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Hybrid simulated annealing and tabu search method for the electric travelling salesman problem with time windows and mixed charging rates

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ABSTRACT

The electric travelling salesman problem with time windows (ETSPTW) is an extension of the well-known travelling salesman problem with time windows (TSPTW). The ETSPTW additionally considers recharging operations of the electric vehicle at identical charging stations. However, different charging technologies used at public or private stations result in different charging times of the electric vehicles. Therefore, this study extends the ETSPTW by additionally considering charging operations at customer locations with different charging rates, called hereafter the electric travelling salesman problem with time windows and mixed charging rates (ETSPTW-MCR). To the best of our knowledge, this is the first study that considers both private and public charging stations for the ETSPTW. In addition to the extended version of the ETSPTW, this paper introduces a new and effective hybrid Simulated Annealing/Tabu Search (SA/TS) algorithm to solve the ETSPTW-MCR problem efficiently. Distinct from the existing hybridization of SA and TS, the proposed hybrid SA/TS algorithm employs efficient search procedures based on the TSPTW restrictions, a modified solution acceptance criterion, and an advanced tabu list structure. Moreover, an improved dynamic programming procedure is integrated to optimally find the charging station visits in shorter computational times. The proposed hybrid SA/TS is tested on several TSPTW and ETSPTW benchmark problems and compared with well-known solution approaches. Results of these experiments show that the proposed algorithm outperforms the other considered competitor algorithms both with regard to solution quality and computational time. Furthermore, 26 new best results are obtained for the ETSPTW instances. In addition, the hybrid algorithm is applied to a new problem set generated for the ETSPTW-MCR by extending the ETSPTW problems found in the literature. Comparisons with the ETSPTW results show that significant distance savings are found for most of the instances by charging the electric vehicle at customer locations. As a result of the computational studies, it should be concluded that the proposed algorithm is capable of finding efficient and more realistic route plans for the electric vehicles.

1. Introduction

The vehicle routing problem (VRP) is one of the most important researched problems due to its great potential to reduce transportation and logistics costs in both the private and public sector. The classical VRP introduced by Dantzig and Ramser (1959) aims to find a route plan for a fleet which has to serve a set of customer locations where the objective is to minimize total transportation cost. Since its first introduction, the VRP with various assumptions has been studied extensively by researchers (Eksioglu, Vural, & Reisman, 2009; Laporte, 2009). With the growing concern about the environmental impact of logistics activities, the green vehicle routing problem (GVRP), a relatively new research field, is introduced by Erdoğan and Miller-Hooks (2012) as an extension of the VRP. The GVRP aims to minimize the transportation cost of conventional internal combustion vehicles and additionally considers their fuel tank capacity. The refueling time is assumed to be constant (Erdoğan & Miller-Hooks, 2012). As a result of the increasing attention on the environmental impact of the transportation, a considerable number of researches have been carried out on the GVRP during the last decade (Lin, Choy, Ho, Chung, & Lam, 2014).

The electric vehicle routing problem (EVRP), which deals with planning routes for electric vehicles, is another research field

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studied recently by researchers because of the promising opportunity of the electric vehicles to reduce transportation costs and pollution effects in comparison to fossil-fuel based engines Pelletier, Jabali, and Laporte (2014). The EVRP is an extension of the GVRP where the battery capacities of the electric vehicles are limited when planning routes. The limited cruising range and long charging times of the electric vehicles make the charging operations a more critical issue compared to the refueling operations in the GVRP (Keskin & Çatay, 2016). Although the service times at charging stations have been significantly reduced with ever-developing technology, charging times of electric vehicles are still time-consuming. Depending on the charging power, charging technologies are divided into three levels: Level I-III (Awasthi et al., 2017). Level I and Level II are referred to as slow and normal charging modes. Due to low power requirements, such stations can be constructed at residential homes or working places as private charging stations. Level III charging technology is a fast charging mode, and its usage is limited to public charging stations because of high voltage requirements (Xu, Meng, Liu, & Yamamoto, 2017). Nevertheless, charging times of the electric vehicles at charging stations still exceed more than half an hour even if a fast charging technology is used. In this context, considerable cost and time reductions can be achieved for logistics companies by encouraging the usage of private charging stations since a certain percentage of the battery can be recharged while the electric vehicle is in the parking position.

Another critical issue for the companies is managing the routing plans, where any improvement in routing plans has the potential to provide a considerable reduction of transportation costs and greenhouse gas emissions. However, the difficulty of finding efficient routing plans for the companies is that most of the routing problems belong to the class of combinatorial optimization problems that are shown to be NP-hard. Therefore, many metaheuristic algorithms have been introduced in the literature. However, obtaining insight in the problem structure of the specific problem under consideration is crucial to develop an efficient expert system that outperforms more generic approaches and human planners.

Based on the aforementioned motivations, this study addresses the electric travelling salesman problem with time windows (ETSPTW) introduced by Roberti and Wen (2016) as a single-vehicle version EVRP, and extends the problem by additionally considering charging operations with different charging rates for an electric vehicle at customer locations. With this new assumption, the extended problem is called the electric travelling salesman problem with time windows and mixed charging rates (ETSPTW-MCR), and formulated as a mixed integer mathematical model. In addition to the new variant of the ETSPTW, an efficient hybrid metaheuristic algorithm is introduced based on two well-known meta-heuristic algorithms: tabu search (TS), and simulated annealing (SA). The proposed hybrid SA/TS combines the advantages of SA and TS to escape local minima by modifying the solution acceptance procedure of SA and the tabu list structure of the TS. Moreover, new components are integrated into the algorithm to search the solution space efficiently.

This paper contributes to the literature in two main aspects: a new perspective for the ETSPTW, and a new solution methodology. In the ETSPTW, the electric vehicle is allowed to recharge its battery only at public charging stations with the same charging technology. To the best of our knowledge, the ETSPTW-MCR has not been discussed in the literature before. By considering recharging at customer locations with slow or normal charging technologies in real life logistics applications, this study provides a new perspective for researchers and company decision-makers. By allowing these recharging operations, a reduction on the total distance travelled is expected since the ETSPTW-MCR provides more flexible charging opportunities for the electric vehicle while still servicing all customers within their allowed time windows. Although, recharging times at private charging stations are longer than the times at public charging stations, ETSPTW-MCR gives extra recharging opportunity to the electric vehicle while waiting at the customer location and reduces the visits to the public charging stations.

In addition to the introduction of the extended version of the ETSPTW, this study contributes to the literature by presenting a new hybrid SA/TS algorithm, which exhibits superior performance on these types of problems. Distinct from the existing hybridization of SA and TS, the novelty of the proposed algorithm can be summarized as follows. An efficient local search procedure consisting of 1-shift, 2-opt, and swapping operations is used to generate new solutions. The standard solution acceptance criterion of the SA is modified. An advanced tabu list structure is introduced to escape local optima and avoid unnecessary computations. As in the solution approach proposed by Roberti and Wen (2016), a dynamic programming procedure is used to obtain charging operation plans. The dynamic programming procedure is improved to speed up the computations. Besides the main contribution of the study, a benchmark problem set is introduced for the ETSPTW-MCR by extending the existing ETSPTW problem sets. Moreover, new best results are found by the proposed algorithm for both the TSPTW and the ETSPTW.

The remainder of this paper is formed as follows: In Section 2, a review of the related literature is presented. Section 3 introduces the ETSPTW-MCR and its formulation as a mixed integer mathematical model. The details of the proposed hybrid SA/TS are given in Section 4. The computational studies for the hybrid SA/TS, comparisons, and discussions are presented in Section 5. This section also includes exact solver solutions for small sized ETSPTW-MCR instances. Finally, a conclusion part with future research perspectives is given in Section 6.

2. Literature review

The ETSPTW is introduced by Roberti and Wen (2016), which can be seen as a generalization of the well-known travelling salesman problem with time windows (TSPTW). In the ETSPTW, an electric vehicle services a set of customers while satisfying customer time window and battery capacity constraints. The battery can be charged at a given set of public charging stations. The authors formulated two different mathematical models for the problem and proposed a metaheuristic approach based on a combination of a general variable neighborhood search (GVNS) procedure and dynamic programming. Hereafter, this metaheuristic is referred to as the three phase heuristic (3P-Heu). In the first two phases, the 3P-Heu uses the GVNS metaheuristic to optimize the vehicle route only taking the time windows constraints into account. Next, an insertion algorithm based on dynamic programming inserts charging stations to the route in order to find a feasible solution for the ETSPTW. The authors analyzed the performance of the 3P-Heu on two different problem sets generated by extending two well-known TSPTW datasets. High-quality results in short computational times are reported.

The ETSPTW can be assumed closely related to TSP variant called the black and white travelling salesman problem (BWTSP). The BWTSP was introduced by Bourgeois, Laporte, and Semet (2003), and has been mostly applied in the field of short-haul airline scheduling and telecommunications. In the BWTSP, the vertex set is divided into two subsets called hereafter the black and white vertices. The BWTSP differs from the TSP in that both the number of white vertices visited and the length of the path between two consecutive black vertices cannot exceed the specified limits. The objective of the problem is to find the shortest Hamiltonian tour that covers all vertices satisfying the cardinality and the length constraints (Bourgeois et al., 2003). A number of researchers have recently studied this problem, such as by Ghiani, Laporte, and Semet (2006), by Li and Alidaee (2016), Muter (2015), and by Gouveia, Leitner, and Ruthmair (2017). This problem shows similarity to the ETSPTW and ETSPTW-MCR in case the black and white vertices are assumed to be charging stations and customer locations, respectively. The length constraint in the BWTSP can be used to model the battery level constraint between two charging stations visits in the case where a full charging policy is followed. However, in the ETSPTW there is no restriction on the number of customer visits between two charging operations. Likewise, a charging station is not limited to a single visit by the electric vehicle, and moreover, the electric vehicle is not even obliged to visit every charging station. Lastly, the length constraint of the BWTSP cannot model a partial charging policy. In addition, the ETSPTW considers customer time windows.

To the best of our knowledge, the study of Roberti and Wen (2016) is the only paper on the ETSPTW. However, the ETSPTW can be seen as a special case of the EVRP, where only a single vehicle is present. In the field of route optimization of electric vehicles, there are only a few studies in the literature due to the EVRP being a relatively new research field. The earliest study on EVRP is proposed by Conrad and Figliozzi (2011) where the charging operations follow a so-called full charging policy. Following a full charging policy, an electric vehicle can depart from a charging station if and only if its battery is fully recharged. In addition to the battery capacity of the electric vehicles, vehicle load capacities and customer time windows are taken into account. The authors proposed a mathematical model for the considered problem which has two objectives. The first objective aims to minimize the number of routes. The second objective minimizes the total travelling distance. An iterative route construction and improvement procedure is proposed by the authors. Wang and Cheu (2013) considered the EVRP for the operations of an electric taxi fleet, and introduced a TS algorithm to minimize total distance travelled and maximum route time by considering recharging operations. Worley, Klabjan, and Sweda (2012) studied the EVRP with charging station siting constraints. They introduced a mixed integer mathematical model for the problem which aims to simultaneously minimize total travelling cost, recharging cost, and station location cost.

Schneider, Stenger, and Goeke (2014) extended the EVRP by considering the EVRP with time windows (EVRPTW), in which a full charging strategy is taken into account. The authors developed a hybrid metaheuristic algorithm consisting of a variable neighborhood search (VNS) algorithm and a TS approach. The performance of the proposed hybrid VNS/TS algorithm is analyzed on different benchmark data sets related to vehicle routing problems. Additionally, the proposed algorithm is tested on a new problem set which is generated by the authors for the EVRPTW. The EVRPTW is extended by Afroditi, Boile, Theofanis, Sdoukopoulos, and Margaritis (2014), Chen, Qi, and Miao (2016), Paz, Granada-Echeverri, and Escobar (2018), Preis, Frank, and Nachtigall (2014), and Montoya, Guéret, Mendoza, and Villegas (2017) with different assumptions. Preis et al. (2014) considered load dependent energy consumptions in urban delivery systems and proposed an adapted tabu search algorithm. Afroditi et al. (2014) used predefined energy consumptions for the electric vehicles. Chen et al. (2016) considered battery swapping operations for the electric vehicles instead of recharging operations. Paz et al. (2018) addressed the EVRPTW with multi-depot consideration. Montoya et al. (2017) used nonlinear charging functions for the electric vehicles and proposed a hybrid metaheuristic algorithm to minimize total time of the operations consisting of travel times and charging times.

In addition to the EVRP following a full charging policy, some researchers focus on partial charging policies where an electric vehicle can leave from a charging station with full capacity or with any battery level depending on the time spent for charging. Felipe, Ortuno, Righini, and Tirado (2014) extended the EVRP by allowing a partial charging strategy using different charging technologies for the electric vehicles and presented three heuristic algorithms to solve the problem: a construction heuristic, a deterministic local search algorithm, and an SA algorithm. According to their computational studies, the SA performs better with respect to other methods for large sized problems. Desaulniers, Errico, Irnich, and Schneider (2016) proposed an exact branch-price-and-cut algorithm to solve the EVRPTW regarding four different charging strategies: at most a single full recharge per route, multiple full recharges per route, at most a single partial recharge per route, and multiple partial recharges per route with partial charging policy. Similarly, Keskin and Çatay (2016) tackled the EVRPTW with a partial charging policy and proposed an adaptive large neighborhood search (ALNS) algorithm for the problem. According to their computational studies, new best results are obtained by the proposed ALNS considering the full charging policy. Moreover, the advantages of the partial charging policy are pointed out by comparing the partial and full charging policies. Another study considering a partial charging policy is presented by Bruglieri, Mancini, Pezzella, Pisacane, and Suraci (2017) where a three phase metaheuristic method based on VNS is introduced to solve the problem. A different assumption for the problem is taken into account by Schiffer and Walther (2017), Schiffer and Walther (2018a,b) and Schiffer, Schneider, and Laporte (2018) where siting decisions for the charging stations are considered simultaneously.

Besides the charging policy for the electric vehicles, some of the papers pay attention to the effects of fleet type on routing plans and total travel cost. Goeke and Schneider (2015) proposed a new variant of the EVRPTW where a mixed fleet of electric and conventional internal combustion vehicles are used for customer visits. Küçükoğlu and Öztürk (2016) proposed a mathematical formulation for the EVRPTW with a heterogeneous fleet consisting of different types of electric vehicles. The advantages of the heterogeneous fleet based on the total distance travelled and the number of vehicles used are pointed out in their computational studies on a small sized problem set generated via the EVRPTW problems proposed by Schneider et al. (2014). Penna et al. (2016) introduced a hybrid iterative local search algorithm for the EVRPTW with a heterogeneous fleet, which is formed by combining an iterative local search algorithm and a set partitioning model. Hiermann, Puchinger, Ropke, and Hartl (2016) introduced an effective ALNS algorithm to solve the EVRPTW with heterogeneous fleet. The performance of the proposed ALNS is tested on various problem sets.

Considering the existing studies, various solution approaches are introduced to solve the EVRP and its variations. Since the VRP is an NP-hard problem, and the EVRP is a generalization of the VRP, the EVRP can equally be considered NP-hard in the strong sense (Desaulniers et al., 2016; Zhang, Gajpal, Appadoo, & Abdulkader, 2018). Therefore, a metaheuristic algorithm based solution approach is employed in most of the studies. Table 1 summarizes the metaheuristic approaches used in the field of EVRP. Also, additional components that are integrated with the algorithms are noted in the last column of Table 1. The additional components, such as dynamic programming, matheuristic, column generation, etc., are used as a subroutine in the algorithms to increase algorithm efficiency. It should be noted that only a few studies consider a population based algorithm, in which a discretization step is required to represent a solution for EVRP since these algorithms are firs introduced for global optimization problems. On the other hand, a permutation order based coding scheme can be used in the genetic algorithm (GA), which allows representing a solution for the EVRP without using any transformation procedure. However, it should be seen from the Table 1 that a solution improvement

Table 1
Metaheuristic solution approaches used for the EVRP.

Paper	ACO	CS	DEA	GA	ILS	LNS/ALNS	MA	SA	TS/ATS	VNS/AVNS	Integrated with
Abdulaal, Cintuglu, Asfour, and Mohammed (2017)				√							Markov Decision Process
Aggoune-Mtalaa, Habbas, Ouahmed, and Khadraoui (2015)				√							TS
Barco, Guerra, Muñoz, and Quijano (2017)			√								
Breunig, Baldacci, Hartl, and Vidal (2019)						√					
Bruglieri, Pezzella, Pisacane, and Suraci (2015b), Bruglieri, Pezzella, Pisacane, and Suraci (2015a), Bruglieri et al. (2017)										√	Matheuristic
Felipe et al. (2014)								√			
Goeke and Schneider (2015)						√					
Hiermann, Puchinger, and Hartl (2014), Hiermann et al. (2016)						√					Dynamic Programming
Hof, Schneider, and Goeke (2017)										√	
Jie, Yang, Zhang, and Huang (2019)						√					Column Generation
Kancharla and Ramadurai (2018)						√					
Keskin and Çatay (2016)						√					
Keskin and Çatay (2018), Keskin, Laporte, and Çatay (2018)						√					Matheuristic
Li-ying and Yuan-bin (2015)										√	TS
Montoya et al. (2017)					√						Heuristic Concentration
Ouahmed, Aggoune-Mtalaa, Habbas, and Khadraoui (2014)				√							TS
Penna et al. (2016)					√						Set Partitioning
Preis et al. (2014)									√		
Rezgui, Chaouachi-Siala, Aggoune-Mtalaa, and Bouziri (2017)							√				GA
Roberti and Wen (2016)										√	Dynamic Programming
Schiffer and Walther (2018a, b)						√					Dynamic Programming
Schiffer et al. (2018)						√					Lower Bounding Procedure
Schneider et al. (2014)										√	TS
Shao, Guan, and Bi (2018), Shao, Guan, Ran, He, and Bi (2017)				√							Dynamic Dijkstra
Wang and Cheu (2013)									√		
Yang et al. (2015)				√							Expert Knowledge
Zhang et al. (2018)	√										ILS
Zhenfeng, Yang, Xiaodan, and Sheng (2017)				√							
Zhou and Tan (2018)		√									

ACO: Ant Colony Optimization, CS: Cuckoo Search, DEA: Differential Evolution Algorithm, GA: Genetic Algorithm, ILS: Iterated Local Search, LNS/ALNS: Large Neighborhood Search/Adaptive Large Neighborhood Search, MA: Memetic Algorithm, SA: Simulated Annealing, TS/ATS: Tabu Search/Adaptive Tabu Search algorithm, VNS/AVNS: Variable Neighborhood Search/Adaptive Variable Neighborhood Search.

mechanism is integrated into GA in most of the studies to increase algorithm performance. Based on the single solution-based algorithms, the LNS and VNS based algorithms are the most used approaches to solve EVRPs. Several variations integrated with different subroutines have been introduced in the literature. Here, it should be expressed that the LNS and VNS based algorithms show better performance for most of the EVRP variants with regards to the computational results of the proposed algorithms. Especially, the adaptive versions of both the algorithms exhibits better performance, since their importance weights of local search mechanisms are adjusted during the search. Finally, it should be pointed out from Table 1 that only a few studies consider SA or TS, and a hybrid structure of SA and TS has not been applied to the EVRP in literature. Furthermore, regarding the ETSPTW in particular, the 3P-Heu is the only solution approach considered so far. Comparing with the 3P-Heu and other algorithms introduced for the EVRP, the proposed hybrid SA/TS is distinctive since it integrates the advantages of both the SA and TS, and operates a number of advanced procedures to take forward the search capability of the algorithm.

3. Problem definition and model formulation

As described by Roberti and Wen (2016), the ETSPTW considers a set of customer and charging station locations where each customer location is to be serviced by an electric vehicle in a specific time interval. The vehicle starts its tour at the depot with a full battery, which depletes proportionally to the distance travelled. Because of the range limit of the current state of electric vehicle technology, the vehicle most likely will have to visit one or more public charging stations during the execution of its tour. This is allowed at any time and it is assumed that the battery is recharged according to a full charging policy. Therefore, the vehicle always departs from a charging station with a full battery. The service time at an electric charging station depends on the battery level of the vehicle when it arrives at the charging station and the station's charging rate. The aim of the ETSPTW is to obtain the best route plan for the electric vehicle that minimizes the total distance travelled while satisfying the time windows and battery capacity constraints. Distinct from the ETSPTW, the ETSPTW-MCR also considers the possible charging operations at those customer locations that have their own private charging stations. Additionally, different charging rates for the public or private stations are taken into account. Charging operations for the ETSPTW-MCR are defined with the following assumptions:

- Each customer location can possibly own a private charging station with a certain charging technology.
- The electric vehicle can be recharged at any customer location containing a charging station.
- Assuming that the waiting time of the electric vehicles before the service is a slack time, the charging operation at a customer location has to be completed before the service starts at the customer.
- The electric vehicle can complete its visit to a customer without performing a charging operation.
- For the ETSPTW, Roberti and Wen (2016) also considered partial charging policy and pointed out the improvements on total distances by allowing partial charging. To investigate the computational feasibility of ETSPTW-MCR and estimate its broadly any potential savings, only a full charging policy is taken into account for both public and private charging stations. In case of a partial charging policy for the ETSPTW-MCR, reduction on the total distances are most likely expected for the electric vehicles.
- Charging rates at public charging stations or private stations at customer locations can be different with respect to the used technology.

As an illustrative example, Fig. 1 shows a route plan that services 15 customer locations (C1,…,C15) in which C4, C7, C9, C10, and C13 have their own private charging station. Moreover, there exist five available public charging stations (S1,...,S5) at different locations. The percentage values on the arcs show the battery level of the electric vehicle when it arrives and departs from a location. A value of 100% indicates that the electric vehicle is fully charged. In this example, the route plan includes charging operations at S1, S3, and S4 (public charging stations) and also at C4 and C7 (private charging stations).

According to the problem definition and considered assumptions, the mathematical model of the ETSPTW-MCR which is derived from the mathematical model of the ETSPTW proposed by Roberti and Wen (2016) is formulated as follows.

Notations

$0,\ N+1$	Depot nodes
F	Set of charging stations
F'	Set of dummy nodes to allow several visits to each charging station in the set of F
V	Set of customers; $V=\{1, 2, \dots, N\}$
V_0, V_{N+1}	Set of customers and depot node; $V_0=V\cup\{0\}$, $V_{N+1}=V\cup\{N+1\}$
V'	Set of customers and charging stations; $V'=V\cup F'$
V'_0, V'_{N+1}	Set of customers, charging stations and depot node; $V'_0 = V'\cup\{0\}$, $V'_{N+1} = V'\cup\{N+1\}$
d_{ij}	Travelling distance from node i to node j; $\forall i\in V'_0,\ j\in V'_{N+1},\ i\neq j$
t_{ij}	Travelling time from node i to node j; $\forall i\in V'_0,\ j\in V'_{N+1},\ i\neq j$
g_i	Recharging rate of the electric vehicle at node i; $\forall i\in V'\cup\{0\}\cup\{N+1\}$
h	Energy consumption rate of the electric vehicle per unit of distance
Q	Battery capacity of the electric vehicle
e_i	Earliest time to start the service allowed at node i; $\forall i\in V\cup\{0\}\cup\{N+1\}$
l_i	Latest time to start the service allowed at node i; $\forall i\in V\cup\{0\}\cup\{N+1\}$

Decision variables

x_{ij}	Binary variable and equal to *1* if the electric vehicle travels from node i to node j, *0* otherwise; $\forall i\in V'_0,\ j\in V'_{N+1},\ i\neq j$
r_i	Binary variable and equal to *1* if the electric vehicle is charged at node i, *0* otherwise; $\forall i\in V'\cup\{0\}\cup\{N+1\}$
p_i	Decision variable to track the service start time at node i; $\forall i\in V'\cup\{0\}\cup\{N+1\}$
y_i	Decision variable to track the battery level of the electric vehicle upon arrival at node i; $\forall i\in V'\cup\{0\}\cup\{N+1\}$
w_i	Non-negative decision variable to identify the charged battery level of the electric vehicle at node i; $\forall i\in V'\cup\{0\}\cup\{N+1\}$
w'_i	Non-negative decision variable to identify the idle battery level of the electric vehicle at node i; $\forall i\in V'\cup\{0\}\cup\{N+1\}$

Objective function

$$Min\ z=\sum_{i\in V'_0}\sum_{j\in V'_{N+1}} d_{ij}x_{ij} \tag{1}$$

Subject to

$$\sum_{j\in V'_{N+1}} x_{ij}=1 \quad \forall i\in V_0 \tag{2}$$

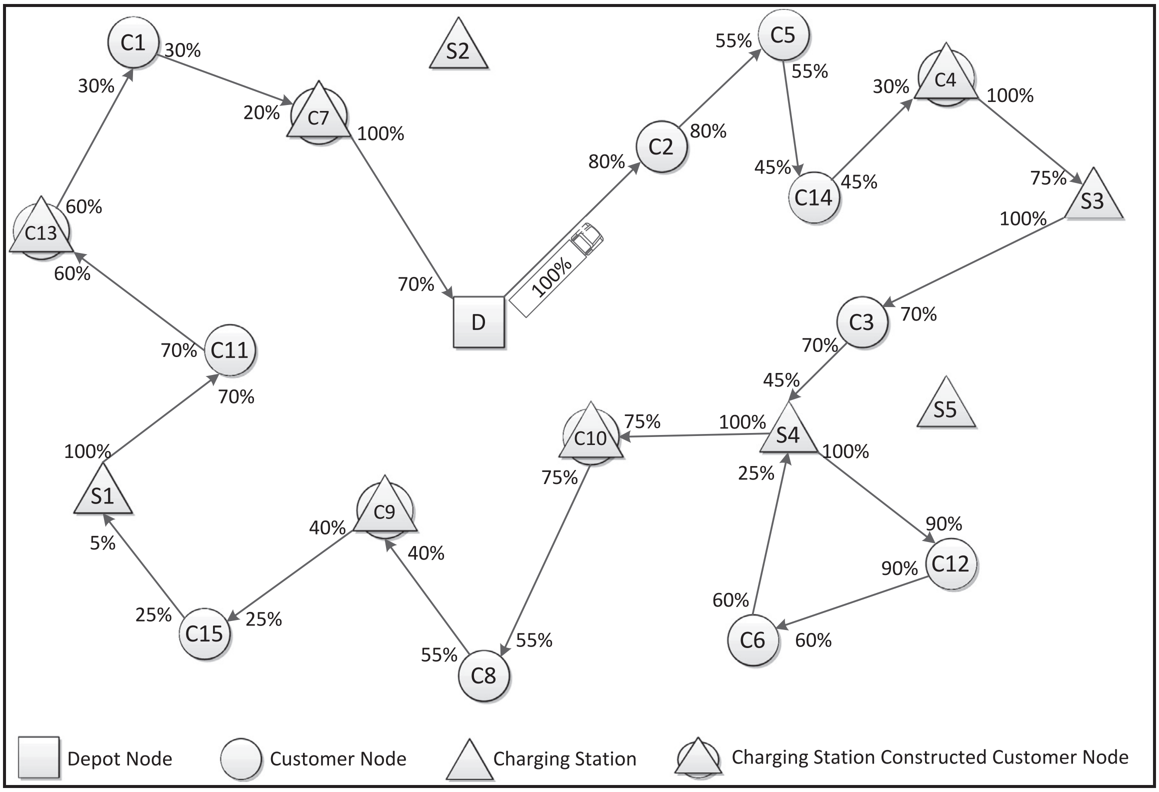

Fig. 1. An illustrative route plan for the ETSPTW-MCR.

$$\sum_{j \in V'_{N+1}} x_{ij} \le r_i \quad \forall i \in F' \tag{3}$$

$$\sum_{i \in V'_0} x_{ij} = \sum_{i \in V'_{N+1}} x_{ji} \quad \forall j \in V' \tag{4}$$

$$p_0 = e_0 \tag{5}$$

$$e_i \le p_i \le l_i \qquad \forall i \in V_{N+1} \tag{6}$$

$$p_i + t_{ij} x_{ij} + w_j g_j \le p_j + l_0 \left(1 - x_{ij}\right) \quad \forall i \in V'_0, \quad \forall j \in V'_{N+1} \tag{7}$$

$$y_0 = Q \tag{8}$$

$$y_j + h d_{ij} x_{ij} \le y_i + w_i + Q\left(1 - x_{ij}\right) \quad \forall i \in V'_0, \quad \forall j \in V'_{N+1} \tag{9}$$

$$w_i + y_i = Q r_i \qquad \forall i \in F' \tag{10}$$

$$w_i + w'_i + y_i = Q \qquad \forall i \in V \tag{11}$$

$$w_i \le Q r_i \qquad \forall i \in V \tag{12}$$

$$w'_i \le Q(1 - r_i) \qquad \forall i \in V \tag{13}$$

The objective function (1) aims to minimize the total travelled distance. Constraints (2) ensure that each customer node is visited exactly once and ensures that the tour starts from the depot node. Constraints (3) guarantee that each dummy charging station node can be visited at most once if it is used by the electric vehicle for a recharging operation. Constraints (4) maintain the flow continuity for the route plan. Constraint (5) sets the service start time at the depot equal to its earliest time window bound. Constraints (6) ensure that the depot node and each customer node have to be visited within their time windows. Constraints (7) track the service start times at customer, charging station and depot nodes by considering the charging times. Constraints (8)–(13) determine the battery levels of the electric vehicle at each node. Constraint (8) ensures that the electric vehicle starts its tour with a full battery. Constraints (9) determine the arrival battery level and possible charging operation at the predecessor node. Constraints (10)–(13) determine the charging amounts of the electric vehicle at the customer or charging station nodes following a full charging policy. For these constraints, it is assumed that a charging station is set up at each customer location. However, if the charging stations are set up at only some of the customer nodes, constraints (12) can be replaced with constraints (14) by defining a new given parameter s_i which takes the value *1* if a charging station is set up at customer node *i*, *0* otherwise; $\forall i \in V$.

$$w_i \le Q s_i r_i \qquad \forall i \in V \tag{14}$$

4. Proposed algorithm

This section presents the details of the proposed hybrid SA/TS which integrates a TS algorithm within an SA algorithm. Simulated annealing is first introduced by Kirkpatrick, Gelatt, and Vecchi (1983) and is a stochastic search that has been successfully applied to many combinatorial optimization problems owing to its stochastic solution acceptance procedure. Tabu search, which is another efficient heuristic algorithm to solve combinatorial optimization problems, is first introduced by Glover in 1986 and uses a memory mechanism to prevent the search from cycling back to previously visited solutions (Glover, 1989, 1990). Considering the accomplished solution acceptance procedure of the SA and the cycling-avoidance memory mechanism of the TS, several hybrid structures of SA and TS can be found in the literature. Distinct from the existing hybrid structures of SA and TS, the proposed hybrid SA/TS uses two different types of tabu lists to escape local optima and operates a dynamic programming procedure to generate charging operation plans optimally for a given customer-only route. Similar to the 3P-Heu introduced by Roberti and Wen (2016), the proposed hybrid SA/TS optimizes the ETSPTW-MCR in two stages. First, the algorithm searches the solution space considering TSPTW constraints. Then, a dynamic programming procedure, called *station_insertion,* is carried out to obtain a feasible solution for the ETSPTW-MCR. The overall framework of the hybrid SA/TS is presented in Algorithm 1 and explained in more detail in the following sub sections.

Algorithm 1 The main steps of the proposed hybrid SA/TS.

Input Problem
Preprocessing
Initialization
Do
    Local Search for TSPTW
    Evaluation of the TSPTW solution for the ETSPTW-MCR
    Solution acceptance procedure
Loop Until Stopping criterion is met

4.1. Preprocessing

In order to reduce the computational time of the algorithm, a preprocessing step is carried out. First, the arcs resulting in infeasibilities with respect to time windows are eliminated if they satisfy one of the following conditions:

$$e_i + d_{ij} > l_j \qquad \forall i \in V_0, \qquad \forall j \in V_{N+1}$$

$$e_i + d_{ij} + d_{j\,N+1} > l_{N+1} \qquad \forall i \in V_0, \qquad \forall j \in \mathrm{V}$$

After elimination of the infeasible arcs, all feasible paths and their distances between the customer/depot nodes are determined. In addition, for each path, the minimum required battery level from the start point of the path to its successor is determined to be used in the *station_insertion* subroutine, where the electric vehicle arrives at a customer location with less than the minimum required battery level to reach the next location, then this solution is specified as infeasible. Finally, unnecessary paths are removed according to the five dominance rules given by Roberti and Wen (2016).

4.2. Initialization

The hybrid SA/TS operates on two different solutions: $\boldsymbol{X}$ and $\boldsymbol{Y}$, both consist of a permutation order of customer locations and represent the TSPTW and ETSPTW-MCR solutions in the algorithm, respectively. The algorithm operates on the $\boldsymbol{X}$ solution in the first stage of the search procedure and on the $\boldsymbol{Y}$ solution in the ETSPTW-MCR procedure. The best found TSPTW solution $\boldsymbol{X}^*$ and the best found ETSPTW-MCR solution $\boldsymbol{Y}^*$ are stored during the search procedure and updated when a better solution is observed for TSPTW or ETSPTW-MCR, respectively.

The solution $\boldsymbol{X}$ is initialized with a permutation of customer nodes according to an increasing value of l_i. This order is not guaranteed to provide a feasible solution with respect to the allowed time windows. However, comparing with a randomly generated solution, it was found that this initial solution resulted in reaching a time-feasible solution quicker.

Since the hybrid SA/TS requires a time-feasible $\boldsymbol{X}$ and a time and battery-feasible $\boldsymbol{Y}$, two operations are applied during the initialization. In the first operation, a set of local search procedures, specified in the following subsection, are randomly applied to get a time-feasible route plan for the electric vehicle. This operator has a similar structure as the "*maketwfeasible*" operator introduced by Roberti and Wen (2016). For these local searches, the objective function used is the summation of all delays ($\sum_{i \in V'} max\{0, p_i - l_i\}$) at customer and depot locations. Until a time-feasible route is obtained, i.e. the objective function is greater than zero, randomly selected local searches are applied to $\boldsymbol{X}$.

In the second operation, a completely feasible route plan $\boldsymbol{Y}$ for the electric vehicle is determined from $\boldsymbol{X}$. Several local search procedures are randomly applied to $\boldsymbol{X}$ for a specific number of iterations (*init_iter*). However, different from the first operations, only feasible moves with regard to the time window constraints are considered in this phase. After each local search procedure, the *station_insertion* subroutine is applied to $\boldsymbol{X}$ if the solution is not present in the tabu list. After the *station_insertion* subroutine, the initialization procedure is terminated and $\boldsymbol{Y}^*$ is updated if a feasible solution for ETSPTW-MCR is obtained. Otherwise, the algorithm continues with the local search procedure to create new solutions. At the end of the *init_iter*, the algorithm is restarted by perturbing the $\boldsymbol{X}$ if a feasible solution $\boldsymbol{Y}$ is still not obtained. The pseudo code of the initialization procedure is given in Algorithm 2.

Algorithm 2 Initialization steps of the hybrid SA/TS.

$X = \emptyset$, $Y = \emptyset$, $Y^* = \emptyset$
Generate X according to increasing order of customer's l_i
Do While $Y^* = \emptyset$
    Do While X is not feasible with respect to TSPTW
        Generate a new solution X by applying local search
    Loop
    Generate Y by applying *station_insertion*
    If Y is feasible with respect to ETSPTW-MCR **Then**
        $Y^* = Y$
    Else
        For $i = 1$ **to** *init_iter*
            Generate a new TSPTW feasible solution X by applying local search
            Update Y by applying *station_insertion*
            If Y is feasible with respect to ETSPTW-MCR **Then**
                $Y^* = Y$
                Exit For
            End If
        Next
    End If
    If $Y^* = \emptyset$ **Then**
        Apply perturbation
    Else
Loop

4.3. Local search

During the local search procedure, the hybrid SA/TS considers a set of moves consisting of 1-shift, 2-opt, and swapping operations. At each iteration, the algorithm randomly selects a move and applies it to $\boldsymbol{X}$ in order to obtain a new solution $\boldsymbol{X}'$. The details of the moves are presented by Da Silva and Urrutia (2010), Gendreau, Hertz, Laporte, and Stan (1998), Ohlmann and Thomas (2007), and Mladenović, Todosijević, and Urošević (2012). For each local search application, a best improvement strategy is used. As described by Da Silva and Urrutia (2010), the shifting operators are applied by considering backward and forward movements. Fig. 2 represents an illustrative example of the considered three move operations. In detail, Fig. 2b–d show the results of 1-shift, 2-opt, and swap operations when they applied to the route given in Fig. 2a.

In addition to the moves described above, a perturbation operator is used to diversify the solution. The perturbation operator

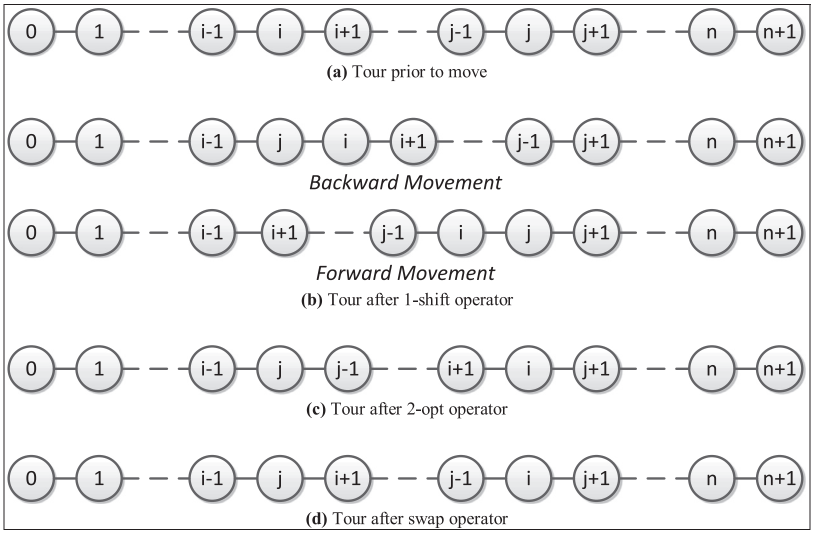

Fig. 2. Illustrative examples for the move operations used in the local search procedure.

removes a number of customer nodes from the route, where the number of customer nodes to be removed is specified with parameter *R*, and inserts them into the route randomly. For the customer insertion, the time windows restrictions are ignored in this step. At the end of the perturbation, as in the initialization step, the local search procedures are iteratively applied to the route until it becomes feasible with respect to the time windows restrictions. The application frequency of the perturbation operator in the algorithm is controlled by the parameter *perturbation*.

4.4. Tabu list structure

Two different tabu lists are used in the hybrid SA/TS, which are independent from each other. The first tabu list is used to escape from local minima during the local search procedure by storing move information of the move operations. This structure not only stores the node information changed in the move, but also keeps the used local search procedure information. After each local search procedure, an accepted move is simply added to the tabu list memory according to the nodes changed and the local search type used in the related move. The stored information in the tabu list is used to prohibit the same nodes for a number of iterations to avoid recreation of a solution feature of the previous solution. Furthermore, the aspiration criterion of TS is taken into account for the first tabu list, which means that a move that is declared tabu will still be accepted if it provides a better solution than the $\boldsymbol{X}^*$. The length of the first tabu list is controlled by the parameter TL_1. If the tabu list length exceeds TL_1, the oldest information in the tabu list is removed. For instance to the first tabu list structure, let the nodes changed in the route at the end of a swap operation be *i* and *j*, respectively. This information is added to the first tabu list as "*sawp*|*i*|*j*". Then, a swap operation of node *i* and node *j* is not allowed during the next TL_1 iterations. Here, it should be noted that, the tabu list does not restrict the inverse move of these nodes, which means that node *j* and node *i* can be swapped to generate new solution.

Distinct from the first tabu list, the second tabu list avoids applying the station insertion procedure to a solution that has been investigated before. Since the station insertion procedure is time consuming for the algorithm, the second tabu list is operated to keep critical information of a route to avoid redundant computations. It was found that using the first and last customer of a route and the arrival times at the first and last customer are sufficient to avoid applying the insertion procedure multiple times to the same solution. When the station insertion procedure is carried out for a newly generated $\boldsymbol{X}$, the specified information is added to the second tabu list. The second tabu list is controlled by the parameter TL_2, and as in the first tabu list, the oldest information is removed when the tabu list length exceeds TL_2.

4.5. Evaluation of the TSPTW solution for the ETSPTW-MCR

After generating a new solution $\boldsymbol{X}'$ at the end of the local search procedure, the *station_insertion* is carried out to obtain $\boldsymbol{Y}$ for the ETSPTW-MCR, if $f(\boldsymbol{X}') < f(\boldsymbol{Y}^*)$ and at least one of the following two criteria is satisfied. Firstly, $\boldsymbol{X}'$ is not tabu with respect to the second tabu list. Secondly, $\boldsymbol{X}'$ has more slack time than $\boldsymbol{Y}^*$, i.e. $slack(\boldsymbol{X}') > slack(\boldsymbol{Y}^*)$. The total slack time of the customers, defined as $slack(\boldsymbol{X}')$, is calculated to determine the potential available charging time of the electric vehicle as follows:

$$slack\left(X'\right) = \sum_{i \in V'_{N+1}} l_i - p_i$$

The *station_insertion* procedure finds the best station insertion for a given route consisting only of customer nodes by using a dynamic programming approach introduced by Roberti and Wen (2016). The dynamic programming approach is also used by Desaulniers et al. (2016), and Schiffer and Walther (2018a,b) effectively to solve EVRP variants. The procedure inserts the predetermined paths between the customer pairs one by one to obtain the best solution for the ETSPTW-MCR. Fig. 3 presents illustrative examples of four different types of paths that can occur between a pair of customer nodes. The first case is a path between two customers without any charging operations and is shown in Fig. 3a. Fig. 3b shows routes including public charging station visits, in which the electric vehicle is recharged at one or more public charging stations. Here, it should be noted for the partial charging policy that only one possible outcome for battery level of the electric vehicle is shown at the successor customer node. However, battery level of the electric vehicle can be variable dependent on the charging time at the station. Therefore, different states for the battery levels are possible for partial charging policy. In case, a private charging station is installed at the successor customer node, the electric vehicle can be recharged at that location as seen in Fig. 3c and d.

Since a full charging policy is taken into account in this study, battery levels and charging times after the first customer location

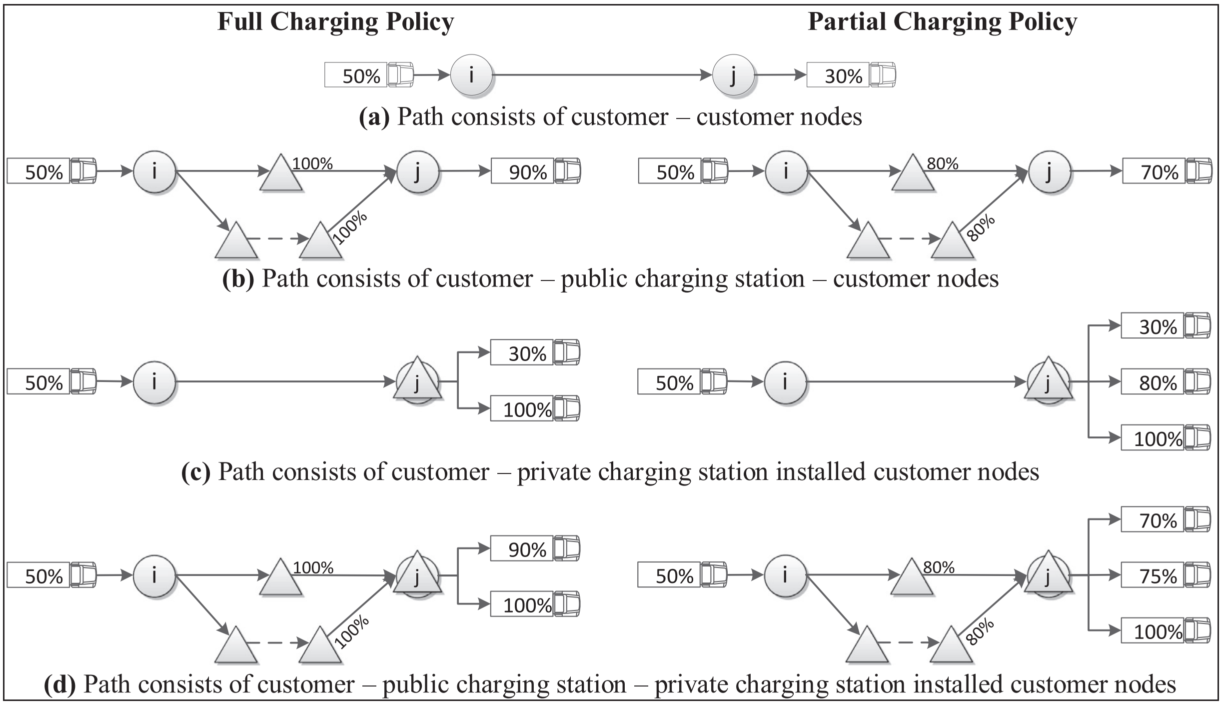

Fig. 3. Illustrative examples for the alternative paths used in the *station_insertion* procedure.

of the paths can be determined in the preprocessing part. For instance, considering a path consisting of three locations (i, k, j), where i and j are customers and k is a public charging station, the battery level of the electric vehicle is always $Q - hd_{kj}$ at location j. In addition, the arrival time at j can be determined by only using the battery level of the electric vehicle at customer location i because the travel times between the locations are fixed. In this way, the dynamic programming labels are calculated in shorter processing times. In addition to the original structure of the dynamic programming approach of Roberti and Wen (2016), the *station_insertion* procedure used in the hybrid SA/TS is improved by adapting the minimum required battery levels for the paths to speed up the computations. With this restriction, a new label can only be considered if the minimum battery level of the label is sufficient to reach the next customer location or a public charging station. The pseudo code of the *station_insertion* procedure is given in Algorithm 3.

4.6. Solution acceptance and cooling procedure

At the end of the main loop of the algorithm, a newly generated $\boldsymbol{X}'$ is accepted or rejected based on the solution acceptance policy of SA. On the other hand, $\boldsymbol{Y}^*$ is updated when the *station_insertion* procedure is carried out for a new generated solution $\boldsymbol{X}'$, where $\boldsymbol{Y}$ is accepted as $\boldsymbol{Y}^*$if and only if $f(\boldsymbol{Y}) < f(\boldsymbol{Y}^*)$. Since the solution quality of $\boldsymbol{Y}$ in the hybrid SA/TS is dependent on $\boldsymbol{X}$, a decrease of $f(\boldsymbol{X})$ can potentially result in a reduction of $f(\boldsymbol{Y})$. However, preliminary tests showed that a good solution for the TSPTW does not always correspond to a good solution for the ETSPTW or ETSPTW-MCR. Therefore, the SA is adjusted with an additional parameter $\omega \in [0, 1]$, which controls whether the search is continued from $\boldsymbol{Y}^*$. In this way, the algorithm can escape from the $\boldsymbol{X}$ related local minimum. The adjusted acceptance procedure works as follows: the algorithm continues with a new solution $\boldsymbol{X}'$, if $f(\boldsymbol{X}') \leq f(\boldsymbol{X})$ or $e^{-\Delta/T} > rnd$, where $\Delta = f(\boldsymbol{X}') - f(\boldsymbol{X})$, T is the temperature, and rnd is a randomly generated number between 0 and 1. Otherwise the algorithm randomly continues with $\boldsymbol{X}$ or $\boldsymbol{Y}^*$ according to the probabilities of ω and $1 - \omega$, respectively. In case $\boldsymbol{Y}^*$ is selected, the route information of the solution is copied to $\boldsymbol{X}$ by ignoring the charging station nodes. The temperature of the hybrid SA/TS is controlled by using a cooling ratio (c) and cooling length (CL), where T is reduced by multiplying with c at the end of each CL iterations. After the cooling procedure, the algorithm continues to search or stops at the end of the maximum iteration number (max_*iter*).

Algorithm 4 presents the pseudo code of the hybrid SA/TS procedure described above, in which integration of the SA, TS, local search, and *station_insertion* procedures are given in more detail.

5. Computational results and discussions

In order to validate the performance of the proposed hybrid SA/TS, extensive computational experiments are performed. The experiments are split into three parts according to problem type: TSPTW, ETSPTW, and ETSPTW-MCR. For the computations, two well-known problem sets for the TSPTW and their extensions are solved by the hybrid SA/TS using an Intel(R) Core(TM) i7-7500 U CPU @ 2.7 GHz with 16 GB RAM. This section initially presents the structure of the considered problem sets and parameter tuning studies for the hybrid SA/TS. Then, the results of the proposed hybrid SA/TS and comparisons with recent existing solution methodologies are given in the following subsections for each problem type. Finally, strengths and limitations of the proposed algorithm, and managerial insights of the results are discussed in the last subsection.

5.1. Benchmark problems

Because the TSPTW has been studied by many researchers, there exist various benchmark problem sets in the literature generated for the TSPTW. However, there exist only two different problem sets for the ETSPTW introduced by Roberti and Wen (2016) which are extensions of the TSPTW problem sets proposed by Gendreau et al. (1998) and Ohlmann and Thomas (2007). Therefore, the computational studies for the TSPTW, ETSPTW and

Algorithm 3 Pseudo code of the station insertion procedure.

```
Input X'
UB = f(Y*) − f(X') //Upper bound for the station insertion cost
RD = f(X') //Remaining distance to be travelled by the electric vehicle
Generate initial label L(0).add({0, Q, 0}) //{time(t), battery level(q), cost(c)}
For i = 1 to N+1
    RD = RD − d_{X'_{i−1}, X'_i}
    For Each label in L(i−1)
        {t, q, c} = L(i−1)(label)
        For Each path between X'_{i−1} and X'_i //Illustrated in Figure (3)
            If c + path distance < UB Then
                If q ≥ minimum required battery level of the path
                    If q ≥ RD Then
                        UB = c + path distance
                    End If
                    Generate the new label {t', q', c'} for node X'_i using the path information
                    If {t', q', c'} is time and battery-feasible Then
                        L(i).add({t', q', c'}) //Added a new label for customer location X'_i
                    End If
                End If
            End If
        Next
    Next
    If L(i).count = 0 Then
        Return −1 //Solution is battery-infeasible
    End If
    Remove the redundant labels in L(i) by applying dominance rule //Described by Roberti and Wen (2016)
Next
Find the best label in L(N+1) and generate Y by going backward
Return Y and f(Y)
```

ETSPTW-MCR are carried out based on these problems in order to make fair comparisons between the algorithms.

For the first part of the computational studies, we used the original TSPTW problem sets proposed by Gendreau et al. (1998) and Ohlmann and Thomas (2007), which we will refer to as the *G* and *OT* sets, respectively. The *G* problem set consists of 140 instances grouped into 28 cases where the number of customer nodes varies between 20 and 100. The *OT* problem set contains 25 instances grouped into 5 cases with a larger number of customer nodes: 150 and 200 customer nodes.

The second part of the computational studies are carried out by using the ETSPTW problems introduced by Roberti and Wen (2016) derived from the *G* and *OT* problems. In order to create small sized problems, the authors used the *G* dataset instances with 20 customers consisting of 25 instances. Large sized problems are generated by using all the *OT* problems. Each TSPTW instance is adapted to ETSPTW by adding a number of charging station (either 5 or 10) locations. One of them is at the depot node location, and the other charging station locations are identified in a systematic way to obtain a feasible solution for the problem. For the charging operations, the energy consumption rate and the charging rate are fixed to 1 and 0.25, respectively. Or put otherwise, the energy consumption rate is chosen such that the required charge for travelling a given arc is equal to the distance of the arc for each instance. Similarly, the recharging time of one unit of battery level is always equal to 0.25 time units at the public charging stations. The vehicle's battery capacity is specified with respect to the best known solution of the corresponding TSPTW instance. Finally, time windows of the customer locations are modified for some of the instances in order to guarantee a feasible solution. In total, 100 test instances are proposed for the ETSPTW where the instances are grouped as follows:

- 25 small sized instances with 5 charging stations generated by using the *G* dataset (called *G-E5*)
- 25 small sized instances with 10 charging stations generated by using the *G* dataset (called *G-E10*)
- 25 large sized instances with 5 charging stations generated by using the *OT* dataset (called *OT-E5*)
- 25 large sized instances with 10 charging stations generated by using the *OT* dataset (called *OT-E10*)

For the ETSPTW-MCR computations, the ETSPTW problems are simply adapted by randomly selecting customer locations to be designated as containing a private charging station. For the private charging stations, three cases are considered to extend the ETSPTW problems: 30%, 70% and 100% of the customers have their own private charging stations. This percentage is referred to as the private charging station ratio. Since the customers are randomly located in the *G* and *OT* datasets, private charging stations are simply chosen by selecting the first 30%, 70% and 100% customer locations. For these stations, a slow or normal charging technology is assumed. Therefore, the charging rate is fixed to 1.5.

The new problem sets for the ETSPTW-MCR are identified by using the *MCR(ρ)* term where ρ is the private charging station construction ratio. According to the ρ value, the number of private charging stations for the ETSPTW-MCR problem set are identified as follows: In small sized instances, first 6, 14, and 20 customers contain a private charging station with respect to the charging station ratio. For instance, *G-E5-MCR(30%)* problems are formed by using the *G-E5* problem set where the first 6 customers have a private charging station for each instance. In the same manner, the number of private charging stations in the large sized instances, in which the problems consist of 150 customer locations, are 45, 100, and 150. Finally, the number of private charging stations for the remaining instances with 200 customer locations are 60, 140, and 200. Fig. 4 presents an illustrative graph representation for the first instance of *OT-E5-MCR(30%)* dataset, in which the depot node with a public charging station, public charging stations, customer locations and private charging station at customer locations are shown. The ETSPTW and ETSPTW-MCR problem sets, and details of the computational results presented in Küçükoğlu, Dewil, and Cattrysse (2017).

Algorithm 4 Pseudo code of the hybrid SA/TS.

```
Input Problem
Preprocessing
Set the parameters of the algorithm
Generate initial solution X and Y // Algorithm 2
For iteration = 1 to Max_iter
    Randomly select a move operator and generate X′ through X regarding the first tabu list
    Add move information to first tabu list and update the list if the tabu list length exceeds TL1
    If f(X′) < f(Y) Then
      If slack(X′) > slack(Y*) or X′ is not tabu with respect to the second tabu list Then
          Generate Y through X′ by applying the station_insertion procedure
          If f(Y) < f(Y*) Then
             Y* = Y
             pcounter = 0
          End If
          Add X′ information to second tabu list and update the list if the tabu list length exceeds TL2
      End If
    End If
    Δ = f(X′) − f(X)
    If Δ < 0 or e^(−Δ/T) > rnd(0, 1) Then
      X = X′
    Else
      If rnd(0, 1) > ω Then
         X = Y*
      End If
    End If
    pcounter = pcounter + 1
    If pcounter = perturbation Then
      Apply perturbation
      Do While X is not feasible with respect to TSPTW
         Generate a new solution X by applying local search
      Loop
    End If
    If iteration mod CL = 0 Then
      T = T × c
    End If
Next
Output Y*
```

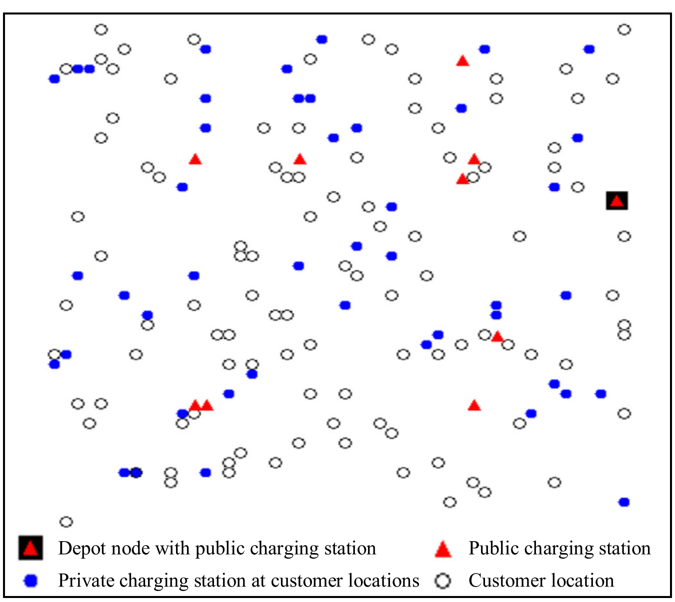

Fig. 4. An illustrative graph representation for the *OT-E5-MCR(30%)* dataset.

5.2. Parameter tuning

Most of the heuristic algorithms work with a set of parameters and the performance of the algorithms are strongly related with their parameter values. In order to find suitable parameters, different approaches are introduced in the literature, such as, hand-made tuning, tuning by analogy, experimental design based tuning, search based tuning, and hybrid tuning (Montero, Riff, & Neveu, 2014). Among them, experimental design based tuning methods, or search based tuning methods are found to be more successful to obtain good parameters. This is especially the case for the algorithms having a large number of parameters. However, these tuning methods can be time consuming when a large number of problems or complex algorithms are taken into account for the experiments (Adenso-Diaz & Laguna, 2006; Coy, Golden, Runger, & Wasil, 2001; Hutter, Hoos, & Stützle, 2007). Therefore, a straightforward tuning method inspired from the study proposed by Keskin and Çatay (2016) is used in the hybrid SA/TS. By selecting five different problems from the *OT-E5* dataset and setting the max_*iter* number to 15000 and $T_0 = 10000$, the parameter values of the hybrid SA/TS are determined as follows: $c = 0.95$, $CL = 100$, $TL_1 = 400$, $TL_2 = 75$, $perturbation = 500$, $R = 30$, $\omega = 0.7$, and $init\_iter = 100$. Details of the parameter tuning study and results are given in Appendix A.

5.3. Computational results for the TSPTW

The first part of the computational studies is carried out to identify the performance of the proposed hybrid SA/TS for the TSPTW. For these computations, the proposed algorithm is adapted to TSPTW by ignoring the *station_insertion* procedure for ETSPTW. Tables 2 and 3 show the results of the experiments for *G* and *OT* data sets, respectively, and compare the hybrid SA/TS solution with three metaheuristic approaches proposed for the TSPTW: a compressed annealing (CA) algorithm introduced by Ohlmann and Thomas (2007), a GVNS algorithm introduced by Da Silva and Urrutia (2010), and a variable iterated greedy VNS algorithm (VIG_VNS) introduced by Karabulut and Tesgetiren (2014). In addition to CA, GVNS, and VIG-VNS, Table 3 compares the hybrid SA/TS

Table 2
Computational results for the *G* dataset.

Problem Group	CA				GVNS				VIG_VNS				SA/TS			
	f_B	f_A	σ	$t(s)$	f_B	f_A	σ	$t(s)$	f_B	f_A	σ	$t(s)$	f_B	f_A	σ	$t(s)$
n20w120	265.6	265.6	0.0	3.1	265.6	265.6	0.0	0.3	265.6	265.6	0.0	0.0	265.6	265.6	0.0	0.2
n20w140	232.8	232.8	0.0	3.9	232.8	232.8	0.0	0.3	232.8	232.8	0.0	0.0	232.8	232.8	0.0	0.2
n20w160	218.2	218.2	0.0	4.0	218.2	218.2	0.0	0.3	218.2	218.2	0.0	0.0	218.2	218.2	0.0	0.2
n20w180	236.6	236.6	0.0	4.0	236.6	236.6	0.0	0.4	236.6	236.6	0.0	0.0	236.6	236.6	0.0	0.3
n20w200	241.0	241.0	0.0	4.1	241.0	241.0	0.0	0.4	241.0	241.0	0.0	0.0	241.0	241.0	0.0	0.3
n40w120	377.8	378.1	1.1	6.0	377.8	377.8	0.0	0.8	377.8	377.8	0.0	0.0	377.8	377.8	0.0	0.5
n40w140	364.4	364.7	1.6	6.0	364.4	364.4	0.0	0.8	364.4	364.4	0.0	0.0	364.4	364.4	0.0	0.5
n40w160	326.8	327.1	0.6	6.0	326.8	326.8	0.0	0.9	326.8	326.8	0.0	0.0	326.8	326.8	0.0	0.6
n40w180	332.0	333.9	2.3	6.2	330.4	331.3	0.8	1.0	330.4	330.4	0.0	0.0	330.4	330.5	0.2	0.7
n40w200	313.8	315.0	1.0	6.3	313.8	314.3	0.4	1.0	313.8	313.8	0.0	0.0	313.8	314.0	0.3	0.7
n60w120	451.0	452.9	2.8	8.3	451.0	451.0	0.1	1.5	451.0	451.0	0.0	0.1	451.0	451.0	0.0	1.6
n60w140	452.4	454.0	2.1	8.6	452.0	452.1	0.2	1.7	452.0	452.0	0.0	0.3	452.0	452.2	0.1	2.4
n60w160	464.6	465.4	2.3	8.4	464.0	464.5	0.2	1.7	464.0	464.0	0.0	0.6	464.0	464.4	0.3	1.8
n60w180	421.6	425.2	4.4	8.6	421.2	421.2	0.1	2.2	421.2	421.2	0.0	0.1	421.2	421.2	0.1	2.3
n60w200	427.4	430.8	5.0	8.4	427.4	427.4	0.0	2.4	427.4	427.4	0.0	0.0	427.4	427.4	0.0	2.5
n80w100	579.2	581.6	2.4	11.5	578.6	578.7	0.2	2.3	578.6	578.6	0.0	0.8	578.6	578.7	0.2	2.4
n80w120	541.4	544.0	2.1	11.5	541.4	541.4	0.0	2.7	541.4	541.4	0.0	2.8	541.4	541.6	0.2	2.5
n80w140	509.8	513.6	4.7	11.3	506.0	506.3	0.2	3.2	506.0	506.0	0.1	2.5	506.0	506.3	0.4	2.7
n80w160	505.4	511.7	5.2	11.2	504.8	505.5	0.7	3.3	504.8	504.8	0.0	0.5	504.8	505.0	0.3	3.1
n80w180	502.0	505.9	4.0	11.4	500.6	501.2	0.9	3.7	500.6	500.6	0.0	3.7	500.6	500.9	0.4	3.0
n80w200	481.4	486.4	4.0	11.1	481.4	481.8	0.1	4.2	481.4	481.7	0.2	3.2	481.4	481.8	0.3	3.1
n100w80	666.4	668.1	2.6	15.9	666.4	666.6	0.2	3.1	666.4	666.4	0.0	0.2	666.4	666.4	0.1	3.1
n100w100	642.2	645.0	2.6	14.6	642.0	642.1	0.1	3.7	640.6	640.6	0.1	1.7	640.6	640.8	0.3	3.8
n100w120	601.2	603.7	2.1	15.0	597.2	597.5	0.3	4.1	597.2	597.2	0.1	8.1	597.2	597.5	0.4	3.7
n100w140	579.2	582.5	3.2	14.9	548.4	548.4	0.0	4.4	548.4	548.4	0.0	1.9	548.4	548.4	0.1	4.0
n100w160	584.0	588.8	3.8	15.0	555.0	555.0	0.1	5.1	555.0	555.2	0.1	1.3	555.0	555.1	0.2	4.7
n100w180	561.6	566.9	4.6	14.9	561.6	561.6	0.0	6.3	561.6	561.7	0.1	2.3	561.6	561.6	0.1	5.3
n100w200	555.4	562.3	5.8	14.9	550.2	551.0	1.2	6.8	550.2	550.2	0.0	5.6	**550.0**	**550.0**	0.0	6.0
Average	444.1	446.5	2.5	9.5	441.3	441.5	0.2	2.5	441.3	441.3	0.0	1.3	441.3	441.4	0.1	2.2

Table 3
Computational results for the *OT* dataset.

Problem Group	CA				GVNS				VIG_VNS				3P-Heu				SA/TS			
	f_B	f_A	σ	$t(s)$	f_B	f_A	σ	$t(s)$	f_B	f_A	σ	$t(s)$	f_B	f_A	σ	$t(s)$	f_B	f_A	σ	$t(s)$
n150w120	725.0	731.1	5.5	24.8	722.0	722.3	0.4	11.8	722.0	722.5	0.8	29.3	722.0	722.2	0.4	10.5	722.2*	722.3	0.4	8.4
n150w140	697.6	705.4	6.7	24.9	693.8	694.8	0.5	13.3	693.8	694.6	1.0	27.2	693.8	694.6	0.7	12.3	693.8	694.7	0.5	10.1
n150w160	673.6	680.9	5.9	25.0	671.0	671.2	0.3	15.0	671.0	672.0	1.5	22.9	671.0	671.6	0.7	13.1	671.0	**671.1**	0.2	12.9
n200w120	806.8	817.0	7.0	34.4	803.6	803.9	0.1	30.3	803.6	804.8	1.8	48.6	803.6	804.2	0.4	25.8	803.6	**803.8**	0.3	15.7
n200w140	804.6	812.6	6.7	35.2	798.0	799.5	1.1	38.0	798.0	802.0	4.6	48.8	798.2	798.9	1.0	30.0	798.0	**798.6**	0.7	21.8
Average	741.5	749.4	6.4	28.9	737.7	738.3	0.5	21.7	737.7	739.2	1.9	35.4	737.7	738.3	0.6	18.3	737.7	738.1	0.4	13.8

* 722.0 is observed during the preliminary experiments.

with 3P-Heu proposed by Roberti and Wen (2016). The columns f_B, f_A, σ, and $t(s)$ for each heuristic algorithm present the best result of 10 runs, the average result of the 10 runs, the standard deviation of the runs, and the average computational time of the runs in seconds, respectively. New best results obtained by the hybrid SA/TS are pointed out with the bold characters in the tables.

Table 2 shows that for the *G* dataset, one new best solution is found by the hybrid SA/TS. For the other problems, the hybrid SA/TS yielded the same results as the GVNS and VIG_VNS approaches which are also better than the CA results. Moreover, the hybrid SA/TS provides better average results with smaller standard deviations with respect to the CA and GVNS. On the other hand, a better average result is found by VIG_VNS with a 0.1 difference with respect to the hybrid SA/TS. When the average results of the experiments for the *G* dataset are analyzed, it should be emphasized that the hybrid SA/TS outperforms the CA and GVNS and finds better results with smaller CPU times. Similar results are also observed for the *OT* dataset which are presented in Table 3. For these computations, the hybrid SA/TS provided better average results for three problem groups. According to the average results of the heuristic methods, a better performance is provided by the hybrid SA/TS. In addition to the CA and GVNS, the hybrid SA/TS additionally outperforms the VIG_VNS by finding better results with smaller CPU times for the *OT* dataset. As a result of the TSPTW experiments, it should be noted that the proposed hybrid SA/TS is capable of consistently finding high-quality results compared to the CA, GVNS, VIG_VNS, and 3P-Heu algorithms.

5.4. Computational results for the ETSPTW

Following the TSPTW computations, the hybrid SA/TS is carried out for the ETSPTW problems by considering both full and partial charging policies. To implement the partial charging policy in the hybrid SA/TS, the *station_insertion* procedure is extended by allowing additional labels with partial battery level for the charging operations as described by Roberti and Wen (2016). In Appendix B, Tables B.1–B.4 introduce the computational results of the hybrid SA/TS and comparisons with 3P-Heu for the *G-E5, G-E10, OT-E5*, and *OT-E10* datasets, respectively. In order to specify the solution quality of the proposed algorithm, the percentage gaps between the hybrid SA/TS and 3P-Heu solutions are given in the tables by considering the best and average results as follows.

$$3P\%_B = \frac{f_B(\text{Hybrid SA/TS}) - f_B(\text{3P} - \text{Heu})}{f_B(\text{3P} - \text{Heu})} \times 100\%$$

Table 4
Summary of the Hybrid SA/TS results for small and large sized ETSPTW problems.

Problem Set	Charging Policy	3P-Heu					SA/TS						
		f_B	ns_P	f_A	σ	$t(s)$	f_B	$3P\%_B$	ns_P	f_A	$3P\%_A$	σ	$t(s)$
G-E5	Full Charging	247.6	3.5	247.6	0.0	0.08	247.5	−0.03	3.4	247.5	−0.03	0.0	0.45
G-E10		243.4	3.6	243.4	0.0	0.08	243.4	0.00	3.4	243.4	0.00	0.0	0.30
OT-E5		750.6	7.3	752.5	1.2	70.67	749.1	−0.22	7.1	751.6	−0.12	1.6	71.69
OT-E10		743.8	7.9	744.8	0.7	55.37	742.7	−0.15	7.5	744.6	−0.02	1.3	64.52
G-E5	Partial Charging	246.4	3.8	246.4	0.0	0.08	246.3	−0.03	3.5	246.3	−0.03	0.0	0.34
G-E10		243.1	4.1	243.1	0.0	0.08	243.1	0.00	3.5	243.1	0.00	0.0	0.29
OT-E5		747.4	7.9	748.8	0.9	72.31	745.8	−0.23	7.3	747.4	−0.20	1.1	73.44
OT-E10		740.6	9.0	741.4	0.6	55.43	739.4	−0.17	7.8	740.4	−0.15	0.7	59.99

$$3P\%_A = \frac{f_A(\text{Hybrid SA/TS}) - f_A(\text{3P} - \text{Heu})}{f_A(\text{3P} - \text{Heu})} \times 100\%$$

In addition to the percentage gaps, the columns specified with ns_P represent the number of public charging stations visits for the solutions. Table 4 summarizes the results obtained by the hybrid SA/TS and comparisons based on the average solutions.

For the small sized instances, our algorithm found the optimal solutions as found by Roberti and Wen (2016). Moreover, when the hybrid SA/TS is compared with the 3P-Heu, the proposed hybrid algorithm obtained better results for two *G-E5* instances. Regarding the number of charging station visits, it should be noted that different values for ns_P are observed for some of the instances because of alternative optimal solutions.

Considering the large sized instances, the performance of the hybrid SA/TS is more evident with respect to the 3P-Heu. Comparing the best results of the algorithms, 26 new best results are obtained by the hybrid SA/TS. For the remaining problems, the results of the hybrid SA/TS are the same as the 3P-Heu results except for two instances. Regarding the best results, the hybrid SA/TS provides a 0.22% and 0.15% improvement on average for the *OT-E5*, and *OT-E10* problems, respectively. Similarly, the average results of the hybrid SA/TS are better than the 3P-Heu.

With respect to the computational effort, the average required CPU time of the hybrid SA/TS is slightly more than the 3P-Heu due to the station insertion procedure calls in the algorithms, where the 3P-Heu calls the dynamic programming procedure almost 500 times (maximum iteration number) while this value is mostly more than a thousand times for our algorithm even for small sized problems. Nevertheless, an increase of a few seconds on the computational time can be reasonable for the hybrid SA/TS in order to obtain better results.

5.5. Computational results for the ETSPTW-MCR

The final part of the computational studies is carried out for the small and large sized ETSPTW-MCR problems. For the small sized instances, the results of the hybrid SA/TS are compared with the GUROBI 7.0.1 solutions obtained with a two hour time limitation. In addition to the comparisons between the hybrid SA/TS and GUROBI solver, the ETSPTW-MCR and ETSPTW results are analyzed for both small and large sized instances. Tables 5 and 6 present the GUROBI solver solutions for the small sized instances. The columns labelled *MIP, LB, Gap%*, and $t(s)$ in the tables indicate the mixed integer programming result, lower bound of the solution, optimality gap of the solution, and solution time of the GUROBI, respectively.

In addition to the GUROBI results, Table 7 summarizes the average results obtained by hybrid SA/TS for both the small and large sized ETSPTW-MCR instances, where the details of the results are presented in Appendix C. The column labelled with ns_C in Table 7 denotes the number of private charging station visits at customer locations as distinct from the public charging station visits. Moreover, Table 7 presents two different comparisons for the hybrid SA/TS solutions with the columns labelled *Gap%* and *ETW%*. *Gap%* specifies the optimality gap between the best solution of the hybrid SA/TS and *LB* of the GUROBI for the small sized ETSPTW-MCR instances. On the other hand, *ETW%* indicates the percentage gap between the best solution of the hybrid SA/TS for the ETSPTW-MCR and best found solution of ETSPTW as follows.

$$ETW\% = \frac{f_B(\text{ETSPTW} - \text{MCR}) - f_B(\text{ETSPTW})}{f_B(\text{ETSPTW})} \times 100\%$$

The results of the computations for small sized ETSPTW-MCR instances show that the hybrid SA/TS found the optimal solutions for the instances whose optimality are proven by the GUROBI. For the remaining problems, the same results with the *MIP* of GUROBI or better results are found by the hybrid SA/TS. Comparing the ETSPTW-MCR results with ETSPTW results, a considerable reduction on travelled distance is observed for most of the instances, where the average savings are more than 1.50% for the *G-E5-MCR(30–100%)* and 0.60% for the *G-E10-MCR(30–100%)* problem sets. Moreover, it can be concluded from the table that charging at customer locations leads to less charging operations at public charging stations.

For the large sized ETSPTW-MCR problems, the results show that significant distance savings are found for most of the instances with up to 3.04% by charging the electric vehicle at private charging stations. When the average *ETW%* are analyzed with respect to private charging station construction ratio, higher decreases are observed for the *OT-E5-MCR(100%)* and *OT-E10-MCR(100%)* problems. As a result of the computations, it should be concluded that the charging at private charging stations can potentially reduce the charging operations at public charging stations, even though the recharging times at private charging stations are longer. Therefore, considerable distance savings can be provided for the ETPSTW by constructing private charging stations at customer locations.

5.6. Discussions

In this sub section, the performance of the proposed solution methodology, its strengths, and weaknesses, and managerial insights of the results are discussed.

5.6.1. Performance of the proposed algorithm

The computational results presented in previous subsections show the efficiency and the robustness of the proposed solution methodology. For both the ETSPTW and ETSPTW-MCR, exact solvers are capable of finding the optimal solution for only small sized problems, insomuch that an optimal solution cannot be found for some of the cases in a specified time limit even though the small sized instances considered in this study consist of only 20 customer nodes. Therefore, an efficient metaheuristic algorithm is more practicable for the real-life applications to find a solution in a reasonable time. With this in mind, the hybrid SA/TS algorithm shows superior performance and outperforms competitor algorithms with regard to solution quality. Another interesting observation of the results is the stability of the hybrid SA/TS solutions.

Table 5
GUROBI results for the *G-E5-MCR(30%)*, *G-E5-MCR(70%)*, and *G-E5-MCR(100%)* problems.

Instance	MCR(30%)				MCR(70%)				MCR(100%)			
	MIP	*LB*	*Gap%*	*t(s)*	*MIP*	*LB*	*Gap%*	*t(s)*	*MIP*	*LB*	*Gap%*	*t(s)*
n20w120s5.1	271	271	0.00	767	271	271	0.00	3622	271	271	0.00	742
n20w120s5.2	249	220	11.65	7200	229	229	0.00	4965	229	220	3.93	7200
n20w120s5.3	317	317	0.00	1757	317	317	0.00	5714	312	303	2.88	7200
n20w120s5.4	314	314	0.00	2236	318	310	2.52	7200	311	298	4.18	7200
n20w120s5.5	249	249	0.00	15	243	243	0.00	14	243	243	0.00	131
n20w140s5.1	181	181	0.00	1316	181	181	0.00	611	178	178	0.00	155
n20w140s5.2	286	253	11.54	7200	283	262	7.42	7200	283	248	12.37	7200
n20w140s5.3	237	237	0.00	370	237	237	0.00	589	237	237	0.00	1333
n20w140s5.4	265	265	0.00	5096	265	255	3.77	7200	265	239	9.81	7200
n20w140s5.5	226	226	0.00	118	226	226	0.00	318	226	226	0.00	2339
n20w160s5.1	244	244	0.00	765	244	244	0.00	885	243	243	0.00	581
n20w160s5.2	208	208	0.00	59	208	208	0.00	170	208	208	0.00	164
n20w160s5.3	210	210	0.00	376	210	210	0.00	28	210	210	0.00	46
n20w160s5.4	204	204	0.00	683	204	204	0.00	310	204	204	0.00	854
n20w160s5.5	249	249	0.00	2569	249	249	0.00	1853	249	247	0.80	7200
n20w180s5.1	256	256	0.00	301	253	253	0.00	184	253	253	0.00	1273
n20w180s5.2	273	273	0.00	252	273	273	0.00	245	267	267	0.00	367
n20w180s5.3	276	276	0.00	4264	274	274	0.00	2065	274	256	6.57	7200
n20w180s5.4	205	205	0.00	181	205	205	0.00	544	205	205	0.00	5863
n20w180s5.5	198	198	0.00	2039	198	184	7.07	7200	196	187	4.59	7200
n20w200s5.1	234	234	0.00	1248	234	234	0.00	271	234	234	0.00	485
n20w200s5.2	210	210	0.00	169	210	210	0.00	183	210	210	0.00	1038
n20w200s5.3	250	250	0.00	1166	250	250	0.00	1529	250	250	0.00	251
n20w200s5.4	296	287	3.04	7200	296	282	4.73	7200	295	281	4.75	7200
n20w200s5.5	236	236	0.00	725	235	235	0.00	251	232	232	0.00	270
Average	245.8	242.9	1.05	1922.9	244.5	241.8	1.02	2414.0	243.4	238.0	2.00	3227.7

Table 6
GUROBI results for the *G-E10-MCR(30%), G-E10-MCR(70%)*, and *G-E10-MCR(100%)* problems.

Instance	MCR(30%)				MCR(70%)				MCR(100%)			
	MIP	*LB*	*Gap%*	*t(s)*	*MIP*	*LB*	*Gap%*	*t(s)*	*MIP*	*LB*	*Gap%*	*t(s)*
n20w120s10.1	270	270	0.00	1051	270	270	0.00	744	270	270	0.00	607
n20w120s10.2	222	207	6.76	7200	222	222	0.00	6798	222	210	5.41	7200
n20w120s10.3	312	312	0.00	7056	312	299	4.17	7200	334	302	9.58	7200
n20w120s10.4	308	308	0.00	1791	307	307	0.00	777	308	304	1.30	7200
n20w120s10.5	243	243	0.00	43	242	242	0.00	36	242	242	0.00	42
n20w140s10.1	179	179	0.00	673	179	179	0.00	4768	178	178	0.00	283
n20w140s10.2	284	247	13.03	7200	283	243	14.13	7200	283	242	14.49	7200
n20w140s10.3	236	236	0.00	748	236	236	0.00	5926	236	236	0.00	1856
n20w140s10.4	260	240	7.69	7200	284	231	18.66	7200	277	220	20.58	7200
n20w140s10.5	225	188	16.44	7200	225	225	0.00	4058	225	225	0.00	1962
n20w160s10.1	244	244	0.00	2342	244	244	0.00	2041	245	240	2.04	7200
n20w160s10.2	204	204	0.00	372	204	204	0.00	545	204	204	0.00	309
n20w160s10.3	210	210	0.00	336	210	210	0.00	847	210	210	0.00	980
n20w160s10.4	204	204	0.00	677	204	183	10.29	7200	204	204	0.00	537
n20w160s10.5	247	247	0.00	2764	247	247	0.00	4058	247	234	5.26	7200
n20w180s10.1	254	254	0.00	6513	253	253	0.00	722	253	253	0.00	2133
n20w180s10.2	272	272	0.00	3719	272	272	0.00	637	266	266	0.00	2066
n20w180s10.3	276	262	5.07	7200	272	254	6.62	7200	274	257	6.20	7200
n20w180s10.4	205	198	3.41	7200	205	205	0.00	1359	205	205	0.00	3480
n20w180s10.5	197	197	0.00	5736	197	180	8.63	7200	196	174	11.22	7200
n20w200s10.1	234	223	4.70	7200	235	219	6.81	7200	234	234	0.00	2861
n20w200s10.2	207	207	0.00	257	207	207	0.00	1388	204	204	0.00	661
n20w200s10.3	249	249	0.00	2682	249	243	2.41	7200	249	249	0.00	6683
n20w200s10.4	295	247	16.27	7200	295	224	24.07	7200	295	243	17.63	7200
n20w200s10.5	228	228	0.00	4768	228	228	0.00	968	228	228	0.00	2334
Average	242.6	235.0	2.94	3677.3	243.3	233.1	3.83	4018.9	243.6	233.4	3.75	3951.8

It can be clearly seen from the experiments that the standard deviations of most of the results are zero or close to zero. Comparing with the other considered algorithms, a better solution is observed for most of the cases. Therefore, the proposed algorithms can be efficiently applied for the route planning of electric vehicles in real-life logistics activities.

Another critical issue on the algorithm performance is parameter tuning. Similar to most of the metaheuristic algorithms, the tuned parameter set directly affects the performance of the algorithm. Hence, a parameter tuning study is made in order to find the best parameter values for the hybrid SA/TS. In addition to the principal parameters of the SA and TS, other parameters used in the algorithm have the potential to improve the solution quality. In preliminary experiments, it is observed that most of the parameter values of the hybrid SA/TS depend on the problem and its size. Therefore, it is possible to obtain better results for the TSPTW, ETSPTW, and ETSPTW-MCR problems in case a problem-based parameter tuning approach is considered.

Finally, comparing with the competitor algorithms considered in the study, the hybrid SA/TS could reach the solutions in similar

Table 7
Summary of the Hybrid SA/TS results for small and large sized ETSPTW-MCR problems.

Problem Set	f_B	ns_P	ns_C	Gap%	ETW%	f_A	σ	$t(s)$
G-E5-MCR(30%)	244.8	2.7	1.0	0.70	−1.14	244.8	0.0	0.24
G-E5-MCR(70%)	244.0	2.6	1.5	0.90	−1.44	244.0	0.0	0.27
G-E5-MCR(100%)	243.2	2.4	1.6	1.95	−1.76	243.2	0.0	0.25
G-E10-MCR(30%)	242.1	2.9	0.8	2.77	−0.60	242.1	0.0	0.25
G-E10-MCR(70%)	241.9	2.9	1.4	3.40	−0.66	241.9	0.0	0.29
G-E10-MCR(100%)	241.4	2.6	1.6	3.09	−0.88	241.4	0.0	0.30
OT-E5-MCR(30%)	743.3	6.4	3.0	–	−0.76	745.5	2.1	85.81
OT-E5-MCR(70%)	742.6	6.2	3.6	–	−0.85	744.2	1.6	167.57
OT-E5-MCR(100%)	741.6	6.2	3.9	–	−0.99	743.3	1.3	230.55
OT-E10-MCR(30%)	739.0	7.0	3.1	–	−0.51	740.3	1.1	76.80
OT-E10-MCR(70%)	737.8	6.5	3.9	–	−0.67	739.2	1.0	149.62
OT-E10-MCR(100%)	737.0	6.4	4.5	–	−0.78	738.2	0.9	209.41

CPU times in general. However, it is difficult to make a fair comparison between the algorithms since the computations are performed on different technological environments.

5.6.2. Strengths and limitation of the proposed algorithm

We can identify the following strengths of the proposed solution approach compared to existing approaches in the literature:

i. The hybrid SA/TS integrates the stochastic solution acceptance procedure of SA and tabu list structure of TS. Both structures increase the diversification capability of the search with regards to SA and TS.
ii. The modified solution acceptance procedure allows to continue the search from the best found ETSPTW-MCR result. As such, the algorithm can escape from the local minimum caused by the local search procedure of the algorithm that only considers time windows constraints during the neighborhood generation.
iii. The hybrid SA/TS operates two different tabu lists. The first tabu list stores move information of the local search procedure as in the traditional TS. The second tabu list is used to avoid applying the *station_insertion* procedure to a solution that has been investigated before. The modified tabu list structure significantly reduces the duplicate computations during the search.
iv. Although, the improved dynamic programming procedure works in the same logic as in the 3P-Heu, reduced computational times are achieved thanks to the additional procedures.
v. An advanced local search mechanism integrated with perturbation operator is applied in the algorithm.

In contrast, the following possible weaknesses should be considered:

i. During the search, the *station_insertion* is carried out for only promising $\boldsymbol{X}$ solutions since the dynamic programming procedure is too time consuming. However, a better $\boldsymbol{X}$ solution does not always guarantee a better time and battery-feasible solution. Because of all time-feasible solutions are not investigated, the proposed approach may fail to notice a new better time and battery-feasible route.
ii. Compared to the heuristic based station insertion procedures used in the existing solution approaches, the *station_insertion* increases the processing time of the algorithm.
iii. Since the hybrid SA/TS is a single solution based approach, a solution generated in each iteration does not interact with any other solution as in the population based approaches.
iv. The proposed algorithm works with a lot of parameters, which have to be well tuned to increase algorithm efficiency.

5.6.3. Managerial insights

Comparing with the ETSPTW results, the ETSPTW-MCR provides a reduction in total travel distance since fewer public charging station visits are required when private charging stations are available at customer locations. Up to 5.02% distance savings are obtained in the experiments when private charging stations are used. The average number of public charging station visits is reduced from about 3.4 to 2.4 for small sized instances and from about 7.5 to 6.2 for large sized instances. The effects of private charging stations is more evident when the ETSPTW and ETSPTW-MCR results are compared to the TSPTW results. For the small sized instances, public charging station usage in ETSPTW increases the average TSPTW result from 238.8 to 247.8 and 243.4 for *G-E5* and *G-E10* problems, respectively. With the private charging stations, these values are reduced to 243.2 and 241.4, which show that the increases on the travel distance caused by the public charging station visits are reduced up to 49.4%. Similar reductions are observed for the large sized problems. As a result, construction of a private charging station at a customer location potentially provides time and distance reductions for the delivery operations since the electric vehicle can be recharged while waiting at the customer location. It should be noted that, a visit to a customer location for just recharging the battery is not allowed in this study since each customer location can be visited only once. In case more than one visit to customer location is allowed, more reduction can be achieved. Considering these savings, logistics companies can evaluate the tradeoff between the investment cost of private charging stations and the additional operational cost when only public charging stations are used. In practice, the Level 1 charging stations are cost-free because electric vehicles come with a basic charger which can plug into a standard outlets. On the other hand, the cost of Level 2 charging stations are available with ∼$1000 in the present market. Furthermore, charging the battery is more expensive from a public charging stations, such as recharging cost of an electric vehicle at home or office is about 2–3€ in most of EU countries while this cost is 10–12€ for public charging stations. Considering that Level 1 and 2 charging technologies are more suitable for a private charging station, an investment on this field may pay for itself in a short time.

Another important outcome of the results is the impact of number of private charging stations. When the three different levels of *MCR(ρ)* are compared, smaller total travel distances and fewer public charging station visits are observed on average when all customer locations include private charging stations. The distance savings according to the ETSPTW increase from 1.14% to 1.76% and from 0.60% to 0.88% for the *G-E5-MCR(ρ)* and *G-E10-MCR(ρ)* instances, respectively. A similar effect is observed for the large sized instances. However, for some of the instances, the same results are observed in each level of *MCR(ρ)* which show that a small number of private charging stations may be sufficient in some cases. Therefore, the number of private charging stations that will be established at customer locations has to be well evaluated by the decision-makers since it is considered as a strategic decision.

In addition to the effects of the number of private charging stations on the total costs, the problem data also affects the route plans. One of the critical points in the problem data are the customer time window intervals, which may increase or decrease the number of visits to the private charging stations. For instance, the time intervals in the last three group instances in the small sized problems (n20w160s5, n20w180s5, and n20w200s5) are larger than the time intervals in the first two group instances (n20w120s5, and n20w140s5). Results of these problems show that less private charging stations are used in the instances whose time windows interval are tight. On the other hand, the distance between the nodes is another important factor for charging station visits. Considering the benchmark problem used in this study, distances between the customer locations and charging stations are very small as in the urban transportation. However, some real-life problems may have clusters of customers in different cities that require long travels between the clusters such as intercity transportation. For such a case, it should be obviously expressed that the usage of the private charging stations will be higher compared to the problems considered in this study.

Finally, considering the operational decision-making processes of the companies, it is crucial to find efficient plans in shorter computational times. It should be noted that the hybrid SA/TS is performed on a single thread. By adapting the algorithm to multi-threading, decision-makers can obtain the routing plans in much shorter CPU times.

6. Conclusion

In this paper, we introduced a new variant of the ETSPTW, namely the ETSPTW-MCR which additionally considers charging operations at customer locations with different charging rates. Distinct from the ETSPTW, the ETSPTW-MCR allows more flexible charging plans for the electric vehicle which leads to a reduction of total travelled distance while servicing the customers. A mixed integer mathematical model is formulated taking into account the new charging possibilities.

In addition to a new variant of the ETSPTW, we proposed a hybrid SA/TS metaheuristic algorithm to solve large sized problems efficiently. The hybrid SA/TS combines the advantages of the solution acceptance procedure of SA and the tabu list structure of TS to escape local minima. A dynamic programming based station insertion procedure is embedded in the algorithm to obtain station visit plans for the electric vehicle optimally by efficiently considering all possible charging operations for a given customer route.

In the computational studies, we extensively analyzed the performance of the proposed algorithm. First, we tested our hybrid SA/TS on two TSPTW problem sets proposed by Gendreau et al. (1998) and Ohlmann and Thomas (2007). For these computations, we compared our hybrid algorithm with three metaheuristic algorithms and achieved better average results in shorter computational times. Second, we applied our hybrid algorithm to the ETSPTW instances introduced by Roberti and Wen (2016). Following full and partial charging policies, new best results are found by the hybrid SA/TS for most of the instances within similar computational times. Finally, the hybrid SA/TS is applied to small and large sized ETSPTW-MCR instances. According to the computational results, we obtained considerable cost reductions for most of the instances comparing to the ETSPTW results.

This study can be extended in different ways. To add more realism and provide a meaningful cost estimation to decision makers, recharging times following non-linear functions can be considered as well as incorporating more realistic energy consumption formulas for the electric vehicle. As in most of the papers related with the EVRP, in this study the energy consumption amounts are determined by using a simple energy consumption coefficient. This assumption can be extended with non-linear functions that consider the vehicle weight, vehicle speed, technical information of the electric vehicle, etc. For the charging operations, real-life constraints, such as legal breaks of the drivers, can be interesting research challenges. In addition to new assumptions for the problem, new solution methodologies can be researched to solve the ETSPTW and ETSPTW-MCR.

Conflict of interest

The authors declare that this manuscript has not been submitted to, nor is under review at, another journal or other publishing venue, and there is no conflict of interests regarding the publication of this article.

Credit authorship contribution statement

İlker Küçükoğlu: Conceptualization, Funding acquisition, Formal analysis, Writing - original draft, Validation, Writing - review & editing. **Reginald Dewil:** Conceptualization, Formal analysis, Writing - original draft, Writing - review & editing. **Dirk Cattrysse:** Conceptualization, Formal analysis, Writing - original draft, Writing - review & editing.

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Appendix A. Parameter tuning

This section presents the details of the parameter tuning study and results of the experiments which are given in Table A.1. The parameter tuning study is carried out to identify best value of eight parameters of hybrid SA/TS: (c, CL, TL_1, TL_2, *perturbation*, R, ω, and $init\_iter$). First, different parameter levels are identified to be tested, where val_{pr} shows the considered parameter values of the levels. At the beginning of the parameter tuning experiments, parameter values of the algorithm are set to average value of the minimum and maximum levels. Then the best value of the parameters are identified regarding the considered parameter levels. For each parameter level, the hybrid SA/TS is carried out for five *OT-E5* problems: n150w120s5.5, n150w140s5.3, n150w160s5.2, n200w120s5.3, and n200w140s5.2. To decide the best value for a parameter, standard deviation of the solutions (σ) is used, where the bold characters show the obtained results for the parameters. When a best level is specified for a parameter, then it is fixed for the algorithm. The parameter identification procedure is repeated for each parameter in the order given in Table A.1 until all parameter values are tuned.

Table A.1
Results of the parameter tuning experiments.

Parameter		Level of the Parameter Tests							
		Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8
c	val_{pr}	0.91	0.93	**0.95**	0.97	0.99			
	σ	1.05	1.21	**1.03**	1.45	1.30			
CL	val_{pr}	25	50	75	**100**	**125**	150		
	σ	1.37	1.19	1.00	**0.99**	**0.99**	1.14		
TL_1	val_{pr}	100	200	300	**400**	500	600		
	σ	1.36	1.22	1.25	**1.03**	1.16	1.25		
TL_2	val_{pr}	25	50	**75**	100	125	150	175	200
	σ	1.13	1.16	**1.12**	1.25	1.25	1.15	1.18	1.25
perturbation	val_{pr}	**500**	750	1000	1250	1500	1750	2000	
	σ	**1.04**	1.06	1.09	1.12	1.15	1.13	1.23	
R	val_{pr}	10	20	**30**	40	50			
	σ	1.10	1.12	**0.94**	1.11	0.98			
ω	val_{pr}	0.2	0.3	0.4	0.5	0.6	**0.7**	0.8	
	σ	1.00	1.08	1.00	1.10	1.05	**0.93**	0.94	
init_iter	val_{pr}	**100**	125	150	175	200			
	σ	**0.96**	1.04	0.99	1.10	1.05			

Appendix B. Detailed results for the ETSPTW problems

Tables B.1–B.4.

Table B.1
Computational results for the *G-E5*.

Instance	Full Charging Policy													Partial Charging Policy											
	3P-Heu					SA/TS							3P-Heu					SA/TS							
	f_B	ns_P	f_A	σ	$t(s)$	f_B	$3P\%_B$	ns_P	f_A	$3P\%_A$	σ	$t(s)$	f_B	ns_P	f_A	σ	$t(s)$	f_B	$3P\%_B$	ns_P	f_A	$3P\%_A$	σ	$t(s)$
n20w120s5.1	271	3	271.0	0.0	0.05	271	0.00	3	271.0	0.00	0.0	0.17	271	4	271.0	0.0	0.05	271	0.00	4	271.0	0.00	0.0	0.19
n20w120s5.2	233	3	233.0	0.0	0.11	233	0.00	3	233.0	0.00	0.0	0.83	225	3	225.0	0.0	0.09	225	0.00	3	225.0	0.00	0.0	0.40
n20w120s5.3	317	3	317.0	0.0	0.07	317	0.00	3	317.0	0.00	0.0	0.59	311	4	311.0	0.0	0.06	311	0.00	4	311.0	0.00	0.0	0.17
n20w120s5.4	314	4	314.0	0.0	0.07	314	0.00	4	314.0	0.00	0.0	0.26	312	4	312.0	0.0	0.07	312	0.00	4	312.0	0.00	0.0	0.25
n20w120s5.5	249	3	249.0	0.0	0.06	249	0.00	3	249.0	0.00	0.0	0.39	249	3	249.0	0.0	0.06	249	0.00	3	249.0	0.00	0.0	0.30
n20w140s5.1	181	4	181.0	0.0	0.08	181	0.00	4	181.0	0.00	0.0	0.15	180	4	180.0	0.0	0.08	180	0.00	3	180.0	0.00	0.0	0.40
n20w140s5.2	279	4	279.0	0.0	0.06	279	0.00	3	279.0	0.00	0.0	0.16	278	4	278.0	0.0	0.07	278	0.00	3	278.0	0.00	0.0	0.22
n20w140s5.3	238	4	238.0	0.0	0.06	238	0.00	3	238.0	0.00	0.0	0.15	238	4	238.0	0.0	0.06	238	0.00	3	238.0	0.00	0.0	0.20
n20w140s5.4	265	3	265.0	0.0	0.10	265	0.00	3	265.0	0.00	0.0	0.76	265	4	265.0	0.0	0.10	265	0.00	4	265.0	0.00	0.0	0.66
n20w140s5.5	229	5	229.0	0.0	0.06	229	0.00	4	229.0	0.00	0.0	0.16	229	5	229.0	0.0	0.06	229	0.00	4	229.0	0.00	0.0	0.18
n20w160s5.1	246	3	246.0	0.0	0.09	246	0.00	3	246.0	0.00	0.0	0.16	246	3	246.0	0.0	0.09	246	0.00	3	246.0	0.00	0.0	0.22
n20w160s5.2	219	3	219.0	0.0	0.07	219	0.00	4	219.0	0.00	0.0	1.08	219	4	219.0	0.0	0.07	219	0.00	4	219.0	0.00	0.0	0.78
n20w160s5.3	210	3	210.0	0.0	0.07	210	0.00	3	210.0	0.00	0.0	0.26	210	3	210.0	0.0	0.07	210	0.00	3	210.0	0.00	0.0	0.23
n20w160s5.4	208	4	208.0	0.0	0.09	208	0.00	3	208.0	0.00	0.0	0.16	208	4	208.0	0.0	0.09	208	0.00	3	208.0	0.00	0.0	0.17
n20w160s5.5	253	4	253.0	0.0	0.08	253	0.00	4	253.0	0.00	0.0	0.26	253	4	253.0	0.0	0.08	253	0.00	4	253.0	0.00	0.0	0.34
n20w180s5.1	262	4	262.0	0.0	0.07	262	0.00	4	262.0	0.00	0.0	0.39	262	5	262.0	0.0	0.07	262	0.00	4	262.0	0.00	0.0	0.51
n20w180s5.2	273	3	273.0	0.0	0.08	273	0.00	3	273.0	0.00	0.0	0.22	273	3	273.0	0.0	0.08	273	0.00	3	273.0	0.00	0.0	0.19
n20w180s5.3	282	4	282.0	0.0	0.12	282	0.00	3	282.0	0.00	0.0	1.75	271	5	271.0	0.0	0.10	271	0.00	3	271.0	0.00	0.0	0.32
n20w180s5.4	206	4	206.0	0.0	0.10	206	0.00	4	206.0	0.00	0.0	0.45	206	4	206.0	0.0	0.10	206	0.00	4	206.0	0.00	0.0	0.63
n20w180s5.5	201	3	201.0	0.0	0.10	201	0.00	3	201.0	0.00	0.0	0.25	201	3	201.0	0.0	0.10	201	0.00	3	201.0	0.00	0.0	0.25
n20w200s5.1	241	3	241.0	0.0	0.09	241	0.00	3	241.0	0.00	0.0	0.32	241	3	241.0	0.0	0.09	241	0.00	3	241.0	0.00	0.0	0.24
n20w200s5.2	221	3	221.0	0.0	0.09	221	0.00	3	221.0	0.00	0.0	1.42	221	3	221.0	0.0	0.09	221	0.00	3	221.0	0.00	0.0	0.73
n20w200s5.3	255	4	255.0	0.0	0.08	**254***	−0.39	4	**254.0**	−0.39	0.0	0.32	255	4	255.0	0.0	0.09	**254***	−0.39	4	**254.0***	−0.39	0.0	0.27
n20w200s5.4	296	3	296.0	0.0	0.10	**295***	−0.34	4	**295.0**	−0.34	0.0	0.20	296	3	296.0	0.0	0.09	**295***	−0.34	4	**295.0***	−0.34	0.0	0.25
n20w200s5.5	240	4	240.0	0.0	0.12	240	0.00	4	240.0	0.00	0.0	0.40	240	4	240.0	0.0	0.12	240	0.00	4	240.0	0.00	0.0	0.35
Average	247.6	3.5	247.6	0.0	0.08	247.5	−0.03	3.4	247.5	−0.03	0.0	0.45	246.4	3.8	246.4	0.0	0.08	246.3	−0.03	3.5	246.3	−0.03	0.0	0.34

* Solutions are presented as an optimal solution by Roberti and Wen (2016)

Table B.2
Computational results for the *G-E10*.

Instance	Full Charging Policy												Partial Charging Policy											
	3P-Heu					SA/TS							3P-Heu					SA/TS						
	f_B	ns_P	f_A	σ	$t(s)$	f_B	$3P\%_B$	ns_P	f_A	$3P\%_A$	σ	$t(s)$	f_B	ns_P	f_A	σ	$t(s)$	f_B	$3P\%_B$	ns_P	f_A	$3P\%_A$	σ	$t(s)$
n20w120s10.1	270	3	270.0	0.0	0.05	270	0.00	3	270.0	0.00	0.0	0.18	270	4	270.0	0.0	0.05	270	0.00	4	270.0	0.00	0.0	0.21
n20w120s10.2	222	3	222.0	0.0	0.09	222	0.00	3	222.0	0.00	0.0	0.22	220	3	220.0	0.0	0.09	220	0.00	3	220.0	0.00	0.0	0.23
n20w120s10.3	312	3	312.0	0.0	0.06	312	0.00	3	312.0	0.00	0.0	0.29	311	5	311.0	0.0	0.06	311	0.00	4	311.0	0.00	0.0	0.25
n20w120s10.4	308	3	308.0	0.0	0.07	308	0.00	3	308.0	0.00	0.0	0.20	307	4	307.0	0.0	0.07	307	0.00	4	307.0	0.00	0.0	0.31
n20w120s10.5	243	4	243.0	0.0	0.06	243	0.00	4	243.0	0.00	0.0	0.22	243	4	243.0	0.0	0.06	243	0.00	4	243.0	0.00	0.0	0.26
n20w140s10.1	179	5	179.0	0.0	0.08	179	0.00	4	179.0	0.00	0.0	0.13	178	4	178.0	0.0	0.08	178	0.00	3	178.0	0.00	0.0	0.19
n20w140s10.2	277	4	277.0	0.0	0.06	277	0.00	4	277.0	0.00	0.0	0.18	277	5	277.0	0.0	0.06	277	0.00	4	277.0	0.00	0.0	0.21
n20w140s10.3	237	4	237.0	0.0	0.07	237	0.00	4	237.0	0.00	0.0	0.17	237	5	237.0	0.0	0.07	237	0.00	4	237.0	0.00	0.0	0.23
n20w140s10.4	260	3	260.0	0.0	0.09	260	0.00	3	260.0	0.00	0.0	0.29	260	5	260.0	0.0	0.09	260	0.00	4	260.0	0.00	0.0	0.30
n20w140s10.5	225	3	225.0	0.0	0.06	225	0.00	4	225.0	0.00	0.0	0.14	225	5	225.0	0.0	0.06	225	0.00	4	225.0	0.00	0.0	0.17
n20w160s10.1	245	3	245.0	0.0	0.09	245	0.00	3	245.0	0.00	0.0	0.20	245	3	245.0	0.0	0.09	245	0.00	3	245.0	0.00	0.0	0.29
n20w160s10.2	208	3	208.0	0.0	0.07	208	0.00	3	208.0	0.00	0.0	0.25	208	3	208.0	0.0	0.06	208	0.00	3	208.0	0.00	0.0	0.24
n20w160s10.3	210	3	210.0	0.0	0.07	210	0.00	3	210.0	0.00	0.0	0.32	210	3	210.0	0.0	0.08	210	0.00	3	210.0	0.00	0.0	0.31
n20w160s10.4	208	4	208.0	0.0	0.08	208	0.00	3	208.0	0.00	0.0	0.16	208	4	208.0	0.0	0.09	208	0.00	3	208.0	0.00	0.0	0.20
n20w160s10.5	248	3	248.0	0.0	0.08	248	0.00	3	248.0	0.00	0.0	0.16	248	3	248.0	0.0	0.08	248	0.00	3	248.0	0.00	0.0	0.29
n20w180s10.1	254	3	254.0	0.0	0.07	254	0.00	3	254.0	0.00	0.0	0.18	254	5	254.0	0.0	0.07	254	0.00	3	254.0	0.00	0.0	0.28
n20w180s10.2	272	4	272.0	0.0	0.08	272	0.00	3	272.0	0.00	0.0	0.18	272	4	272.0	0.0	0.08	272	0.00	3	272.0	0.00	0.0	0.21
n20w180s10.3	273	3	273.0	0.0	0.10	273	0.00	3	273.0	0.00	0.0	0.93	270	5	270.0	0.0	0.10	270	0.00	3	270.0	0.00	0.0	0.36
n20w180s10.4	206	4	206.0	0.0	0.11	206	0.00	4	206.0	0.00	0.0	0.74	206	4	206.0	0.0	0.11	206	0.00	4	206.0	0.00	0.0	0.61
n20w180s10.5	199	4	199.0	0.0	0.10	199	0.00	3	199.0	0.00	0.0	0.31	199	4	199.0	0.0	0.10	199	0.00	3	199.0	0.00	0.0	0.25
n20w200s10.1	239	3	239.0	0.0	0.09	239	0.00	3	239.0	0.00	0.0	0.39	239	3	239.0	0.0	0.09	239	0.00	3	239.0	0.00	0.0	0.36
n20w200s10.2	213	5	213.0	0.0	0.09	213	0.00	4	213.0	0.00	0.0	0.60	213	5	213.0	0.0	0.09	213	0.00	4	213.0	0.00	0.0	0.51
n20w200s10.3	250	4	250.0	0.0	0.09	250	0.00	4	250.0	0.00	0.0	0.22	250	4	250.0	0.0	0.09	250	0.00	4	250.0	0.00	0.0	0.26
n20w200s10.4	295	4	295.0	0.0	0.10	295	0.00	4	295.0	0.00	0.0	0.40	295	4	295.0	0.0	0.10	295	0.00	4	295.0	0.00	0.0	0.26
n20w200s10.5	233	5	233.0	0.0	0.13	233	0.00	4	233.0	0.00	0.0	0.39	233	5	233.0	0.0	0.13	233	0.00	4	233.0	0.00	0.0	0.43
Average	243.4	3.6	243.4	0.0	0.08	243.4	0.00	3.4	243.4	0.00	0.0	0.30	243.1	4.1	243.1	0.0	0.08	243.1	0.00	3.5	243.1	0.00	0.0	0.29

Table B.3
Computational results for the *OT-E5*.

Instance	Full Charging Policy												Partial Charging Policy											
	3P-Heu					SA/TS							3P-Heu					SA/TS						
	f_B	ns_P	f_A	σ	$t(s)$	f_B	$3P\%_B$	ns_P	f_A	$3P\%_A$	σ	$t(s)$	f_B	ns_P	f_A	σ	$t(s)$	f_B	$3P\%_B$	ns_P	f_A	$3P\%_A$	σ	$t(s)$
n150w120s5.1	750	9	753.3	2.4	37.41	750	0.00	8	**753.0**	−0.04	3.5	21.89	747	9	750.1	2.5	35.47	**746**	−0.13	8	**747.5**	−0.35	1.4	34.92
n150w120s5.2	663	7	665.3	1.1	33.84	663 (*662)	0.00	7	667.7	0.36	3.1	41.27	657	6	657.8	0.6	30.60	**655**	−0.30	7	**657.1**	−0.11	0.9	44.87
n150w120s5.3	770	7	772.1	1.0	44.76	770	0.00	7	**771.5**	−0.08	1.0	60.09	769	8	770.0	0.6	43.47	769	0.00	8	**769.9**	−0.01	0.7	62.15
n150w120s5.4	735	6	738.6	2.6	44.80	**730**	−0.68	6	**730.8**	−1.06	1.2	107.71	735	6	737.6	2.0	47.44	**727**	−1.09	6	**730.7**	−0.94	1.6	113.29
n150w120s5.5	708	7	712.8	2.0	45.76	**705**	−0.42	7	**708.8**	−0.56	3.1	50.00	708	8	709.4	1.0	49.90	**705**	−0.42	7	**707.9**	−0.21	2.2	67.12
n150w140s5.1	757	7	757.6	0.7	117.24	**755**	−0.26	7	**755.2**	−0.32	0.4	74.62	753	8	754.0	0.8	125.36	**751**	−0.27	8	**751.2**	−0.37	0.6	119.42
n150w140s5.2	773	8	773.9	1.0	40.17	773	0.00	8	774.8	0.12	1.9	51.51	772	8	772.0	0.0	39.52	772	0.00	8	772.4	0.05	0.5	47.46
n150w140s5.3	632	8	635.0	1.3	35.10	**631**	−0.16	8	**634.4**	−0.09	2.1	36.33	626	8	626.5	0.9	32.66	626	0.00	8	**626.0**	−0.08	0.0	37.48
n150w140s5.4	687	7	687.0	0.0	27.86	687	0.00	7	687.0	0.00	0.0	21.57	687	8	687.0	0.0	28.90	687	0.00	7	687.0	0.00	0.0	27.44
n150w140s5.5	674	6	674.0	0.0	42.05	674	0.00	6	674.2	0.03	0.4	34.74	669	6	669.0	0.0	39.33	669	0.00	6	669.0	0.00	0.0	36.54
n150w160s5.1	734	8	735.0	0.4	61.37	**732**	−0.27	7	**733.8**	−0.16	1.0	49.40	729	7	729.4	0.7	55.46	**727**	−0.27	7	**727.9**	−0.21	0.7	56.47
n150w160s5.2	708	8	712.9	3.4	66.66	**701** (***700**)	−0.99	8	720.9	1.12	7.7	107.33	696	7	698.5	1.1	57.15	**692**	−0.57	7	698.5	0.00	5.4	118.01
n150w160s5.3	637	7	639.4	1.0	44.15	**625**	−1.88	7	**630.4**	−1.41	4.6	37.18	618	8	623.9	3.2	37.01	**614**	−0.65	8	**616.7**	−1.15	0.9	36.19
n150w160s5.4	692	8	693.4	1.2	38.72	692	0.00	7	**693.3**	−0.01	1.2	46.16	692	8	692.9	0.7	43.13	**680**	−1.73	7	**688.3**	−0.66	2.9	44.85
n150w160s5.5	677	7	677.9	0.8	31.50	**676**	−0.15	7	**677.4**	−0.07	0.8	62.79	677	8	677.6	0.5	33.29	677	0.00	7	**677.1**	−0.07	0.3	69.02
n200w120s5.1	818	6	818.3	0.5	80.97	818	0.00	6	**818.0**	−0.04	0.0	72.16	818	7	818.3	0.5	97.46	818	0.00	6	**818.1**	−0.02	0.3	97.42
n200w120s5.2	748	7	748.6	0.7	76.74	749	0.13	7	749.9	0.17	0.6	85.19	746	9	746.5	0.5	85.86	746	0.00	8	747.3	0.11	1.7	85.63
n200w120s5.3	898	8	900.8	1.8	95.75	899	0.11	7	901.7	0.10	1.3	89.61	898	9	900.1	1.4	110.98	900	0.22	8	902.3	0.24	0.9	92.22
n200w120s5.4	790	7	790.9	0.3	106.17	790	0.00	7	**790.3**	−0.08	0.5	34.38	790	7	790.9	0.3	113.57	790	0.00	7	**790.5**	−0.05	0.5	40.37
n200w120s5.5	863	8	866.0	1.8	173.54	**858**	−0.58	7	**863.1**	−0.33	2.7	93.41	862	9	864.0	1.0	212.83	**860**	−0.23	6	**861.5**	−0.29	1.1	139.56
n200w140s5.1	831	7	836.3	2.2	89.79	**830**	−0.12	7	**830.5**	−0.69	0.7	73.63	831	8	836.3	2.2	98.89	**830**	−0.12	7	**831.4**	−0.59	1.5	107.83
n200w140s5.2	797	7	799.9	1.4	171.91	797	0.00	8	800.3	0.05	1.3	220.22	789	8	791.0	1.5	127.63	**788**	−0.13	7	**790.0**	−0.13	1.2	159.62
n200w140s5.3	764	7	765.0	1.7	71.03	764	0.00	6	**764.6**	−0.05	0.7	65.33	763	8	763.9	1.4	71.05	763	0.00	7	**763.2**	−0.09	0.4	44.05
n200w140s5.4	821	8	821.0	0.0	86.18	821 (***820**)	0.00	8	821.0	0.00	0.0	81.24	816	11	816.0	0.0	80.26	816	0.00	9	816.1	0.01	0.3	65.76
n200w140s5.5	838	8	838.0	0.0	103.40	**837**	−0.12	8	838.0	0.00	0.5	174.61	836	8	836.1	0.3	110.50	836	0.00	8	836.4	0.04	0.8	88.20
Average	750.6	7.3	752.5	1.2	70.67	749.1	−0.22	7.1	751.6	−0.12	1.6	71.69	747.4	7.9	748.8	0.9	72.31	745.8	−0.23	7.3	747.4	−0.20	1.1	73.44

* Solutions are observed during the preliminary experiments.

Table B.4
Computational results for the *OT-E10*.

Instance	Full Charging Policy												Partial Charging Policy											
	3P-Heu					SA/TS							3P-Heu					SA/TS						
	f_B	ns_P	f_A	σ	$t(s)$	f_B	$3P\%_B$	ns_P	f_A	$3P\%_A$	σ	$t(s)$	f_B	ns_P	f_A	σ	$t(s)$	f_B	$3P\%_B$	ns_P	f_A	$3P\%_A$	σ	$t(s)$
n150w120s10.1	746	7	746.7	0.5	30.45	746	0.00	7	**746.5**	−0.03	0.5	21.26	740	10	740.9	0.3	28.45	740	0.00	7	**740.4**	−0.07	0.5	25.25
n150w120s10.2	653	9	654.7	1.0	28.71	653	0.00	8	655.8	0.17	1.6	57.51	653	9	654.6	0.9	29.45	**652**	−0.15	8	**653.8**	−0.12	1.1	40.76
n150w120s10.3	766	8	768.3	1.1	37.61	766	0.00	7	**766.9**	−0.18	1.1	39.63	765	10	766.4	0.9	39.17	765	0.00	8	**765.7**	−0.09	0.5	97.31
n150w120s10.4	721	6	722.9	1.4	40.55	**717**	−0.55	6	**720.5**	−0.33	3.0	125.02	721	7	722.1	0.8	41.85	**714**	−0.97	7	**715.5**	−0.91	1.1	135.52
n150w120s10.5	693	8	694.6	1.1	26.72	693	0.00	7	697.6	0.43	3.0	51.37	693	9	693.0	0.0	26.76	693	0.00	8	693.3	0.04	0.5	47.63
n150w140s10.1	747	8	747.3	0.5	60.50	**746**	−0.13	7	747.4	0.01	0.8	51.02	744	9	745.2	1.1	69.45	**742**	−0.27	7	**742.0**	−0.43	0.0	56.34
n150w140s10.2	768	8	768.0	0.0	35.42	768	0.00	7	768.6	0.08	1.3	31.46	764	7	764.0	0.0	34.83	764	0.00	7	764.0	0.00	0.0	31.15
n150w140s10.3	627	9	628.2	1.0	32.76	**626**	−0.16	9	**626.8**	−0.22	0.4	32.15	623	9	623.5	0.9	32.58	**622**	−0.16	8	**622.0**	−0.24	0.0	38.71
n150w140s10.4	683	9	683.0	0.0	27.22	683	0.00	7	683.0	0.00	0.0	22.70	683	9	683.0	0.0	28.20	683	0.00	7	683.0	0.00	0.0	22.53
n150w140s10.5	673	8	673.0	0.0	41.33	**672**	−0.15	7	673.3	0.04	0.7	35.44	668	10	668.0	0.0	39.19	**667**	−0.15	7	**667.7**	−0.04	0.5	51.51
n150w160s10.1	713	7	713.0	0.0	29.90	713	0.00	8	713.1	0.01	0.3	28.77	713	7	713.0	0.0	30.63	713	0.00	7	713.1	0.01	0.3	19.31
n150w160s10.2	700	6	704.1	3.0	59.46	**696**	−0.57	6	709.7	0.80	7.3	111.12	688	8	689.4	0.8	52.69	**684**	−0.58	7	692.0	0.38	5.1	92.54
n150w160s10.3	628	7	630.2	1.7	39.82	**625** (***624**)	−0.48	7	**628.6**	−0.25	2.7	35.65	617	9	618.7	1.7	36.79	**614**	−0.49	9	**615.1**	−0.58	1.4	36.20
n150w160s10.4	686	9	686.4	0.7	34.39	**684**	−0.29	7	**684.8**	−0.23	0.4	38.32	686	9	686.4	0.7	37.15	**685**	−0.15	8	**685.0**	−0.20	0.0	38.46
n150w160s10.5	676	7	676.1	0.3	31.09	676	0.00	7	676.3	0.03	0.5	54.16	673	8	673.0	0.0	32.48	673	0.00	7	673.0	0.00	0.0	53.81
n200w120s10.1	806	8	806.1	0.3	65.82	**805**	−0.12	9	806.1	0.00	0.9	75.15	805	9	805.9	0.3	66.96	805	0.00	9	**805.0**	−0.11	0.0	35.33
n200w120s10.2	738	9	738.1	0.3	60.01	**736**	−0.27	8	**737.9**	−0.03	0.7	57.93	736	10	736.9	0.3	62.62	737	0.14	9	737.0	0.01	0.0	55.74
n200w120s10.3	891	8	891.5	0.5	74.06	891	0.00	8	**891.0**	−0.06	0.0	88.80	891	10	891.5	0.5	80.90	891	0.00	8	**891.4**	−0.01	0.5	80.52
n200w120s10.4	790	7	790.9	0.3	106.08	**788**	−0.25	8	**789.9**	−0.13	1.1	42.09	790	7	790.9	0.3	113.74	**788**	−0.25	8	**789.2**	−0.21	0.8	44.65
n200w120s10.5	857	10	857.8	0.6	89.71	**855** (***854**)	−0.23	8	**856.7**	−0.13	1.3	76.83	854	10	854.2	0.4	87.33	**849**	−0.59	9	**851.5**	−0.32	1.8	50.20
n200w140s10.1	831	8	833.4	1.3	89.53	**829**	−0.24	7	**829.9**	−0.42	0.7	90.22	827	10	829.1	1.1	85.82	**826**	−0.12	8	**827.3**	−0.22	0.7	87.02
n200w140s10.2	789	8	789.8	0.6	107.43	**788**	−0.13	8	**788.9**	−0.11	0.7	244.25	778	9	780.1	1.1	82.85	**776**	−0.26	8	**778.6**	−0.19	1.3	173.52
n200w140s10.3	763	7	764.5	1.8	72.18	764 (*763)	0.13	8	**764.3**	−0.03	0.5	58.48	762	9	763.3	1.4	71.98	**761**	−0.13	8	**761.0**	−0.30	0.0	45.53
n200w140s10.4	820	8	820.0	0.0	84.88	**818**	−0.24	8	**819.7**	−0.04	1.3	83.16	812	11	812.0	0.0	70.13	812	0.00	8	812.0	0.00	0.0	67.71
n200w140s10.5	830	8	830.9	0.3	78.74	830	0.00	8	831.6	0.08	1.4	60.50	830	9	830.9	0.3	103.84	830	0.00	8	**830.5**	−0.05	0.5	72.41
Average	743.8	7.9	744.8	0.7	55.37	742.7	−0.15	7.5	744.6	−0.02	1.3	64.52	740.6	9.0	741.4	0.6	55.43	739.4	−0.17	7.8	740.4	−0.15	0.7	59.99

* Solutions are observed during the preliminary experiments.

Appendix C. Detailed results for the ETSPTW-MCR problems

Tables C1–C4.

Table C.1
Computational results for the *G-E5-MCR(30%)*, *G-E5-MCR(70%)*, and *G-E5-MCR(100%)* problems.

Instance	*MCR(30%)*								*MCR(70%)*								*MCR(100%)*							
	f_B	ns_P	ns_C	Gap%	ETW%	f_A	σ	$t(s)$	f_B	ns_P	ns_C	Gap%	ETW%	f_A	σ	$t(s)$	f_B	ns_P	ns_C	Gap%	ETW%	f_A	σ	$t(s)$
n20w120s5.1	271	3	1	0.00	0.00	271.0	0.0	0.20	271	3	1	0.00	0.00	271.0	0.0	0.21	271	3	1	0.00	0.00	271.0	0.0	0.19
n20w120s5.2	233	3	0	5.58	0.00	233.0	0.0	0.34	229	2	2	0.00	−1.72	229.0	0.0	0.32	229	2	1	3.93	−1.72	229.0	0.0	0.26
n20w120s5.3	317	3	0	0.00	0.00	317.0	0.0	0.27	317	3	0	0.00	0.00	317.0	0.0	0.38	312	3	2	2.88	−1.58	312.0	0.0	0.19
n20w120s5.4	314	4	0	0.00	0.00	314.0	0.0	0.21	311	3	1	0.32	−0.96	311.0	0.0	0.22	311	3	1	4.18	−0.96	311.0	0.0	0.18
n20w120s5.5	249	3	1	0.00	0.00	249.0	0.0	0.19	243	2	2	0.00	−2.41	243.0	0.0	0.18	243	2	3	0.00	−2.41	243.0	0.0	0.16
n20w140s5.1	181	4	0	0.00	0.00	181.0	0.0	0.21	181	4	1	0.00	0.00	181.0	0.0	0.20	178	3	3	0.00	−1.66	178.0	0.0	0.18
n20w140s5.2	279	3	0	9.32	0.00	279.0	0.0	0.21	279	3	0	6.09	0.00	279.0	0.0	0.23	279	3	0	11.11	0.00	279.0	0.0	0.19
n20w140s5.3	237	3	1	0.00	−0.42	237.0	0.0	0.21	237	3	1	0.00	−0.42	237.0	0.0	0.22	237	3	1	0.00	−0.42	237.0	0.0	0.20
n20w140s5.4	265	3	1	0.00	0.00	265.0	0.0	0.29	265	3	1	3.77	0.00	265.0	0.0	0.29	265	3	1	9.81	0.00	265.0	0.0	0.26
n20w140s5.5	226	3	1	0.00	−1.31	226.0	0.0	0.19	226	3	1	0.00	−1.31	226.0	0.0	0.19	226	3	1	0.00	−1.31	226.0	0.0	0.18
n20w160s5.1	244	3	1	0.00	−0.81	244.0	0.0	0.23	244	3	2	0.00	−0.81	244.0	0.0	0.24	243	2	2	0.00	−1.22	243.0	0.0	0.19
n20w160s5.2	208	2	2	0.00	−5.02	208.0	0.0	0.20	208	2	3	0.00	−5.02	208.0	0.0	0.23	208	2	2	0.00	−5.02	208.0	0.0	0.20
n20w160s5.3	210	3	1	0.00	0.00	210.0	0.0	0.22	210	3	1	0.00	0.00	210.0	0.0	0.22	210	2	1	0.00	0.00	210.0	0.0	0.18
n20w160s5.4	204	2	1	0.00	−1.92	204.0	0.0	0.26	204	2	2	0.00	−1.92	204.0	0.0	0.30	204	2	2	0.00	−1.92	204.0	0.0	0.28
n20w160s5.5	249	2	3	0.00	−1.58	249.0	0.0	0.20	249	2	4	0.00	−1.58	249.0	0.0	0.22	249	2	4	0.80	−1.58	249.0	0.0	0.21
n20w180s5.1	256	2	2	0.00	−2.29	256.0	0.0	0.20	253	1	2	0.00	−3.44	253.0	0.0	0.20	253	1	2	0.00	−3.44	253.0	0.0	0.19
n20w180s5.2	273	3	1	0.00	0.00	273.0	0.0	0.21	273	3	2	0.00	0.00	273.0	0.0	0.22	267	2	2	0.00	−2.20	267.0	0.0	0.18
n20w180s5.3	276	2	1	0.00	−2.13	276.0	0.0	0.36	274	2	1	0.00	−2.84	274.0	0.0	0.44	274	2	1	6.57	−2.84	274.0	0.0	0.40
n20w180s5.4	205	3	1	0.00	−0.49	205.0	0.0	0.28	205	3	1	0.00	−0.49	205.0	0.0	0.60	205	3	2	0.00	−0.49	205.0	0.0	0.68
n20w180s5.5	198	2	1	0.00	−1.49	198.0	0.0	0.25	198	2	2	7.07	−1.49	198.0	0.0	0.42	196	1	2	4.59	−2.49	196.0	0.0	0.43
n20w200s5.1	234	1	2	0.00	−2.90	234.0	0.0	0.24	234	2	2	0.00	−2.90	234.0	0.0	0.25	234	2	2	0.00	−2.90	234.0	0.0	0.32
n20w200s5.2	210	2	2	0.00	−4.98	210.0	0.0	0.25	210	2	2	0.00	−4.98	210.0	0.0	0.28	210	2	2	0.00	−4.98	210.0	0.0	0.47
n20w200s5.3	250	2	1	0.00	−1.57	250.0	0.0	0.24	250	2	1	0.00	−1.57	250.0	0.0	0.24	250	2	1	0.00	−1.57	250.0	0.0	0.20
n20w200s5.4	295	4	1	2.71	0.00	295.0	0.0	0.23	295	4	1	4.41	0.00	295.0	0.0	0.23	295	4	1	4.75	0.00	295.0	0.0	0.18
n20w200s5.5	236	3	1	0.00	−1.67	236.0	0.0	0.25	235	2	2	0.00	−2.08	235.0	0.0	0.31	232	2	1	0.00	−3.33	232.0	0.0	0.27
Average	244.8	2.7	1.0	0.70	−1.14	244.8	0.0	0.24	244.0	2.6	1.5	0.90	−1.44	244.0	0.0	0.27	243.2	2.4	1.6	1.95	−1.76	243.2	0.0	0.25

Table C.2
Computational results for the *G-E10-MCR(30%)*, *G-E10-MCR(70%)*, and *G-E10-MCR(100%)* problems.

Instance	*MCR(30%)*								*MCR(70%)*								*MCR(100%)*							
	f_B	ns_P	ns_C	Gap%	ETW%	f_A	σ	$t(s)$	f_B	ns_P	ns_C	Gap%	ETW%	f_A	σ	$t(s)$	f_B	ns_P	ns_C	Gap%	ETW%	f_A	σ	$t(s)$
n20w120s10.1	270	3	1	0.00	0.00	270.0	0.0	0.21	270	3	1	0.00	0.00	270.0	0.0	0.22	270	3	1	0.00	0.00	270.0	0.0	0.19
n20w120s10.2	222	3	0	6.76	0.00	222.0	0.0	0.25	222	3	0	0.00	0.00	222.0	0.0	0.26	222	3	0	5.41	0.00	222.0	0.0	0.22
n20w120s10.3	312	3	0	0.00	0.00	312.0	0.0	0.24	312	3	1	4.17	0.00	312.0	0.0	0.28	312	3	1	3.21	0.00	312.0	0.0	0.27
n20w120s10.4	308	3	0	0.00	0.00	308.0	0.0	0.22	307	3	1	0.00	−0.32	307.0	0.0	0.23	307	3	1	0.98	−0.32	307.0	0.0	0.23
n20w120s10.5	243	4	0	0.00	0.00	243.0	0.0	0.19	242	3	3	0.00	−0.41	242.0	0.0	0.19	242	3	3	0.00	−0.41	242.0	0.0	0.12
n20w140s10.1	179	4	0	0.00	0.00	179.0	0.0	0.20	179	4	1	0.00	0.00	179.0	0.0	0.20	178	3	3	0.00	−0.56	178.0	0.0	0.19
n20w140s10.2	274	3	1	9.85	−1.08	274.0	0.0	0.23	274	3	1	11.31	−1.08	274.0	0.0	0.28	274	3	1	11.68	−1.08	274.0	0.0	0.23
n20w140s10.3	236	4	1	0.00	−0.42	236.0	0.0	0.22	236	4	1	0.00	−0.42	236.0	0.0	0.31	236	4	1	0.00	−0.42	236.0	0.0	0.25
n20w140s10.4	260	3	0	7.69	0.00	260.0	0.0	0.24	260	3	0	11.15	0.00	260.0	0.0	0.29	260	3	0	15.38	0.00	260.0	0.0	0.20
n20w140s10.5	225	4	0	16.44	0.00	225.0	0.0	0.21	225	4	1	0.00	0.00	225.0	0.0	0.23	225	4	1	0.00	0.00	225.0	0.0	0.22
n20w160s10.1	244	3	1	0.00	−0.41	244.0	0.0	0.24	244	3	2	0.00	−0.41	244.0	0.0	0.28	243	2	2	1.23	−0.82	243.0	0.0	0.29
n20w160s10.2	204	2	1	0.00	−1.92	204.0	0.0	0.22	204	2	1	0.00	−1.92	204.0	0.0	0.26	204	2	1	0.00	−1.92	204.0	0.0	0.29
n20w160s10.3	210	3	1	0.00	0.00	210.0	0.0	0.23	210	3	1	0.00	0.00	210.0	0.0	0.25	210	2	1	0.00	0.00	210.0	0.0	0.20
n20w160s10.4	204	2	1	0.00	−1.92	204.0	0.0	0.24	204	2	2	10.29	−1.92	204.0	0.0	0.30	204	2	2	0.00	−1.92	204.0	0.0	0.28
n20w160s10.5	247	3	2	0.00	−0.40	247.0	0.0	0.23	247	3	3	0.00	−0.40	247.0	0.0	0.28	246	2	4	4.88	−0.81	246.0	0.0	0.29
n20w180s10.1	254	3	1	0.00	0.00	254.0	0.0	0.24	253	2	1	0.00	−0.39	253.0	0.0	0.29	253	2	1	0.00	−0.39	253.0	0.0	0.29
n20w180s10.2	272	3	1	0.00	0.00	272.0	0.0	0.22	272	3	1	0.00	0.00	272.0	0.0	0.22	266	2	2	0.00	−2.21	266.0	0.0	0.22
n20w180s10.3	273	3	0	4.03	0.00	273.0	0.0	0.39	272	3	1	6.62	−0.37	272.0	0.0	0.45	272	3	1	5.51	−0.37	272.0	0.0	0.56
n20w180s10.4	205	3	1	3.41	−0.49	205.0	0.0	0.47	205	3	1	0.00	−0.49	205.0	0.0	0.81	205	3	2	0.00	−0.49	205.0	0.0	1.31
n20w180s10.5	197	2	2	0.00	−1.01	197.0	0.0	0.25	197	3	3	8.63	−1.01	197.0	0.0	0.30	196	2	3	11.22	−1.51	196.0	0.0	0.30
n20w200s10.1	234	1	2	4.70	−2.09	234.0	0.0	0.26	234	2	2	6.41	−2.09	234.0	0.0	0.25	234	2	2	0.00	−2.09	234.0	0.0	0.22
n20w200s10.2	207	2	2	0.00	−2.82	207.0	0.0	0.28	207	2	2	0.00	−2.82	207.0	0.0	0.30	204	2	2	0.00	−4.23	204.0	0.0	0.32
n20w200s10.3	249	2	1	0.00	−0.40	249.0	0.0	0.26	249	2	1	2.41	−0.40	249.0	0.0	0.25	249	2	1	0.00	−0.40	249.0	0.0	0.26
n20w200s10.4	295	4	1	16.27	0.00	295.0	0.0	0.26	295	3	2	24.07	0.00	295.0	0.0	0.25	295	3	2	17.63	0.00	295.0	0.0	0.20
n20w200s10.5	228	3	1	0.00	−2.15	228.0	0.0	0.28	228	3	1	0.00	−2.15	228.0	0.0	0.33	228	3	1	0.00	−2.15	228.0	0.0	0.34
Average	242.1	2.9	0.8	2.77	−0.60	242.1	0.0	0.25	241.9	2.9	1.4	3.40	−0.66	241.9	0.0	0.29	241.4	2.6	1.6	3.09	−0.88	241.4	0.0	0.30

Table C.3
Computational results for the *OT-E5-MCR(30%)*, *OT-E5-MCR(70%)*, and *OT-E5-MCR(100%)* problems.

Instance	MCR(30%)							MCR(70%)							MCR(100%)						
	f_B	ns_P	ns_C	*ETW%*	f_A	σ	$t(s)$	f_B	ns_P	ns_C	*ETW%*	f_A	σ	$t(s)$	f_B	ns_P	ns_C	*ETW%*	f_A	σ	$t(s)$
n150w120s5.1	747	8	1	−0.40	747.1	0.3	23.95	747	8	2	−0.40	747.0	0.0	25.10	745	7	3	−0.67	746.5	0.8	32.42
n150w120s5.2	657	6	5	−0.76	664.1	3.6	44.00	656	6	5	−0.91	659.7	3.9	62.48	654	6	6	−1.21	659.2	3.5	89.93
n150w120s5.3	770	7	0	0.00	771.0	1.1	126.98	771	7	0	0.13	771.2	0.4	392.13	765	8	1	−0.65	766.8	1.3	480.28
n150w120s5.4	726	5	2	−0.55	727.2	1.5	269.99	726	5	2	−0.55	726.8	1.7	729.43	725	5	2	−0.68	727.9	1.9	777.25
n150w120s5.5	704	7	3	−0.14	707.4	2.3	54.21	703	6	3	−0.28	704.9	1.9	123.44	701*	6	4	−0.57	704.1	1.8	192.06
n150w140s5.1	754	7	1	−0.13	756.8	4.3	275.39	754	7	1	−0.13	754.7	0.8	701.03	754	7	4	−0.13	755.1	1.7	990.81
n150w140s5.2	770	8	2	−0.39	771.8	1.5	39.07	771	7	4	−0.26	772.9	1.1	49.66	769	7	3	−0.52	771.3	0.9	142.44
n150w140s5.3	626	6	5	−0.79	629.0	3.2	55.28	625	6	7	−0.95	626.9	1.8	86.96	625	6	9	−0.95	625.7	1.6	102.36
n150w140s5.4	683	6	4	−0.58	683.0	0.0	23.37	683	6	5	−0.58	683.0	0.0	27.37	683	6	5	−0.58	683.0	0.0	36.04
n150w140s5.5	670	6	2	−0.59	671.2	1.0	49.72	670	6	3	−0.59	671.1	1.2	85.74	670	7	3	−0.59	671.3	0.9	177.47
n150w160s5.1	722	6	3	−1.37	724.4	1.7	39.08	721	6	3	−1.50	725.5	3.5	55.50	721	6	3	−1.50	722.5	1.7	66.74
n150w160s5.2	681	6	3	−2.71	689.7	8.8	90.75	681	6	4	−2.71	688.1	9.3	124.67	679	5	5	−3.00	683.1	3.7	237.52
n150w160s5.3	613	6	3	−1.92	618.9	6.1	28.22	611	5	4	−2.24	613.5	2.7	27.34	607	6	3	−2.88	612.1	3.0	28.99
n150w160s5.4	683	6	3	−1.30	684.9	1.4	43.73	681	6	4	−1.59	682.9	1.6	50.93	681	6	4	−1.59	683.3	1.3	85.49
n150w160s5.5	674	7	3	−0.30	674.4	0.8	71.07	670	6	4	−0.89	670.0	0.0	65.66	669	6	4	−1.04	669.9	0.3	115.35
n200w120s5.1	810	5	3	−0.98	810.9	0.9	92.26	808	5	4	−1.22	809.2	1.0	133.49	808	5	4	−1.22	809.2	1.0	188.15
n200w120s5.2	733	5	6	−2.01	733.1	0.3	64.74	732	5	7	−2.14	732.5	0.5	76.30	732	5	6	−2.14	732.0	0.0	122.25
n200w120s5.3	896	7	3	−0.22	897.4	2.8	72.61	896	7	4	−0.22	896.6	0.7	116.14	895	6	4	−0.33	897.1	2.2	207.96
n200w120s5.4	787	6	3	−0.38	787.1	0.3	45.98	787	6	4	−0.38	787.0	0.0	56.04	787	6	3	−0.38	787.2	0.4	95.74
n200w120s5.5	859	7	3	0.35	863.3	2.6	196.75	857	7	2	0.12	858.6	1.7	311.36	857	7	3	0.12	858.7	1.4	514.53
n200w140s5.1	830	7	2	0.00	831.1	1.2	156.23	830	7	3	0.00	831.0	0.8	521.49	829	7	3	−0.12	829.5	0.8	634.70
n200w140s5.2	773	5	4	−3.01	775.2	2.0	61.52	773	5	4	−3.01	774.7	1.8	86.00	773	5	5	−3.01	774.3	0.9	117.43
n200w140s5.3	764	6	4	0.00	764.4	0.5	58.77	763	6	4	−0.13	763.6	0.5	64.54	763	6	6	−0.13	763.3	0.5	55.80
n200w140s5.4	817	8	3	−0.37	818.8	2.1	99.81	817	8	3	−0.37	818.1	1.6	141.77	817	8	3	−0.37	817.6	0.5	195.18
n200w140s5.5	833	7	3	−0.48	835.1	1.9	61.87	833	7	3	−0.48	834.9	1.4	74.64	831	6	2	−0.72	831.6	1.0	76.87
Average	743.3	6.4	3.0	−0.76	745.5	2.1	85.81	742.6	6.2	3.6	−0.85	744.2	1.6	167.57	741.6	6.2	3.9	−0.99	743.3	1.3	230.55

* 699 is observed during the preliminary experiments.

Table C.4
Computational results for the *OT-E10-MCR(30%)*, *OT-E10-MCR(70%)*, and *OT-E10-MCR(100%)* problems.

Instance	*MCR(30%)*							*MCR(70%)*							*MCR(100%)*						
	f_B	ns_P	ns_C	*ETW%*	f_A	σ	$t(s)$	f_B	ns_P	ns_C	*ETW%*	f_A	σ	$t(s)$	f_B	ns_P	ns_C	*ETW%*	f_A	σ	$t(s)$
n150w120s10.1	743	7	2	−0.40	743.8	1.0	28.90	742	7	3	−0.54	743.3	0.9	37.03	742	7	4	−0.54	742.7	0.5	47.07
n150w120s10.2	650	7	4	−0.46	652.8	2.0	38.67	649	7	5	−0.61	652.5	2.0	34.46	650	7	5	−0.46	652.1	1.4	65.32
n150w120s10.3	764	8	1	−0.26	765.2	1.3	173.56	762	7	1	−0.52	764.0	0.8	673.73	757	8	2	−1.17	758.7	1.3	510.91
n150w120s10.4	717	6	1	0.00	719.9	1.7	254.53	714	6	3	−0.42	717.9	2.7	778.82	714	6	3	−0.42	717.3	3.5	1192.32
n150w120s10.5	695	7	4	0.29	697.0	2.1	56.86	692	6	5	−0.14	695.8	1.7	111.66	694*	5	4	0.14	695.1	1.3	160.12
n150w140s10.1	740	7	2	−0.80	740.9	0.7	195.03	737	6	4	−1.21	740.0	1.2	316.30	734	7	5	−1.61	734.2	0.6	363.69
n150w140s10.2	768	7	3	0.00	768.3	0.5	36.07	767	7	5	−0.13	767.5	0.5	40.54	767	7	4	−0.13	767.4	0.5	76.31
n150w140s10.3	619	7	4	−1.12	619.2	0.4	34.14	619	7	4	−1.12	619.2	0.4	35.66	618	6	6	−1.28	618.2	0.4	30.40
n150w140s10.4	680	6	3	−0.44	680.0	0.0	25.99	680	6	4	−0.44	680.0	0.0	25.17	680	6	4	−0.44	680.0	0.0	19.95
n150w140s10.5	669	8	3	−0.45	670.0	0.8	35.33	668	6	3	−0.60	669.6	1.2	65.52	667	7	4	−0.74	667.4	0.5	99.08
n150w160s10.1	713	7	2	0.00	713.1	0.3	28.32	711	7	3	−0.28	711.0	0.0	29.01	710	6	4	−0.42	710.0	0.0	21.61
n150w160s10.2	680	5	3	−2.30	689.2	7.6	125.21	680	5	4	−2.30	684.7	5.0	129.27	679	5	5	−2.44	683.1	3.9	190.60
n150w160s10.3	613	6	3	−1.76	615.3	1.4	27.67	612	5	5	−1.92	613.8	1.5	33.54	605	5	5	−3.04	611.9	2.8	26.17
n150w160s10.4	680	7	3	−0.58	681.1	0.7	35.56	679	6	3	−0.73	680.2	1.0	40.50	679	6	3	−0.73	680.4	0.7	69.18
n150w160s10.5	673	7	3	−0.44	673.0	0.0	78.24	669	6	4	−1.04	669.0	0.0	90.96	669	6	4	−1.04	669.0	0.0	221.62
n200w120s10.1	805	9	4	0.00	805.7	0.5	44.84	802	6	5	−0.37	803.1	1.2	54.36	802	6	6	−0.37	802.6	0.5	102.14
n200w120s10.2	728	6	6	−1.09	728.0	0.0	50.05	727	6	7	−1.22	727.0	0.0	57.62	727	6	7	−1.22	727.0	0.0	58.28
n200w120s10.3	890	8	2	−0.11	890.5	1.0	75.24	890	8	3	−0.11	890.3	0.5	115.31	889	8	4	−0.22	889.5	0.5	179.63
n200w120s10.4	787	6	3	−0.13	787.6	0.5	36.81	787	6	3	−0.13	787.0	0.0	55.42	787	6	5	−0.13	787.0	0.0	69.95
n200w120s10.5	854	8	3	0.00	855.8	0.9	111.61	855	8	2	0.12	855.9	1.0	189.38	854	8	4	0.00	855.4	1.0	287.62
n200w140s10.1	829	7	3	0.00	830.0	0.8	133.25	828	7	4	−0.12	829.4	0.8	315.23	828	7	4	−0.12	829.2	1.0	539.65
n200w140s10.2	770	6	5	−2.28	771.1	0.9	63.57	770	6	5	−2.28	771.2	0.9	104.74	770	5	6	−2.28	771.3	0.7	146.98
n200w140s10.3	763	7	4	0.00	763.9	0.6	58.05	761	6	5	−0.26	762.1	0.7	65.84	761	6	7	−0.26	761.8	0.8	78.94
n200w140s10.4	814	8	4	−0.49	815.9	1.6	112.26	814	8	4	−0.49	815.3	0.9	275.26	814	8	5	−0.49	815.5	0.8	603.44
n200w140s10.5	830	8	2	0.00	831.1	1.2	60.25	830	7	4	0.00	830.9	0.7	65.19	829	6	3	−0.12	829.4	0.7	74.23
Average	739.0	7.0	3.1	−0.51	740.3	1.1	76.80	737.8	6.5	3.9	−0.67	739.2	1.0	149.62	737.0	6.4	4.5	−0.78	738.2	0.9	209.41

* 693 is observed during the preliminary experiments.

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