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OPTIMIZATION OF LOGISTIC SYSTEMS IN INDUSTRY 4.0 ENVIRONMENT

PHD THESES

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CONTENTS

1. THEORETICAL BACKGROUND

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 [1] 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.

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 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].

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 [2], 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.

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

Table 1: 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 2: 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].

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. 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.

3.1. 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. 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. The evaluation methodology focused 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.

3.2. 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 1). 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.
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.

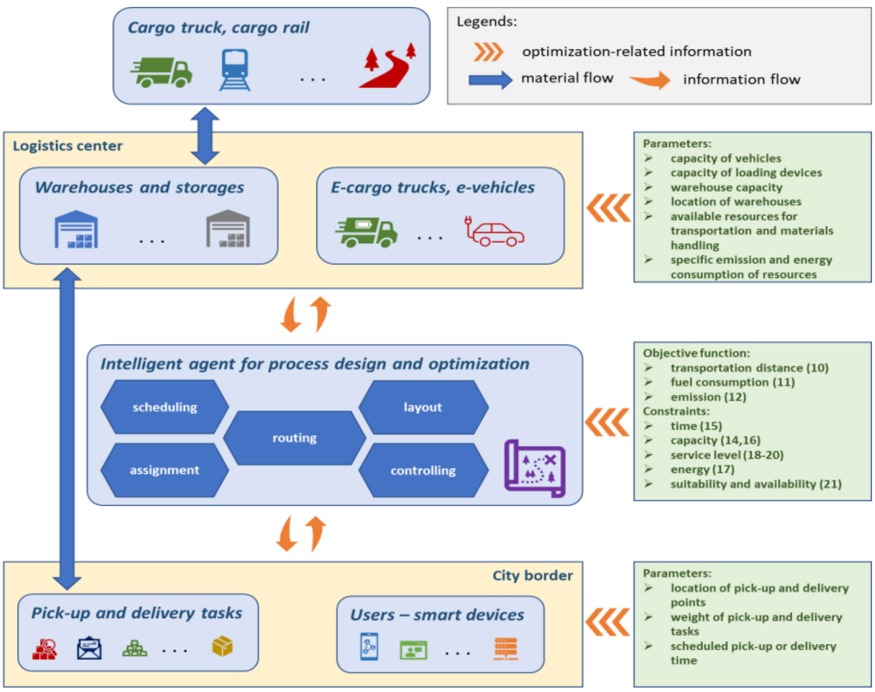


Figure 1: Model of multi-echelon collection and distribution system in downtown areas

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].

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

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 2. 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.
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.
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 [3]. It gives the required real distances and time in which vehicles move between given locations.

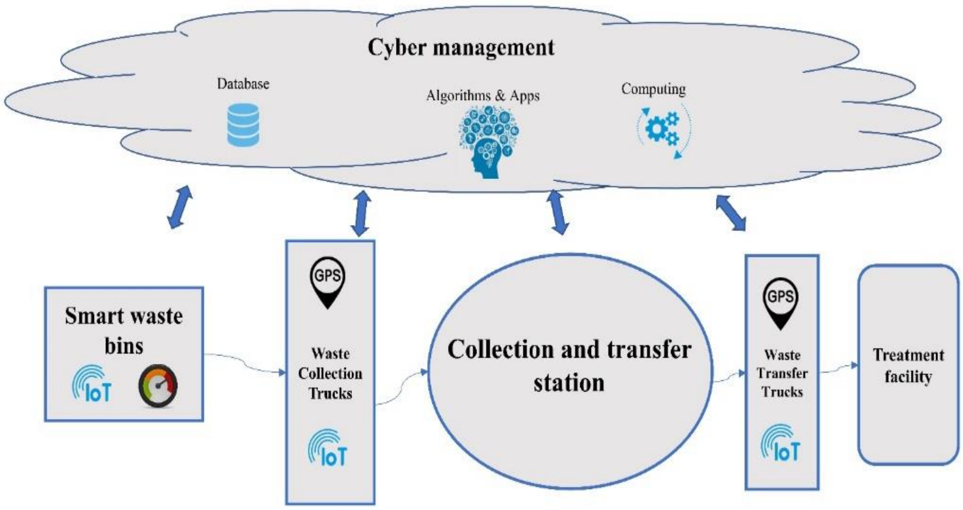


Figure 2: Cyber-physical waste management system scheme

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 [4]. 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 [5]. 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 [6]. Such cases did not apply here, where the locations of the bins were sparsely scattered around the city.

3.4. 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. 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.

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

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 [3]. 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.

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. 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 3 next to the used locations' order coding for 2 trucks case that is applied in the coming case study.

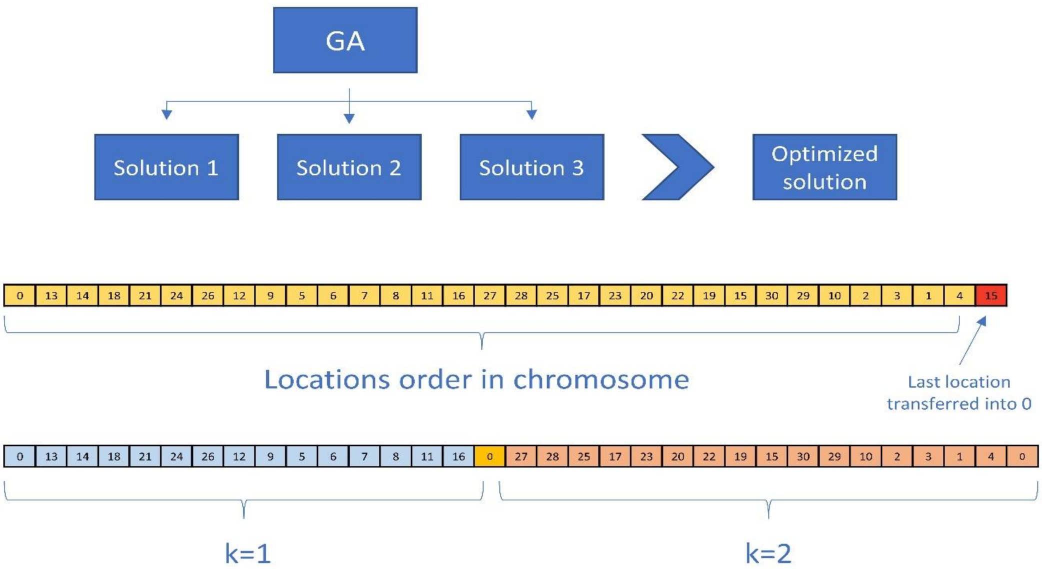


Figure 3: GA optimization methodology

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.

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 [4]. 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 $K = \{1, 2, \ldots, m\}$, the mentioned

trucks are stationed at the goods storage station at the beginning. The index set $I = \{0,1,2,\ldots,n\}$ 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.

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.
In the first scenario, two trucks were needed. Execution of the whole code is 14.62 seconds. Also, the total energy and distance for a random solution are mentioned.

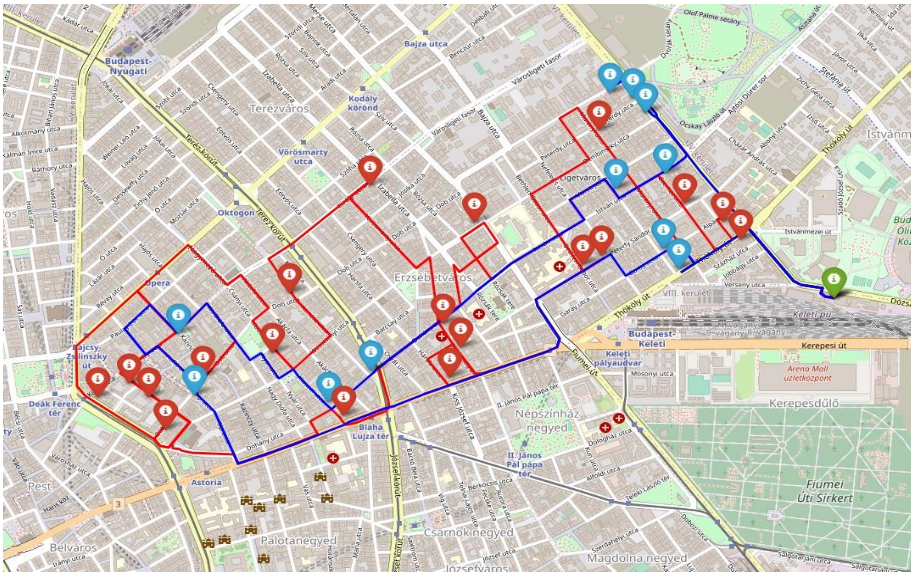


Figure 4: Optimized solution for the second scenario (electric)

In the second scenario, two trucks were needed as well. The execution of the whole code is 13.95 seconds. Also, the total energy and distance for a random solution are mentioned. Figure 4 show the actual routes for the optimized solution. Red and blue colors are used to distinguish each truck's route.
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.

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 [7] 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 [8]. 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 [9].

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.

The conclusion of 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.

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 [10]. 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 [11], a common consciousness of such adoption's usefulness is widespread, especially regarding the energy saving [12]. 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.

The tackled data is collected within the EMS project. The sample (N=798) contains data collected in Lithuania [13], Slovakia [14], Austria [15], Croatia, and Slovenia [16] 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 5. 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, abridgments for the tackled technologies are mentioned.

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.

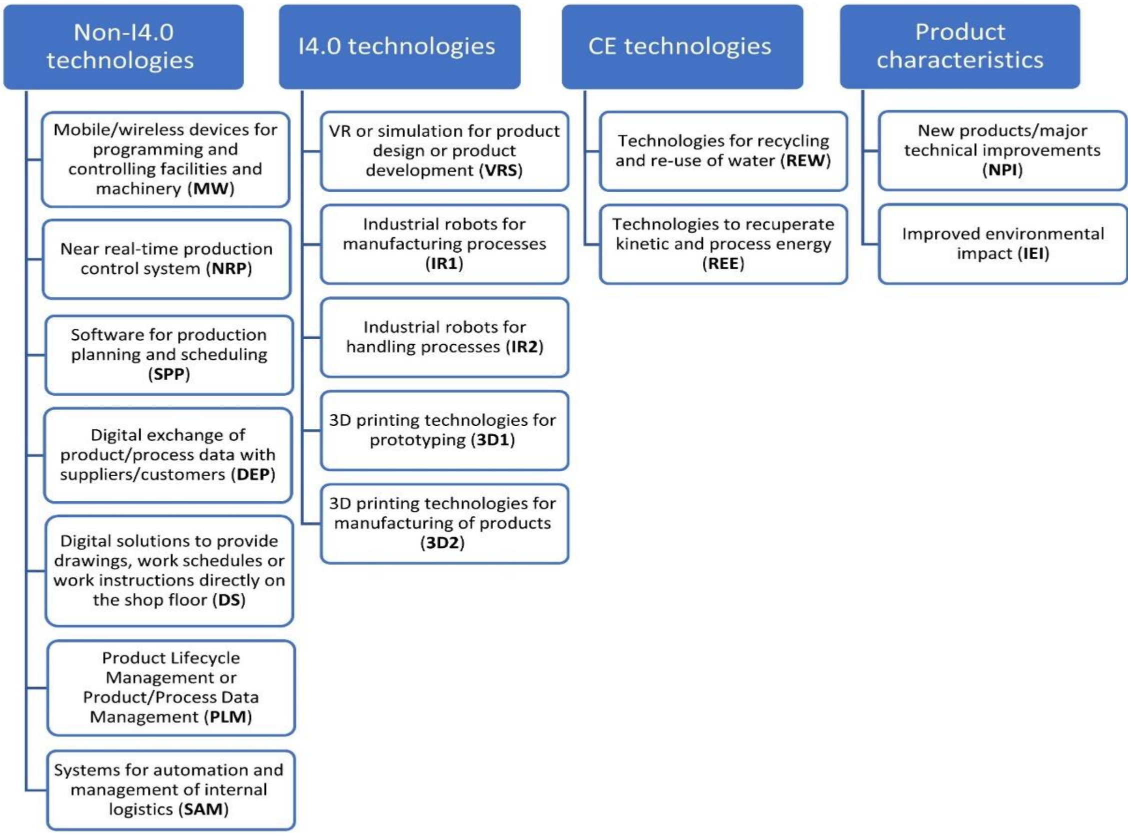


Figure 5: Used technologies and product innovation (variables) with abridgments

According to the available data and depending on the classified technologies, 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 6) 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).

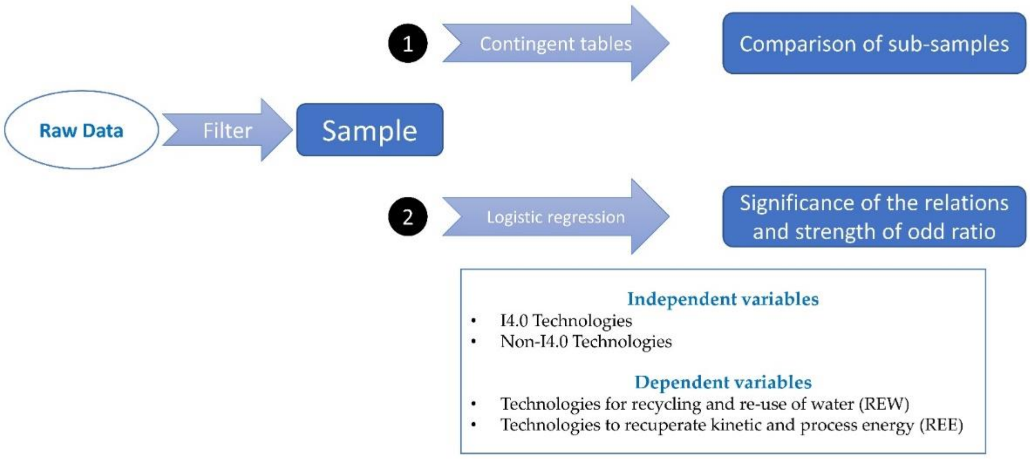


Figure 6: Research model 1 for testing H1a and H1b

Since there is data related to the product characteristics that can be connected to CE indirectly 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.

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. 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.

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). 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.
Within the second 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. 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.
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. 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, 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. 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).

5.2. 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 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.

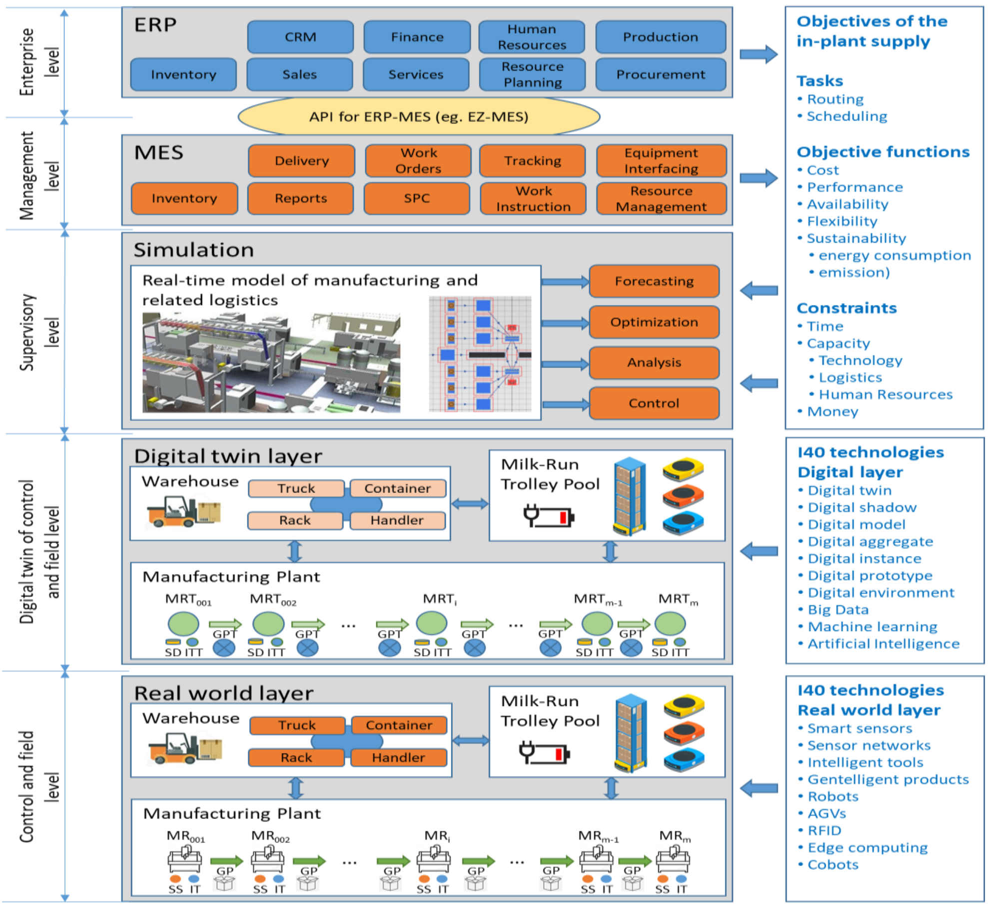
On the other hand, four of the twelve (resp. fourteen) tackled technologies did not show any significant relation with CE technologies (research model 1) or CE improvements of products (research model 2) that are namely MW, DS, DEP, and 3D2. The results, from the view of tackled Industry 4.0 and non-Industry 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.

5.3. 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.

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.
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 7).



Legends:
MR_j: Manufacturing resource in the real world layer; SS: Smart sensor in the real world layer
IT: Intelligent tool; GP: Gentelligent product; MRT_j: Digital twin of the manufacturing resource
SD: Sensor data; ITT: Digital twin of the intelligent tool; GPT: Digital twin of the gentelligent product (digital prototype)

Figure 7: Structure of Industry 4.0 technologies supported by milk-run-based in-plant supply

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.

5.4. 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.

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 optimization model of the Industry 4.0 technologies supported by real-time milk-run-based in-plant supply. 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).

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.
- sources and destinations of MES data-based supply demands.
- predefined specific time frames for MES data-based supply demands.

- real-time supply demands for a predefined specific time window.
- sources and destinations of real-time generated supply demands.
- predefined specific time frames for real-time generated supply demands.
- 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.

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. The loading of milk-run trolleys is shown in Figure 8. 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.

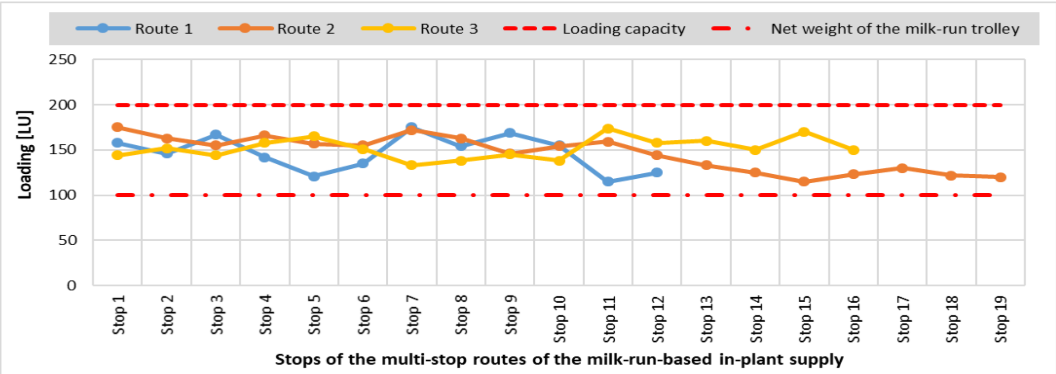


Figure 8: The optimized loading capacity of the three milk-run trolleys

The cumulative energy consumption of the three routes is shown in Figure 9. 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.

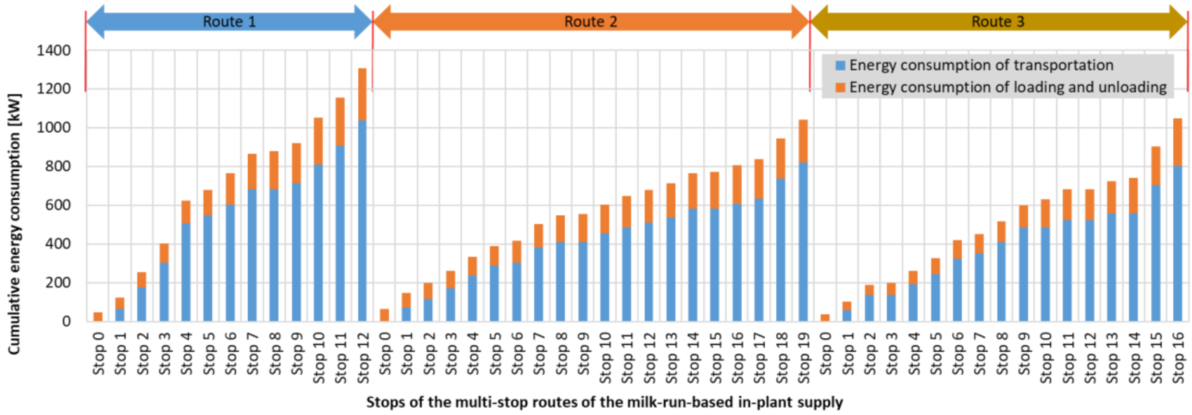


Figure 9: Cumulative energy consumption of the three milk-run routes in the conventional real-time case

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.

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. It was possible to integrate one unloading operation at C_01 and one loading operation of the same component at C_17.

In the case of route 2, 19 in-plant supply demands are performed and all of them are between the predefined time windows. 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 10 represent the real-time added routes segments.

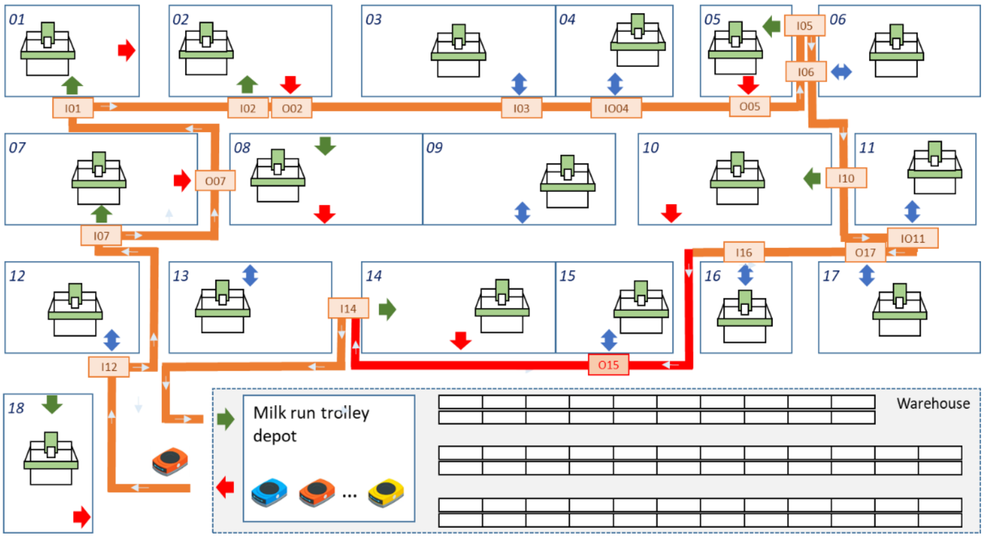


Figure 10: The modified second route

In the case of route 3, 17 in-plant supply demands are performed and all of them are between the predefined time window. 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 10 represent the real-time added routes segments.

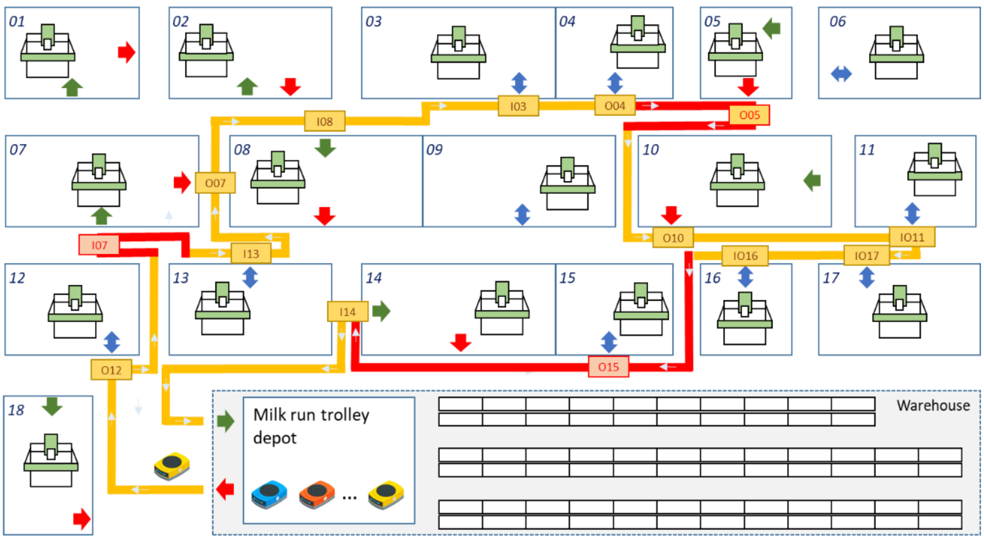


Figure 11: The modified third route

The loading of milk-run trolleys in the case of scenario 2 is shown in Figure 11. 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.

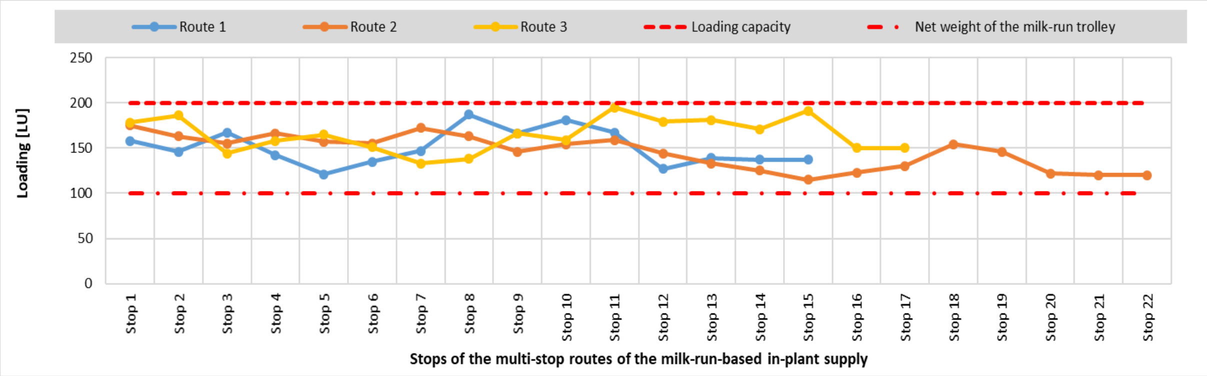


Figure 12: The optimized loading capacity of the three milk-run trolleys

The cumulative energy consumption of the three routes is shown in Figure 12. 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.

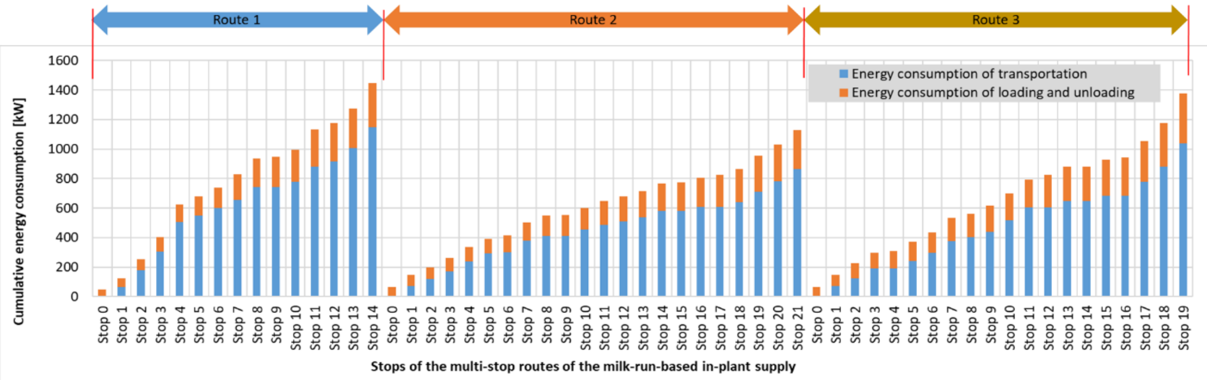


Figure 13: The optimized loading capacity of the three milk-run trolleys

5.5. Results discussion and conclusions

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.

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 scientific contributions of the dissertation are:

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.

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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.

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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.

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