166]. Also, an opportunity for leveraging the IoT was CE digitalization practices, for instance, implementing environments for smart industry [167] or control loops with dynamic feedback [168].

Simulation. Numerous studies were conducted to investigate the simulations' effects on circular business models and product lifecycle management [146]. Other studies identified various ways where simulation can support CE. For instance, material flow modeling [169] or using simulation tools to support the decision of products' remanufacturing [170] [171]. In a case study, simulation was discussed as a supporting tool in recycling for calculating the performance indexes of recycling [172].

Big Data and Analytics. BDA was considered an easy way to digitalize the CE [173]. However, the possibilities of this way varied in many directions. For instance, developing automated assessments of the potential secondary materials value [174], using open-source tools, open data, procedures, and services for encouraging the action of reusing [175] and the service of cloud platforms for data collection and analysis [176]. Also, BDA was considered within the integrative frameworks in innovative business models [177] for managing the products' lifecycle [178] or implementing smart manufacturing activities [179]. Moreover, improving disassembly sequence planning [180] and recycling issues during product design [181].

Robots. In a study about human-robot collaboration [182], a recycling line that is used for computer cathodic ray tube dismantling with a special focus on plastics was investigated. Only the tasks that need human skills were assigned to human operators while all other tasks were done by robots. The study resulted in a more efficient material recovery than the previously manual processes, primarily in terms of raising the quantity of recovered materials and plastic, which means higher revenues with significant additional benefits regarding the work environment via keeping humans away from the most dangerous tasks. Other studies also emphasized the advantages of human-robot collaboration for recycling [183], assembly, and disassembly [184] processes in several areas of frameworks for manufacturing and remanufacturing while focusing on their usefulness to support CE. Better productivity and profitability are usually achieved by assigning dangerous tasks to robots while other tasks with value-added allocated to humans.

Cyber-physical systems. CPSs were the least discussed Industry 4.0 technology for boosting CE practices [146]. However, CPSs showed an obvious orientation to support the CE direction. Many researchers saw CPSs as an orientation to enhance the management of products' lifecycle or the development of new services, primarily for maintenance [185]. A few cases showed that the focus was on practices of remanufacturing and the management of multiple users' systems, for instance, in natural resource extraction [186]. Also, a CPS was introduced for waste management optimization

that focused on sustainability and energy efficiency [S2] that showed effective results in saving the used energy.
As a conclusion to this introduction and brief literature review, the following notes are considered:

- The literature stated various applications of the developed Industry 4.0 technologies in the manufacturing areas with a high potential of raising the CE. It reflected a possibility of direct/indirect impact on the CE orientation.
- Industry 4.0 technologies contribute directly to digitalization, full product life analysis, dynamic feedback, and other tools that allow deeper and more inclusive analysis and optimization in the tackled system.
- Many studies focused on finding analysis tools that measure the sustainable impact of applying Industry 4.0 technologies. However, most of these studies had a narrow domain and limited results because they tackled limited manufacturing areas. Also, analyzing this impact can be complex research easily due to the various Industry 4.0 applications and compound data that cannot be attributed to specific reasons directly.
- A scientific gap in the correlation between Industry 4.0 and its impact on CE does exist. While the correlation of this potential relationship attempted to be shown, validating the correlation is very limited.

5.1.2. Methodology and data

While the literature revealed various Industry 4.0 technologies that can be applied in the manufacturing area, researching the real application of those technologies is considered a real challenge due to the needed time to adopt them in the companies. Mostly, this adoption requires a lot of time, effort, and training. After that, empirical research is needed to collect the data from these companies. From this perspective, one of the strongest pillars of this conducted research is to have inclusive data that almost covered all the manufacturing companies in the tackled countries. It was collected within the EMS project that is coordinated by the Fraunhofer Institute for Systems and Innovation Research [187]. The latest survey was carried out in eleven countries in 2018. It covered a core of indicators in the innovation fields. However, not all the mentioned Industry 4.0 technologies in the literature were used in this project. Therefore, according to the used data sample, only AM, robots, and simulation partially are to be analyzed (since only product simulation technology is covered). On the other hand, the literature included two aspects of CE, one showed CE as a promising approach toward sustainability and the other one showed the need to measure this potential impact because it is difficult to provide direct influence due to the various playing factors in practice. Within the mentioned survey used in this research, I worked on mapping related CE. Therefore, according to the data available in the sample, I analyzed the adopted technologies related to water recycling and reusing and kinetic and process energy recuperating in the manufacturing companies. While no direct conception was structured about if there are patterns between applying such technologies and the size, products type, conducted research and development actions, sector or another specification of the companies [188], a common consciousness of such adoption's usefulness is widespread, especially regarding the energy saving [189]. Moreover, other actions were considered in the manufacturing companies that are connected to CE indirectly, as they reflect major improvements in the products or process and improved environmental impact. These actions are to be considered under a separate category titled product characteristics.
Regarding the used methods in the literature, various studies used different methods to reach their desired results. In a study about connecting CE and Industry 4.0 [190], the cause-and-effect relationship was used between various dimensions of Industry 4.0 and CE in the supply chain area. The dimensions of Industry 4.0 were obtained through the analysis of exploratory factors. 161 responses from Indian manufacturing companies were the sample data. Also, they performed a cause-and-effect relationship through DEMATEL analysis. Other studies also addressed different hypotheses to be analyzed in a specific way. In a study that examined the role of Industry 4.0 on CE

practices and the capability of the supply chain to increase the company's performance [191], eight hypotheses were presented while structural equation modeling was used for analyzing them. Also, in investigating how Industry 4.0 technologies and stakeholder pressure influence circular product design and impact company performance [192], five hypotheses were assumed. Partial least squares path modeling for data analysis was used. In another study [193], a qualitative analysis of selected case studies aimed to answer three research questions. The results were visualized to highlight applying digital technologies' effects on processes, companies, products, and supply chain within the transition into CE. Likewise, in a study regarding adopting the Industry 4.0 technologies pattern in manufacturing companies [144], four hypotheses were presented about using smart manufacturing technologies. The first step to analyzing the data was by identifying the tackled companies into several maturity scales regarding their adoption level of smart manufacturing technologies. Two groups with distinct technological levels were needed at a minimum for testing the hypotheses and finding out different patterns between these groups to explain the Industry 4.0 adoption. Then, a hierarchical cluster analysis was used to determine the adequate number of groups for sample division. After having the cluster compositions obtained, an analysis of the demographic aspect of the cluster members was performed. Pearson's Chi-squared test was used to reject the null hypothesis that stated there is no association among the variables. Also, the test of Fisher's exact was used for associations to reach four observations or less.

As it was shown, there is a wide spectrum of approaches and methods used in the literature to investigate Industry 4.0's impact on CE. The rationale of the methodology is based on the research questions and available data. The general research question is if there are relationships between the use of Industry 4.0 and CE in manufacturing companies. The data comprises a sample of central European manufacturing companies, which includes the use of selected Industry 4.0 and CE technologies. To find out if there are relationships, the raw data were filtered at the beginning to exclude any invalid entries, and then, the methodology was built into two steps. First step: grouping the data to see if there are some differences in the use of technologies in the subsample groups. For this, contingent tables were used. This helped to find out where to expect possible relations between technologies. In this step, I also included non-Industry 4.0 technologies to see if there are differences between the use of Industry 4.0 and non-Industry 4.0 technologies. Second step: logistic regression (by IBM SPSS Statistics 25 software) was used to validate the expected relations. Before starting the logistic regression, a correlation test was applied to the independent variables to affirm their independence. It should be mentioned that even in a case where logistic regression shows a statistically significant relation between Industry 4.0 and CE technology, it does not reflect a causal relationship. Therefore, the odd ratio was used to reflect the strength of these possible relationships, but it cannot affirm them as a direct influence. In other words, this methodology can only show relations, but not affirm if Industry 4.0 supports or enhances the CE. This is one limitation of the used methodology. Nevertheless, showing the existence of the significant relationship can help other researchers to focus on this relationship and investigate causality.

The tackled data is collected within the EMS project. The sample (N=798) contains data collected in Lithuania [194], Slovakia [195], Austria [196], Croatia, and Slovenia [197] as part of the EMS in 2018. The numbers of companies in Lithuania, Slovakia, Austria, Croatia, and Slovenia are respectively 199, 114, 253, 105, and 127. These five countries were chosen since they represent relatively similar numbers of manufacturing companies. Also, the sample size of each country is considered separately small for conducting statistical tests. By analyzing the EMS data, the technologies that have a direct connection with this research were selected and stated in Figure 47. The mutually used questions within the EMS project in the mentioned five countries were considered since a few differences exist between one country and another in the actual practice of the survey. Also, used abridgments for the tackled technologies are mentioned in Figure 47.

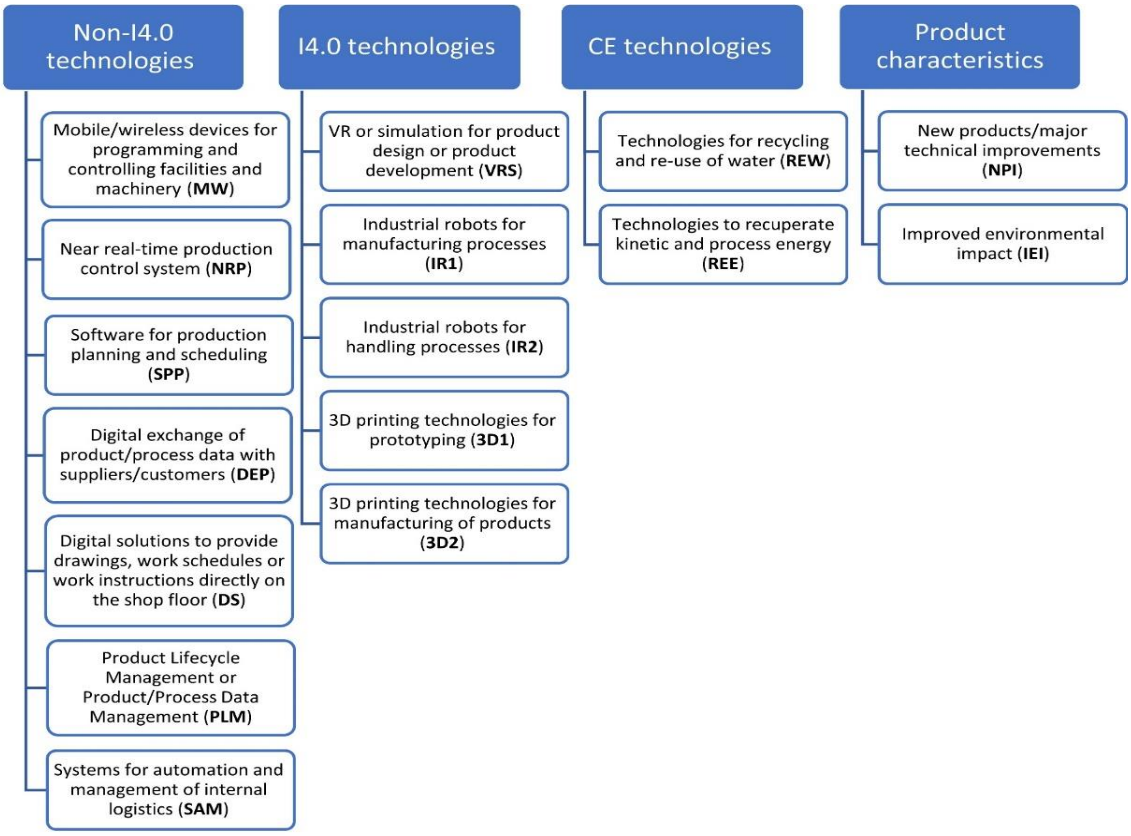

Figure 47: Used technologies and product innovation (variables) with abridgments

To be able to connect the used data with the aim of this research, the related data are classified into four categories. First, non-Industry 4.0 technologies that provide solutions based on digital and automation, however, they are not modern and/or innovative to be considered as Industry 4.0 technologies depending on the literature. Second, Industry 4.0 technologies that are related to literature. Third, CE technologies that show taken actions in the companies for water saving by reusing or recycling, or for energy recuperating. Fourth, product characteristics that can be connected to CE indirectly by showing major improvements or new products that reflect the research and development aspect of the company as well as improved environmental impact of a new or improved product, for instance, extended product life, improved recycling, or reduced environmental pollution.

5.1.3. Hypotheses building

According to the available data and depending on the classified technologies (Figure 47), I built a research question, if there is a relationship (potentially effect) between the mentioned Industry 4.0 + non-Industry 4.0 technologies and adopting the mentioned CE technologies in manufacturing companies. Based on that, two hypotheses were developed:

H1a: Implementation of CE technologies that support recycling and re-use of water is related to the adoption of Industry 4.0 technologies.

H1b: Implementation of CE technologies that support recuperating process energy is related to the adoption of Industry 4.0 technologies.

The research model (Figure 48) is the same for testing the two hypotheses in two steps, with only a difference in the dependent variable. While in the validation of H1a, the dependent variable is “technologies for recycling re-use water”, in the case of H1b, it is “technologies to recuperate kinetic and process energy”. For the independent variables, I have used all technologies which are included in the data sample (Industry 4.0 and non-Industry 4.0 technologies) (Figure 47).

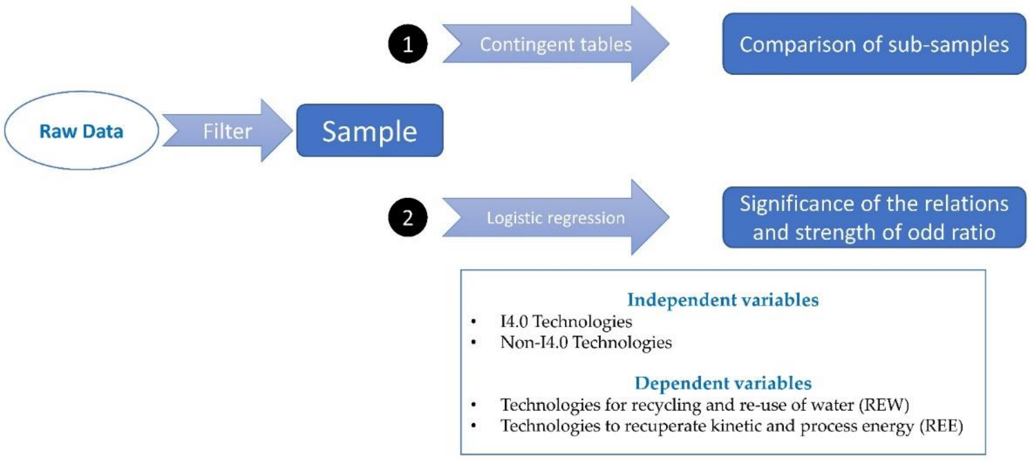

Figure 48: Research model 1 for testing H1a and H1b

Since there is data related to the product characteristics that can be connected to CE indirectly (Figure 47) in the sample, I also built a second research question, if there is a relation (potentially effect) between the use of Industry 4.0 + CE technologies and improved environmental impact of the product. Based on that, two additional hypotheses were developed:
H2a: Introducing new products or major technical improvements is related to the implementation of Industry 4.0 technologies.
H2b: The development of products that lead to an improved environmental impact is related to the implementation of Industry 4.0 technologies.
The research model (Figure 49) represents the same two steps methodology as above for testing both hypotheses, with changing the independent and the dependent variables. While in the validation of H2a the dependent variable is "introducing new products or major technical improvements of products", in the case of H2b it is "improved environmental impact of a new (or improved) product". Even though H2a is not directly connected to CE, I used it to allow us to find out if the use of specific Industry 4.0 technologies has a different relation to new product development and its improved environmental impact. In this model, as the independent variables, I have used all technologies in the data sample, including Industry 4.0, non- Industry 4.0, and CE technologies (Figure 47).

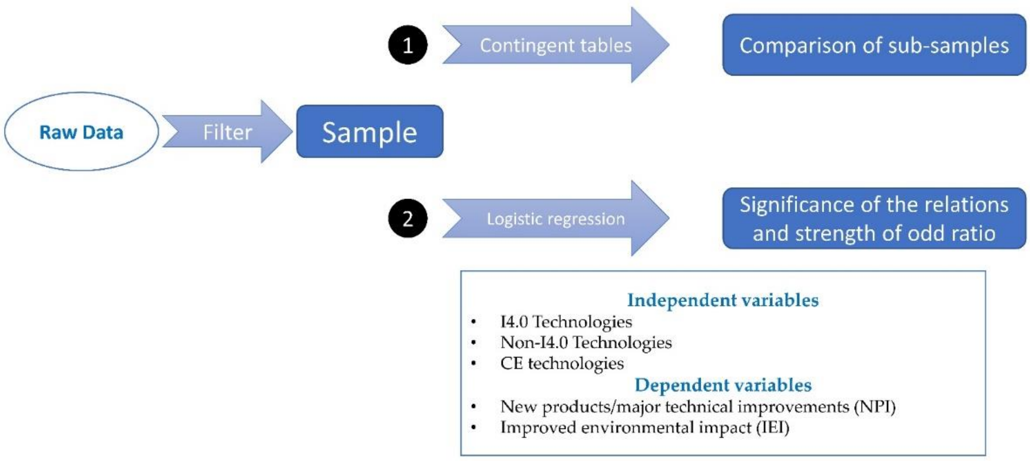

Figure 49: Research model 2 for testing H2a and H2b

For analyzing the results, the significance was considered, which is referred to as 'Sig' where it should be equal to or less than 0.05/0.1 to consider them acceptable. The results that achieved this condition were highlighted with dark grey color for a significance less than 0.05 and with light grey color for a significance equal to or less than 0.1. After that, Exp(B) was considered, which refers to the odd ratio that simply comes from B raised to the exponent. The odd ratio indicates no effect when its value is 1. When the odds ratio is greater than 1, it indicates that the specific predictor increases the odds of the output, while an odds ratio less than 1 indicates the specific predictor decreases the odds of the outcome [198]. Therefore, Sig and Exp(B) are to be used to discuss the results where the higher Exp(B) means more likely to have an impact on the dependent variable.

5.2. Results and discussion

This section is divided into two sub-sections for presenting the results of the two models.

5.2.1. Relations investigation of the research model 1

Within this model, possible relations for the impact of used technologies in the areas of production control, digital factory, automation and robotics, and AM technologies on the adoption of REW (resp. REE) technologies were analyzed. The differences between the companies' percentages that use Industry 4.0 (but also non- Industry 4.0) technologies in the whole sample compared to the subsample of companies that are using REW (resp. REE) technologies in the manufacturing companies are presented in Table 25 and Figure 50.

Table 25: Comparison of companies that use Industry 4.0/non-Industry 4.0 technologies

Technology	Whole sample	Subsample of companies that use REW	Subsample of companies that use REE
MW	34.63	39.58	44.59
DS	46.04	53.93	55.41
SPP	61.39	76.44	75.78
DEP	43.76	56.68	53.92
NRP	35.07	52.36	48.65
SAM	27.72	39.79	39.91
PLM	19.07	28.75	27.957
VRS	25.52	34.375	31.82
IR1	27.34	40.84	35.87
IR2	24.22	41.67	42.79
3D1	15.56	21.35	23.42
3D2	10.33	13.54	13.96

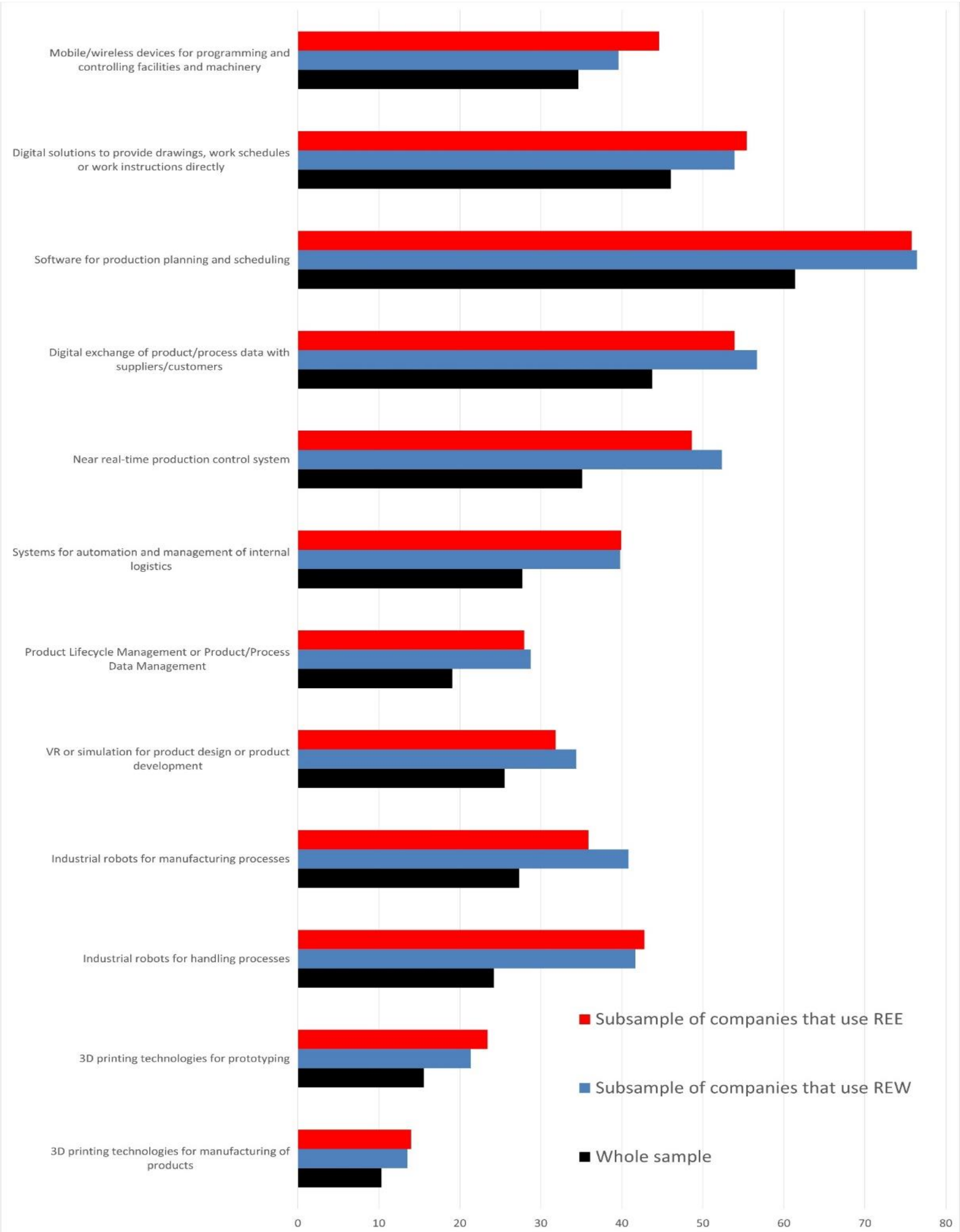

Figure 50: Comparison of companies' percentages that use Industry 4.0 or non-Industry 4.0 technology

By comparing the percentages for the whole sample and subsample of companies that use REW, I can find the highest differences in the case of three technologies (industrial robots for handling processes, near real-time production control system, and software for production planning and scheduling). There are also other three technologies showing differences (industrial robots for manufacturing processes, the digital exchange of product/process data with suppliers/customers, and systems for automation and management of internal logistics). Based on this, relationships between the use of these technologies and the use of REW are expected. By comparing the percentages for the whole sample and subsample of companies that use REE, I can find the highest differences also in the case of three technologies (industrial robots for handling processes, near real-time production control system, and software for production planning and scheduling). There are also other three technologies showing differences (systems for automation and management of internal logistics, the

digital exchange of product/process data with suppliers/customers, and mobile/wireless devices for controlling facilities and machinery. Based on this, I expect relationships between the use of these technologies and the use of REE. The statistical test is applied to validate the expected relationship and support or deny the hypothesis. The method for testing is the logistic regression by IBM SPSS Statistics 25 software. For the H1a test, the sample was N = 543 after filtering the raw data. Before testing, a correlation test was applied to the 12 independent variables (Figure 47, Industry 4.0, non-Industry 4.0). The tackled variables (technologies) appeared to be independent where the highest correlation value was 0.3638 except for 3D1 and 3D2 technologies, which showed 0.533. These values allow us to consider the 12 technologies as independent variables. The results of the logistic regression are presented in Table 26.
As Table 26 shows, four technologies of SPP, NRP, IR1, and IR2 showed statistically significant relationships with the dependent variable REW. IR2 and NRP showed the strongest significance of relationship and influence (Exp(B)) on the REW. Based on this, I can conclude that the significance of the relationship between the use of specific technology and the use of REW, is not dominantly influenced by whether it is Industry 4.0 technology or not.

Table 26: Results of logistic regression (research model 1, dependent variable – REW)

Technology	B	Std. Err.	Wald	df	Sig	Exp(B)	CI 95%	
							Lower	Upper
MW	-0.222	0.231	0.925	1	0.336	.801	0.510	1.259
DS	0.076	0.229	0.109	1	0.742	1.079	0.688	1.691
SPP	0.463	0.266	3.029	1	0.082	1.588	.943	2.674
DEP	0.342	0.222	2.373	1	0.123	1.407	0.911	2.174
NRP	0.667	0.236	7.992	1	0.005	1.949	1.227	3.096
SAM	0.151	0.237	0.405	1	0.525	1.163	0.731	1.849
PLM	0.059	0.281	0.044	1	0.834	1.061	0.612	1.839
VRS	0.192	0.252	0.581	1	0.446	1.212	0.739	1.988
IR1	0.466	0.235	3.928	1	0.047	1.594	1.005	2.527
IR2	0.711	0.233	9.336	1	0.002	2.035	1.290	3.210
3D1	-0.217	0.322	0.452	1	0.502	.805	0.428	1.515
3D2	-0.190	0.366	0.270	1	0.603	.827	0.403	1.695
Constant	-2.077	0.228	82.922	1	0.000	.125		

To validate the expected relationship in H1b, I used the logistics regression test again. Before this analysis, I filtered the raw data accordingly (final N = 546 companies). The correlation test is the same as the previous one (same 12 technologies).
The results of the logistic regression test are presented in Table 27. Four technologies of SPP, NRP, SAM, and IR2 showed statistically significant relationships with the dependent variable REE. IR2 and SPP showed the strongest significance of relationship and influence (Exp(B)) on the REE. I can conclude also in the case of REE (similarly to REW), that the significance of the relationship between the use of specific technology and the use of REE, is not dominantly influenced by whether it is Industry 4.0 technology or not. It is important to highlight that NRP showed a 0.106 significance result in Table 27. Even if it is more than the significant step of 0.1, it is very close to it, therefore, it was considered equal to 0.1.

Table 27: Results of logistic regression (research model 1, dependent variable – REE)

Technology	B	Std. Err.	Wald	df	Sig	Exp(B)	CI 95%	
							Lower	Upper
MW	0.205	0.216	0.897	1	0.344	1.227	0.803	1.875
DS	0.196	0.220	0.800	1	0.371	1.217	0.791	1.872
SPP	0.631	0.254	6.152	1	0.013	1.879	1.142	3.094
DEP	0.078	0.214	0.133	1	0.715	1.081	0.710	1.646
NRP	0.370	0.229	2.614	1	0.106	1.448	0.925	2.266
SAM	0.389	0.226	2.952	1	0.086	1.475	0.947	2.298
PLM	0.011	0.271	0.002	1	0.969	1.011	0.594	1.720
VRS	0.018	0.246	0.005	1	0.942	1.018	0.629	1.647

IR1	0.006	0.232	0.001	1	0.978	1.006	0.639	1.585
IR2	0.973	0.226	18.447	1	0.000	2.645	1.697	4.124
3D1	0.041	0.307	0.018	1	0.893	1.042	0.571	1.902
3D2	-0.384	0.355	1.171	1	0.279	0.681	0.340	1.875
Constant	-1.940	0.221	77.411	1	0.000	0.144		

5.2.2. Relations investigation of the research model 2

Within this model, possible relations for the impact of used technologies in the areas of production control, digital factory, automation and robotics, and AM technologies on the new or improved product development (NPI), (resp. improved environmental impact (IEI) of the product) were analyzed. The differences between the companies' percentages that use Industry 4.0, non- Industry 4.0, and CE technologies in the whole sample compared to the subsample of companies that have done NPI, (resp. IEI) are presented in Table 28 and Figure 50.

Table 28: Comparison of companies that use the Industry 4.0 or non-Industry 4.0 technology

Technology	Whole sample	Subsample of companies that have done NPI	Subsample of companies that have done IEI
MW	34.63	43.17	36.99
DS	46.04	48.89	61.19
SPP	61.39	56.22	75.34
DEP	43.76	43.18	47.22
NRP	35.07	44.89	43.58
SAM	27.72	28.89	36.24
PLM	19.07	20.41	33.52
VRS	25.52	32.20	42.99
IR1	27.34	29.03	39.37
IR2	24.23	21.43	39.09
3D1	15.56	12.43	25.91
3D2	10.33	13.07	18.81
REW	25.77	26.9	32.39
REE	29.59	27.06	33.95

By comparing the percentages for the whole sample and subsample of companies that have done NPI, I can find the highest differences are in the case of three technologies (NRP, MW, and VRS). Other technologies showed less significant differences, but interestingly, some were negative (the highest negative difference was SPP), but in value it was small. Based on this, I expect a relationship between the use of these technologies and the execution of NPI.

By comparing the whole sample and subsample percentages of companies that have done IEI, highest differences in the case of five technologies (DS, SPP, PLM, VRS, and IR2) are found. Also, two other technologies (IR1 and 3D1) showed moderate differences. Based on this, I expect more relationships between the use of these technologies and the execution of IEI.

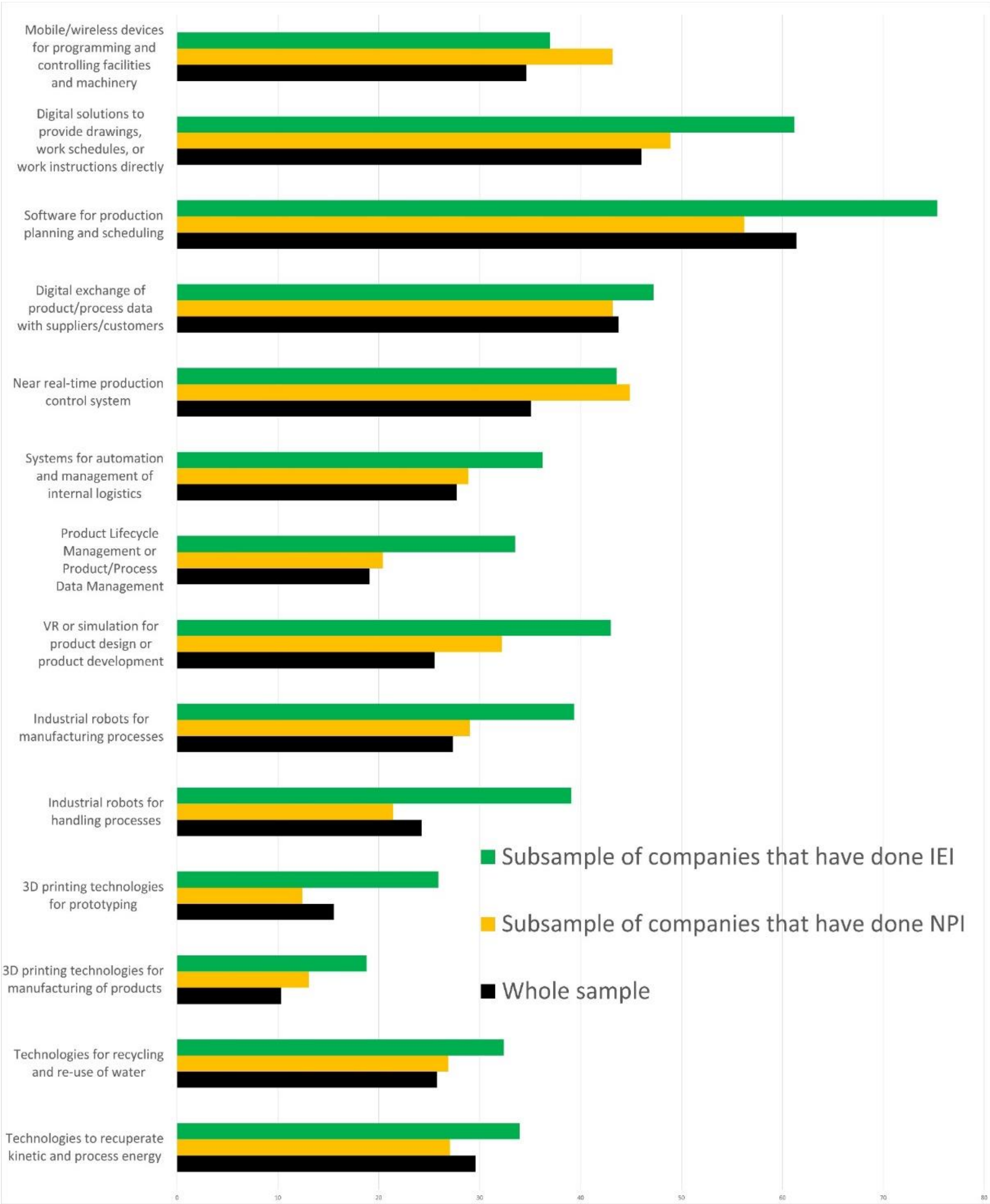

Figure 51: Comparison of companies' percentages that use I4.0, non-I4.0, or CE technology

To validate the expected relationship in H2a, I used the logistics regression test again. Before this analysis, the raw data was filtered accordingly (final N = 535 companies) and made the correlation test for 14 technologies (12 technologies + 2 CE technologies). The highest correlation value for the two new variables (technologies) was 0.346, which is still low and allows us to consider the 14 technologies as independent variables. The results of the logistic regression are presented in Table 29.

As Table 29 shows, only the two technologies of VRS and 3D1 showed statistically significant relationships with the dependent variable NPI. They both showed strong significance of relationship and influence (Exp(B)). Based on this, surprisingly, the significant relationships are not between technologies that I expect according to the differences identified above (Figure 51), but the main finding is, that it seems that Industry 4.0 technologies dominate over non-Industry 4.0 and CE technologies in having significant relationships with the execution of NPI in manufacturing companies.

Table 29: Results of logistic regression (research model 2, dependent variable – NPI)

Technology	B	Std. Err.	Wald	df	Sig	Exp(B)	CI 95%	
							Lower	Upper
MW	-0.096	0.227	0.179	1	0.672	.908	0.583	1.417
DS	0.143	0.214	0.447	1	0.504	1.154	0.759	1.755
SPP	-0.187	0.228	0.676	1	0.411	.829	0.531	1.296
DEP	0.140	0.210	0.444	1	0.505	1.150	0.763	1.734
NRP	0.272	0.239	1.293	1	0.255	1.312	0.821	2.097
SAM	0.175	0.247	0.499	1	0.480	1.191	0.733	1.934
PLM	0.420	0.316	1.764	1	0.184	1.522	0.819	2.830
VRS	0.825	0.273	9.105	1	0.003	2.281	1.335	3.898
IR1	0.069	0.235	0.086	1	0.769	1.071	0.676	1.698
IR2	0.270	0.244	1.222	1	0.269	1.310	0.812	2.113
3D1	0.748	0.361	4.298	1	0.038	2.113	1.042	4.286
3D2	0.427	0.417	1.048	1	0.306	1.533	0.677	3.472
REW	0.196	0.236	0.686	1	0.408	1.216	0.765	1.932
REE	-0.168	0.226	0.550	1	0.458	.845	0.542	1.318
Constant	0.013	0.176	0.005	1	0.942	1.013		

In the last part of the analysis, to validate the expected relationship in H2b, I used the logistics regression test again. Before the analysis, the raw data were filtered accordingly (final N = 430 companies). The correlation test is the same as the previous one (same 14 technologies). The results of the logistic regression are presented in Table 30.

As shown in Table 30, four technologies of SPP, PLM, VRS, and IR2 showed statistically significant relationships with the dependent variable IEI. The strongest significance of relationship and influence (Exp(B)) on the IEI has PLM. Interestingly, despite the expected higher number of technologies to be related to the execution of IEI, the regression does not prove it. Nevertheless, in contrast to the execution of NPI, it seems that the significance of the relationship between the use of specific technology and the execution of IEI is not dominantly influenced by whether it is Industry 4.0 technology or not.

Table 30: Results of logistic regression (research model 2, dependent variable – IEI)

Technology	B	Std. Err.	Wald	df	Sig	Exp(B)	CI 95%	
							Lower	Upper
MW	-0.190	0.247	0.592	1	0.441	0.827	0.510	1.342
DS	0.345	0.241	2.045	1	0.153	1.412	0.880	2.266
SPP	0.454	0.266	2.897	1	0.089	1.574	0.934	2.653
DEP	-0.383	0.241	2.538	1	0.111	0.682	0.425	1.092
NRP	-0.270	0.262	1.064	1	0.302	0.763	0.457	1.275
SAM	-0.018	0.259	0.005	1	0.944	0.982	0.591	1.631
PLM	0.949	0.300	10.001	1	0.002	2.583	1.434	4.651
VRS	0.620	0.255	5.916	1	0.015	1.858	1.128	3.061
IR1	0.167	0.244	0.468	1	0.494	1.181	0.733	1.904
IR2	0.573	0.256	5.014	1	0.025	1.773	1.074	2.927
3D1	0.078	0.325	0.057	1	0.811	1.081	0.572	2.042
3D2	0.481	0.375	1.643	1	0.200	1.618	0.775	3.375
REW	0.071	0.256	0.077	1	0.782	1.074	0.650	1.773
REE	0.139	0.251	0.307	1	0.580	1.149	0.702	1.880
Constant	-1.244	0.213	34.072	1	0.000	0.288		

5.3. Discussion of the results

The investigation of the relations between the use of Industry 4.0 and CE technologies (research model 1) showed that in general, it seems that both Industry 4.0 technologies and non-Industry 4.0 technologies could have significant relations with CE technologies. Interestingly, both have significant relation with three identical technologies (IR2, NRP, and SPP) and one different for each. The most significant relation (measured by Sig. and Exp(B)) in the case of both CE technologies is IR2, i.e., industrial robots for handling processes. This relation could possibly be connected to the technological level of the company. The existence of the relation with the second identical technology

(NRP), for both CE technologies (especially the REW) could be caused by specific characteristics of the production process. The third commonly related technology (SPP) (especially significant for REE) can support previous arguments, that the company that uses REW or REE should be on some technological level and have a specific production process, where it can apply SPP. In the case of REW, there is one different significant technology (IR1). Explanation of significant relation with IR1 in the case of REW can lead us to the sectors such as automotive, electronics, etc., where the use of IR1 is widespread, so again to some specifics of the production process. In the case of REE, the different technology is SAM. I can only assume that some specifics of the production process can play a role in this relation.

The results showed significant relations of CE technologies (REW and REE) with robotics (IR1 and IR2), which is in partial agreement with e.g., the review of [148], who stated that there is most evidence of the positive impact of AM and robotics on circularity in companies. This found relation (in the case of IR2) is also in accordance with Álvarez-de-los-Mozos et al. [182] and Renteria et al. [183]. However, another study [146] stated that AM could be exploited to improve energy consumption, which is not in line with the results. Another finding [148] that showed AM and VRS having the potential to reduce energy consumption, is also not supported by the results. In addition, they showed for robotics, that CE energy indicators vary in a range between 1.7 and 2.7 (on Likert-scale 0-4), i.e., the value of the influence is medium-high, however, the impact on the CE water variable has been less valued than 1.7. The results indicated the opposite situation since in the case REE has a significant relation with only one robotics variable (IR2) and REW has a significant relationship with both robotics variables (IR1, IR2), but I should be aware of the different methodologies and variables in both studies. Nevertheless, the results are in line with additional findings of [148] that identified small energy reductions (less than 5%) in relation to the use of robots, despite the energy consumption of the robots. When looking solely at the REE technologies, a significant relationship is found with SPP and SAM, in accordance with Rosa et al. [146], Bloomfield et al. [147], Lahrour et al. [162], and Leino et al. [163] and in case of NRP with Rosa et al. [146] and Hatzivasilis et al. [167]. When looking separately at REW technologies, significant relation was found with NRP that is in line with Rosa et al. [146] and Hatzivasilis et al. [167], while in the case of SPP with Rosa et al. [146], Bloomfield et al. [147], and Nascimento et al. [164].

The investigation of the relation between Industry 4.0, non-Industry 4.0, and CE technologies and execution of new or improved product development (NPI) (resp. new or improved products with improved environmental impact (IEI)) (research model 2) showed major differences. In the case of NPI as dependent variable, two technologies (VRS and 3D1) showed statistically significant relationships. Here, the explanation is quite clear since both VRS and 3D1 are logically tight to product development. Moreover, this result confirms the validity of the data and analyses. Lastly, it should be mentioned that clear dominance of Industry 4.0 technologies appears here. In the case of IEI as a dependent variable, the situation is different. Like NPI, VRS (as a product development tool) created significant relations with IEI. Nevertheless, even higher significance (also influence (Exp(B)) is in the PLM (Product lifecycle management or product/process data management). These are important findings that PLM has the potential to be an influential factor in the improvement of the environmental impact of the products. There were also other two technologies (SPP and IR2) that showed statistically significant relationships with IEI. This is not so straightforward to explain, but I assume similarly to above, that it can be connected to the technological level of the company and specifics of the production process. Lastly, it should be mentioned that no clear dominance of Industry 4.0 technologies over non-Industry 4.0 was found. In addition, it seems that there was not a clear connection between the use of CE technologies and the development of a product with improved environmental impact.

The results in the case of NPI (as a dependent variable) supported the literature findings [144], which showed there is a connection between the adoption of Smart Manufacturing and Smart Product technologies. The finding on VRS relation to product development was also in accordance with Rosa et al. [146], Kuik et al. [170], and Wang et al. [171]). Another study [146] showed that Industry 4.0 technologies can have a positive effect on the lifecycle management of products, while I found similarly that the use of virtual reality and robotics is related to the development of the IEI (improved environmental impact of a new product) by the company. The results [148] that showed robotics to have a medium influence (1.5 - 2.2 on Likert-scale 0-4) on reuse and recovery characteristics of the products are also in agreement with the found results since I identified the relationship between the use of robots (IR2) and IEI. Moreover, the relationship between IEI of the product and VRS technology is in line with the findings of Kuik et al. [170] and Wang et al. [171], while the relation with IR2 is in accordance with Álvarez-de-los-Mozos et al. [182] and Daneshmand et al. [184]. Finally, a relationship was found between IEI with PLM and SPP is also supportive of previous studies (Rosa et al. [146] and Unruh [161]). The results of the analysis, from the view of tackled Industry 4.0 and non-Industry 4.0 technologies, showed a statistically significant relationship with dependent variables (REW, REE, NPI, IEI) in a few of them. Interestingly there were only two technologies (SPP and IR2) that showed a significant relationship (so potential impact) on the CE technologies (REW, REE) but also on the development of the product with improved environmental impact (IEI). What is behind this wider “pro-environmental” scope of these two technologies (in comparison to others) is not clear but could guide the focus of future research in this field.

The results showed that eight of the tackled twelve (resp. fourteen) technologies have a significant relation with CE technologies (research model 1) or CE improvements of products (research model 2). Regarding CE technologies (REW and REE), the investigation of their relations with the use of Industry 4.0 technologies showed, that in general, it seems, that both Industry 4.0 technologies and non-Industry 4.0 technologies could have significant relations with them, so they could be potentially influenced or enhanced by both. Interestingly, both CE technologies have significant relation with three identical technologies (IR2, NRP, and SPP) and one different for each, while in both cases the most significant is IR2. The explanation of the findings directs us to the characteristics like the technological level of the company or specifics of the production process. My findings support previous studies that showed a positive impact of robotics on circularity in companies but are not in line with studies that showed AM or virtual reality could be exploited to improve energy consumption.

Regarding CE improvements of products (environmental impact (IEI) of new or improved products), the investigation of its relations with the use of Industry 4.0 technologies showed no clear dominance of Industry 4.0 technologies over non-Industry 4.0. It was found that VRS as Industry 4.0 (resp. product development) technology relates significantly, but also non-Industry 4.0 (PLM technology) has even higher significance. I consider this identified relation an important finding because it reveals the PLM´s potential to be an influential factor in the improvement of the environmental impact of the products. A significant relation with the other two technologies, SPP and IR2, is not so straightforward to explain, but I assume that the technological level of the company and specifics of the production process could lie behind it. Regarding the relationship with CE technologies, it seems that there is no connection between product development with IEI and these technologies. The findings are not in contradiction with previous studies, for example, that Industry 4.0 technologies can have a positive effect on the lifecycle management of products or that robotics has a medium influence on the reuse and recovery characteristics of the products.

On the other hand, four of the twelve (resp. fourteen) tackled technologies did not show any significant relation with CE technologies (research model 1) or CE improvements of products (research model 2) that are namely MW, DS, DEP, and 3D2. The results, from the view of tackled Industry 4.0 and non-Industry 4.0 technologies, showed that there are only two technologies (SPP and IR2) have a significant relationship (so potential impact) on the CE technologies (REW, REE) but also on the development of the product with improved environmental impact (IEI). This wider CE relationship can guide the focus of future research in this field. The results confirm the potential CE efficiency growth in manufacturing companies by adopting the Industry 4.0 technologies. While not all the technologies showed significant relations, the achieved results still give strong affirmation in accordance with the literature review in the direction of that various application of the developed Industry 4.0 technologies have a high potential of raising the CE. The results gain special importance since it is based on a large sample of companies (N=798) and handles numerous technologies, but it has some limitations regarding its focus on Central Europe and the manufacturing industry.

5.4. Energy consumption optimization of milk-run-based in-plant supply solution

Smart factories are equipped with Industry 4.0 technologies including smart sensors, digital twins, big data, and embedded software solutions. The application of these technologies contributes to real-time decision-making, and this can improve the efficiency of both manufacturing and related logistics processes. Therefore, the transformation of conventional milk-run-based in-plant supply solutions into a cyber-physical milk-run supply is to be discussed, where the application of Industry 4.0 technologies makes it possible to make real-time decisions regarding scheduling, routing, and resource planning.

5.4.1. Introduction

The purpose is to describe a novel mathematical model, which makes it possible to integrate the MES data-based and real-time generated supply demands to decrease the energy consumption and virtual GHG emission of milk-run trolleys. The scope is an optimization approach that is based on the application of Industry 4.0 technologies with the aim of improving the efficiency, flexibility, and sustainability of the in-plant supply. This in-plant supply system is based on Industry 4.0 technologies including digital twin and milk-run approaches with the aim of energy consumption optimization. A numerical analysis is presented for the two described models in different scenarios with comparative analysis among them.

Starting with a brief literature about the impact of Industry 4.0 technologies on the optimization of energy consumption of milk-run-based in-plant supply solutions. Manufacturing sector benefits from new technological development including new product development, time-to-market reduction, cost-effective use of manufacturing resources, and personalized production supplying [199]. To validate smart manufacturing, essential issues should be taken into consideration, which include interoperability, developing the integration of the technologies, developing the technologies themselves, and customization of the support for technology development and implementation as required practically [200]. Smart factory expresses the integration and combination of Industry 4.0 technologies in the manufacturing sector. The terms ‘smart’ and ‘intelligent’ are used interchangeably to show various aspects of ‘smartness’ or ‘intelligence’ by applying advanced manufacturing systems. The found papers in a review study [201] covered various areas of smartness/intelligence of the future factory next to a broad range of activities and proposed models, algorithms, methodologies, frameworks, and other tools, which support developing and applying the technology to fit the actual needs in manufacturing covering different recognition levels toward the implementation and deployment in the real factory. Also, to encounter the highly diverse customer demands within new manufacturing systems next to the constantly increasing product variety and continuous mass customization, the single-model assembly lines transferred to mixed-model assembly lines in manufacturing [202]. The mixed model for the assembling line in the mass production method works on the assembly of several variants of finished products within the same assembly line that contributes to the realization of lean production in automobile companies. However, the big number of component variables makes it more difficult for just-in-time materials to arrive within the mixed-model assembling lines, which leads to a significant challenge in the problem of supplying the materials in manufacturing systems [203].

One of the important methods in delivery is the milk-run, which allows the movement of small quantities of various items with predictable lead times from many suppliers to a customer. The main goal of this method is to minimize the costs of transportation that come from minimizing the transportation distance and maximizing the vehicle capacities. The uncertainties and effects in the arrival times of vehicles and loading times of shipments are also to be considered in modeling the problems of milk-run [66]. A milk-run material-feeding problem was analyzed and used in different approaches such as being researched based on a two-level logistics network for mixed-model assembly lines that was proposed as a series of material-feeding tasks and performed by a group of electrical vehicles between the central warehouse and the line-integrated. That problem aimed to minimize the number of used vehicles number and at the same time, to maximum the electric vehicles traveling distance, which leads to the same direction of raising the efficiency of cost and energy requests within the just-in-time production of automobile manufacturing [204]. While Industry 4.0 and manufacturing digitalization were once considered among coming directions [205], they are currently considered a main part of the manufacturing plans for transformation into a more customer-oriented inclusion within the mass customization as this is among the strategic priorities for manufacturers who are looking for sustainable competitiveness [206]. This supported the planning of the regular small-lot deliveries from a decentralized storage point into various locations. Loading and delivery schedule problems aimed to be optimized. The optimization included the selection of material types and quantities next to the best sequence of materials that should be delivered to each assembly station at each time with the aim of minimizing the total cost related to material transportation and storage at stations [88]. For instance, by raising productivity efficiency [207] or decreasing GHG emissions. An investigation of Industry 4.0 technologies' adoption in manufacturing companies confirmed the efficiency growth because of this adoption [S11] where the automation of production planning and scheduling next to industrial robots for handling processes showed significant relationships with improving the environmental impact and productivity.

5.4.2. Structure of Industry 4.0-based in-plant supply

As the literature showed, the application of Industry 4.0 technologies can lead to a significant increase in the performance of manufacturing and service processes. It is especially important in the case of in-plant supply processes of manufacturing systems, where the availability, flexibility, and efficiency of logistics processes have a great impact on the manufacturing operations, therefore, it is unavoidable to apply Industry 4.0 technologies to improve conventional in-plant supply systems and transform them into CPSs. This transformation can lead to real-time in-plant supply optimization, which is important to take dynamically changing demands, status, and failure data into consideration (Figure 52).

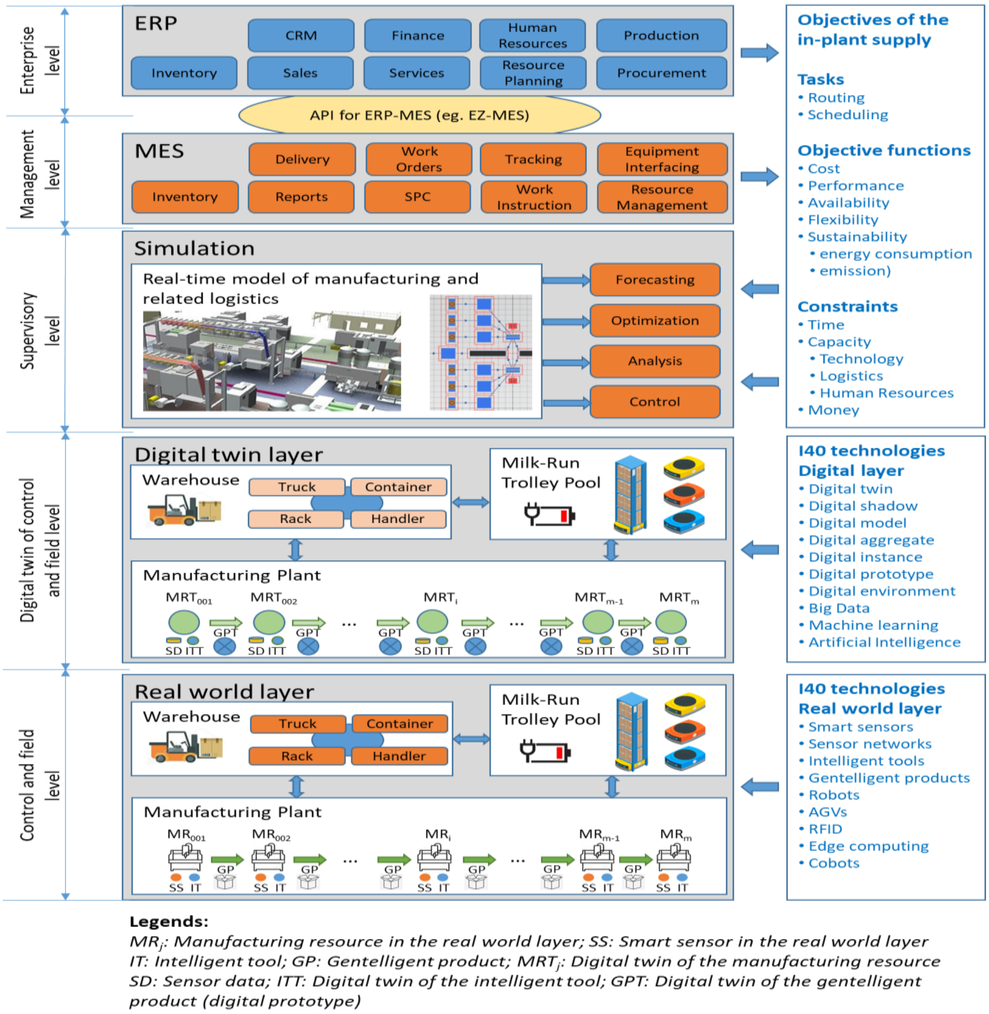

Figure 52: Structure of Industry 4.0 technologies supported by milk-run-based in-plant supply

The structural model of Industry 4.0 technologies supported by milk-run-based in-plant supply includes the following levels:

- Enterprise level: the enterprise level is represented by Enterprise Resource Planning (ERP), where all strategic decisions are made. The ERP includes the following main modules: inventory, sales, finance, services, human resources, procurement or purchasing, and customer relationship management. The production module focuses on scheduling and quantitative analysis, while the shop-floor process operations are managed by the MES in real-time, based on the results of the supervisory level, as mentioned in Pyramid Solutions [208].
- Management level: the management level is represented by the MES, which focuses on productivity and cost efficiency by using the following MES modules and functions: delivery, inventory, reports, work orders, statistical process control, work orders, tracking, work instructions, resource management, and equipment interfacing.
- Supervisory level: the supervisory level supports the optimization processes of MES through simulation, analysis, and forecasting. The simulation model of the discrete event simulation software is a dynamic real-time model, which is permanently upgraded by the digital twin of the real-world system, including technological and logistics processes. The technological processes include the manufacturing zone, while logistics includes the warehousing zone and the resources of in-plant supply, e.g., the milk-run trolley pool. The supervisory level is

responsible for the support of MES functions, including optimization of shop floor processes and in-plant supply optimization.

- Digital twin of the control and field level: in the digital level of the model, three levels of maturity of digital twin solutions are defined: digital model, digital shadow, and digital twin. In the case of the digital model, we are talking about a digital copy of the physical system, where the data exchange is performed manually in both directions between the physical and digital systems. In the case of digital shadow, status and failure data is uploaded from the physical system to the digital shadow, while in the other direction, the data upload is automatic. In the case of the digital twin, the data exchange is performed automatically. The digital twin is a digital reproduction of the physical system, which represents all parameters of the physical system based on status information and failure data from sensors, sensor networks, and sensor hubs. Big data is especially important in the case of the digital twin because sensors collect data with big volume, velocity, and variety. The digital aggregate represents processes, the digital prototype products, while the digital environment is a copy of the physical environment of the physical system. The digital twin generates a real-time model based on the status information and failure data of the manufacturing system, warehouse, and in-plant supply logistics, and this real-time model is uploaded to the discrete event simulation. The real-time upgraded simulation model is a very important part of the model because the simulation and optimization of the integrated manufacturing and in-plant supply system can be efficiently performed only with a real-time upgraded model, including the status of resources and processes.
- Control and field level: this level is represented by the real-world system, where the physical components of the manufacturing and logistics operations are integrated into a value chain. The physical level of the model includes the following Industry 4.0 technologies: smart sensors, sensor networks, sensor hubs, edge computing, intelligent tools, gentelligent products or components, robots, AGVs, cobots, and RFID technologies for the identification or location detection. The monitoring of technological and logistics resources is performed by smart sensors and sensor networks. These smart sensors, sensor networks, and sensor hubs collect data from the physical system and perform predefined preprocessing and statistical analysis to create a predefined specific input regarding status information and failure data. The preprocessed information is sent to an IoT gateway through RFID, Bluetooth, or Message Queue Telemetry Transport, which is the standard messaging protocol for IoT solutions. The monitoring of the tool condition can be automatized by using intelligent tools, where in-built micro-sensors can send information regarding the status of the machining tool [209]. Gentelligent products generate information about their creation, distribution, and use, including their life cycle. Gentelligent products in the physical processes can support the decision-making regarding operations required in the manufacturing and logistics processes [210]. In the model, the sensor data comes from manufacturing resources, warehouse equipment, milk-run trolleys, products, and operators.

Based on the above-mentioned application, it is possible to define a mathematical model and to optimize the in-plant supply taking not only MES data-based predefined supply demands but also real-time through the supervisory level generated in-plant supply demands into consideration.

5.5. Mathematical model of Industry 4.0 supported in-plant supply optimization

The objective function of the optimization model is the energy efficiency of the milk-run-based in-plant supply, while time and capacity-related constraints are taken into consideration. Depending on the source of the in-plant supply demand, two different types of scheduling can be defined. In-plant supply demands generated by the MES can be scheduled before a specific, predefined time window, while new in-plant supply demands generated by the supervisory level must be scheduled in real-time. The supervisory level can generate real-time in-plant demands depending on the status information and failure data uploaded from the digital twin of the manufacturing, warehouse, or milk-run trolley depot zone, and the prescheduled, MES-based routing must be upgraded to fulfill the new in-plant supply demands. In this section, the conventional milk-run-based in-plant supply model and the real-time milk-run-based in-plant supply model supported by Industry 4.0 technologies are described.

5.5.1. Conventional milk-run-based in-plant supply optimization

The optimization model of the conventional milk-run-based in-plant supply includes the following main parts:

- the objective function (minimization of energy consumption and emission),
- time-based constraints,
- capacity-based constraints,
- sequence-based constraints,
- energy-based constraints,
- decision variable (optimal routing and scheduling of MES-based and real-time supply demands).

In the case of conventional optimization, two solutions are defined: in the first case only MES data-based in-plant supply demands are taken into consideration, while in the second case, real-time demands are also added to the routes as separated supply operations.

The objective function of the milk-run-based in-plant supply can be defined depending on the routing and scheduling of the milk-run trolleys:

$$\begin{aligned} C_{EC} = \sum_{i=1}^{m+\xi} \Bigg[& l_{i,0,x_{i,1}} \cdot q_{i,0,x_{i,1}} \cdot e\left(q_{i,0,x_{i,1}}\right) + l_{i,x_{i,i_{max}},0} \cdot q_{i,x_{i,i_{max}},0} \cdot e\left(q_{i,x_{i,i_{max}},0}\right) \\ & + \sum_{j=1}^{i_{max}-1} l_{i,x_{i,j},x_{i,j+1}} \cdot q_{i,x_{i,j},x_{i,j+1}} \cdot e\left(q_{i,x_{i,j},x_{i,j+1}}\right) + \sum_{j=0}^{i_{max}} e^{MH} \cdot (\Delta q_{i,j}) \Bigg] \rightarrow min \end{aligned} \tag{57}$$

where C_{EC} is the energy consumption of the milk-run-based in-plant supply solution within the time frame of the analysis, $l_{i,0,x_{i,1}}$ is the length of the route scheduled between the milk-run trolley depot and the first station of the in-plant supply in the case of route i, $q_{i,0,x_{i,1}}$ is the weight of the loading of the milk-run trolley between the milk-run trolley depot and the first station of the in-plant supply in the case of route i, $l_{i,x_{i,i_{max}},0}$ is the length of the route scheduled between the last station and the milk-run trolley depot of the in-plant supply in the case of route i, $q_{,x_{i,i_{max}},0}$ is the weight of the loading of the milk-run trolley between the last station and the milk-run trolley depot of the in-plant supply in the case of route i, $l_{i,x_{i,j},x_{i,j+1}}$ is the length of the route scheduled between station j and station j+1 in the case of the milk-run route i, $q_{i,x_{i,j},x_{i,j+1}}$ is the weight of the loading of the milk-run trolley between station j and station j+1 in the case of the milk-run route i, e is the specific energy consumption of the milk-run trolley depending on the weight of the loading of the milk-run trolleys: $e = e(q)$, i_{max} is the number of stations assigned to route i, $x_{\alpha,\beta}$ is the assignment matrix, which is the decision variable of the optimization problem, as the ID of βth station of route α. based on MES-data generated in-plant supply demands, e^{MH} is the specific energy consumption of material handling operations and $\Delta q_{i,j}$ is the weight of loaded/unloaded products at the station j of route i (difference of weight before and after station i).

Time-related constraints of the conventional optimization. In the case of MES-generated in-plant supply demand the time-related constraint can be defined depending on the scheduled route for the first station of the route as follows:

$$\forall i: \tau_{i,x_{i,1}}^{min} \leq \frac{l_{i,0,x_{i,1}}}{v(q_{i,0,x_{i,1}})} \leq \tau_{i,x_{i,1}}^{max} \tag{58}$$

where $\tau_{i,x_{i,1}}^{min}$ is the lower limit of the arrival time of the milk-run trolley to the first station of the scheduled route i, $\tau_{i,x_{i,1}}^{max}$ is the upper limit of the arrival time of the milk-run trolley to the first station of the scheduled route i, $v\left(q_{i,0,x_{i,1}}\right)$ is the velocity of the milk-run trolley depending on the loading between the milk-run trolley depot and the first station of route i.
In the same way, the time limit for the stations before the last station is as follows:

$$\forall i,, j_i^*: \tau_{i,x_{i,j_i^*}}^{min} \leq \frac{l_{i,0,x_{i,1}}}{v(q_{i,0,x_{i,1}})} + \frac{\sum_{j=1}^{j_i^*} l_{i,x_{i,j},x_{i,j+1}}}{v(q_{i,x_{i,j},x_{i,j+1}})} \leq \tau_{i,x_{i,j_i^*}}^{max} \tag{59}$$

where j_i^* is a station between the first station and the depot of the milk-run trolley and $0 < j_i^* < i_{max} - 1$, $v\left(q_{i,x_{i,j},x_{i,j+1}}\right)$ is the velocity of the milk-run trolley depending on the loading between station j and j+1.
Time-related constraints are defined for the depot of the milk-run trolley:

$$\forall i: \tau_{i,x_{i,i_{max}}}^{min} \leq \frac{l_{i,0,x_{i,1}}}{v(q_{i,0,x_{i,1}})} + \frac{\sum_{j=1}^{i_{max}-1} l_{i,x_{i,j},x_{i,j+1}}}{v(q_{i,x_{i,j},x_{i,j+1}})} + \frac{l_{i,x_{i,i_{max}},0}}{v(q_{,x_{i,i_{max}},0})} \leq \tau_{i,x_{i,i_{max}}}^{max} \tag{60}$$

In the case of a conventional milk-run-based in-plant supply, new supply demands are assigned to new supply routes, which means that new milk-runs must be initialized, and this can lead to a significantly increased cost. In the case of conventional in-plant supply, the time-related constraints can be taken into consideration, where the number of routes can be increased by the number of demands generated by the supervisory level.
The time-related constraint for the first station of the routes after adding new milk-runs based on the real-time supply demands to the scheduled supply demands can be defined as follows:

$$\forall \sigma: \tau_{\sigma,x_{\sigma,1}}^{min} \leq \frac{l_{\sigma,0,x_{\sigma,1}}}{v(q_{\sigma,0,x_{\sigma,1}})} \leq \tau_{\sigma,x_{\sigma,1}}^{max} \text{ and } \sigma = m + \xi, \tag{61}$$

where σ is the number of routes after adding new milk-runs based on the real-time in-plant supply demand, ξ is the number of supply demands generated by the supervisory level.
In the same way, the time limit for the stations before the last station after adding new milk-runs based on the real-time supply-demand is as follows:

$$\forall \sigma, j_\sigma^*: \tau_{\sigma,x_{\sigma,j_\sigma^*}}^{min} \leq \frac{l_{\sigma,0,x_{\sigma,1}}}{v(q_{\sigma,0,x_{\sigma,1}})} + \frac{\sum_{j=1}^{j_\sigma^*} l_{\sigma,x_{\sigma,j},x_{\sigma,j+1}}}{v(q_{\sigma,x_{\sigma,j},x_{\sigma,j+1}})} \leq \tau_{\sigma,x_{\sigma,j_\sigma^*}}^{max} \tag{62}$$

The case of conventional scheduling of real-time in-plant supply demands time-related constraints are defined for the depot of the milk-run trolley after adding new milk-runs based on the real-time supply-demand as follows:

$$\forall \sigma: \tau_{\sigma,x_{\sigma,\sigma_{max}}}^{min} \leq \frac{l_{\sigma,0,x_{\sigma,1}}}{v(q_{\sigma,0,x_{\sigma,1}})} + \frac{\sum_{j=1}^{\sigma_{max}} l_{\sigma,x_{\sigma,j},x_{\sigma,j+1}}}{v(q_{\sigma,x_{\sigma,j},x_{\sigma,j+1}})} + \frac{l_{\sigma,x_{\sigma,\sigma_{max}},0}}{v(q_{,x_{\sigma,\sigma_{max}},0})} \leq \tau_{\sigma,x_{\sigma,\sigma_{max}}}^{max} \tag{63}$$

where σ_{max} is the number of milk-run routed after adding new milk-runs to the MES-based scheduled routes.
The capacity-based constraint takes the capacity of the milk-run trolleys into consideration. In the case of MES data-based in-plant supply optimization the capacity-based constraint can be defined as follows:
in the case of the first station:

$$\forall i: q_{i,0,x_{i,1}} \leq q_i^{max} \tag{64}$$

in the case of the station between the start and end point of the route (these points are generally in the milk-run trolley depot):

$$\forall i, j_i^*: q_{i,0,x_{i,1}} + \sum_{j=1}^{j_i^*} q_{i,x_{i,j},x_{i,j+1}} \leq q_i^{max} \tag{65}$$

in the case of the last station of the route (generally in the milk-run trolley depot after arrival):

$$\forall i: q_{i,0,x_{i,1}} + q_{x_{i,i_{max}},0} + \sum_{j=1}^{i_{max}-1} q_{i,x_{i,j},x_{i,j+1}} \leq q_i^{max} \tag{66}$$

This capacity-based constraint can be transformed to take real-time demands added to the scheduled route into consideration:

in the case of the first station:

$$\forall\sigma: q_{\sigma,0,x_{\sigma,1}} \leq q_{\sigma}^{max} \tag{67}$$

in the case of the station between the start and end point of the route (these points are generally in the milk-run trolley depot):

$$\forall\sigma, j_{\sigma}^{*}: q_{\sigma,0,x_{\sigma,1}} + \sum_{j=1}^{j_{\sigma}^{*}} q_{\sigma,x_{\sigma,j},x_{\sigma,j+1}} \leq q_{\sigma}^{max} \tag{68}$$

in the case of the last station of the route (generally in the milk-run trolley depot after arrival):

$$\forall\sigma: q_{\sigma,0,x_{\sigma,1}} + q_{,x_{\sigma,\sigma_{max}},0} + \sum_{j=1}^{\sigma_{max}} q_{\sigma,x_{\sigma,j},x_{\sigma,j+1}} \leq q_{\sigma}^{max} \tag{69}$$

Sequence-related constraints of the conventional optimization. I can also describe sequencing-related constraints, where specific sequences of stations can be predefined. This sequencing-related constraint can be written as follows in the case of MES data-based optimization using an $\exists(x)P(x)$ existential quantifier:

$$\forall i, j: \exists\left(x_{i,j}\right)x_{i,j+1} = r_{i,j} \tag{70}$$

where $r_{i,j}$ defines the succeeded station.

This sequence-based constraint can be transformed to take real-time demands added to the scheduled route into consideration:

$$\forall\sigma, j: \exists\left(x_{\sigma,j}\right)x_{\sigma,j+1} = r_{\sigma,j} \tag{71}$$

Energy consumption-related constraints of conventional optimization. The milk-run trolleys are working with electricity; therefore, the capacity of their batteries is also an important energy-based constraint, which is especially important in the case of heavy loadings and long in-plant supply distances.

This energy consumption-based constraint can be defined in the case of conventional in-plant supply routing and scheduling as follows:

in the case of MES data-based conventional routing and scheduling:

$$\forall i: l_{i,0,x_{i,1}} \cdot q_{i,0,x_{i,1}} \cdot e(q_{i,0,x_{i,1}}) + l_{i,x_{i,i_{max}},0} \cdot q_{,x_{i,i_{max}},0} \cdot e(q_{,x_{i,i_{max}},0}) + \sum_{j=1}^{i_{max}-1} l_{i,x_{i,j},x_{i,j+1}} \cdot q_{i,x_{i,j},x_{i,j+1}} \cdot e(q_{i,x_{i,j},x_{i,j+1}}) \leq bc_i \tag{72}$$

in the case of conventional optimization of MES data-based and added real-time demands:

$$\forall\sigma: l_{\sigma,0,x_{\sigma,1}} \cdot q_{\sigma,0,x_{\sigma,1}} \cdot e(q_{\sigma,0,x_{\sigma,1}}) + l_{\sigma,x_{\sigma,\sigma_{max}},0} \cdot q_{,x_{\sigma,\sigma_{max}},0} \cdot e(q_{,x_{\sigma,\sigma_{max}},0}) + \sum_{j=1}^{\sigma_{max}} l_{\sigma,x_{\sigma,j},x_{\sigma,j+1}} \cdot q_{\sigma,x_{\sigma,j},x_{\sigma,j+1}} \cdot e(q_{\sigma,x_{\sigma,j},x_{\sigma,j+1}}) \leq bc_{\sigma} \tag{73}$$

where bc_i is the available capacity of the battery in the case of MES data-based routing and bc_{σ} is the available capacity of the battery in the case of conventional integrated routing of MES data-based and real-time in-plant supply optimization.

5.5.2. Real-time milk-run-based in-plant supply optimization

The optimization model of the Industry 4.0 technologies supported by real-time milk-run-based in-plant supply is presented in Figure 53.

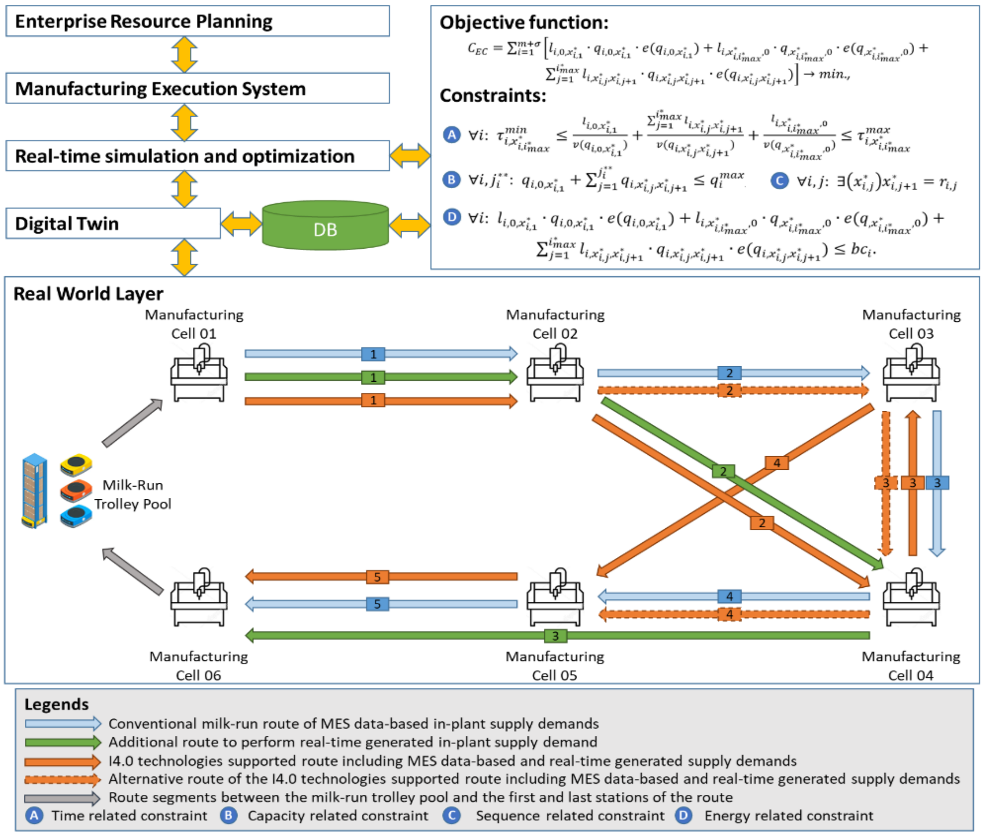

Figure 53: Industry 4.0 technologies supported real-time milk-run-based in-plant supply optimization model

The model includes the following main parts:

- the objective function (minimization of the energy consumption and emission after adding MES data-based and real-time in-plant supply demands),
- time-based constraints (both the MES data-based and the real-time supply demands must be performed within a predefined specific time window),
- capacity-based constraints (it is not allowed to exceed the capacity of the milk-run trolleys),
- sequence-based constraints (the predefined sequences of stations must be taken into consideration),
- energy-based constraints (the available energy of the battery must be taken into consideration),
- decision variable (optimal routing and scheduling of MES-based and real-time supply demands).

In the case of Industry 4.0 technologies-based optimization, the real-time data regarding failures and status can be taken into consideration and the existing, scheduled routes can be rescheduled in real-time, therefore no additional milk-run routes must be started.

In the case of the Industry 4.0 technologies-based in-plant supply operation, it is possible to optimize the MES data-based scheduled routes and modify the existing routes re-time to add the new in-plant supply demands generated by the supervisory level. In this case, the objective function can be transformed into a new objective function, where the milk-runs perform not only the MES data-based supply demands but also the real-time demands generated by the supervisory level:

$$C_{EC} = \sum_{i=1}^{m} \Big[l_{i,0,x^*_{i,1}} \cdot q_{i,0,x^*_{i,1}} \cdot e(q_{i,0,x^*_{i,1}}) + l_{i,x^*_{i,i^*_{max}},0} \cdot q_{x^*_{i,i^*_{max}},0} \cdot e(q_{x^*_{i,i^*_{max}},0}) + \sum_{j=1}^{i^*_{max}-1} l_{i,x^*_{i,j},x^*_{i,j+1}} \cdot q_{i,x^*_{i,j},x^*_{i,j+1}} \cdot e(q_{i,x^*_{i,j},x^*_{i,j+1}}) \Big] \rightarrow min \quad (74)$$

where $x^*_{\alpha,\beta}$ is and assignment matrix, which is the decision variable of the optimization problem, as the ID of β station of route α. based on real-time in-plant supply demands generated by the supervisory level and i^*_{max} is the number of stations added to route i including both MES-based and supervisory level-based in-plant supply demands. In the case of real-time scheduling, the time-related constraints can be modified, because in this case the real-time in-plant supply demands are integrated into the MES data-based scheduled routes.

In the case of real-time in-plant supply optimization, the time-related constraint can be defined depending on the scheduled route for the first station of the route as follows:

$$\forall i: \tau^{min}_{i,x^*_{i,1}} \leq \frac{l_{i,0,x^*_{i,1}}}{v(q_{i,0,x^*_{i,1}})} \leq \tau^{max}_{i,x^*_{i,1}} \tag{75}$$

where $\tau^{min}_{i,x^*_{i,1}}$ is the lower limit of the arrival time of the milk-run trolley to the first station of the scheduled route i after adding all real-time supply-demand generated by the supervisory level, $\tau^{max}_{i,x^*_{i,1}}$ is the upper limit of the arrival time of the milk-run trolley to the first station of the scheduled route i after adding all real-time supply-demand generated by the supervisory level, $v\left(q_{i,0,x^*_{i,1}}\right)$ is the velocity of the milk-run trolley depending on the loading between the milk-run trolley depot and the first station of route i after adding all real-time supply-demand generated by the supervisory level. If the rescheduling of the in-plant supply routes is performed after the milk-run trolley passes the first station of their route, then $\tau^{min}_{i,x^*_{i,1}} = \tau^{min}_{i,x_{i,1}}$ and $\tau^{max}_{i,x^*_{i,1}} = \tau^{max}_{i,x_{i,1}}$. In the case of real-time in-plant supply optimization, the time limit in the same way for the stations before the last station is as follows:

$$\forall i, j^{**}_i: \tau^{min}_{i,x^*_{i,j^{**}_i}} \leq \frac{l_{i,0,x^*_{i,1}}}{v(q_{i,0,x^*_{i,1}})} + \frac{\sum_{j=1}^{j^{**}_i} l_{i,x^*_{i,j},x^*_{i,j+1}}}{v(q_{i,x^*_{i,j},x^*_{i,j+1}})} \leq \tau^{max}_{i,x^*_{i,j^{**}_i}} \tag{76}$$

where j^{**}_i is a station between the first station and the depot of the milk-run trolley after adding the real-time in-plant supply demands to the scheduled milk-run.

Also, these time-related constraints are defined for the depot of the milk-run trolley as follows:

$$\forall i: \tau^{min}_{i,x^*_{i,i^*_{max}}} \leq \frac{l_{i,0,x^*_{i,1}}}{v(q_{i,0,x^*_{i,1}})} + \frac{\sum_{j=1}^{i^*_{max}-1} l_{i,x^*_{i,j},x^*_{i,j+1}}}{v(q_{i,x^*_{i,j},x^*_{i,j+1}})} + \frac{l_{i,x^*_{i,i^*_{max}},0}}{v(q_{,x^*_{i,i^*_{max}},0})} \leq \tau^{max}_{i,x^*_{i,i^*_{max}}} \tag{77}$$

The capacity-based constraint takes the capacity of the milk-run trolleys into consideration. In the case of the scheduling and routing of both MES data-based and real-time supply demands, the capacity-based constraint can be defined as follows:

in the case of the first station:

$$\forall i: q_{i,0,x^*_{i,1}} \leq q^{max}_i \tag{78}$$

In the case of the stations between the start and end point of the route (these points are generally in the milk-run trolley depot):

$$\forall i, j^{**}_i: q_{i,0,x^*_{i,1}} + \sum_{j=1}^{j^{**}_i} q_{i,x^*_{i,j},x^*_{i,j+1}} \leq q^{max}_i \tag{79}$$

In the case of the last station of the route (generally in the milk-run trolley depot):

$$\forall i: q_{i,0,x^*_{i,1}} + q_{x^*_{i,i_{max}},0} + \sum_{j=1}^{i_{max}-1} q_{i,x^*_{i,j},x^*_{i,j+1}} \leq q^{max}_i \tag{80}$$

Sequencing-related constraints are described, where specific sequences of stations can be predefined including existing in-plant supply tasks and new real-time tasks to be scheduled. This sequencing-related constraint can be written as follows:

$$\forall i, j: \exists\left(x^*_{i,j}\right) x^*_{i,j+1} = r_{i,j} \tag{81}$$

This energy consumption-based constraint can be defined in the case of the Industry 4.0-supported real-time in-plant supply routing and scheduling as follows:

$$\forall i: l_{i,0,x^*_{i,1}} \cdot q_{i,0,x^*_{i,1}} \cdot e(q_{i,0,x^*_{i,1}}) + l_{i,x^*_{i,i^*_{max}},0} \cdot q_{,x^*_{i,i^*_{max}},0} \cdot e(q_{,x^*_{i,i^*_{max}},0}) + \sum_{j=1}^{i^*_{max}-1} l_{i,x^*_{i,j},x^*_{i,j+1}} \cdot q_{i,x^*_{i,j},x^*_{i,j+1}} \cdot e(q_{i,x^*_{i,j},x^*_{i,j+1}}) \leq bc_i \tag{82}$$

5.5.3. Optimization numerical analysis

Within the frame of this section, the above-described in-plant supply models are validated using two different scenarios. The optimization of the scenarios was performed by Excel Evolutive Solver, but

in the case of large-scale problems other solvers for NP-hard problems can be used. The first scenario analyses the conventional scheduling and routing of MES data-based in-plant supply and the conventional scheduling and routing of real-time in-plant supply generated by the supervisory level, while the second scenario focuses on the computational results of real-time milk-run-based in-plant supply optimization supported by Industry 4.0 technologies.
The input parameters of both optimization problems are the followings:

- the layout of the plant includes the manufacturing zone, warehousing zone, and milk-run trolley depot, which defines the location of each manufacturing and logistics resource and the distances among them.
- MES data-based supply demands for a predefined specific time window (Table 31).
- sources and destinations of MES data-based supply demands (Table 31).
- predefined specific time frames for MES data-based supply demands (Table 31).
- real-time supply demands for a predefined specific time window (Table 32).
- sources and destinations of real-time generated supply demands (Table 32).
- predefined specific time frames for real-time generated supply demands (Table 32).
- capacity and net weight of milk-run trolleys.
- the average velocity of milk-run trolleys.
- specific energy consumption of transportation of components by milk-run trolleys depending on the weight of loading.
- specific energy consumption of material handling operations (loading and unloading of milk-run trolleys), depending on the weight of components.
- The following assumptions are taken into consideration in the numerical analysis:
- it is not allowed to exceed time-related constraints (time windows for supply demands),
- it is not allowed to exceed the capacity of milk-run trolleys,
- the number of available milk-run trolleys is limited, and it is not allowed to exceed,
- the MES-generated supply demands are not changing within a time window,
- it is not allowed to exceed the available energy of milk-run trolleys (battery capacity is limited),
- the velocity of milk-run trolleys is constant, but in further models, acceleration can also be taken into consideration,
- real-time generated supply demands are scheduled within the current time window.

Table 31: MES data-based supply demands of the in-plant supply optimization problem

C_ID[1]	**Type**[2]	**From**[3]	**To**[4]	**LOAD**[5]	**TFRAME**[6]	**C_ID**[1]	**Type**[2]	**From**[3]	**To**[4]	**LOAD**[5]	**TFRAME**[6]
C_01	LO	C_00	-	9	03:50:00-03:53:00	C_10	LO	C_00	-	8	03:59:00-04:04:00
C_02	UNLO	-	C_10	40	03:40:00-03:42:00	C_10	UNLO	-	C_00	7	04:24:00-04:25:00
C_02	LO	C_00	-	2	03:52:00-03:53:00	C_11	LO	C_00	-	10	04:00:00-04:04:00
C_02	UNLO	-	C_04	17	03:52:00-03:57:00	C_11	UNLO	-	C_16	8	04:02:00-04:05:00
C_03	LO	C_14	-	21	03:42:00-03:45:00	C_11	LO	C_07	-	7	04:24:00-04:27:00
C_03	UNLO	-	C_00	15	03:42:00-03:44:00	C_11	UNLO	-	C_00	36	04:27:00-04:30:00
C_03	LO	C_00	-	9	03:54:00-03:57:00	C_12	LO	C_00	-	12	03:28:00-03:30:00
C_03	LO	C_00	-	18	04:21:00-04:24:00	C_12	LO	C_00	-	12	03:47:00-03:50:00
C_04	LO	C_07	-	14	03:44:00-03:47:00	C_12	UNLO	-	C_13	8	04:15:00-04:17:00
C_04	LO	C_02	-	17	03:55:00-03:57:00	C_13	LO	C_12	-	8	04:15:00-04:20:00
C_04	UNLO	-	C_00	8	03:55:00-03:57:00	C_13	UNLO	-	C_08	14	04:16:00-04:20:00
C_04	UNLO	-	C_00	5	04:22:00-04:24:00	C_14	UNLO	-	C_03	21	03:30:00-03:32:00
C_05	UNLO	-	C_00	5	03:56:00-03:59:00	C_14	LO	C_00	-	2	04:06:00-04:08:00
C_05	LO	C_00	-	15	03:57:00-04:04:00	C_14	LO	C_16	-	20	04:30:00-04:35:00
C_06	LO	C_07	-	11	03:58:00-04:04:00	C_15	UNLO	-	C_00	10	03:46:00-03:50:00
C_07	LO	C_00	-	21	03:35:00-03:40:00	C_16	LO	C_00	-	25	03:30:00-03:35:00
C_07	UNLO	-	C_04	14	03:35:00-03:40:00	C_16	LO	C_11	-	8	04:03:00-04:05:00
C_07	LO	C_00	-	8	03:48:00-03:50:00	C_16	LO	C_00	-	10	04:28:00-04:30:00
C_07	UNLO	-	C_06	11	03:48:00-03:50:00	C_16	UNLO	-	C_14	20	04:30:00-04:32:00
C_07	UNLO	-	C_11	7	04:18:00-04:20:00	C_17	UNLO	-	C_00	7	04:03:00-04:06:00

C_08	LO	C_13	-	14	04:19:00-04:22:00	C_17	LO	C_00	-	16	04:27:00-04:30:00
C_10	LO	C_02	-	40	03:45:00-03:47:00	C_17	UN	-	C_00	2	04:28:00-04:30:00

[1] C_ID=Identification number of the assembly or manufacturing cell. [2] Type=Type of the material handling operation at the assembly or manufacturing cell (LO=loading and UNLO=Unloading). [3] From=Source of the components to be transported to the assembly or manufacturing cell. [4] To=Destination of the components loaded at a specific assembly or manufacturing cell. [5] LOAD=Load of the milk-run trolley [LU]. [6] CLO=Cumulative loading after passing the specific station [LU].

Table 32: Real-time generated supply demands of the in-plant supply optimization problem

C_ID[1]	Type[2]	From[3]	To[4]	LOAD[5]	TFRAME[6]
C_01	UNLO	-	C_17	12	03:40:00-03:42:00
C_17	LO	C_01	-	12	03:46:00-03:50:00
C_17	UNLO	-	C_15	24	04:03:00-04:06:00
C_15	LO	C_17	-	24	04:03:00-04:08:00
C_07	UNLO	C_00	-	34	04:15:00-04:17:00
C_05	UNLO	-	C_15	21	04:20:00-04:30:00
C_15	LO	C_05	-	21	04:22:00-04:35:00

5.5.4. Conventional milk-run-based in-plant supply optimization

The conventional milk-run-based in-plant supply includes two main phases. Within the first phase, the MES data-based supply demands are scheduled, while in the second phase, real-time generated supply demands are scheduled and assigned to new supply routes of milk-run trolleys.
In the first part of scenario 1, three different milk-run routes are defined for MES data-based in-plant supply demands. These routes represent a theoretical scenario. This part of scenario 1 takes only the MES data-based supply demands of the in-plant supply optimization problem into consideration (Table 31). In the case of route 1, 10 in-plant supply demands are performed and all of them are between the predefined time window (Figure 54 and Table 33).

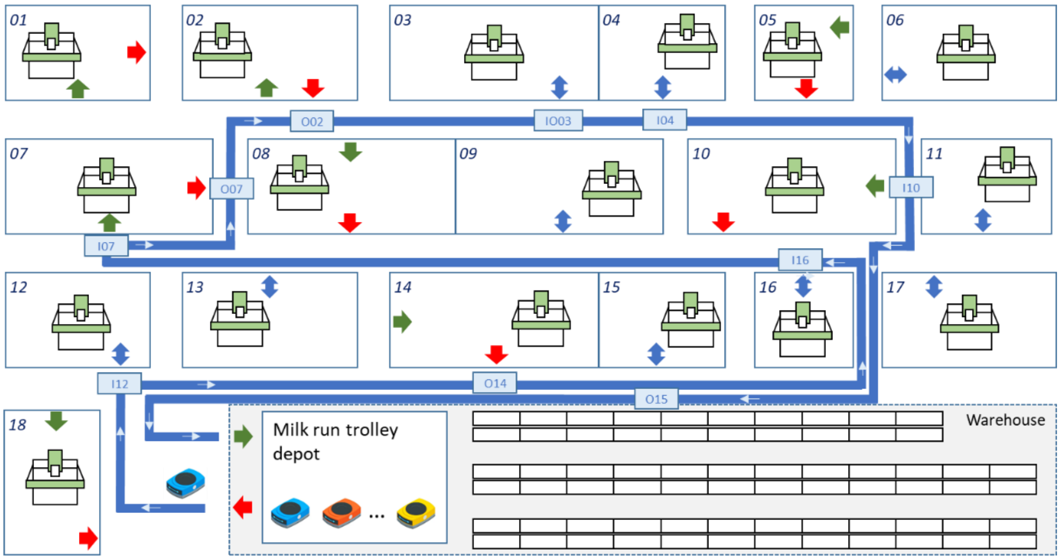

Figure 54: First route of the conventional milk-run-based in-plant supply includes MES data-based supply demands

Table 33: Numerical results of predefined in-plant material supply operations within route 1

S_ID*	C_ID[1]	Type[2]	From[3]	To[4]	LOAD[5]	CLO[6]	TFRAME[7]	TSCHED[8]	ECT[9]	ECH[10]	EC[11]
S_00	C_00	-	-	-	100	158	-	3:27:36		49.5	49.5
S_01	C_12	LO	C_00	-	12	146	03:28:00-03:30:00	3:29:10	65.8	10.2	125.5
S_02	C_14	UNLO	-	C_03	21	167	03:30:00-03:32:00	3:31:35	111.4	17.9	254.9
S_03	C_16	LO	C_00	-	25	142	03:30:00-03:35:00	3:34:00	127.4	21.4	403.7
S_04	C_07	LO	C_00	-	21	121	03:35:00-03:40:00	3:38:04	203.6	17.9	625.2
S_05	C_07	UNLO	-	C_04	14	135	03:35:00-03:40:00	3:39:28	42.0	12.0	679.1

S_06	C_02	UNLO	-	C_10	40	175	03:40:00-03:43:00	3:40:58	53.1	34.2	766.4
S_07	C_03	LO	C_14	-	21	154	03:42:00-03:45:00	3:42:38	80.9	17.9	865.2
S_08	C_03	UNLO	-	C_00	15	169	03:42:00-03:46:00	3:43:10	0.0	12.8	878.1
S_09	C_04	LO	C_07	-	14	155	03:44:00-03:47:00	3:44:10	31.3	12.0	921.3
S_10	C_10	LO	C_02	-	40	115	03:45:00-03:48:00	3:46:14	96.8	34.2	1052.2
S_11	C_15	UNLO	-	C_00	10	125	03:46:00-03:50:00	3:48:50	95.7	8.5	1156.5
S_12	C_00	-	-	-	0	125	-	3:51:56	130.1	21.4	1307.9

[*] S_ID=Identification number of the stop of milk-run trolleys. [1] C_ID=Identification number of the assembly or manufacturing cell. [2] Type=Type of the material handling operation at the assembly or manufacturing cell (LO=loading and UNLO=Unloading). [3] From=Source of the components to be transported to the assembly or manufacturing cell. [4] To=Destination of the components loaded at a specific assembly or manufacturing cell. [5] LOAD=Load of the milk-run trolley in the loading unit [LU]. [6] CLO=Cumulative loading after passing the specific station in the loading unit. [7] TFRAME=Predefined time frame; it is not allowed to exceed this lower and upper limit of the delivery time window. [8] TSCHED=Scheduled arrival and departure times of the milk-run trolley at the assembly or manufacturing cells. [9] ECT=Transportation-related energy consumption of the milk-run trolley. [10] ECH=Material handling (loading and unloading) related energy consumption at the assembly or manufacturing cells. [11] EC=Total energy consumption including transportation and material handling-related energy consumption.

In the case of route 2, 17 in-plant supply demands are performed and all of them were between the predefined time window (Figure 55 and Table 34).

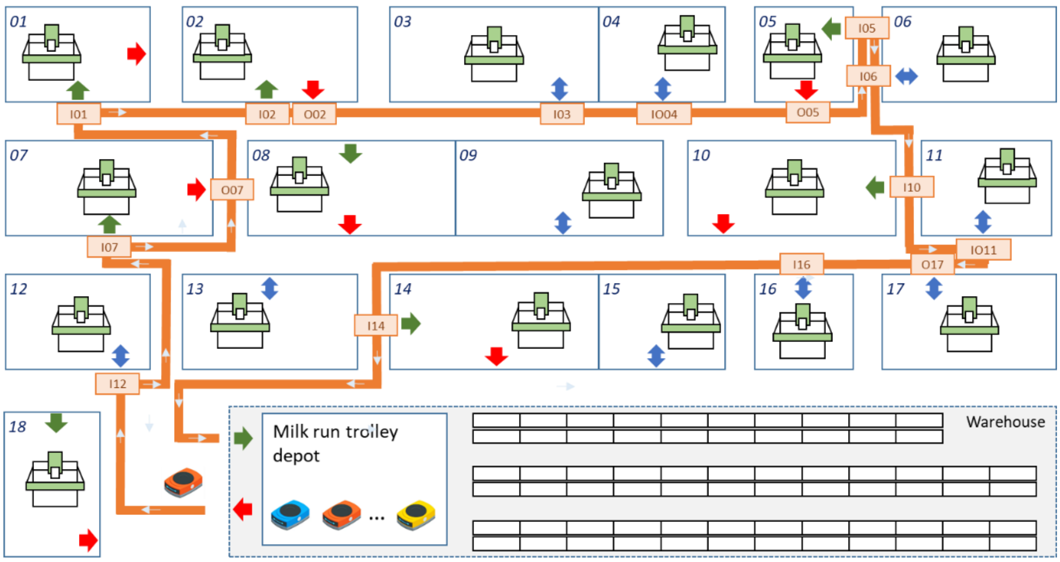

Figure 55: second route of the conventional milk-run-based in-plant supply

Table 34: Numerical results of predefined in-plant material supply operations within route 2

S_ID*	S_ID[1]	Type[2]	From[3]	To[4]	LOAD[5]	CLO[6]	TFRAME[7]	TSCHED[8]	ECT[9]	ECH[10]	EC[11]
S_00	C_00	-	-	-	100	175	-	3:45:40	-	64.1	64.1
S_01	C_12	LO	C_00	-	12	163	03:47:00-03:50:00	3:47:14	72.8	10.2	147.1
S_02	C_07	LO	C_00	-	8	155	03:48:00-03:50:00	3:48:27	45.2	6.8	199.2
S_03	C_07	UNLO	-	C_06	11	166	03:48:00-03:50:00	3:49:50	53.8	9.4	262.4
S_04	C_01	LO	C_00	-	9	157	03:50:00-03:53:00	3:51:20	65.3	7.7	335.3
S_05	C_02	LO	C_00	-	2	155	03:52:00-03:53:00	3:52:44	54.5	1.7	391.5
S_06	C_02	UNLO	-	C_04	17	172	03:52:00-03:57:00	3:53:26	10.8	14.5	416.7
S_07	C_03	LO	C_00	-	9	163	03:54:00-03:57:00	3:55:07	79.6	7.7	504.0
S_08	C_04	LO	C_02	-	17	146	03:55:00-03:57:00	3:56:06	30.2	14.5	548.7
S_09	C_04	UNLO	-	C_00	8	154	03:55:00-03:57:00	3:56:38	0.0	6.8	555.5
S_10	C_05	UNLO	-	C_00	5	159	03:56:00-03:59:00	3:57:51	42.7	4.3	602.5
S_11	C_05	LO	C_00	-	15	144	03:57:00-04:04:00	3:58:54	33.1	12.8	648.4
S_12	C_06	LO	C_07	-	11	133	03:58:00-04:04:00	3:59:50	23.3	9.4	681.1
S_13	C_10	LO	C_00	-	8	125	03:59:00-04:04:00	4:00:53	27.7	6.8	715.6
S_14	C_11	LO	C_00	-	10	115	04:00:00-04:04:00	4:02:16	43.4	8.5	767.5
S_15	C_11	UNLO	-	C_16	8	123	04:02:00-04:05:00	4:02:48	0.0	6.8	774.3
S_16	C_17	UNLO	-	C_00	7	130	04:03:00-04:06:00	4:03:51	25.6	6.0	805.9
S_17	C_16	LO	C_11	-	8	122	04:03:00-04:06:00	4:04:54	27.1	6.8	839.8
S_18	C_14	LO	C_00	-	2	120	04:06:00-04:11:00	4:07:33	104.4	1.7	945.9
S_19	C_00	-	-	-	0	120	-	4:09:44	80.5	17.1	1043.5

In the case of route 3, 14 in-plant supply demands are performed and all of them were between the predefined time window (Figure 56 and Table 35).

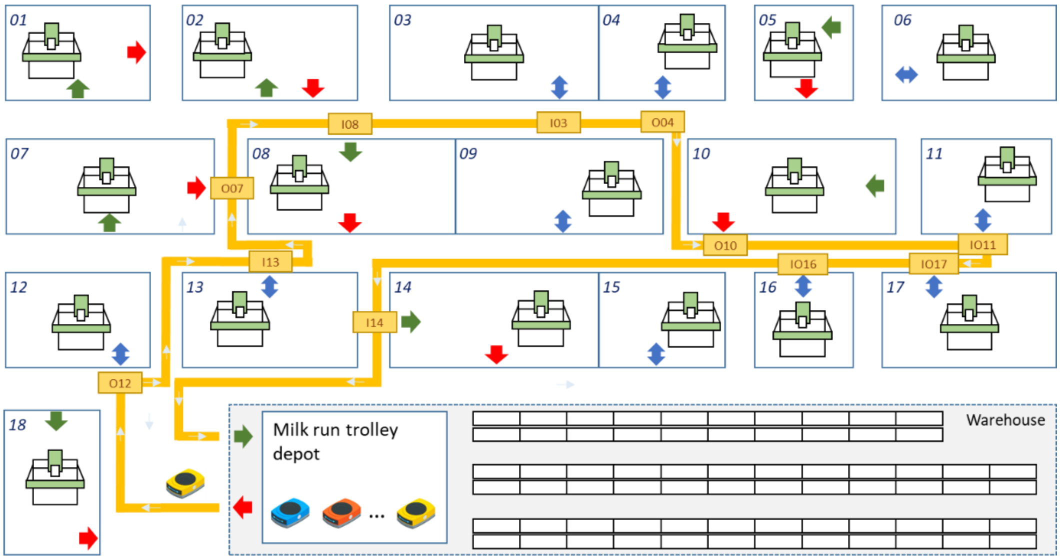

Figure 56: third route of the conventional milk-run-based in-plant supply includes MES data-based supply demands

Table 35: Numerical results of the scheduling of predefined in-plant material supply operations performed by the milk-run trolley within route 3

S_ID*	S_ID[1]	Type[2]	From[3]	To[4]	LOAD[5]	CLO[6]	TFRAME[7]	TSCHED[8]	ECT[9]	ECH[10]	EC[11]
S_00	C_00	-	-	-	100	144		4:13:51		37.6	37.6
S_01	C_12	UNLO	-	C_13	8	152	04:15:00-04:17:00	4:15:25	59.9	6.8	104.3
S_02	C_13	LO	C_12	-	8	144	04:15:00-04:20:00	4:17:12	77.3	6.8	188.5
S_03	C_13	UNLO	-	C_08	14	158	04:16:00-04:20:00	4:17:44	0.0	12.0	200.5
S_04	C_07	UNLO	-	C_11	7	165	04:18:00-04:21:00	4:19:07	54.8	6.0	261.3
S_05	C_08	LO	C_13	-	14	151	04:19:00-04:22:00	4:20:27	53.4	12.0	326.6
S_06	C_03	LO	C_00	-	18	133	04:21:00-04:24:00	4:22:18	80.3	15.4	422.3
S_07	C_04	UNLO	-	C_00	5	138	04:22:00-04:25:00	4:23:18	24.6	4.3	451.2
S_08	C_10	UNLO	-	C_00	7	145	04:24:00-04:30:00	4:24:55	60.6	6.0	517.8
S_09	C_11	LO	C_07	-	7	138	04:24:00-04:30:00	4:26:45	77.1	6.0	600.9
S_10	C_11	UNLO	-	C_00	36	174	04:27:00-04:30:00	4:27:17	0.0	30.7	631.6
S_11	C_17	LO	C_00	-	16	158	04:27:00-04:33:00	4:28:20	36.2	13.7	681.5
S_12	C_17	UN	-	C_00	2	160	04:28:00-04:33:00	4:28:52	0.0	1.7	683.2
S_13	C_16	LO	C_00	-	10	150	04:28:00-04:33:00	4:29:55	33.3	8.5	725.1
S_14	C_16	UNLO	-	C_14	20	170	04:30:00-04:33:00	4:30:27	0.0	17.1	742.1
S_15	C_14	LO	C_16	-	20	150	04:30:00-04:37:00	4:33:06	145.5	17.1	904.7
S_16	C_00	-	-	-	0	150		4:35:17	100.6	42.7	1048.0

The loading of milk-run trolleys is shown in Figure 57. As the figure demonstrates, the conventional optimization of MES-generated supply demands was successful, because not only the time window for each supply demand was taken into consideration, but also the predefined loading capacity of milk-trolleys was not exceeded.

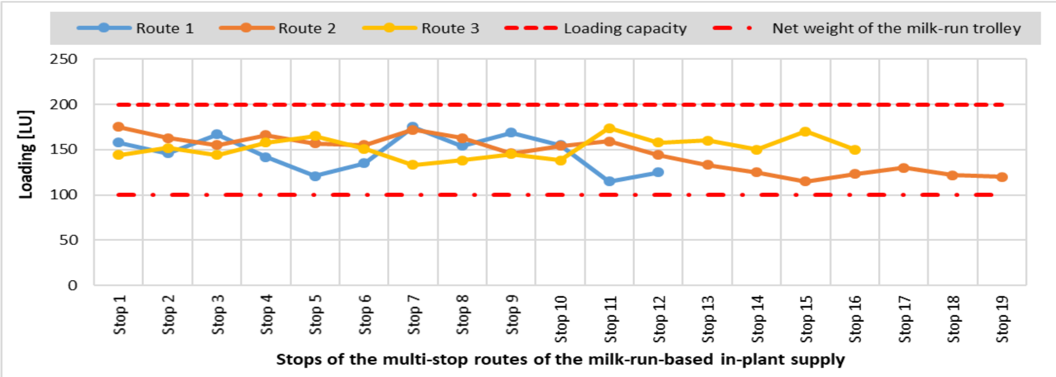

Figure 57: The optimized loading capacity of the three milk-run trolleys

The cumulative energy consumption of the three routes is shown in Figure 58. The total energy consumption was computed for 100 routes. The total energy consumption including transportation and material handling operations was 1307.9 kW for the first route, 1043.5 kW for the second route, and 1048 kW for the third route, which means a total energy consumption of 3399.4 kW out of which 2661.5 kW is for transportation and 737.9 kW is for loading and unloading of components. The loading and unloading operations include all material handling operations both in the warehouse and at the stop stations of the milk-run trolleys.

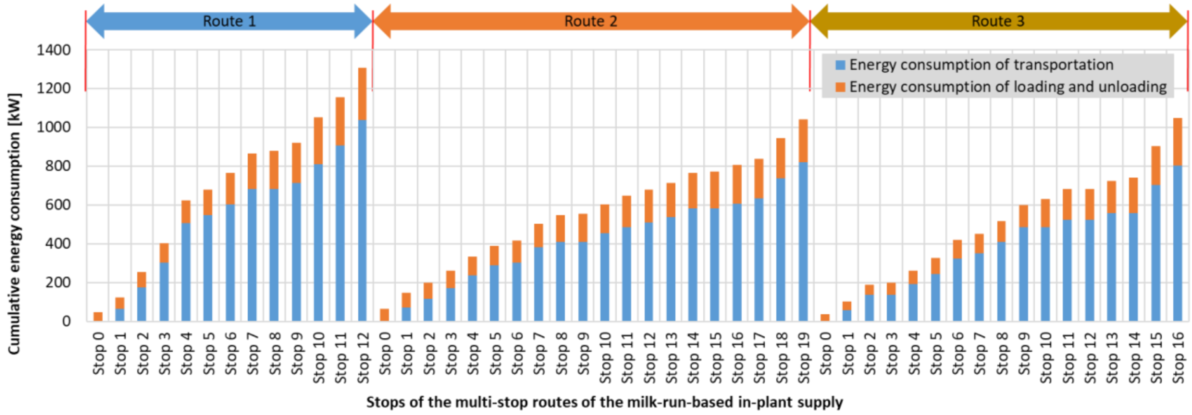

Figure 58: Cumulative energy consumption of the three milk-run routes in the conventional real-time case

In the second part of scenario 1, three different milk-run routes are defined for real-time generated in-plant supply demands. This part of scenario 1 takes only real-time generated supply demands of the in-plant supply optimization problem into consideration (Table 2). In the case of route 1, 2 in-plant supply demands are performed and all of them are between the predefined time window (Figure 59 and Table 36).

It is not possible to integrate the supply of real-time generated demands into one milk-run route because the defined time windows are different (the difference between the minimum of the lower time limits and the maximum of the upper time limits is 55 minutes) and it is not allowed for the milk-run trolleys to wait in the manufacturing zone.

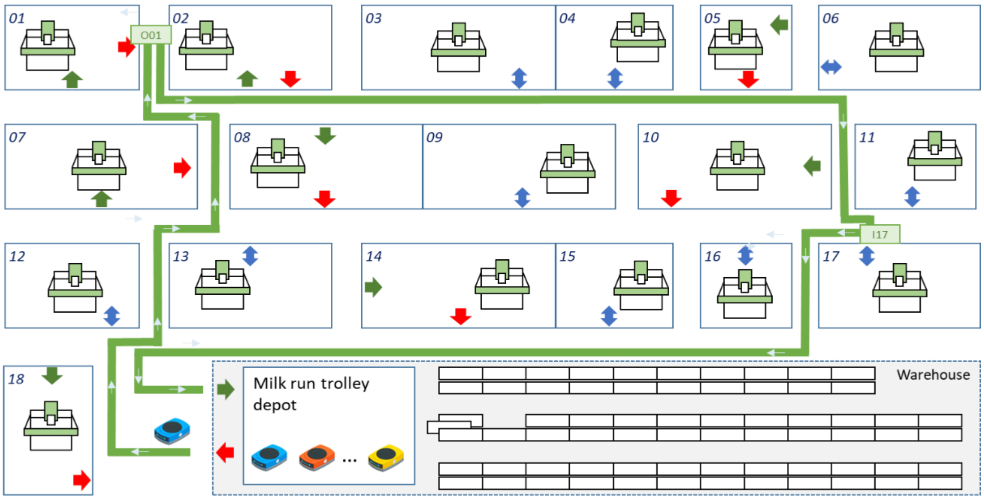

Figure 59: The first route of the conventional milk-run-based in-plant supply includes real-time supply demand

Table 36: Numerical results of the conventional optimization of real-time supply demands within the additional route 4

S_ID*	C_ID[1]	Type[2]	From[3]	To[4]	LOAD[5]	CLO[6]	TFRAME[7]	TSCHED[8]	ECT[9]	ECH[10]	EC[11]
S_00	C_00	-	-	-	100	100	-	3:38:20		0.0	0.0
S_01	C_01	UNLO	-	C_17	12	112	03:40:00-03:42:00	3:41:19	99.4	10.2	109.7
S_02	C_17	LO	C_01	-	12	100	03:46:00-03:50:00	3:46:39	217.6	10.2	337.5
S_03	C_00	-	-	-	0	100	-	3:51:28	173.4	0.0	510.9

In the case of route 2, 2 in-plant supply demands are performed and all of them are between the predefined time window (Figure 60 and Table 37).

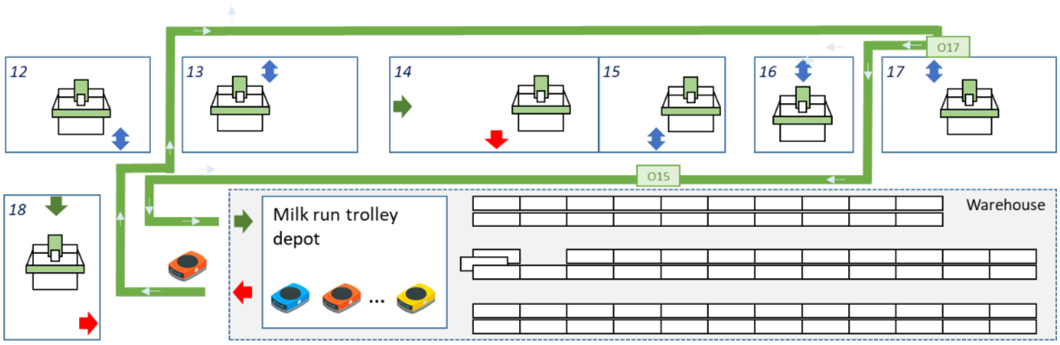

Figure 60: The second route of the conventional milk-run-based in-plant supply includes real-time supply demand

Table 37: Numerical results of the conventional optimization of real-time supply demands within additional route 5

S_ID*	C_ID[1]	Type[2]	From[3]	To[4]	LOAD[5]	CLO[6]	TFRAME[7]	TSCHED[8]	ECT[9]	ECH[10]	EC[11]
S_00	C_00	-	-	-	100	100	-	4:01:40		0.0	0.0
S_01	C_17	UNLO	-	C_15	24	124	04:03:00-04:06:00	4:06:29	173.4	20.5	193.9
S_02	C_15	LO	C_17	-	24	100	04:03:00-04:08:00	4:08:44	86.0	20.5	300.5
S_03	C_00	-	-	-	0	100	-	4:11:50	104.1	0.0	404.5

In the case of route 3, 3 in-plant supply demands are performed and all of them are between the predefined time window (Figure 61 and Table 38).

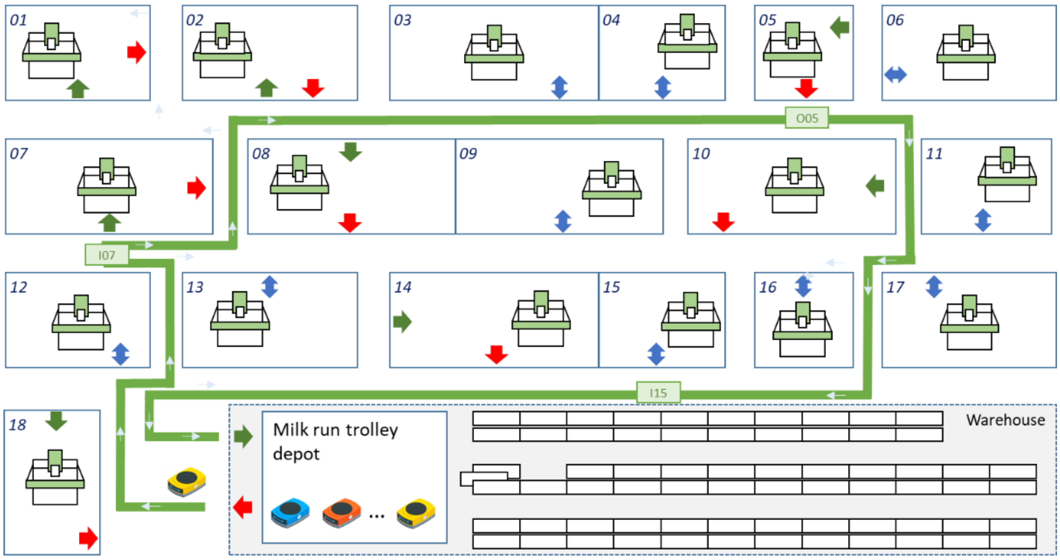

Figure 61: The third route of the conventional milk-run-based in-plant supply includes real-time supply demand

Table 38: Numerical results of the conventional optimization of real-time supply demands within additional route 6

S_ID*	C_ID[1]	Type[2]	From[3]	To[4]	LOAD[5]	CLO[6]	TFRAME[7]	TSCHED[8]	ECT[9]	ECH[10]	EC[11]
S_00	C_00	-	-	-	100	134	-	4:13:51		29.0	29.0
S_01	C_07	LO	C_00	-	34	100	04:15:00-04:17:00	4:16:06	93.0	29.0	151.0
S_02	C_05	UNLO	-	C_15	21	121	04:20:00-04:30:00	4:20:44	166.5	17.9	335.5
S_03	C_15	LO	C_05	-	21	100	04:22:00-04:35:00	4:23:23	103.5	17.9	456.9
S_04	C_00	-	-	-	0	100	-	4:25:38	69.4	0.0	526.3

The conventional routing of real-time generated supply demands was successful because not only the time window for each supply demand was taken into consideration but also the predefined loading capacity of milk-run trolleys was not exceeded (the loading of milk-run trolleys was quite low because there were only 2 or 3 supply demands assigned to a milk-run route). The total energy consumption was computed for 100 routes. The total energy consumption including transportation and material handling operations was 510.9 kW for the first route, 404.5 kW for the second route, and 526.3 kW for the third route, which means a total energy consumption of 1441.8 kW out of which 923.3 kW is for transportation and 518.4 kW is for loading and unloading of components. The loading and unloading operations include all material handling operations both in the warehouse and at the stop stations of the milk-run trolleys.

5.5.5. Real-time milk-run-based in-plant supply optimization

In the first part of scenario 2, three different milk-run routes are defined integrating MES data-based in-plant supply demands and real-time supply demands generated by the supervisory level. Industry 4.0 technologies make it possible to use real-time data to reschedule and reroute existing milk-runs by adding the new supply demands. In this case, no additional routes and trolleys are required. This part of scenario 1 takes both MES data-based supply demands and real-time generated demands. In the case of route 1, 12 in-plant supply demands are performed and all of them are between the predefined time window (Figure 62 and Table 39). It was possible to integrate one unloading operation at C_01 and one loading operation of the same component at C_17. Red lines of the route in Figure 62 represent the real-time added routes segments. Colored rows in Table 39 represent the real-time added supply demands generated by the supervisory level using the results of the optimization based on the digital twin model.

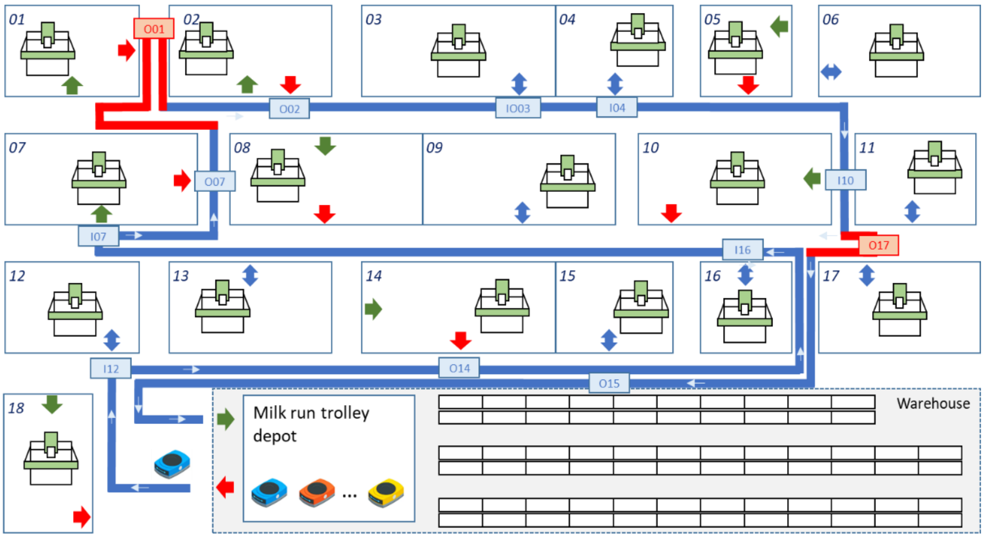

Figure 62: The modified first route

Table 39: Numerical results of real-time generated specific in-plant material supply operations within route 1

S_ID*	C_ID[1]	Type[2]	From[3]	To[4]	LOAD[5]	CLO[6]	TFRAME[7]	TSCHED[8]	ECT[9]	ECH[10]	EC[11]
S_00	C_00	-	-	-	100	158	-	3:27:36		49.5	49.5
S_01	C_12	LO	C_00	-	12	146	03:28:00-03:30:00	3:29:10	65.8	10.2	125.5
S_02	C_14	UNLO	-	C_03	21	167	03:30:00-03:32:00	3:31:35	111.4	17.9	254.9
S_03	C_16	LO	C_00	-	25	142	03:30:00-03:35:00	3:34:00	127.4	21.4	403.7
S_04	C_07	LO	C_00	-	21	121	03:35:00-03:40:00	3:38:04	203.6	17.9	625.2
S_05	C_07	UNLO	-	C_04	14	135	03:35:00-03:40:00	3:39:28	42.0	12.0	679.1
S_06	C_01	UNLO	-	C_17	12	147	03:40:00-03:42:00	3:40:54	50.0	10.2	739.3
S_07	C_02	UNLO	-	C_10	40	187	03:40:00-03:43:00	3:42:25	57.8	34.2	831.3
S_08	C_03	LO	C_14	-	21	166	03:42:00-03:45:00	3:44:05	86.5	17.9	935.7
S_09	C_03	UNLO	-	C_00	15	181	03:42:00-03:46:00	3:44:37	0.0	12.8	948.5
S_10	C_04	LO	C_07	-	14	167	03:44:00-03:47:00	3:45:37	33.5	12.0	994.0
S_11	C_10	LO	C_02	-	40	127	03:45:00-03:48:00	3:47:41	104.3	34.2	1132.4
S_12	C_17	LO	C_01	-	12	139	03:46:00-03:50:00	3:48:54	35.2	10.2	1177.9
S_13	C_15	UNLO	-	C_00	10	137	03:46:00-03:50:00	3:49:56	88.1	8.5	1274.5
S_14	C_00	-	-	-	0	137	-	3:53:02	142.6	31.6	1448.7

In the case of route 2, 19 in-plant supply demands are performed and all of them are between the predefined time window (Figure 63 and Table 40). It was possible to integrate one transshipment operation which includes one unloading operation at C_17 and one loading operation with the same component at C_15. Red lines of the route in Figure 63 represent the real-time added routes segments. The colored rows in Table 40 represent the real-time added supply demands generated by the supervisory level using the results of the optimization based on the digital twin model

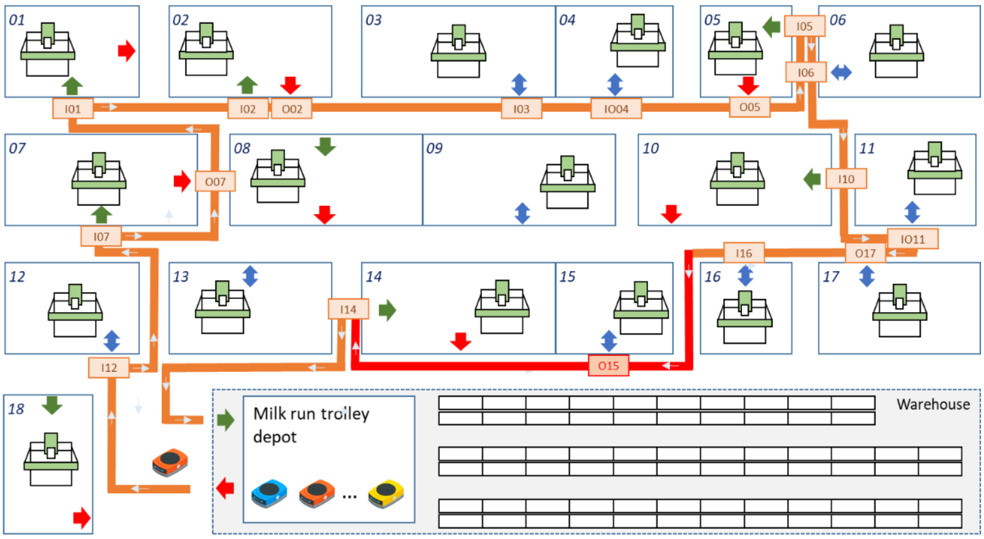

Figure 63: The modified second route

Table 40: Numerical results of real-time generated specific in-plant material supply operations within route 2

S_ID[*]	S_ID[1]	Type[2]	From[3]	To[4]	LOAD[5]	CLO[6]	TFRAME[7]	TSCHED[8]	ECT[9]	ECH[10]	EC[11]
S_00	C_00	-	-	-	100	175	-	3:45:40	-	64.1	64.1
S_01	C_12	LO	C_00	-	12	163	03:47:00-03:50:00	3:47:14	72.8	10.2	147.1
S_02	C_07	LO	C_00	-	8	155	03:48:00-03:50:00	3:48:27	45.2	6.8	199.2
S_03	C_07	UNLO	-	C_06	11	166	03:48:00-03:50:00	3:49:50	53.8	9.4	262.4
S_04	C_01	LO	C_00	-	9	157	03:50:00-03:53:00	3:51:20	65.3	7.7	335.3
S_05	C_02	LO	C_00	-	2	155	03:52:00-03:53:00	3:52:44	54.5	1.7	391.5
S_06	C_02	UNLO	-	C_04	17	172	03:52:00-03:57:00	3:53:26	10.8	14.5	416.7
S_07	C_03	LO	C_00	-	9	163	03:54:00-03:57:00	3:55:07	79.6	7.7	504.0
S_08	C_04	LO	C_02	-	17	146	03:55:00-03:57:00	3:56:06	30.2	14.5	548.7
S_09	C_04	UNLO	-	C_00	8	154	03:55:00-03:57:00	3:56:38	0.0	6.8	555.5
S_10	C_05	UNLO	-	C_00	5	159	03:56:00-03:59:00	3:57:51	42.7	4.3	602.5
S_11	C_05	LO	C_00	-	15	144	03:57:00-04:04:00	3:58:54	33.1	12.8	648.4
S_12	C_06	LO	C_07	-	11	133	03:58:00-04:04:00	3:59:50	23.3	9.4	681.1
S_13	C_10	LO	C_00	-	8	125	03:59:00-04:04:00	4:00:53	27.7	6.8	715.6
S_14	C_11	LO	C_00	-	10	115	04:00:00-04:04:00	4:02:16	43.4	8.5	767.5
S_15	C_11	UNLO	-	C_16	8	123	04:02:00-04:05:00	4:02:48	0.0	6.8	774.3
S_16	C_17	UNLO	-	C_00	7	130	04:03:00-04:06:00	4:03:51	25.6	6.0	805.9
S_17	C_17	UNLO	-	C_15	24	154	04:03:00-04:06:00	4:04:23	0.0	20.5	826.4
S_18	C_16	LO	C_11	-	8	146	04:03:00-04:06:00	4:05:26	32.1	6.8	865.3
S_19	C_15	LO	C_17	-	24	122	04:03:00-04:08:00	4:07:10	70.9	20.5	956.7
S_20	C_14	LO	C_00	-	2	120	04:06:00-04:11:00	4:09:11	73.4	1.7	1031.8
S_21	C_00	-	-	-	0	120	-	4:11:22	80.5	17.1	1129.3

In the case of route 3, 17 in-plant supply demands are performed and all of them are between the predefined time window (Figure 64 and Table 41). It was possible to integrate one transshipment operation and one loading operation. The transshipment includes one unloading operation at C_05 and one loading operation with the same component at C_15, while the loading operation is performed between the warehouse (C_00) and C_07. Red lines of the route in Figure 64 represent the real-time added routes segments. The colored rows in Table 41 represent the real-time added supply demands generated by the supervisory level using the results of the optimization based on the digital twin model.

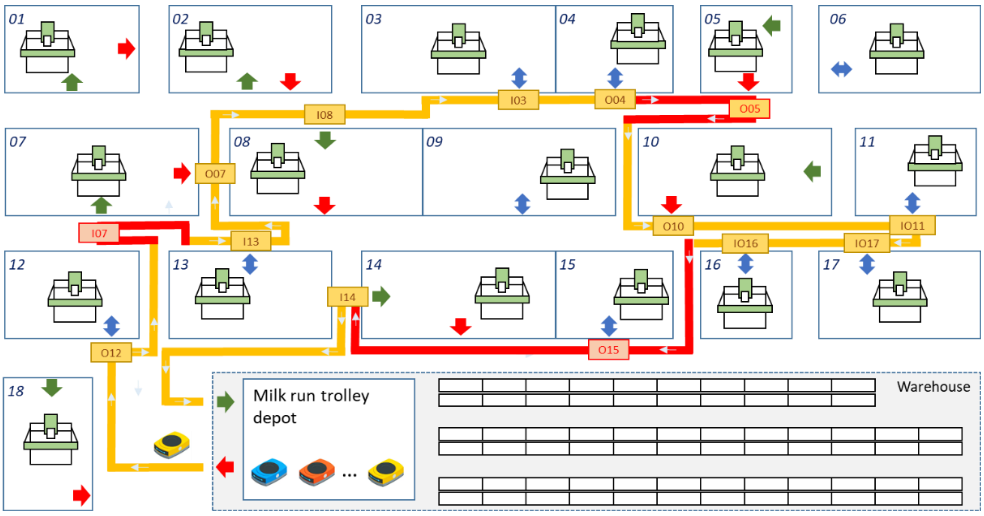

Figure 64: The modified third route

Table 41: Numerical results of real-time generated specific in-plant material supply operations within route 3

S_ID[*]	S_ID[1]	Type[2]	From[3]	To[4]	LOAD[5]	CLO[6]	TFRAME[7]	TSCHED[8]	ECT[9]	ECH[10]	EC[11]
S_00	C_00	-	-	-	100	178		4:13:51		66.6	66.6
S_01	C_12	UNLO	-	C_13	8	186	04:15:00-04:17:00	4:15:25	74.1	6.8	147.5
S_02	C_07	LO	C_00	-	34	152	04:15:00-04:17:00	4:16:38	51.6	29.0	228.2
S_03	C_13	LO	C_12	-	8	144	04:15:00-04:20:00	4:18:11	63.3	6.8	298.3
S_04	C_13	UNLO	-	C_08	14	158	04:16:00-04:20:00	4:18:43	0.0	12.0	310.2
S_05	C_07	UNLO	-	C_11	7	165	04:18:00-04:21:00	4:20:07	54.8	6.0	371.0
S_06	C_08	LO	C_13	-	14	151	04:19:00-04:22:00	4:21:27	53.4	12.0	436.4
S_07	C_03	LO	C_00	-	18	133	04:21:00-04:24:00	4:23:18	80.3	15.4	532.1
S_08	C_04	UNLO	-	C_00	5	138	04:22:00-04:25:00	4:24:17	24.6	4.3	561.0
S_09	C_05	UNLO	0	C_15	21	159	04:20:00-04:30:00	4:25:30	38.3	17.9	617.2
S_10	C_10	UNLO	-	C_00	7	166	04:24:00-04:30:00	4:27:14	77.2	6.0	700.4
S_11	C_11	LO	C_07	-	7	159	04:24:00-04:30:00	4:29:05	88.3	6.0	794.7
S_12	C_11	UNLO	-	C_00	36	195	04:27:00-04:30:00	4:29:37	0.0	30.7	825.4
S_13	C_17	LO	C_00	-	16	179	04:27:00-04:33:00	4:30:40	40.6	13.7	879.6
S_14	C_17	UN	-	C_00	2	181	04:28:00-04:33:00	4:31:12	0.0	1.7	881.4
S_15	C_16	LO	C_00	-	10	171	04:28:00-04:33:00	4:32:15	37.7	8.5	927.6
S_16	C_16	UNLO	-	C_14	20	191	04:30:00-04:33:00	4:32:47	0.0	17.1	944.6
S_17	C_15	LO	C_05	-	21	170	04:22:00-04:35:00	4:34:30	92.8	17.9	1055.3
S_18	C_14	LO	C_16	-	20	150	04:30:00-04:37:00	4:36:32	102.2	17.1	1174.6
S_19	C_00	-	-	-	0	150		4:39:41	159.6	42.7	1376.9

The loading of milk-run trolleys in the case of scenario 2 is shown in Figure 65. As the figure demonstrates, the integrated real-time optimization of MES-generated supply demands and real-time demands was successful, because not only the time window for each supply demand was taken into consideration but also the predefined loading capacity of milk-trolleys was not exceeded.

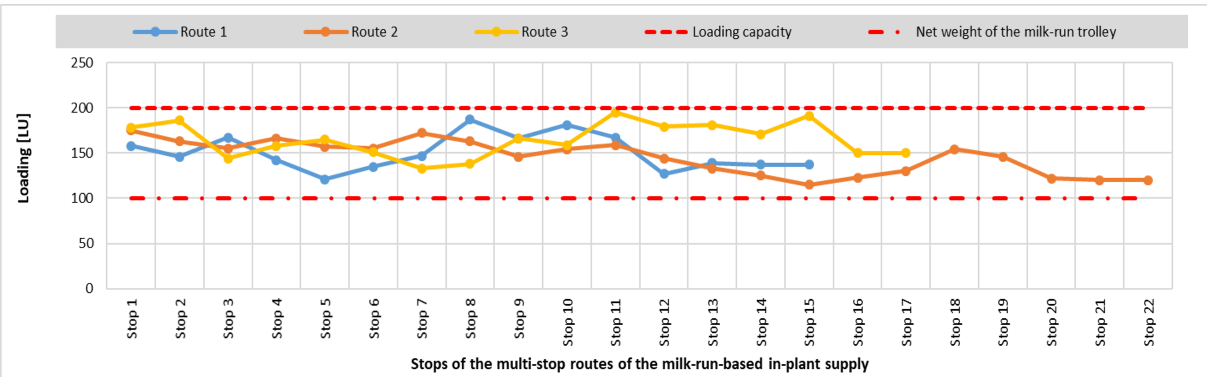

Figure 65: The optimized loading capacity of the three milk-run trolleys

The cumulative energy consumption of the three routes is shown in Figure 66. The total energy consumption was computed for 100 routes. The total energy consumption including transportation and material handling operations was 1448.7 kW for the first route, 1129.3 kW for the second route, and 1376.9 kW for the third route, which means a total energy consumption of 3954.9 kW out of which 3051.4 kW is for transportation and 903.5 kW is for loading and unloading of components. The loading and unloading operations include all material handling operations both in the warehouse and at the stop stations of the milk-run trolleys.

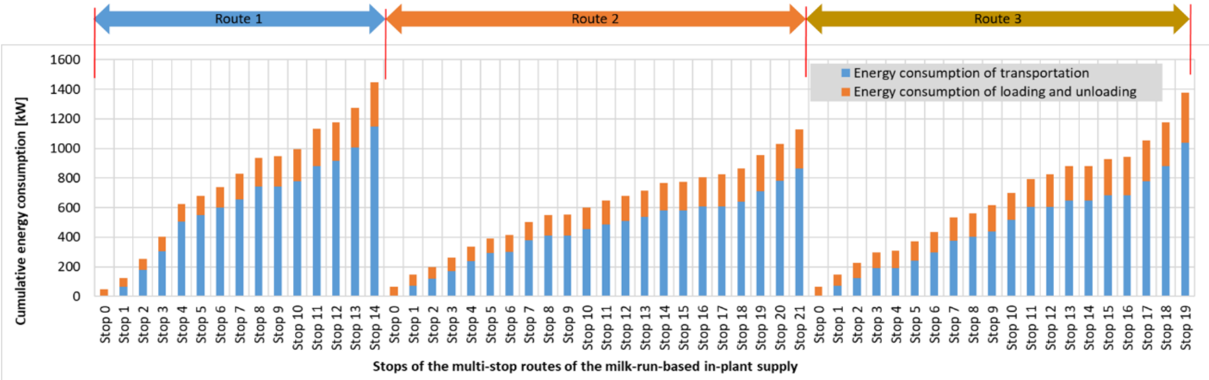

Figure 66: The optimized loading capacity of the three milk-run trolleys

5.6. Results discussion and conclusions

Based on the above-mentioned scenarios, it is possible to compare the results of conventional and Industry 4.0 technologies-based real-time optimization of in-plant supply. As Table 42 shows, the average length of the required route per supply demand was 89.27 m/demand in the case of conventional optimization, while it was 33.19 m/demand in the case of real-time optimization. This transportation length reduction leads to a significant energy consumption reduction, which means, that the average energy consumption per supply demand was 1.46 kW/demand in the case of conventional optimization, and 0.81 kW/demand in the case of real-time optimization. These both parameters can be analyzed for weight units. The average length of the required route per weight unit was in the case of conventional routing 5.47 m/kg, while in the case of real-time optimization 2.17 m/kg. The average energy consumption per weight unit was 0.089 kW/kg in the case of conventional supply optimization and 0.053 kW/kg in the case of real-time routing. The average idle capacity was 72 kg in the case of conventional optimization, and 45 kg in the case of real-time optimization. The capacity utilization of the milk-run trolleys was in the case of conventional routing 28.4% while in the case of real-time routing 54.2%. An important constraint of in-plant supply optimization is the time-related constraint, which defines, that it is allowed to exceed the given time window for each supply demands I have analyzed the average deviance of actual the supply time from the average of the lower and upper limit of each time window. This average deviation was in the case of conventional optimization 88 sec, while in the case of real-time routing 52 sec. The same result is shown by the comparison of total deviances, which is in the case of conventional optimization 48 min, while in the case of real-time optimization 43 min.

Table 42: Comparison of the computational results

R_ID[1]	ALRpD[2]	AECpD[3]	ALRpWU[4]	AECpWU[5]	AICpR[6]	CUT[7]	ADfTW[8]	TTfTW[9]
Scenario 1								
Route 1	52.81	118.9	2.49	5.61	53	46.8%	00:00:51	00:09:25
Route 2	25.08	57.97	2.70	6.25	54	46.2%	00:00:40	00:11:57
Route 3	27.87	69.87	2.18	5.46	48	52.0%	00:00:43	00:10:50
Route 4	186.85	255.45	15.57	21.29	96	4.0%	00:00:50	00:01:40
Route 5	138.75	202.25	5.78	8.43	92	8.0%	00:02:36	00:05:13
Route 6	104.23	175.43	4.11	6.93	86	13.8%	00:03:09	00:09:28
Total	89.27	146.65	5.47	8.99	72	28.4%	00:01:28	00:48:33

Scenario 2								
Route 1	47.82	111.44	2.42	5.64	48	51.4%	00:00:51	00:11:06
Route 2	23.5	56.47	2.19	5.25	53	46.5%	00:00:42	00:13:59
Route 3	28.27	76.49	1.90	5.14	35	64.5%	00:01:02	00:18:36
Total	33.19	81.47	2.17	5.34	45	54.2%	00:00:52	00:43:42

[1] R_ID=Route ID. [2] ALRpD=Average length of the required route per supply demand. [3] AECpD=Average energy consumption per supply demand. [4] ALRpWU=Average length of the required route per weight unit. [5] AECpWU=Average energy consumption per weight unit. [6] AICpR=Average idle capacity per route. [7] CUT=Capacity utilization of the milk-run trolley. [8] ADfTW=Average deviance from the average of the predefined time window. [9] TTfTW=Total deviance from the average of the predefined time window.

The presented new approach was supported by presenting detailed mathematical modeling. For having a reference function that can be compared to the new optimization model, an objective function of conventional milk-run-based in-plant supply optimization was presented. It depended on the routing and scheduling of the milk-run trolleys. All the models and related capacities and constraints were described in detail. After that, the objective function of Industry 4.0 supported milk-run-based in-plant supply optimization was presented in detail as well. A numerical analysis was done to compare the results of the two scenarios for various routes. The loading and unloading operations included the material handling operations both in the warehouse and at the stop stations of the milk-run trolleys.

As the comparison of the results showed, the average length of the required route per supply demand was 89.27 m/demand in the case of conventional optimization, while it was 33.19 m/demand in the case of real-time optimization. This reflects 62.8% route length saving. On other hand, the average energy consumption per supply demand was 1.46 kW/demand in the case of conventional optimization, and 0.81 kW/demand in the case of real-time optimization. This reflects 44.5% energy saving. Also, the average energy consumption per weight unit was 0.089 kW/kg in the case of conventional supply optimization and 0.053 kW/kg in the case of real-time routing. This reflects 40.4% energy saving that goes along with the previous study [66] that showed how the optimization model helped to minimize the travel distance and along with other studies [207], [62], and [67] where using Industry 4.0 optimization and milk run routes showed raising the energy efficiency for manufacturing systems in the automotive industry. Also, this supports the previous studies [S11], and [68] that showed a positive impact of Industry 4.0 technologies on the scheduling processes in manufacturing systems. Moreover, the average idle capacity was 72 kg in the case of conventional optimization and 45 kg in the case of real-time optimization. The capacity utilization of the milk-run trolleys was in the case of conventional routing 28.4% while in the case of real-time routing 54.2%. While this supports the previous study [66] that showed how the presented optimization in maximizing the vehicle capacities, it helps to clarify the not clear results of other studies like [64] that showed counterproductive outcomes.

The comparison of the conventional and real-time optimization showed that the application of Industry 4.0 technologies can significantly increase the efficiency of in-plant supply as well as energy efficiency. This is attributed to the usage of the digital twin in the first place where prolonged and failure processes are avoidable. The results encourage this adoption and urge further steps of applying it in the routing and scheduling processes. Especially using the milk-run trolleys that showed a big advantage as one of the tools that support Industry 4.0 technologies engagement. The described model makes it possible to compare the impact of the application of Industry 4.0 technologies on the operation parameters of routing and scheduling of milk-run trolleys in a manufacturing plant. It focuses on the mathematical description of conventional and real-time optimization of in-plant supply processes, where in the case of conventional solution the MES data-based and real-time supply demands are scheduled in a conventional way, while in the case of real-time optimization MES generated and real-time demands are taken into consideration using digital twin technology, dynamic simulation models and real-time optimization. The results showed a high advantage for the Industry 4.0 technologies-based real-time optimization of in-plant supply above the conventional one. This encourages and validates the adoption of the Industry 4.0 technologies in the in-plant supply operation and manufacturing generally.

The added value is in the description of the impact of the application of Industry 4.0 technologies on the energy efficiency and performance of milk-run-based in-plant supply, while time, capacity, sequencing, and energy-related constraints are taken into consideration. The scientific contribution is the mathematical modeling of routing and scheduling problems for conventional and real-time optimization. The results can be generalized because the model can be applied to different milk-run-based services (e.g., optimization of parcel delivery services). Managerial decisions can be influenced by the results of this research because the described method makes it possible to analyze available solutions for routing and scheduling of milk-run-based in-plant supply and find a suitable application of Industry 4.0 technologies to convert the conventional solution into a CPS, which can lead to potential real-time optimization. The scientific result of this research work is the mathematical description of conventional and Industry 4.0 technologies supported by real-time in-plant supply. The mathematical model makes it possible to compare both solutions while optimizing the in-plant supply focusing on real-time generated supply demands. However, there are also limitations, which provides direction for further research. Within the frame of the mentioned model, the supply demands were taken into consideration as deterministic parameters, but it is possible to analyze in-plant supply in the case of stochastic parameters, where uncertainties can be taken into consideration using fuzzy models. Also, the model can be extended to a more complex model including other environmental aspects. Industry 4.0 technologies are generally expensive technologies; therefore, another direction is the optimization of the investment cost of using Industry 4.0 technologies, where not only the investment but also the operational costs can be analyzed.

The obtained results can be used in the future as input parameters for a digital twin-based dynamic simulation, where the status of the manufacturing and related logistics system can be continuously updated to have a state-of-the-art model of the real-world system. Furthermore, the obtained results can also be used for managerial decisions regarding the investment of Industry 4.0 technologies, sizing of milk-run trolley pool, and strategic design of routing. The applied approach included an evaluation methodology, which made it possible to analyze and compare the energy efficiency and logistics performance of conventional and Industry 4.0 technologies supported by milk-run-bases in-plant supply solutions in the case of real-time generated supply demands. The results of the numerical analysis of case studies showed that the deployment of Industry 4.0 technologies can lead to increased energy efficiency which has a great impact on the efficiency of the whole manufacturing system.

This chapter included the main contribution to Thesis 5.

Thesis 5: Investigating the Industry 4.0 technologies adoption effect on CE. A research collaboration with the Technical University of Kosice facilitated access an important data from the European Manufacturing Survey (EMS) project. An innovative way was used to analyze and discuss this impact by using many tools including statistical ones. Furthermore, energy consumption optimization of milk-run-based in-plant supply solution was presented. The found system was described and detailed. A novel mathematical model, which made it possible to integrate the MES data-based and real-time generated supply demands to decrease the energy consumption and virtual GHG emission of milk-run trolleys. An optimization numerical analysis was used to compare the results and validate the model. [S11, S13].

6. THESES OF THE DISSERTATION

The main new scientific contributions of the dissertation can be summarized as follows:

Thesis 1: Building a comprehensive systematic literature review that presented, analyzed, and summarized the impact of Industry 4.0 in logistics systems in the light of sustainability and green environment. The literature was based on a developed mixed systemic methodology. The presented literature tackled the development and differences of optimization algorithms as they take an essential role in solving complex problems. Therefore, benchmark tests were used to compare and analyze the most used four algorithms' performance. The comparison was on two bases; the optimized average cost achieved by the algorithms and the average consumed time for code execution. Also, an upgrade for GA was presented with an explanation of the used coding system. Furthermore, a case study was solved using the described upgraded GA. [S1, S3, S4, S5, S10, S12].

Thesis 2: After an analysis was done based on real data for waste management in Europe generally and Hungary specifically, a proposed CPS for waste collection was presented with details about its parts and processes from the logistics point of view. As there is no available one found, a conventional city logistics solution was presented and described with its mathematical modeling to have it as a reference baseline. Then, a multi-echelon collection and distribution optimization system was described and detailed. A numerical analysis was used to compare the two systems and clarify their effectiveness. The optimization aimed at scheduling, assignment, routing layout design, and controlling tasks that focus on time, distance, energy consumption, and emission-related objective functions. Also, it focused on an e-vehicle-based solution, where the efficiency of the whole system could be increased by using existing Industry 4.0 technologies, like smart devices, radiofrequency identification, digital twin solutions, and cloud and fog computing to solve big data problems of large-scale system including a wide range of users, transportation resources and goods. [S7, S8, S9].

Thesis 3: CPS for waste management focusing on energy efficiency and sustainability was presented and discussed. The developed mathematical modeling was described. Also, a case study in the VIII district in Budapest was used to validate the system for two scenarios of thirty and twenty smart bins. The designed system encompassed the following aspects: IoT, smart bins with multi-percentage sensors, data and information analysis, vehicles' actual routes, energy and emissions optimization, multi-echelon system, time windows, and flexibility. The system's flexibility was demonstrated through the dynamic nature of the collection and transfer station's tasks based on the given situation. [S2, S4, S6].

Thesis 4: Presenting three case studies. The first one was in the Miskolc city center where the VRP problem was optimized by three algorithms next to a random route that is used as a comparison reference. The second one was in Kosice city center to validate a capacitive collection system using five algorithms. The adopted IoT tools allowed applying the constraints of vehicle maximum limit of goods, total collected goods for each vehicle, vehicles' flexibility, one/two ways consideration, and real routes' distances calculation. According to the results, GA is the advised algorithm to use, because it showed stable optimization effectiveness in both applications in contrast to the other algorithms. Furthermore, a last-mile supply optimization system within urban areas focusing on RL consideration was presented and described. The designed system incorporated cloud computing, real routes of vehicles, analysis of collected data, energy consumption optimization, and time windows. Also, a mathematical model was developed to optimize the total energy consumption. Real thirty locations in Budapest in the VII district were described and used for the third case study for finding the solutions of the optimized routes and energy consumption by GA for both diesel and electric trucks. The results were analyzed and compared against a random solution to clarify the presented optimization's effectiveness. [S4, S5, S10].

Thesis 5: Investigating the Industry 4.0 technologies adoption effect on CE. A research collaboration with the Technical University of Kosice facilitated access an important data from the European Manufacturing Survey (EMS) project. An innovative way was used to analyze and discuss this impact by using many tools including statistical ones. Furthermore, energy consumption optimization of milk-run-based in-plant supply solution was presented. The found system was described and detailed. A novel mathematical model, which made it possible to integrate the MES data-based and real-time generated supply demands to decrease the energy consumption and virtual GHG emission of milk-run trolleys. An optimization numerical analysis was used to compare the results and validate the model. [S11, S13].

LIST OF AUTHOR'S PUBLICATION IN THE SAME RESEARCH FIELD

S1. Akkad, M.Z.; Bányai, T. Applying Sustainable Logistics in Industry 4.0 Era. Lecture Notes in Mechanical Engineering 2021, 22, 222–234. 10.1007/978-981-15-9529-5_19.

S2. Akkad, M.Z.; Haidar, S.; Bányai, T. Design of Cyber-Physical Waste Management Systems Focusing on Energy Efficiency and Sustainability. Designs 2022, Vol. 6, Page 39 2022, 6, 39. 10.3390/DESIGNS6020039.

S3. Akkad, M.Z.; Bányai, T. Analytical Review on the Modern Optimization Algorithms in Logistics. Advanced Logistic Systems - Theory and Practice 2020, 14, 25–31. 10.32971/ALS.2020.006.

S4. Akkad, M.Z.; Rajab, Y.; Bányai, T. Vehicle Routing for Municipal Waste Collection Systems: Analysis, Comparison and Application of Heuristic Methods. Lecture Notes in Mechanical Engineering 2023, 694–708. 10.1007/978-3-031-15211-5_58/COVER.

S5. Akkad, M.Z.; Haidar, S.; Rabee, R.; Banyai, T. Efficiency optimization of vehicle routing problem with considering IoT - a case study in Slovakia. 2022 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies, 3ICT 2022 2022, 372–379. 10.1109/3ICT56508.2022.9990687.

S6. Bányai, T.; Somody, D.; Akkad, M.Z. Integration of an intelligent waste collection system into city logistics processes. Multidiszciplináris Tudományok 2021, 11, 146–158. 10.35925/J.MULTI.2021.2.20.

S7. Akkad, M.Z.; Bányai, T. Analysis And Comparison Of The Waste Management Development In Hungary And Slovakia. Cutting & Tools in Technological System 2022, 22–31. 10.20998/2078-7405.2022.96.03.

S8. Akkad, M.Z.; Bányai, T. Cyber-physical waste collection system: A logistics approach. In Proceedings of the Solutions for Sustainable Development - Proceedings of the 1st International Conference on Engineering Solutions for Sustainable Development, ICESSD 2019; CRC Press, 2020; pp. 160–168.

S9. Akkad, M.Z.; Bányai, T. Multi-objective approach for optimization of city logistics considering energy efficiency. Sustainability (Switzerland) 2020, 12. 10.3390/SU12187366.

S10. Akkad, M.Z.; Rabee, R.; Banyai, T. Energy Efficiency Optimization Of Last Mile Supply System With Reverse Logistics Consideration. Acta Logistica 2022, 9, 315–323. 10.22306/AL.V9I3.315.

S11. Akkad, M.Z.; Šebo, J.; Bányai, T. Investigation of the Industry 4.0 Technologies Adoption Effect on Circular Economy. Sustainability 2022, Vol. 14, Page 12815 2022, 14, 12815. 10.3390/SU141912815.

S12. Bányai, T.; Akkad, M.Z. The Impact of Industry 4.0 on the Future of Green Supply Chain. In Green Supply Chain - Competitiveness and Sustainability; IntechOpen, 2021 ISBN 978-1-83968-301-5. 10.5772/INTECHOPEN.98366.

S13. Akkad, M.Z.; Bányai, T. Energy Consumption Optimization of Milk-Run-Based In-Plant Supply Solutions: An Industry 4.0 Approach. Processes 2023, Vol. 11, Page 799 2023, 11, 799. 10.3390/PR11030799.

REFERENCES

1. Roblek, V.; Meško, M.; Krapež, A. A Complex View of Industry 4.0: *Sage Open* **2016**, *6*. 10.1177/2158244016653987.
2. Liao, Y.; Deschamps, F.; Loures, E. de F.R.; Ramos, L.F.P. Past, present and future of Industry 4.0 - a systematic literature review and research agenda proposal. *Int J Prod Res* **2017**, *55*, 3609–3629. 10.1080/00207543.2017.1308576.
3. Bakon, K.; Holczinger, T.; Sule, Z.; Jasko, S.; Abonyi, J. Scheduling Under Uncertainty for Industry 4.0 and 5.0. *IEEE Access* **2022**, *10*, 74977–75017. 10.1109/ACCESS.2022.3191426.
4. Trenovski, B.; Trpkova-Nestorovska, M.; Merdzan, G.; Kozheski, K. Labour productivity in terms of the fourth industrial revolution. **2022**, *1*. 10.20544/SERBE.02.01.20.P03.
5. Folgado, F.J.; Calderón, D.; González, I.; Calderón, A.J. Review of Industry 4.0 from the Perspective of Automation and Supervision Systems: Definitions, Architectures and Recent Trends. *Electronics 2024, Vol. 13, Page 782* **2024**, *13*. 10.3390/ELECTRONICS13040782.
6. Zhong, R.Y.; Xu, X.; Klotz, E.; Newman, S.T. Intelligent Manufacturing in the Context of Industry 4.0: A Review. *Engineering* **2017**, *3*, 616–630. 10.1016/J.ENG.2017.05.015.
7. Glistau, E.; Machado, N.I.C. Industry 4.0, logistics 4.0 and materials - Chances and solutions. *Materials Science Forum* **2018**, *919*, 307–314. 10.4028/WWW.SCIENTIFIC.NET/MSF.919.307.
8. Felho, C.; Kundrak, J. CAD-Based Modelling of Surface Roughness in Face Milling. **2014**. 10.5281/ZENODO.1092207.
9. Lu, Y. Industry 4.0: A survey on technologies, applications and open research issues. *J Ind Inf Integr* **2017**, *6*, 1–10. 10.1016/J.JII.2017.04.005.
10. Xu, J.; Huang, E.; Hsieh, L.; Lee, L.H.; Jia, Q.S.; Chen, C.H. Simulation optimization in the era of Industrial 4.0 and the Industrial Internet. *Journal of Simulation* **2016**, *10*, 310–320. 10.1057/S41273-016-0037-6.
11. Hofmann, E.; Rüsch, M. Industry 4.0 and the current status as well as future prospects on logistics. *Comput Ind* **2017**, *89*, 23–34. 10.1016/J.COMPIND.2017.04.002.
12. UN DESA | United Nations Department of Economic and Social Affairs Available online: https://www.un.org/en/development/desa/news/population/world-urbanization-prospects-2014.html (accessed on Jun 1, 2024).
13. Guo, S.; Nie, R.; Yu, Z. Syngas production from biomass gasification in China: A clean strategy for sustainable development. *Energy Sources* **2019**, *41*, 911–917. 10.1080/15567036.2018.1520335.
14. Shen, L.; Min, F.; Liu, L.; Zhu, J.; Xue, C.; Cai, C.; Zhou, W.; Wang, C. Application of gaseous pyrolysis products of the waste cooking oil as coal flotation collector. *Fuel* **2019**, *239*, 446–451. 10.1016/J.FUEL.2018.11.056.
15. Baronti, C.; Curini, R.; D'Ascenzo, G.; Di Corcia, A.; Gentili, A.; Samperi, R. Monitoring natural and synthetic estrogens at activated sludge sewage treatment plants and in a receiving river water. *Environ Sci Technol* **2000**, *34*, 5059–5066. 10.1021/ES001359Q.
16. McKay, G. Dioxin characterisation, formation and minimisation during municipal solid waste (MSW) incineration: review. *Chemical Engineering Journal* **2002**, *86*, 343–368. 10.1016/S1385-8947(01)00228-5.
17. Bányai, T.; Tamás, P.; Illés, B.; Stankevičiūtė, Ž.; Bányai, Á. Optimization of Municipal Waste Collection Routing: Impact of Industry 4.0 Technologies on Environmental Awareness and Sustainability. *International Journal of Environmental Research and Public Health 2019, Vol. 16, Page 634* **2019**, *16*, 634. 10.3390/IJERPH16040634.
18. Xiao, Y.; Watson, M. Guidance on Conducting a Systematic Literature Review. *J Plan Educ Res* **2019**, *39*, 93–112. 10.1177/0739456X17723971.
19. Choi, B.C.; Shin, H.S.; Lee, S.Y.; Hur, T. Life cycle assessment of a personal computer and its effective recycling rate. *International Journal of Life Cycle Assessment* **2006**, *11*, 122–128. 10.1065/LCA2004.12.196/METRICS.
20. Yue, X.; Cai, H.; Yan, H.; Zou, C.; Zhou, K. Cloud-assisted industrial cyber-physical systems: An insight. *Microprocess Microsyst* **2015**, *39*, 1262–1270. 10.1016/J.MICPRO.2015.08.013.
21. Dwivedi, Y.K.; Hughes, L.; Ismagilova, E.; Aarts, G.; Coombs, C.; Crick, T.; Duan, Y.; Dwivedi, R.; Edwards, J.; Eirug, A.; et al. Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *Int J Inf Manage* **2021**, *57*. 10.1016/J.IJINFOMGT.2019.08.002.
22. Lopes de Sousa Jabbour, A.B.; Jabbour, C.J.C.; Godinho Filho, M.; Roubaud, D. Industry 4.0 and the circular economy: a proposed research agenda and original roadmap for sustainable operations. *Ann Oper Res* **2018**, *270*, 273–286. 10.1007/S10479-018-2772-8/TABLES/3.

23. Pournader, M.; Shi, Y.; Seuring, S.; Koh, S.C.L. Blockchain applications in supply chains, transport and logistics: a systematic review of the literature. *Int J Prod Res* **2020**, *58*, 2063–2081. 10.1080/00207543.2019.1650976.
24. Winkelhaus, S.; Grosse, E.H. Logistics 4.0: a systematic review towards a new logistics system. *Int J Prod Res* **2020**, *58*, 18–43. 10.1080/00207543.2019.1612964.
25. Sanders, A.; Elangeswaran, C.; Wulfsberg, J. Industry 4.0 implies lean manufacturing: Research activities in industry 4.0 function as enablers for lean manufacturing. *Journal of Industrial Engineering and Management* **2016**, *9*, 811–833. 10.3926/jiem.1940.
26. Kovács, G.; Kot, S. New logistics and production trends as the effect of global economy changes. *Polish Journal of Management Studies* **2016**, *14*, 115–126. 10.17512/PJMS.2016.14.2.11.
27. Prause, G. E-Residency: a business platform for Industry 4.0? *Entrepreneurship and Sustainability Issues* **2016**, *3*, 216–227. 10.9770/JESI.2016.3.3(1).
28. Weinberger, M.; Bilgeri, D.; Fleisch, E. IoT business models in an industrial context. *At-Automatisierungstechnik* **2016**, *64*, 699–706. 10.1515/AUTO-2016-0054.
29. Jurenoks, A. Developing the Reconfiguration Method to Increase Life Expectancy of Dynamic Wireless Sensor Network in Container Terminal. *Applied Computer Systems* **2016**, *20*, 15–20. 10.1515/ACSS-2016-0010.
30. Trappey, A.J.C.; Trappey, C. V.; Fan, C.-Y.; Hsu, A.P.T.; Li, X.-K.; Lee, I.J.Y. IoT patent roadmap for smart logistic service provision in the context of Industry 4.0. *Journal of the Chinese Institute of Engineers* **2017**, *40*, 593–602. 10.1080/02533839.2017.1362325.
31. Choi, S.; Kang, G.; Jun, C.; Lee, J.Y.; Han, S. Cyber-physical systems: a case study of development for manufacturing industry. *International Journal of Computer Applications in Technology* **2017**, *55*, 289–297. 10.1504/IJCAT.2017.086018.
32. Erkollar, A.; Oberer, B. FLEXTRANS 4.0–Smart Logistics for Smart Cities. *Sigma Journal of Engineering and Natural Sciences* **2017**, *8*, 269–277.
33. Chaberek-Karwacka, G. The Influence of New Information Technologies in Supply Chains Logistics on Mobility in Urban Areas. *Studies of the Industrial Geography Commission of the Polish Geographical Society* **2017**, *31*, 84–94. 10.24917/20801653.312.6.
34. Szozda, N. Industry 4.0 and its impact on the functioning of supply chains. *Logforum* **2017**, *13*. 10.17270/J.LOG.2017.4.2.
35. Chen, T.; Tsai, H.-R. Ubiquitous manufacturing: Current practices, challenges, and opportunities. *Robot Comput Integr Manuf* **2017**, *45*, 126–132. 10.1016/j.rcim.2016.01.001.
36. Prause, G.; Atari, S. On sustainable production networks for Industry 4.0. *Entrepreneurship and Sustainability Issues* **2017**, *4*, 421–431. 10.9770/jesi.2017.4.4(2).
37. Strandhagen, J.W.; Alfnes, E.; Strandhagen, J.O.; Vallandingham, L.R. The fit of Industry 4.0 applications in manufacturing logistics: a multiple case study. *Adv Manuf* **2017**, *5*, 344–358. 10.1007/s40436-017-0200-y.
38. Strandhagen, J.O.; Vallandingham, L.R.; Fragapane, G.; Strandhagen, J.W.; Stangeland, A.B.H.; Sharma, N. Logistics 4.0 and emerging sustainable business models. *Adv Manuf* **2017**, *5*, 359–369. 10.1007/s40436-017-0198-1.
39. Karia, N. Knowledge resources, technology resources and competitive advantage of logistics service providers. *Knowledge Management Research & Practice* **2018**, *16*, 414–426. 10.1080/14778238.2018.1496570.
40. Bányai, T.; Illés, B.; Bányai, Á. Smart scheduling: An integrated first mile and last mile supply approach. *Complexity* **2018**, *2018*. 10.1155/2018/5180156.
41. Lee, C.K.M.; Lv, Y.; Ng, K.K.H.; Ho, W.; Choy, K.L. Design and application of Internet of things-based warehouse management system for smart logistics. *Int J Prod Res* **2018**, *56*, 2753–2768. 10.1080/00207543.2017.1394592.
42. Oeser, G.; Aygün, T.; Balan, C.-L.; Corsten, T.; Dechêne, C.; Ibald, R.; Paffrath, R.; Schuckel, M.T. Implications of the ageing population for the food demand chain in Germany. *International Journal of Retail & Distribution Management* **2018**, *46*, 163–193. 10.1108/IJRDM-01-2017-0012.
43. Bressanelli, G.; Adrodegari, F.; Perona, M.; Saccani, N. Exploring How Usage-Focused Business Models Enable Circular Economy through Digital Technologies. *Sustainability* **2018**, *10*, 639. 10.3390/su10030639.
44. Bányai, T. Real-time decision making in first mile and last mile logistics: How smart scheduling affects energy efficiency of hyperconnected supply chain solutions. *Energies (Basel)* **2018**, *11*. 10.3390/EN11071833.
45. Lin, C.-C.; Yang, J.-W. Cost-Efficient Deployment of Fog Computing Systems at Logistics Centers in Industry 4.0. *IEEE Trans Industr Inform* **2018**, *14*, 4603–4611. 10.1109/TII.2018.2827920.
46. Gong, L.; Zou, B.; Kan, Z. Modeling and Optimization for Automobile Mixed Assembly Line in Industry 4.0. *Journal of Control Science and Engineering* **2019**, *2019*, 1–10. 10.1155/2019/3105267.
47. Sell, R.; Rassõlkin, A.; Wang, R.; Otto, T. Integration of autonomous vehicles and Industry 4.0. *Proceedings of the Estonian Academy of Sciences* **2019**, *68*, 389. 10.3176/proc.2019.4.07.

48. Tsai, W.-H.; Chu, P.-Y.; Lee, H.-L. Green Activity-Based Costing Production Planning and Scenario Analysis for the Aluminum-Alloy Wheel Industry under Industry 4.0. *Sustainability* **2019**, *11*, 756. 10.3390/su11030756.
49. Sicari, S.; Rizzardi, A.; Coen-Porisini, A. Smart transport and logistics: A Node-RED implementation. *Internet Technology Letters* **2019**, *2*. 10.1002/itl2.88.
50. Bányai, Á.; Illés, B.; Glistau, E.; Machado, N.I.C.; Tamás, P.; Manzoor, F.; Bányai, T. Smart Cyber-Physical Manufacturing: Extended and Real-Time Optimization of Logistics Resources in Matrix Production. *Applied Sciences* **2019**, *9*, 1287. 10.3390/app9071287.
51. Liu, C.; Zhou, Y.; Cen, Y.; Lin, D. Integrated application in intelligent production and logistics management: technical architectures concepts and business model analyses for the customised facial masks manufacturing. *Int J Comput Integr Manuf* **2019**, *32*, 522–532. 10.1080/0951192X.2019.1599434.
52. Neal, A.D.; Sharpe, R.G.; Conway, P.P.; West, A.A. smaRTI—A cyber-physical intelligent container for industry 4.0 manufacturing. *J Manuf Syst* **2019**, *52*, 63–75. 10.1016/j.jmsy.2019.04.011.
53. Lee, C.K.M.; Lin, B.; Ng, K.K.H.; Lv, Y.; Tai, W.C. Smart robotic mobile fulfillment system with dynamic conflict-free strategies considering cyber-physical integration. *Advanced Engineering Informatics* **2019**, *42*, 100998. 10.1016/j.aei.2019.100998.
54. Zhang, K.; Wan, M.; Qu, T.; Jiang, H.; Li, P.; Chen, Z.; Xiang, J.; He, X.; Li, C.; Huang, G.Q. Production service system enabled by cloud-based smart resource hierarchy for a highly dynamic synchronized production process. *Advanced Engineering Informatics* **2019**, *42*, 100995. 10.1016/j.aei.2019.100995.
55. Bougdira, A.; Akharraz, I.; Ahaitouf, A. A traceability proposal for industry 4.0. *J Ambient Intell Humaniz Comput* **2020**, *11*, 3355–3369. 10.1007/s12652-019-01532-7.
56. Garrido-Hidalgo, C.; Olivares, T.; Ramirez, F.J.; Roda-Sanchez, L. An end-to-end Internet of Things solution for Reverse Supply Chain Management in Industry 4.0. *Comput Ind* **2019**, *112*, 103127. 10.1016/j.compind.2019.103127.
57. Queiroz, M.M.; Pereira, S.C.F.; Telles, R.; Machado, M.C. Industry 4.0 and digital supply chain capabilities. *Benchmarking: An International Journal* **2021**, *28*, 1761–1782. 10.1108/BIJ-12-2018-0435.
58. Garay-Rondero, C.L.; Martinez-Flores, J.L.; Smith, N.R.; Caballero Morales, S.O.; Aldrette-Malacara, A. Digital supply chain model in Industry 4.0. *Journal of Manufacturing Technology Management* **2019**, *31*, 887–933. 10.1108/JMTM-08-2018-0280.
59. Tobon-Valencia, E.; Lamouri, S.; Pellerin, R.; Moeuf, A. Modeling of the Master Production Schedule for the Digital Transition of Manufacturing SMEs in the Context of Industry 4.0. *Sustainability (Switzerland)* **2022**, *14*. 10.3390/SU141912562.
60. Rossit, D.G.; Nesmachnow, S.; Rossit, D.A. A Multi Objective Evolutionary Algorithm based on Decomposition for a Flow Shop Scheduling Problem in the Context of Industry 4.0. *International Journal of Mathematical, Engineering and Management Sciences* **2022**, *7*, 433–454. 10.33889/IJMEMS.2022.7.4.029.
61. Li, M.; Li, M.; Ding, H.; Ling, S.; Huang, G.Q. Graduation-inspired synchronization for industry 4.0 planning, scheduling, and execution. *J Manuf Syst* **2022**, *64*, 94–106. 10.1016/J.JMSY.2022.05.017.
62. Patil, S.A.; Gokhale, P.K. AI-federated novel delay-aware link-scheduling for Industry 4.0 applications in IoT networks. *International Journal of Pervasive Computing and Communications* **2022**. 10.1108/IJPCC-12-2021-0297.
63. Serrano-Ruiz, J.C.; Mula, J.; Poler, R. Development of a multidimensional conceptual model for job shop smart manufacturing scheduling from the Industry 4.0 perspective. *J Manuf Syst* **2022**, *63*, 185–202. 10.1016/J.JMSY.2022.03.011.
64. Fernandez-Viagas, V.; Framinan, J.M. Exploring the benefits of scheduling with advanced and real-time information integration in Industry 4.0: A computational study. *J Ind Inf Integr* **2022**, *27*. 10.1016/J.JII.2021.100281.
65. Pekarcikova, M.; Trebuna, P.; Kliment, M.; Schmacher, B.A.K. MILK RUN TESTING THROUGH TECNOMATIX PLANT SIMULATION SOFTWARE. *International Journal of Simulation Modelling* **2022**, *21*, 101–112. 10.2507/IJSIMM21-1-593.
66. Çakir, E.; Ulukan, Z.; Kahraman, C.; Sağlam, C.Ö.; Kuleli Pak, B.; Pekcan, B. Intuitionistic fuzzy multi-objective milk-run modelling under time window constraints. *Journal of Intelligent and Fuzzy Systems* **2022**, *42*, 47–62. 10.3233/JIFS-219174.
67. Quan, C.; He, Q.; Ye, X.; Cheng, X. Optimization of the Milk-run route for inbound logistics of auto parts under low-carbon economy. *J Algorithm Comput Technol* **2021**, *15*. 10.1177/17483026211065387.
68. Bocewicz, G.; Nielsen, I.; Gola, A.; Banaszak, Z. Reference model of milk-run traffic systems prototyping. *Int J Prod Res* **2021**, *59*, 4495–4512. 10.1080/00207543.2020.1766717.
69. Kumar, P.; Michael, L.K.; Mathew, A.O.; Sriram, K. Optimisation of milk run logistics for an automotive component manufacturer – A case study. *SRAC - Romanian Society for Quality* **2019**, *20*, 27–34.
70. THE 17 GOALS | Sustainable Development Available online: https://sdgs.un.org/goals (accessed on Jun 1, 2024).

71. Ranieri, L.; Digiesi, S.; Silvestri, B.; Roccotelli, M. A Review of Last Mile Logistics Innovations in an Externalities Cost Reduction Vision. *Sustainability 2018, Vol. 10, Page 782* **2018**, *10*, 782. 10.3390/SU10030782.
72. Katoch, S.; Chauhan, S.S.; Kumar, V. A review on genetic algorithm: past, present, and future. *Multimed Tools Appl* **2021**, *80*, 8091–8126. 10.1007/S11042-020-10139-6.
73. Rogers, D.S.; Tibben-Lembke, R.S.; University of Nevada, Reno.C. for L.Management.; Reverse Logistics Executive Council. Going backwards : reverse logistics trends and practices. **1999**.
74. Fleischmann, M.; Bloemhof-Ruwaard, J.M.; Dekker, R.; Van Der Laan, E.; Van Nunen, J.A.E.E.; Van Wassenhove, L.N. Quantitative models for reverse logistics: A review. *Eur J Oper Res* **1997**, *103*, 1–17. 10.1016/S0377-2217(97)00230-0.
75. Rogers, D.S.; Melamed, B.; Lembke, R.S. Modeling and Analysis of Reverse Logistics. *Journal of Business Logistics* **2012**, *33*, 107–117. 10.1111/J.0000-0000.2012.01043.X.
76. Dowlatshahi, S. A strategic framework for the design and implementation of remanufacturing operations in reverse logistics. *Int J Prod Res* **2007**, *43*, 3455–3480. 10.1080/00207540500118118.
77. Meade, L.M.; Sarkis, J.; Presley, A. The theory and practice to Reverse Logistics. *International Journal of Logistics Systems and Management* **2007**, *3*, 56–84. 10.1504/IJLSM.2007.012070.
78. Rubio, S.; Chamorro, A.; Miranda, F.J. Characteristics of the research on reverse logistics (1995–2005). *Int J Prod Res* **2007**, *46*, 1099–1120. 10.1080/00207540600943977.
79. Voigt, D.; Filho, N.C.; Macedo, M.A.; Braga, T.G.; Garbin da Rocha, R.U. Performance Evaluation of Reverse Logistics: Opportunities for Future Research. *Sustainability 2019, Vol. 11, Page 5291* **2019**, *11*, 5291. 10.3390/SU11195291.
80. Koziel, S.; Yang, X.-S. Computational Optimization, Methods and Algorithms. **2011**, *356*. 10.1007/978-3-642-20859-1.
81. Yang, X.S. *Engineering Optimization: An Introduction with Metaheuristic Applications*; John Wiley and Sons., 2010; ISBN 9780470582466. 10.1002/9780470640425.
82. Yang, X.S.; Chien, S.F.; Ting, T.O. Bio-Inspired Computation and Optimization: An Overview. *Bio-Inspired Computation in Telecommunications* **2015**, 1–21. 10.1016/B978-0-12-801538-4.00001-X.
83. Sun, Y.; Yan, H.; Lu, C.; Bie, R.; Thomas, P. A holistic approach to visualizing business models for the internet of things. *Communications in Mobile Computing 2012 1:1* **2012**, *1*, 1–7. 10.1186/2192-1121-1-4.
84. Dev, N.K.; Shankar, R.; Qaiser, F.H. Industry 4.0 and circular economy: Operational excellence for sustainable reverse supply chain performance. *Resour Conserv Recycl* **2020**, *153*, 104583. 10.1016/J.RESCONREC.2019.104583.
85. Yang, X.S. Optimization algorithms. *Studies in Computational Intelligence* **2011**, *356*, 13–31. 10.1007/978-3-642-20859-1_2.
86. Kovács, L.; Agárdi, A.; Bányai, T. Fitness Landscape Analysis and Edge Weighting-Based Optimization of Vehicle Routing Problems. *Processes 2020, Vol. 8, Page 1363* **2020**, *8*, 1363. 10.3390/PR8111363.
87. Shoja, A.; Molla-Alizadeh-Zavardehi, S.; Niroomand, S. Hybrid adaptive simplified human learning optimization algorithms for supply chain network design problem with possibility of direct shipment. *Appl Soft Comput* **2020**, *96*, 106594. 10.1016/J.ASOC.2020.106594.
88. Fathi, M.; Ghobakhloo, M. Enabling mass customization and manufacturing sustainability in Industry 4.0 Context: A novel heuristic algorithm for in-plant material supply optimization. *Sustainability (Switzerland)* **2020**, *12*. 10.3390/SU12166669.
89. Jafarnejad Ghomi, E.; Rahmani, A.M.; Qader, N.N. Service load balancing, scheduling, and logistics optimization in cloud manufacturing by using genetic algorithm. *Concurr Comput* **2019**, *31*, e5329. 10.1002/CPE.5329.
90. Brajević, I.; Ignjatović, J. An upgraded firefly algorithm with feasibility-based rules for constrained engineering optimization problems. *J Intell Manuf* **2019**, *30*, 2545–2574. 10.1007/S10845-018-1419-6/METRICS.
91. Bányai, T.; Illés, B.; Gubán, M.; Gubán, Á.; Schenk, F.; Bányai, Á. Optimization of Just-In-Sequence Supply: A Flower Pollination Algorithm-Based Approach. *Sustainability 2019, Vol. 11, Page 3850* **2019**, *11*, 3850. 10.3390/SU11143850.
92. Yang, W.; Xie, Q.; Li, M. Inventory Control Method of Reverse Logistics for Shipping Electronic Commerce Based on Improved Multi-objective Particle Swarm Optimization Algorithm. *J Coast Res* **2019**, *83*, 786–790. 10.2112/SI83-128.1.
93. Tarhini, A.A.; Yunis, M.M.; Chamseddine, M. Natural optimization algorithms for the cross-dock door assignment problem. *IEEE Transactions on Intelligent Transportation Systems* **2016**, *17*, 2324–2333. 10.1109/TITS.2016.2519104.
94. De Santis, R.; Montanari, R.; Vignali, G.; Bottani, E. An adapted ant colony optimization algorithm for the minimization of the travel distance of pickers in manual warehouses. *Eur J Oper Res* **2018**, *267*, 120–137. 10.1016/J.EJOR.2017.11.017.

95. Deng, S.; Li, Y.; Guo, H.; Liu, B. Solving a Closed-Loop Location-Inventory-Routing Problem with Mixed Quality Defects Returns in E-Commerce by Hybrid Ant Colony Optimization Algorithm. *Discrete Dyn Nat Soc* **2016**, *2016*. 10.1155/2016/6467812.
96. Chen, L.; Ma, M.; Sun, L. Heuristic swarm intelligent optimization algorithm for path planning of agricultural product logistics distribution. *Journal of Intelligent & Fuzzy Systems* **2019**, *37*, 4697–4703. 10.3233/JIFS-179304.
97. Qiao, W.; Yang, Z. Modified Dolphin Swarm Algorithm Based on Chaotic Maps for Solving High-Dimensional Function Optimization Problems. *IEEE Access* **2019**, *7*, 110472–110486. 10.1109/ACCESS.2019.2931910.
98. Jaafari, A.; Zenner, E.K.; Panahi, M.; Shahabi, H. Hybrid artificial intelligence models based on a neuro-fuzzy system and metaheuristic optimization algorithms for spatial prediction of wildfire probability. *Agric For Meteorol* **2019**, *266–267*, 198–207. 10.1016/J.AGRFORMET.2018.12.015.
99. Atabaki, M.S.; Mohammadi, M.; Naderi, B. Hybrid Genetic Algorithm and Invasive Weed Optimization via Priority Based Encoding for Location-Allocation Decisions in a Three-Stage Supply Chain. *Asia-Pacific Journal of Operational Research* **2017**, *34*. 10.1142/S0217595917500087.
100. Alam, T.; Qamar, S.; Dixit, A.; Benaida, M. Genetic Algorithm: Reviews, Implementations, and Applications. *International Journal of Engineering Pedagogy (iJEP)* **2020**, *10*, 57–77. 10.3991/IJEP.V10I6.14567.
101. Whitley, D. A genetic algorithm tutorial. *Statistics and Computing 1994 4:2* **1994**, *4*, 65–85. 10.1007/BF00175354.
102. Goldberg, D.E.; Holland, J.H. Genetic Algorithms and Machine Learning. *Machine Learning 1988 3:2* **1988**, *3*, 95–99. 10.1023/A:1022602019183.
103. Holland, J.H. Genetic algorithms. *Sci Am* **1992**, *267*, 66–72. 10.1038/SCIENTIFICAMERICAN0792-66.
104. Mirjalili, S.; Song Dong, J.; Sadiq, A.S.; Faris, H. Genetic Algorithm: Theory, Literature Review, and Application in Image Reconstruction. *Studies in Computational Intelligence* **2020**, *811*, 69–85. 10.1007/978-3-030-12127-3_5.
105. Kramer, O. Genetic algorithms. *Studies in Computational Intelligence* **2017**, *679*, 11–19. 10.1007/978-3-319-52156-5_2.
106. Arabali, A.; Ghofrani, M.; Etezadi-Amoli, M.; Fadali, M.S.; Baghzouz, Y. Genetic-algorithm-based optimization approach for energy management. *IEEE Transactions on Power Delivery* **2013**, *28*, 162–170. 10.1109/TPWRD.2012.2219598.
107. Kennedy, J.F.; Eberhart, R.C.; Shi, Yuhui. Swarm intelligence. In; Morgan Kaufmann Publishers, 2001; p. 512 ISBN 9780080518268. 10.1016/B978-1-55860-595-4.X5000-1.
108. Kennedy, J.; Eberhart, R. Particle swarm optimization. *Proceedings of ICNN'95 - International Conference on Neural Networks 4*, 1942–1948. 10.1109/ICNN.1995.488968.
109. Wang, D.; Tan, D.; Liu, L. Particle swarm optimization algorithm: an overview. *Soft comput* **2018**, *22*, 387–408. 10.1007/S00500-016-2474-6/FIGURES/2.
110. Shi, Y.; Eberhart, R. Modified particle swarm optimizer. *Proceedings of the IEEE Conference on Evolutionary Computation, ICEC* **1998**, 69–73. 10.1109/ICEC.1998.699146.
111. Zhan, S.H.; Lin, J.; Zhang, Z.J.; Zhong, Y.W. List-Based Simulated Annealing Algorithm for Traveling Salesman Problem. *Comput Intell Neurosci* **2016**, *2016*. 10.1155/2016/1712630.
112. Guilmeau, T.; Chouzenoux, E.; Elvira, V. Simulated Annealing: A Review and a New Scheme. *IEEE Workshop on Statistical Signal Processing Proceedings* **2021**, *2021-July*, 101–105. 10.1109/SSP49050.2021.9513782.
113. Johnson, D.S.; Aragon, C.R.; McGeoch, L.A.; Schevon, C. Optimization by Simulated Annealing: An Experimental Evaluation; Part I, Graph Partitioning. *Oper Res* **1989**, *37*, 865–892. 10.1287/OPRE.37.6.865.
114. Kirkpatrick, S.; Gelatt, C.D.; Vecchi, M.P. Optimization by Simulated Annealing. *Science (1979)* **1983**, *220*, 671–680. 10.1126/SCIENCE.220.4598.671.
115. Černý, V. Thermodynamical approach to the traveling salesman problem: An efficient simulation algorithm. *Journal of Optimization Theory and Applications 1985 45:1* **1985**, *45*, 41–51. 10.1007/BF00940812.
116. Zhou, A.H.; Zhu, L.P.; Hu, B.; Deng, S.; Song, Y.; Qiu, H.; Pan, S. Traveling-salesman-problem algorithm based on simulated annealing and gene-expression programming. *Information (Switzerland)* **2018**, *10*. 10.3390/INFO10010007.
117. Dorigo, M.; Stützle, T. The Ant Colony Optimization Metaheuristic: Algorithms, Applications, and Advances. In *Handbook of Metaheuristics*; Fred Glover, G.A.K., Ed.; Springer New York, NY, 2003; pp. 250–285 ISBN 978-0-306-48056-0. 10.1007/0-306-48056-5_9.
118. Ahmed, Z.E.; Saeed, R.A.; Mukherjee, A.; Ghorpade, S.N. Energy optimization in low-power wide area networks by using heuristic techniques. In *LPWAN Technologies for IoT and M2M Applications*; Elsevier, 2020; pp. 199–223. 10.1016/B978-0-12-818880-4.00011-9.
119. Yun, H.Y.; Jeong, S.J.; Kim, K.S. Advanced harmony search with ant colony optimization for solving the traveling salesman problem. *J Appl Math* **2013**, *2013*. 10.1155/2013/123738.

120. Mesjasz-Lech, A.; Michelberger, P. Sustainable Waste Logistics and the Development of Trade in Recyclable Raw Materials in Poland and Hungary. *Sustainability 2019, Vol. 11, Page 4159* **2019**, *11*, 4159. 10.3390/SU11154159.
121. Proposal for a Directive of the European Parliament and of the Council Amending Directive 94/62/EC on Packaging and Packaging Waste Available online: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52015PC0596 (accessed on Jun 1, 2024).
122. Bing, X.; Bloemhof, J.M.; Ramos, T.R.P.; Barbosa-Povoa, A.P.; Wong, C.Y.; van der Vorst, J.G.A.J. Research challenges in municipal solid waste logistics management. *Waste Management* **2016**, *48*, 584–592. 10.1016/J.WASMAN.2015.11.025.
123. Straka, M.; Rosova, A.; Malindzakova, M.; Khouri, S.; Culkova, K. Evaluating the Waste Incineration Process for Sustainable Development through Modelling, Logistics, and Simulation. *Pol J Environ Stud* **2018**, *27*, 2739–2748. 10.15244/PJOES/81062.
124. Winkler, H.; Kaluza, B. Sustainable Supply Chain Networks – A New Approach For Effective Waste Management. *WIT Transactions on Ecology and the Environment* **2006**, *92*, 501–510. 10.2495/WM060521.
125. Das, S.; Lee, S.H.; Kumar, P.; Kim, K.H.; Lee, S.S.; Bhattacharya, S.S. Solid waste management: Scope and the challenge of sustainability. *J Clean Prod* **2019**, *228*, 658–678. 10.1016/J.JCLEPRO.2019.04.323.
126. Gomes, M.I.; Barbosa-Povoa, A.P.; Novais, A.Q. Modelling a recovery network for WEEE: A case study in Portugal. *Waste Management* **2011**, *31*, 1645–1660. 10.1016/J.WASMAN.2011.02.023.
127. Mar-Ortiz, J.; Adenso-Diaz, B.; González-Velarde, J.L. Design of a recovery network for WEEE collection: the case of Galicia, Spain. *Journal of the Operational Research Society* **2011**, *62*, 1471–1484. 10.1057/JORS.2010.114.
128. Demirel, E.; Demirel, N.; Gökçen, H. A mixed integer linear programming model to optimize reverse logistics activities of end-of-life vehicles in Turkey. *J Clean Prod* **2016**, *112*, 2101–2113. 10.1016/J.JCLEPRO.2014.10.079.
129. Chung, S. shan; Lau, K. yan; Zhang, C. Generation of and control measures for, e-waste in Hong Kong. *Waste Management* **2011**, *31*, 544–554. 10.1016/J.WASMAN.2010.10.003.
130. Grunow, M.; Gobbi, C. Designing the reverse network for WEEE in Denmark. *CIRP Annals* **2009**, *58*, 391–394. 10.1016/J.CIRP.2009.03.036.
131. Kinobe, J.R.; Bosona, T.; Gebresenbet, G.; Niwagaba, C.B.; Vinnerås, B. Optimization of waste collection and disposal in Kampala city. *Habitat Int* **2015**, *49*, 126–137. 10.1016/J.HABITATINT.2015.05.025.
132. Gamberini, R.; Gebennini, E.; Rimini, B. An innovative container for WEEE collection and transport: Details and effects following the adoption. *Waste Management* **2009**, *29*, 2846–2858. 10.1016/J.WASMAN.2009.07.006.
133. Yu, M.C.; Wu, P.S. A simulation study of the factors influencing the design of a waste collection channel in Taiwan. *International Journal of Logistics: Research and Applications* **2010**, *13*, 257–271. 10.1080/13675561003724646.
134. Municipal waste by waste management operations Available online: https://ec.europa.eu/eurostat/cache/metadata/en/env_wasmun_esms.htm (accessed on Jun 1, 2024).
135. Recycling rate of municipal waste Available online: https://ec.europa.eu/eurostat/cache/metadata/en/cei_wm011_esmsip2.htm (accessed on Jun 1, 2024).
136. Larsen, A.W.; Vrgoc, M.; Christensen, T.H.; Lieberknecht, P. Diesel consumption in waste collection and transport and its environmental significance. *Waste Management & Research* **2009**, *27*, 652–659. 10.1177/0734242X08097636.
137. Openrouteservice Available online: https://openrouteservice.org/ (accessed on Jun 1, 2024).
138. Ai, T.J.; Kachitvichyanukul, V. Particle swarm optimization and two solution representations for solving the capacitated vehicle routing problem. *Comput Ind Eng* **2009**, *56*, 380–387. 10.1016/j.cie.2008.06.012.
139. Ismail, Z.; Ramli, M.F. Capacitated Arc Routing Problem with Time Window. In; 2008; pp. 25–34.
140. De Maio, A.; Laganà, D.; Musmanno, R.; Vocaturo, F. Arc routing under uncertainty: Introduction and literature review. *Comput Oper Res* **2021**, *135*, 105442. 10.1016/J.COR.2021.105442.
141. Akhtar, M.; Hannan, M.A.; Begum, R.A.; Basri, H.; Scavino, E. Backtracking search algorithm in CVRP models for efficient solid waste collection and route optimization. *Waste Management* **2017**, *61*, 117–128. 10.1016/j.wasman.2017.01.022.
142. Emission Standards: Europe: Heavy-Duty Truck and Bus Engines Available online: https://dieselnet.com/standards/eu/hd.php (accessed on Jun 1, 2024).
143. How Many Amps For Electric Car Chargers? Available online: https://www.sunsolarelectrical.ca/blog/amps-for-electric-car-chargers/ (accessed on Jun 1, 2024).
144. Frank, A.G.; Dalenogare, L.S.; Ayala, N.F. Industry 4.0 technologies: Implementation patterns in manufacturing companies. *Int J Prod Econ* **2019**, *210*, 15–26. 10.1016/J.IJPE.2019.01.004.

145. Borowski, P.F. Innovative Processes in Managing an Enterprise from the Energy and Food Sector in the Era of Industry 4.0. *Processes 2021, Vol. 9, Page 381* **2021**, *9*, 381. 10.3390/PR9020381.
146. Rosa, P.; Sassanelli, C.; Urbinati, A.; Chiaroni, D.; Terzi, S. Assessing relations between Circular Economy and Industry 4.0: a systematic literature review. *Int J Prod Res* **2019**, *58*, 1662–1687. 10.1080/00207543.2019.1680896.
147. Bloomfield, M.; Borstrock, S. Modeclix. The additively manufactured adaptable textile. *Mater Today Commun* **2018**, *16*, 212–216. 10.1016/J.MTCOMM.2018.04.002.
148. Laskurain-Iturbe, I.; Arana-Landín, G.; Landeta-Manzano, B.; Uriarte-Gallastegi, N. Exploring the influence of industry 4.0 technologies on the circular economy. *J Clean Prod* **2021**, *321*, 128944. 10.1016/J.JCLEPRO.2021.128944.
149. McDowall, W.; Geng, Y.; Huang, B.; Barteková, E.; Bleischwitz, R.; Türkeli, S.; Kemp, R.; Doménech, T. Circular Economy Policies in China and Europe. *J Ind Ecol* **2017**, *21*, 651–661. 10.1111/JIEC.12597.
150. Geissdoerfer, M.; Savaget, P.; Bocken, N.M.P.; Hultink, E.J. The Circular Economy – A new sustainability paradigm? *J Clean Prod* **2017**, *143*, 757–768. 10.1016/J.JCLEPRO.2016.12.048.
151. Geng, Y.; Doberstein, B. Developing the circular economy in China: Challenges and opportunities for achieving "leapfrog development." *International Journal of Sustainable Development and World Ecology* **2008**, *15*, 231–239. 10.3843/SUSDEV.15.3:6.
152. Su, B.; Heshmati, A.; Geng, Y.; Yu, X. A review of the circular economy in China: moving from rhetoric to implementation. *J Clean Prod* **2013**, *42*, 215–227. 10.1016/J.JCLEPRO.2012.11.020.
153. Fahimnia, B.; Sarkis, J.; Gunasekaran, A.; Farahani, R. Decision models for sustainable supply chain design and management. *Annals of Operations Research 2017 250:2* **2017**, *250*, 277–278. 10.1007/S10479-017-2428-0.
154. Ghisellini, P.; Cialani, C.; Ulgiati, S. A review on circular economy: the expected transition to a balanced interplay of environmental and economic systems. *J Clean Prod* **2016**, *114*, 11–32. 10.1016/J.JCLEPRO.2015.09.007.
155. Ellen MacArthur Foundation; McKinsey Center for Business and Environment. *Growth within: a circular economy vision for a competitive Europe*; 2015.
156. Zhao, S.; Zhu, Q. Remanufacturing supply chain coordination under the stochastic remanufacturability rate and the random demand. *Ann Oper Res* **2017**, *257*, 661–695. 10.1007/S10479-015-2021-3.
157. Bocken, N.M.P.; Olivetti, E.A.; Cullen, J.M.; Potting, J.; Lifset, R. Taking the Circularity to the Next Level: A Special Issue on the Circular Economy. *J Ind Ecol* **2017**, *21*, 476–482. 10.1111/JIEC.12606.
158. Murray, A.; Skene, K.; Haynes, K. The Circular Economy: An Interdisciplinary Exploration of the Concept and Application in a Global Context. *Journal of Business Ethics 2015 140:3* **2017**, *140*, 369–380. 10.1007/S10551-015-2693-2.
159. Rüßmann, M.; Lorenz, M.; Gerbert, P.; Waldner, M.; Justus, J.; Engel, P.; Harnisch, M. *Industry 4.0 The Future of Productivity and Growth in Manufacturing Industries*; 2015.
160. Dutta, D.; Prinz, F.B.; Rosen, D.; Weiss, L. Layered Manufacturing: Current Status and Future Trends. *J Comput Inf Sci Eng* **2001**, *1*, 60–71. 10.1115/1.1355029.
161. Unruh, G. Circular Economy, 3D Printing, and the Biosphere Rules: *Calif Manage Rev* **2018**, *60*, 95–111. 10.1177/0008125618759684.
162. Lahrour, Y.; Brissaud, D. A Technical Assessment of Product/Component Re-manufacturability for Additive Remanufacturing. *Procedia CIRP* **2018**, *69*, 142–147. 10.1016/J.PROCIR.2017.11.105.
163. Leino, M.; Pekkarinen, J.; Soukka, R. The Role of Laser Additive Manufacturing Methods of Metals in Repair, Refurbishment and Remanufacturing – Enabling Circular Economy. *Phys Procedia* **2016**, *83*, 752–760. 10.1016/J.PHPRO.2016.08.077.
164. Nascimento, D.L.M.; Alencastro, V.; Quelhas, O.L.G.; Caiado, R.G.G.; Garza-Reyes, J.A.; Lona, L.R.; Tortorella, G. Exploring Industry 4.0 technologies to enable circular economy practices in a manufacturing context: A business model proposal. *Journal of Manufacturing Technology Management* **2019**, *30*, 607–627. 10.1108/JMTM-03-2018-0071/FULL/XML.
165. Esmaeilian, B.; Wang, B.; Lewis, K.; Duarte, F.; Ratti, C.; Behdad, S. The future of waste management in smart and sustainable cities: A review and concept paper. *Waste Management* **2018**, *81*, 177–195. 10.1016/J.WASMAN.2018.09.047.
166. Reuter, M.A.; Matusewicz, R.; Van Schaik, A. Lead, Zinc and their Minor Elements: Enablers of a Circular Economy. *World of Metallurgy - ERZMETALL* **2015**, *68*, 132–146.
167. Hatzivasilis, G.; Fysarakis, K.; Soultatos, O.; Askoxylakis, I.; Papaefstathiou, I.; Demetriou, G. The Industrial Internet of Things as an enabler for a Circular Economy Hy-LP: A novel IIoT protocol, evaluated on a wind park's SDN/NFV-enabled 5G industrial network. *Comput Commun* **2018**, *119*, 127–137. 10.1016/J.COMCOM.2018.02.007.

168. Reuter, M.A. Digitalizing the Circular Economy: Circular Economy Engineering Defined by the Metallurgical Internet of Things. *Metallurgical and Materials Transactions B: Process Metallurgy and Materials Processing Science* **2016**, *47*, 3194–3220. 10.1007/S11663-016-0735-5/FIGURES/16.
169. Schäfers, P.; Walther, A. Modelling Circular Material Flow and the Consequences for SCM and PPC. *Global Journal of Business Research* **2017**, *11*, 91–100.
170. Kuik, S.S.; Kaihara, T.; Fujii, N. Product Recovery Configuration Decisions for Achieving Sustainable Manufacturing. *Procedia CIRP* **2016**, *41*, 258–263. 10.1016/J.PROCIR.2016.01.195.
171. Wang, X.V.; Wang, L. Digital twin-based WEEE recycling, recovery and remanufacturing in the background of Industry 4.0. *Int J Prod Res* **2018**, *57*, 3892–3902. 10.1080/00207543.2018.1497819.
172. Van Schaik, A.; Reuter, M.A. Recycling Indices Visualizing the Performance of the Circular Economy. *World of Metallurgy-ERZMETALL* **2016**, *69*, 201–2016.
173. Nobre, G.C.; Tavares, E. Scientific literature analysis on big data and internet of things applications on circular economy: a bibliometric study. *Scientometrics* **2017**, *111*, 463–492. 10.1007/S11192-017-2281-6/TABLES/5.
174. Davis, C.B.; Aid, G.; Zhu, B. Secondary Resources in the Bio-Based Economy: A Computer Assisted Survey of Value Pathways in Academic Literature. *Waste Biomass Valorization* **2017**, *8*, 2229–2246. 10.1007/S12649-017-9975-0/TABLES/1.
175. Franquesa, D.; Navarro, L.; Bustamante, X. A circular commons for digital devices. *ACM International Conference Proceeding Series* **2016**. 10.1145/2926676.2926684.
176. Lindström, J.; Hermanson, A.; Blomstedt, F.; Kyösti, P. A Multi-Usable Cloud Service Platform: A Case Study on Improved Development Pace and Efficiency. *Applied Sciences 2018, Vol. 8, Page 316* **2018**, *8*, 316. 10.3390/APP8020316.
177. Jabbour, C.J.C.; Jabbour, A.B.L. de S.; Sarkis, J.; Filho, M.G. Unlocking the circular economy through new business models based on large-scale data: An integrative framework and research agenda. *Technol Forecast Soc Change* **2019**, *144*, 546–552. 10.1016/J.TECHFORE.2017.09.010.
178. Li, J.; Tao, F.; Cheng, Y.; Zhao, L. Big Data in product lifecycle management. *The International Journal of Advanced Manufacturing Technology 2015 81:1* **2015**, *81*, 667–684. 10.1007/S00170-015-7151-X.
179. Kusiak, A. Smart manufacturing. *Int J Prod Res* **2017**, *56*, 508–517. 10.1080/00207543.2017.1351644.
180. Marconi, M.; Germani, M.; Mandolini, M.; Favi, C. Applying data mining technique to disassembly sequence planning: a method to assess effective disassembly time of industrial products. *Int J Prod Res* **2018**, *57*, 599–623. 10.1080/00207543.2018.1472404.
181. Lin, K.Y. User experience-based product design for smart production to empower industry 4.0 in the glass recycling circular economy. *Comput Ind Eng* **2018**, *125*, 729–738. 10.1016/J.CIE.2018.06.023.
182. Álvarez-de-los-Mozos, E.; Rentería-Bilbao, A.; Díaz-Martín, F. WEEE Recycling and Circular Economy Assisted by Collaborative Robots. *Applied Sciences 2020, Vol. 10, Page 4800* **2020**, *10*, 4800. 10.3390/APP10144800.
183. Renteria, A.; Alvarez-De-Los-Mozos, E. Human-Robot Collaboration as a new paradigm in circular economy for WEEE management. *Procedia Manuf* **2019**, *38*, 375–382. 10.1016/J.PROMFG.2020.01.048.
184. Daneshmand, M.; Noroozi, F.; Corneanu, C.; Mafakheri, F.; Fiorini, P. Industry 4.0 and prospects of circular economy: a survey of robotic assembly and disassembly. *International Journal of Advanced Manufacturing Technology* **2022**, 1–28. 10.1007/S00170-021-08389-1/FIGURES/9.
185. Herterich, M.M.; Uebernickel, F.; Brenner, W. The Impact of Cyber-physical Systems on Industrial Services in Manufacturing. *Procedia CIRP* **2015**, *30*, 323–328. 10.1016/J.PROCIR.2015.02.110.
186. Martín Gómez, A.M.; Aguayo González, F.; Marcos Bárcena, M. Smart eco-industrial parks: A circular economy implementation based on industrial metabolism. *Resour Conserv Recycl* **2018**, *135*, 58–69. 10.1016/J.RESCONREC.2017.08.007.
187. European Manufacturing Survey - Fraunhofer ISI Available online: https://www.isi.fraunhofer.de/en/themen/wertschoepfung/fems.html (accessed on Jun 1, 2024).
188. Šebo, J.; Šebová, M.; Palčič, I. Implementation of Circular Economy Technologies: An Empirical Study of Slovak and Slovenian Manufacturing Companies. *Sustainability 2021, Vol. 13, Page 12518* **2021**, *13*, 12518. 10.3390/SU132212518.
189. Reddy, K.N.; Kumar, A. Capacity investment and inventory planning for a hybrid manufacturing – remanufacturing system in the circular economy. *Int J Prod Res* **2020**, *59*, 2450–2478. 10.1080/00207543.2020.1734681.
190. Rajput, S.; Singh, S.P. Connecting circular economy and industry 4.0. *Int J Inf Manage* **2019**, *49*, 98–113. 10.1016/J.IJINFOMGT.2019.03.002.
191. Yu, Z.; Khan, S.A.R.; Umar, M. Circular economy practices and industry 4.0 technologies: A strategic move of automobile industry. *Bus Strategy Environ* **2022**, *31*, 796–809. 10.1002/BSE.2918.

192. Pinheiro, M.A.P.; Jugend, D.; Lopes de Sousa Jabbour, A.B.; Chiappetta Jabbour, C.J.; Latan, H. Circular economy-based new products and company performance: The role of stakeholders and Industry 4.0 technologies. *Bus Strategy Environ* **2022**, *31*, 483–499. 10.1002/BSE.2905.
193. Rossi, J.; Bianchini, A.; Guarnieri, P. Circular Economy Model Enhanced by Intelligent Assets from Industry 4.0: The Proposition of an Innovative Tool to Analyze Case Studies. *Sustainability 2020, Vol. 12, Page 7147* **2020**, *12*, 7147. 10.3390/SU12177147.
194. Vilkas, M.; Rauleckas, R.; Šeinauskienė, B.; Rutelionė, A. Lean, Agile and Service-oriented performers: templates of organising in a global production field. *Total Quality Management & Business Excellence* **2019**, *32*, 1122–1146. 10.1080/14783363.2019.1676639.
195. Šebo, J.; Kádárová, J.; Malega, P. Barriers and motives experienced by manufacturing companies in implementing circular economy initiatives: The case of manufacturing industry in Slovakia. *ICTEP 2019 - International Council of Environmental Engineering Education - "Technologies of Environmental Protection" - Proceedings* **2019**, 226–229. 10.1109/ICTEP48662.2019.8968969.
196. Zahradnik, G.; Dachs, B.; Rhomberg, W.; Leitner, K.-H. *Trends Und Entwicklungen In Der Österreichischen Produktion Highlights aus dem European Manufacturing Survey*; 2019.
197. Palčič, I.; Prester, J. Impact of Advanced Manufacturing Technologies on Green Innovation. *Sustainability 2020, Vol. 12, Page 3499* **2020**, *12*, 3499. 10.3390/SU12083499.
198. Kakhki, F.D.; Freeman, S.A.; Mosher, G.A. Use of logistic regression to identify factors influencing the post-incident state of occupational injuries in agribusiness operations. *Applied Sciences (Switzerland)* **2019**, *9*. 10.3390/APP9173449.
199. Romero, M.; Guédria, W.; Panetto, H.; Barafort, B. Towards a Characterisation of Smart Systems: A Systematic Literature Review. *Comput Ind* **2020**, *120*, 103224. 10.1016/J.COMPIND.2020.103224.
200. Kang, H.S.; Lee, J.Y.; Choi, S.; Kim, H.; Park, J.H.; Son, J.Y.; Kim, B.H.; Noh, S. Do Smart manufacturing: Past research, present findings, and future directions. *International Journal of Precision Engineering and Manufacturing - Green Technology* **2016**, *3*, 111–128. 10.1007/S40684-016-0015-5/METRICS.
201. Rosso, R.S.U.; Tsuzuki, M. de S.G.; Barari, A.; Macchi, M. Transition towards Smart Factories. *Int J Comput Integr Manuf* **2022**, *35*, 341–344. 10.1080/0951192X.2022.2080451.
202. Zhang, H.; Zhang, X.; Gao, X.Z.; Song, S. Self-organizing multiobjective optimization based on decomposition with neighborhood ensemble. *Neurocomputing* **2016**, *173*, 1868–1884. 10.1016/J.NEUCOM.2015.08.092.
203. Fager, P. Kit preparation for mixed-model assembly: efficiency impact of confirmation methods. *Industrial Management and Data Systems* **2019**, *119*, 547–560. 10.1108/IMDS-07-2018-0287/FULL/XML.
204. Zhou, B.; Zhao, L. A multi-objective decomposition evolutionary algorithm based on the double-faced mirror boundary for a milk-run material feeding scheduling optimization problem. *Comput Ind Eng* **2022**, *171*. 10.1016/J.CIE.2022.108385.
205. Machado, C.G.; Winroth, M.P.; Ribeiro da Silva, E.H.D. Sustainable manufacturing in Industry 4.0: an emerging research agenda. *Int J Prod Res* **2019**, *58*, 1462–1484. 10.1080/00207543.2019.1652777.
206. Fathi, M.; Nourmohammadi, A.; Ghobakhloo, M.; Yousefi, M. Production Sustainability via Supermarket Location Optimization in Assembly Lines. *Sustainability 2020, Vol. 12, Page 4728* **2020**, *12*, 4728. 10.3390/SU12114728.
207. Francuz, Á.; Bányai, T. Optimisation Of Milkrun Routes In Manufacturing Systems In The Automotive Industry. *Cutting & Tools in Technological System* **2022**, 32–41. 10.20998/2078-7405.2022.96.04.
208. 3 Major Differences Between an MES and ERP System | Pyramid Solutions Available online: https://pyramidsolutions.com/intelligent-manufacturing/blog-im/3-differences-between-mes-and-erp/ (accessed on Jun 1, 2024).
209. Lee, W.J.; Mendis, G.P.; Sutherland, J.W. Development of an Intelligent Tool Condition Monitoring System to Identify Manufacturing Tradeoffs and Optimal Machining Conditions. *Procedia Manuf* **2019**, *33*, 256–263. 10.1016/J.PROMFG.2019.04.031.
210. Lachmayer, R.; Mozgova, I.; Scheidel, W. An Approach to Describe Gentelligent Components in their Life Cycle. *Procedia Technology* **2016**, *26*, 199–206. 10.1016/J.PROTCY.2016.08.027.