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RESEARCH ARTICLE

Mathematical Modelling Approaches for Integrated Single Machine Scheduling and Electric Vehicle Routing Problem

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ABSTRACT

In recent years, increasing CO_2 emissions and resource utilization has adversely affected the environment. Sustainability efforts have been initiated to decrease these effects, including environmentally friendly electric vehicles in vehicle fleets used for transportation. The electric vehicle routing problem (EVRP) has emerged in the literature, and numerous studies have been conducted, considering specific constraints related to electric vehicles. Due to various charging feature constraints, EVRP diverges from the classical vehicle routing problem (VRP) and becomes more complex. In addition to the load capacity constraints of classical VRP, electric vehicles must deliver products to customers via an optimal vehicle route while considering battery capacity limitations. This study addresses the integrated single-machine scheduling and electric vehicle routing problem. After scheduling and processing customer product requests on a single machine, electric vehicle routes must be created to deliver these products to customers. To meet customer expectations, the objective function of the problem aims to minimize the costs associated with customer product delivery delays. Two mathematical models, i.e., mixed-integer linear programming (MILP) and constraint programming (CP) models, are presented to solve this problem. The results and performances of these models are compared on a set of instances. Numerical results indicate that the CP model has superior performance than the MILP model for the problem.

Keywords: Electric vehicle routing, single machine scheduling, mixed-integer linear programming, constraint programming, integrated scheduling and routing

1. Introduction

In recent years, increasing resource consumption, CO2, and greenhouse gas emissions have led to serious problems such as environmental pollution and global warming. Efforts to reduce and prevent these environmental damages aim to promote sustainability practices and reduce carbon footprints. Due to the harm caused by traditional vehicles that consume fossil fuel, sustainability initiatives are being implemented to change the vehicle fleets used in the transportation sector. In place of traditional vehicles causing air pollution, and high fossil fuel consumption, environmentally friendly electric vehicles with very low emissions have started to be included in vehicle fleets. Due to their low energy consumption, the trend towards electric vehicles is expected to increase even further in the near future.

Electric vehicles have some structural and technical characteristics that differentiate them from traditional vehicles; thus, their routing decisions also vary. The electric vehicle routing problem (EVRP) has battery capacity constraints besides the load capacity constraints observed in the classical vehicle routing problem (VRP). Thus, electric vehicles have to frequent battery charging locations along their route for battery charging, making electric vehicle routing decisions more challenging and complex than the classical vehicle routing decisions.

In the considered problem in this study, products requested by customers are scheduled on a single machine in the desired quantity. After processing the customer requests on a single machine, it is necessary to distribute them to customers using electric vehicles. Thus, in this study, the integrated single-machine scheduling and electric vehicle routing problem (SM-EVRP) is addressed. The objective function of the studied problem aims to minimize the costs associated with delays in customer product delivery to meet customer expectations. To address this integrated problem, a Mixed-Integer Linear Programming (MILP) model

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and a Constraint Programming (CP) model have been developed. The developed mathematical models are tested on various-sized instances and their solutions are compared to assess the performance of the mathematical models.

In the literature, single-machine scheduling problems have been extensively addressed for many years, enriched with various constraints and objective functions. Koulamas (2010) presented a literature review for the single-machine scheduling problem (SMSP) with total tardiness criterion. When the studies on the SMSP with tardiness objective are examined; it is seen that various exact and heuristic solution methods have been presented for addressing this problem. Tanaka and Araki (2013) studied the SMSP with sequence-dependent setup times (SDST) that minimized total weighted tardiness for jobs, which was solved using a dynamic programming–based algorithm. Similarly, Luo and Chu (2006) studied the SMSP with SDST to minimize total tardiness and proposed the branch-bound algorithm to solve the problem. Ozcelik et al. (2022) studied the SMSP with stochastic SDST, where the objective of the problem is to minimize the total expected setup, earliness, and tardiness costs. Liao and Juan (2007) studied the SMSP with SDST. The problem aims to minimize total weighted delay, and an ant colony algorithm was proposed for the problem.

The demand for electric vehicles has steadily increased given the increasing importance of sustainability efforts in today's world. In this line, the EVRP has emerged in the literature. Numerous studies have been conducted on the routing of electric vehicles with various charging characteristics. In the study conducted by Kucukoglu et al. (2021), a detailed literature review is presented for EVRP. As seen from the literature review of Kucukoglu et al. (2021), the EVRP with a single depot has been extensively examined in the literature regarding various constraints. For instance, Keskin and Çatay (2016) studied the EVRP with time windows and a single depot to minimize the total distance. The authors proposed an adaptive large neighborhood search algorithm for solving the problem. Küçükoğlu and Öztürk (2016) studied the EVRP with a heterogeneous fleet located at a single depot and proposed a mixed-integer mathematical model to minimize the route lengths of electric vehicles. Bruglieri et al. (2015) studied the EVRP with time windows and a single depot and proposed a mixed-integer mathematical model and variable neighborhood search branching to solve the problem. Schneider et al. (2014) studied the EVRP with time windows and a single depot. They proposed a mixed-integer programming model and a hybrid heuristic algorithm using a tabu search and a variable neighborhood search. Felipe et al. (2014) also studied the EVRP with multiple charging technologies and partial recharges. The authors proposed a simulated annealing framework and local search techniques for solving the problem.

Studies integrating machine scheduling problems and VRP have become widespread in the literature, especially in recent years. In the studies by Berghman et al. (2023) and Moons et al. (2017), a literature review has been conducted on integrated scheduling and VRP. As seen from these literature reviews, there are studies on integrated single-machine scheduling and VRP without considering electric vehicles. He et al. (2022) studied integrated SMSP and VRP and presented a mixed integer programming model. The objective of the problem is to minimize the weighted sum of delivery times of customers as well as distribution costs. The authors proposed an enhanced branch-and-price algorithm for solving the problem. Long et al. (2022) studied integrated SMSP and VRP. A multi-objective optimization model has been considered to minimize the total holding, distribution, and tardiness costs. The authors proposed a level-based multi-objective particle swarm algorithm to solve the problem. Wang et al. (2019) addressed the integrated SMSP and VRP with heterogeneous vehicles to minimize the total cost and carbon emissions and proposed a tabu search algorithm to address the problem. Jamili et al. (2016) studied the integrated SMSP and VRP and presented an integer linear programming model. The objective of the problem is to minimize the average delivery time and total distribution cost. The authors proposed a tabu search metaheuristic and local search algorithm to solve the problem. Li et al. (2016) presented an integer programming model for the integrated SMSP and VRP. The problem aims to minimize delivery costs and waiting time of customers. They proposed a non-dominated genetic algorithm with elite strategy for solving the problem. Low et al. (2014) also studied the integrated SMSP and VRP and presented an adaptive genetic algorithm. However, to the best of the authors' knowledge, no study integrates single-machine scheduling with EVRP in the literature.

The VRP has been studied for years in the literature. Various variants have led to the development of not only MILP models but also CP models. Öztop, Kizilay, and Çil (2021) studied periodic VRP with time window constraints and proposed MILP and CP models to solve the problem, aiming to minimize the total travel time. Yüksel et al. (2021) studied the milk delivery problem. MILP and CP models were developed to solve the problem to minimize the total cost arising from fuel consumption and delays. Ha et al. (2020) studied the VRP with synchronization constraints. A CP model and an adaptive large neighborhood search algorithm were presented. Hojabri et al. (2018) studied a VRP with time windows. A CP model and a large neighborhood search algorithm were proposed as the solution method. Also, Öztop (2022) proposed a CP model for the open VRP. However, the number of studies developing CP models for the EVRP is quite limited. Booth & Beck (2019) addressed the EVRP with time windows and developed MILP and CP models for addressing the homogeneous fleet problem. Lam et al. (2022) studied the EVRP with time window constraints to minimize the total cost, for which a CP model and branch-cut-price algorithm were proposed.

Due to increasing costs in today's conditions, solving production planning and product distribution problems effectively has become increasingly important to reduce the associated total costs. In the literature, these problems were solved in an integrated manner for various industrial applications. For instance, the integrated production scheduling and distribution problem has been addressed for perishable products in the studies of Farahani et al. (2012), Chen et al. (2019), and Devapriya et al. (2016). Since perishable products are time-sensitive, integrated scheduling is important in these production systems (Ulrich 2013; Moons et al. 2017). Integrated production scheduling and distribution have also been applied to other industries such as furniture manufacturing (Mohammadi et al. 2020), metalworking (Wang et al. 2019), and metal packing (Fu et al. 2017) industries. Similarly, in the literature, some studies involve industrial applications for the EVRP. For instance, Zhao et al. (2020) studied the EVRP in cold chain logistics for the distribution of fresh products. Zhao and Lu (2019) addressed a real-world EVRP for a logistics company. By integrating electric vehicles in fleets, industries can considerably reduce distribution costs and carbon footprint. Owing to the environmental benefits of electric vehicles, it is expected that the usage of electric vehicles in the industry will increase in the future. As a result, regarding the industrial applications of integrated production and distribution scheduling problems and EVRP, it can be said that the integrated SM-EVRP discussed in this study can be applied in various industrial sectors.

As mentioned above no study integrates single-machine scheduling and EVRP in the literature. Thus, this study considers the integrated single-machine scheduling and EVRP for the first time in the literature. Moreover, novel mathematical models, i.e., the MILP and CP models, are proposed to address this complex problem. The problem being studied distinguishes itself from other works in the literature with these characteristics. Therefore, this study contributes to both the literature on integrated production and distribution problems and the literature on EVRP. In terms of managerial insights, the proposed models can provide effective solutions for the integrated SM-EVRP of companies and help managers to accelerate their sustainability efforts in product delivery while ensuring customer satisfaction. As the integrated problem is being studied for the first time, this study is expected to serve as an important resource for future researchers. The contributions of this study can be listed as follows:

- The integrated SM-EVRP has been addressed to minimize customer product delivery tardiness costs.
- A MILP model is developed for the integrated SM-EVRP.
- A CP model is proposed for the integrated SM-EVRP.
- The performance of the mathematical models is tested on a set of various-sized instances.

The subsequent sections of this paper have been planned as follows: In the second section, a detailed problem definition of the addressed problem is provided, clarifying the related assumptions of the problem. In the third section, the formulations for the developed MILP and CP models are presented. In the fourth section, the numerical results of the mathematical models are presented for comparing their performances. The study is summarized and concluded in the fifth section.

2. Problem Definition

In the SM-EVRP, products requested by customers (jobs) are produced on a single machine. After the completion of the processing of jobs on the machine, these products are distributed to customers using electric vehicles. The SM-EVRP aims to obtain the job processing order and a route plan for electric vehicles that minimize the costs associated with delays in customer product delivery. The detailed assumptions for the SM-EVRP are as follows:

- There is a single machine in the production system.
- The processing times of jobs are independent of the job processing order and are known at the beginning.
- All jobs are ready at the beginning.
- At a time, the machine can produce only one job.
- The job processing times cannot be divided.
- The setup times of jobs are independent of the job processing order and are involved in the processing time.
- Each electric vehicle's route must start and end at the depot.
- Each customer must be visited by precisely one electric vehicle.
- Electric vehicles can visit a battery charging station between any two nodes on their route to recharge their batteries.
- Electric vehicles have a certain load capacity and a certain battery limit.
- Each battery charging station can be visited by multiple electric vehicles.
- The battery level of each electric vehicle is fully charged at a charging station visit.
- Each electric vehicle can start its route once all the jobs assigned to that vehicle are completed on the single machine.
- Each customer has a certain due date for receiving a product and a certain tardiness penalty cost.

The sets and parameters used in the developed mathematical models are given in Table 1.

Table 1. Sets and parameters

Sets and Parameters
0, N + 1: Depot nodes (0: starting depot, N + 1: ending depot)
F: Charging station set {1, 2, …, S}
F′: Dummy charging station set
V: Customer set, {1, 2, …, N}
V_0: Customer and depot (0) set
V_{N+1}: Customer and depot (N + 1) set
V′: Customer and charging station set
V'_0: Customer, charging station, and depot (0) set
V'_{N+1}: Customer, charging station, and depot (N + 1) set
$V'_{0,N+1}$: Customer, charging station, depot (0), and depot (N + 1) set
K: Vehicle set
N: Number of customers
$\boldsymbol{Q_k}$**:** Battery limit of electric vehicle k
$\boldsymbol{h_k}$**:** Battery charge consumption rate for electric vehicle k
$\boldsymbol{C_k}$**:** Load capacity of electric vehicle k
$\boldsymbol{d_{i,j}}$**:** Travel distance from point i to point j
$\boldsymbol{q_i}$**:** Product demand quantity of customer i
$\boldsymbol{s_i}$**:** Service time for customer i
$\boldsymbol{l_0}$: A sufficiently large number
$\boldsymbol{l_i}$**:** Latest time to arrive at the customer i
$\boldsymbol{g_k}$**:** Unit charging time for electric vehicle k
$\boldsymbol{tc_i}$**:** Penalty cost incurred for arriving late to customer i
$\boldsymbol{process_i}$**:** Processing time for job i

3. Mathematical Models

3.1. Mixed-Integer Linear Programming Model

In the development of the MILP model for SM-EVRP, it is benefited from the MILP models for EVRP presented in the studies of Kucukoglu et al. (2021) and Schneider et al. (2014). The decision variables for the developed MILP model are explained below.

Decision Variables

$x_{i,j,k}$: 1 if electric vehicle k visits from node i to node j; *0* otherwise, $\forall i, j \epsilon V'_{0,N+1}, i \neq j, \forall k \epsilon K$
$z_{i,r}$: 1 if job i is processed at position r on the machine; *0* otherwise, $\forall i, r \epsilon V$
$y_{i,k}$: Battery level of vehicle k in node i, $\forall i \epsilon V'_{0,N+1}, \forall k \epsilon K$
p_i: Delivery time of products to customer i
$Comp_i$: Completion time for job i on the machine
Str_k: Departure time of electric vehicle k from the depot
T_i: Delivery delay quantity for customer i

The developed MILP model's constraints and objective function are given below.

Objective Function:

$$MinZ = \sum_{j \epsilon V} tc_j \times T_j. \tag{1}$$

Constraints:

$$\sum_{j \epsilon V'_{N+1}} \sum_{k \in K} x_{i,j,k} = 1, \forall i \in V. \tag{2}$$

$$\sum_{j \epsilon V'_{N+1}} \sum_{k \in K} x_{i,j,k} \leq 1, \forall i \in F'. \tag{3}$$

$$\Sigma_{j \epsilon V'_{N+1}} x_{0,j,k} = 1, \forall k \in K \tag{4}$$

$$\Sigma_{i \epsilon V'_0} x_{i,j,k} = \Sigma_{i \epsilon V'_{N+1}} x_{j,i,k}, \forall j \in V^{'}, \forall k \in K. \tag{5}$$

$$y_{j,k} \leq y_{i,k} - (h_k \times d_{i,j}) \times x_{i,j,k} + Q_k \times (1 - x_{i,j,k}), \forall i \in V, \forall j \in V^{'}_{N+1}, \forall k \in K. \tag{6}$$

$$y_{j,k} \leq Q_k - (h_k \times d_{i,j}) \times x_{i,j,k}, \forall i \in F^{'} \cup \{0\}, \forall j \epsilon V^{'}_{N+1}, \forall k \in K. \tag{7}$$

$$y_{0,k} \leq Q_k, \forall k \in K. \tag{8}$$

$$\Sigma_{i \epsilon V} \Sigma_{j \epsilon V'_{N+1}} q_i \times x_{i,j,k} \leq C_k, \forall k \in K. \tag{9}$$

$$p_i + (d_{i,j} + s_i) \times \sum_{k \epsilon K} x_{i,j,k} \leq p_j + l_0 \times \left(1 - \sum_{k \in K} x_{i,j,k}\right), \forall i \in V, \forall j \in V^{'}_{N+1:j \neq N+1.} \tag{10}$$

$$p_i + (d_{i,j} \times x_{i,j,k}) + g_k \times (Q_k - y_{i,k}) \leq p_j + (l_0 + g_k \times Q_k) \times (1 - x_{i,j,k}), \forall i \in F^{'}, \forall j \in V^{'}_{N+1}, \forall k \in K. \tag{11}$$

$$\Sigma_{i \epsilon V'_{0,N+1}} x_{i,N+1,k} = 1, \forall k \in K. \tag{12}$$

$$p_j - l_j \leq T_j, \forall j \in V. \tag{13}$$

$$\sum_{r \epsilon V} z_{i,r} = 1, \forall i \in V. \tag{14}$$

$$\sum_{i \in V} z_{i,r} = 1, \forall r \in V. \tag{15}$$

$$Comp_i \geq process_i, \forall i \in V. \tag{16}$$

$$Comp_j + l_0 \times (1 - z_{i,(r-1)}) + l_0 \times (1 - z_{j,r}) \geq Comp_i + process_j, \forall i, j, r \in V : r > 1. \tag{17}$$

$$Str_k \geq Comp_j - l_0 \times (1 - \Sigma_{i \in V'_{0,N+1}} x_{i,j,k}), \forall k \in K, \forall j \in V. \tag{18}$$

$$p_j \geq Str_k + d_{0,j} - l_0 \times (1 - x_{0,j,k}) \forall k \in K, \forall j \in V^{'}_{N+1}. \tag{19}$$

The objective function (1) aims to minimize customer product delivery tardiness costs. Constraint (2) guarantees that each customer is served precisely once by an electric vehicle. Constraint (3) guarantees that each dummy charging station is visited by an electric vehicle at most once. Constraint (4) guarantees that each electric vehicle starts its route from the depot. Constraint (5) ensures the flow balance of routes for each node and electric vehicle. Constraint (6) calculates the battery amount of each vehicle after visiting each customer on the route. Constraint (7) calculates the battery amount of each vehicle after visiting each charging station on the route. Constraint (8) ensures that the battery amount of each electric vehicle leaving the depot is at most equal to the vehicle's battery capacity. Constraint (9) ensures that the total load of the customers visited by each electric vehicle along its route is at most equal to the vehicle's load capacity. Constraint (10) computes the start time for delivery at each customer along the route. Constraint (11) calculates the start time for delivery at the first customer on the route after an electric vehicle departs from the battery charging station, regarding the charging time to replenish its battery and the travel time between nodes. Constraint (12) ensures that each electric vehicle completes its route at the depot. Constraint (13) calculates the product delivery delay amount for each customer based on their due dates. Constraint (14) guarantees that each job is allocated to just one position of the machine. Constraint (15) guarantees that only one job is allocated to each position of the machine. Constraint (16) ensures that the finishing time of each job on the machine is at least equal to the processing time of the job. Constraint (17) calculates the finishing time of each job on the machine based on its processing time and the order in which it is assigned. Constraint (18) calculates the departure time of each electric vehicle from the depot based on the maximum completion time of jobs allocated to that vehicle. Constraint (19) computes the start time for delivery at the first customer on the route for each electric vehicle after it leaves the depot.

3.2. Constraint Programming Model

The decision variables for the developed CP model are explained below.

Decision Variables

$cust_i$: Interval variable for visiting node $i \in V$ with size s_i

$y_{i,k}$: Optional interval variable for serving node i $\in V'_{0,N+1}$ by vehicle $k \in K$

seq_k:Sequence variable for vehicle $k \in K$ over $\{y_{i,k} | i \in V'_{0,N+1}\}$

$level_{i,k}$: Battery level of the vehicle $k \in K$ at node $i \in V'_{0,N+1}$, between 0 and Q_k

T_i: Tardiness amount for the customer $i \in V$

z_i: Interval variable for job $i \in V$ with size $process_i$

mseq: Sequence variable for machine over $\{z_i | i \in V\}$

Str_k: Departure time from the depot for the vehicle $k \in K$

The developed CP model's constraints and objective function are given below.

Objective Function:

$$MinZ = \Sigma_{j \in V} tc_j \times T_j. \tag{20}$$

Constraints:

$$alternative(cust_i, all(k \in K), y_{i,k}), \forall i \in V. \tag{21}$$

$$\Sigma_{k \in K} presenceOf(y_{i,k}) \leq 1, \forall i \in F'. \tag{22}$$

$$\Sigma_{i \in V} q_i \times presenceOf(y_{i,k}) \leq C_k, \forall k \in K. \tag{23}$$

$$first(seq_k, y_{0,k}), \forall k \in K. \tag{24}$$

$$last(seq_k, y_{N+1,k}), \forall k \in K. \tag{25}$$

$$presenceOf(y_{0,k}) = 1, \forall k \in K. \tag{26}$$

$$presenceOf(y_{N+1,k}) = 1, \forall k \in K. \tag{27}$$

$$noOverlap(seq_k, d_{ij}, 1), \forall k \in K. \tag{28}$$

$$level_{0,k} = Q_k, \forall k \in K. \tag{29}$$

$$level_{typeOfNext(seq_k, y_{i,k}, i, i), k} \leq level_{i,k} - (h_k \times d_{i,typeOfNext(seq_k, y_{i,k}, i, i)}), \forall i \in V, \forall k \in K. \tag{30}$$

$$level_{typeOfNext(seq_k, y_{i,k}, i, i), k} \leq Q_k - (h_k \times d_{i,typeOfNext(seq_k, y_{i,k}, i, i)}), \forall i \in F' \cup \{0\}, \forall k \in K. \tag{31}$$

$$endOf(y_{i,k}) \geq startOf(y_{i,k}) + g_k \times (Q_k - level_{i,k}), \forall i \in F', \forall k \in K. \tag{32}$$

$$startOf(y_{j,k}) - l_j \leq T_j, \forall j \in V, \forall k \in K. \tag{33}$$

$$presenceOf(z_j) = 1, \forall j \in V. \tag{34}$$

$$noOverlap(mseq). \tag{35}$$

$$Str_k \geq endOf(z_i) - l_0 \times (1 - presenceOf(y_{i,k})), \forall i \epsilon V, \forall k \in K \tag{36}$$

$$startOf(y_{0,k}) \geq Str_k, \forall k \in K. \tag{37}$$

The CP and MILP models have identical objectives (20), aiming to minimize the cost of customer product delivery delays. It calculates the delay amount for each customer and determines the value of the function by multiplying each customer's delay with the corresponding penalty cost. Constraint (21) ensures that each customer is visited precisely once by a vehicle. Constraint (22) ensures that each dummy charging station is visited by a vehicle at most once. Constraint (23) ensures that the total load of the customers visited along the route of each vehicle does not surpass the vehicle capacity. Constraint (24) ensures that each electric vehicle starts its route from the depot using the *first* command. Constraint (25) ensures that each electric vehicle concludes its route at the depot using the last command. Constraints (26) and (27) ensure the presence of the starting and ending depots for each vehicle using the *presenceOf* command. Constraint (28) ensures that there are no overlapping visits along the route of each electric vehicle using the *noOverlap* command. Constraint (29) guarantees that each electric vehicle starts from the depot with a fully charged battery. Constraint (30) calculates the battery amount of each vehicle after visiting each customer on the route using the *typeOfNext* command by considering the charge loss rate based on the distance traveled. Similarly, Constraint (31) computes the battery amount of each vehicle after visiting each charging station. Constraint (32) calculates the departure time for each electric vehicle from each charging station using the *endOf* command by considering the time spent at the charging station. Constraint (33) computes the product delivery delay amount for each customer. Constraint (34) provides that each job is allocated to just one position of the machine. Constraint (35) guarantees that the order of assigned jobs to the machine does not overlap using the *noOverlap* command. Constraints (36) and (37) calculate the time for each electric vehicle to start its route from the depot with the *startOf* command based on the maximum ending time of jobs assigned to that vehicle.

4. Computational Results

The MILP and CP models were solved using IBM ILOG CPLEX 12.10. Various-sized instances were created to evaluate the performance of the models. While generating these instances, the location and service time information for customers and battery charging stations were obtained from the instances in the study of Goeke (2019). The traveling distance between two locations equals the resultant Euclidean distance rounded to an integer. As mentioned in Section 2, electric vehicles can visit any battery charging station on their route to recharge their batteries. To ensure that sufficient number of charging stations are available for each customer, dummy charging stations were defined as many as the number of customers for each charging station. Thus, $N \times S$ dummy charging stations were defined in total. The generated instances included 42 different scenarios with the number of customers varying from 6 to 16; number of charging stations varying from 2 to 5; random customer product demands in the range of [10, 80]; random job processing times in the range of [10, 60]; and random customer product delivery tardiness costs in the range of [0.1, 0.5]. Due dates of the customers were generated based on various due-date tightness factors. Namely, due date values taken from the study of Goeke (2019) were divided by a due-date tightness factor varying between 2–4. All electric vehicles were assumed to have identical structural features. Each vehicle has a battery charge consumption rate of 1 unit, a load capacity of 200 units, a battery limit of 78 units, and a unit charging time of 3. The generated instances are available in Dataset (2024). The solutions of the developed mathematical models were obtained within a time limit of 1800 seconds; results are given in Table 2.

Table 2. Computational results

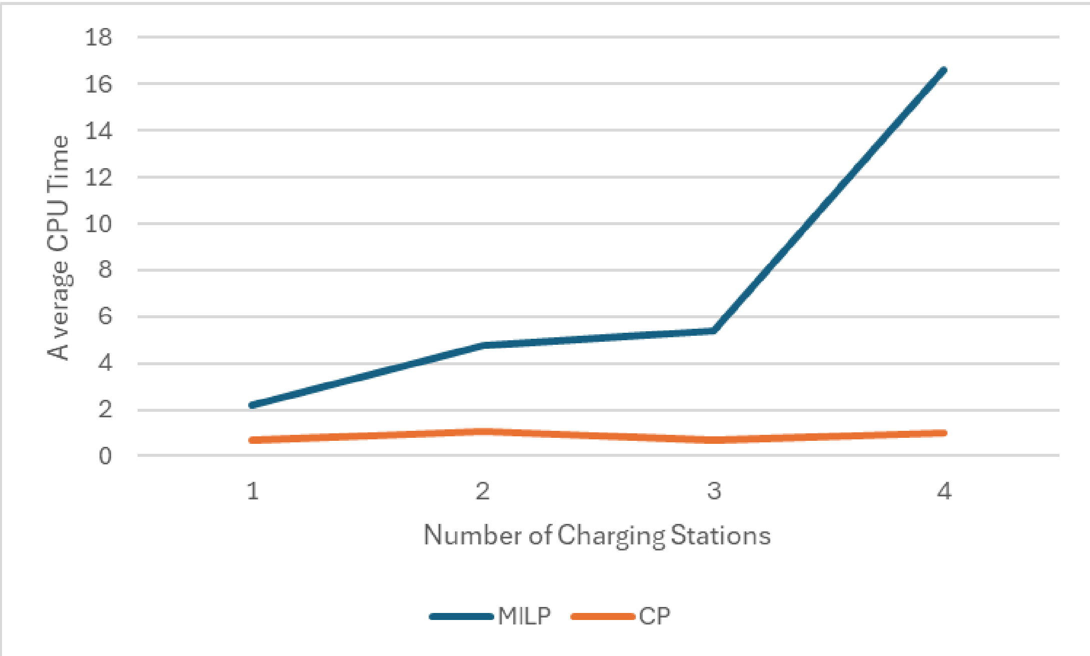
Instance	Number Of Customers	Number Of Charging Stations	Number Of Vehicles	MILP		CP		Best Lower Bound
				Objective Function Value	CPU (s)	Objective Function Value	CPU (s)	
c101C6-1-1	6	3	4	2.59	1800	**0**	1.45	0
c101C6-1-2	6	3	4	**0**	31.86	**0**	79.84	0
c101C6-2-1	6	3	4	21.21	1800	**11.64**	1800	0
c101C6-2-2	6	3	4	41.57	1800	**30.39**	1800	0
c101C6-3-1	6	3	4	50.06	1800	**47.44**	1800	0
c101C6-3-2	6	3	4	**99.18**	1800	**99.18**	1800	0
c103C6-1-1	6	2	4	**0**	0.94	**0**	0.67	0
c103C6-1-2	6	2	4	**0**	3.44	**0**	0.69	0
c103C6-2-1	6	2	4	**0.44**	19.94	**0.44**	0.77	0.44
c103C6-2-2	6	2	4	**7.6**	28.03	**7.6**	0.79	7.6
c103C6-3-1	6	2	4	**7.03**	11.97	**7.03**	1.81	7.03
c103C6-3-2	6	2	4	**1.7**	13.7	**1.7**	0.85	1.7
c206C6-1-1	6	4	4	**0**	1.55	**0**	1.19	0
c206C6-1-2	6	4	4	**0**	1.55	**0**	0.24	0
c206C6-2-1	6	4	4	**0**	1.74	**0**	0.74	0
c206C6-2-2	6	4	4	**0**	1.55	**0**	0.86	0
c206C6-3-1	6	4	4	**0**	13.53	**0**	0.92	0
c206C6-3-2	6	4	4	**0**	12.03	**0**	1.18	0
c208C6-1-1	6	3	4	**0**	1.09	**0**	635	0
c208C6-1-2	6	3	4	**0**	0.64	**0**	52.5	0
c208C6-2-1	6	3	4	**0**	1.28	**0**	242	0
c208C6-2-2	6	3	4	**0**	4.06	**0**	584.86	0
c208C6-3-1	6	3	4	**0**	6.27	**0**	737	0
c208C6-3-2	6	3	4	**0**	1.72	**0**	807.73	0
c104C10-1-1	10	4	6	75.48	1800	**0**	4.66	0
c104C10-1-2	10	4	6	89.02	1800	**0**	4.79	0
c104C10-2-1	10	4	6	460.43	1800	**0**	17.2	0
c104C10-2-2	10	4	6	20.02	1800	**4.8**	1800	0
c104C10-3-1	10	4	6	411.1	1800	**85.63**	1800	0
c104C10-3-2	10	4	6	554.17	1800	**71.34**	1800	0
c101C12-1-1	12	5	7	*	1800	**77.55**	1800	0
c101C12-1-2	12	5	7	*	1800	**0**	81.12	0
c101C12-2-1	12	5	7	1507.08	1800	**156.9**	1800	0
c101C12-2-2	12	5	7	1211.3	1800	**106.92**	1800	0
c101C12-3-1	12	5	7	*	1800	**379.91**	1800	0
c101C12-3-2	12	5	7	*	1800	**420.4**	1800	0
c103C16-1-1	16	5	9	*	1800	**14.05**	1800	0
c103C16-1-2	16	5	9	*	1800	**3.92**	1800	0
c103C16-2-1	16	5	9	*	1800	**109.79**	1800	0
c103C16-2-2	16	5	9	2325.91	1800	**393.11**	1800	0
c103C16-3-1	16	5	9	*	1800	**651.86**	1800	1.12
c103C16-3-2	16	5	9	*	1800	**593.03**	1800	1.6
			Average		**989.45**		**849.02**	

In Table 2, the instances in the "Instance" column are labeled according to the original instance and due-date tightness factor. Two instances are generated for each combination of the due-date tightness factor by randomly generating various parameters for the original instance. For example, c101C6-1 has a more flexible due-date tightness factor, whereas c101C6-2 has a tighter due-date tightness factor. Similarly, c101C6-3 has a tighter due-date tightness factor than c101C6-2. The objective function values and CPU times (in seconds) are reported for each model. A CPU value of 1800 s indicates that the problem could not be optimally solved within the given time limit. The symbol "*" indicates that the MILP model could not find a feasible solution for that instance within the 1800-s limit. The CPU row shows the average solution times for the developed MILP and CP models. The values in the last column of Table 2 represent the best lower bounds for the instances obtained by the models after reaching the time limit.

The analysis of results shown in Table 2 indicate that the MILP model achieved optimal solutions within the 1800-s limit for 19 out of 42 instances. In contrast, the CP model found optimal solutions for 24 out of 42 instances. Both models yielded the same objective function value for 20 instances. The developed CP model found better solutions for 22 instances compared to the MILP model, which confirmed the difference in their performances. When analyzing the average solution times for the developed mathematical models, the MILP model had an average solution time of 989.45 s, whereas the CP model had an average solution time of 849.02 s. When the results were examined, it was observed that the MILP model struggled to find feasible solutions for larger instances with 12 and 16 customers within the 1800-s limit. The solution quality of the MILP model decreased considerably with increasing number of customers and charging stations. However, the CP model is still able to find feasible solutions for such larger instances. This indicates that the CP formulation performs better than the MILP formulation in achieving better solutions in less computational time for the integrated SM-EVRP. The CP model has superior performance than the MILP model in this regard.

The effect of the number of charging stations on the solution times of the MILP and CP models was also analyzed. In this analysis, four instances with six customers were run by the MILP and CP models by considering four different numbers of charging stations. The average solution time values were calculated for each number of charging stations over four instances. Average solution times of each model for different numbers of charging stations are provided in Figure 1. As shown in the figure, the solution time of the MILP model increases as the number of charging stations increases, whereas that of the CP model does not change considerably. In addition, the solution time of the CP model is less than that of MILP model for these instances, similar to the results listed in Table 2. Thus, the CP model has stable solution times for different numbers of charging stations and outperforms the MILP model.

Figure 1. Solution time of the models for different number of charging stations



In terms of limitations of the models, it has been observed that the obtained lower bound values are low, usually 0, for both models when optimal results cannot be achieved within the time limit. Both models have difficulty in finding good quality lower bounds, particularly for large-sized problems. Hence, in future studies, developing a good-quality lower bound for the problem would be a promising research direction to improve the performance of the models.

5. Conclusion

In this study, the integrated SM-EVRP has been addressed. Electric vehicles, which are increasingly becoming part of vehicle fleets in supply chains due to sustainability initiatives, have different routing decisions than conventional vehicles. The various battery constraints and charging station visits associated with electric vehicles make the EVRP more challenging and complex. The consideration of the integrated SM-EVRP in this study is highly significant for enhancing the efficiency of production and logistics activities simultaneously. The inclusion of electric vehicles in vehicle fleets, with their significantly low energy consumption and nearly zero emissions, presents an opportunity for companies to improve their energy efficiency and minimize the environmental impact of traditional vehicles. By simultaneously considering machine scheduling and product distribution processes in supply chain systems, the overall process efficiency can be improved. In terms of contributions of this study, it is noteworthy that the SM-EVRP has been addressed herein for the first time, and the MILP and CP models have been proposed for the problem. The objective of the developed mathematical models is the minimization of customer product delivery delay costs, aiming to enhance customer satisfaction. A comparison of the mathematical models on a set of instances revealed that the CP model demonstrated superior performance than the MILP model. For the generated instances, the CP model obtained a greater number of optimal solutions and lower CPU values than the MILP model. Nevertheless, both mathematical models successfully obtained optimal results for most of the small-sized instances. Numerical analysis revealed that the CP model could also find a feasible solution for large-sized instances. In future studies, a lower bound for the problem can be developed and added to the CP model, so that it can better evaluate the quality of solutions for large-sized instances. Moreover, heuristic methods can be presented to solve larger-sized instances. The inclusion of SDST for single machine scheduling part of the problem can also considered. Additionally, more complex scheduling environments, such as the flowshop scheduling problem, can also be integrated with the EVRP in future research studies.

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