35th European Modeling & Simulation Symposium
20th International Multidisciplinary Modeling & Simulation Multiconference

2724-0029 © 2023 The Authors.
doi: xx.xxxx/xxxx

Electric Vehicles Routing Simulation and Optimization under Smart Charging Strategies

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Abstract

This work deals with the problem of optimizing the routing of electric vehicles (EVs) for logistics operations. The objective is minimizing the charging/discharging cost considering the shortest path for each EV that must deliver freight to a group of customers. An optimization approach solves the Electric Vehicle Routing Problem and is formulated as an Integer Linear Programming problem. Moreover, to validate the performance of the proposed optimization method, we adopt SUMO software to model and simulate the Electric Vehicle Routing Problem problem solution. The method's efficacy is demonstrated through a real case study in the Apulia region of Italy, where different traffic scenarios are simulated using SUMO. The simulation results highlight the impact of traffic on travel times, emphasizing the need for validation and potential modifications of optimization results using simulation tools. Additionally, different traffic scenarios are simulated in SUMO environment, and the results show the impact of traffic on the travelling times.

Keywords: Electric Vehicle Routing Problem; Optimization; Simulation, Charging stations

1. Introduction

Today many companies integrate electric vehicles (EVs) into their fleets (Fanti et al., 2018) for logistics operations. Hence, the Electric Vehicle Routing Problem (EVRP) has gained significance in logistics to introduce EVs that reduce carbon emissions (Felipe et al., 2014). A single EV serves each client node in the EVRP, and each charging station can be made available for more than one EV (Lin et al.,2016; Paz et al.,2018).

It is necessary to avoid the battery State of Charge (SoC) of EVs goes beyond a lower bound. Smart-Charging is a new method that enables the charging and discharging of energy in the battery to establish balance and avoid exceeding energy peaks (Kucukoglu et al., 2021; Conrad et al., 2011). When discharge occurs, the EV battery supplies energy back to the grid. A multi-objective optimization approach is used to solve the EVRP in (Sadeghian et al., 2022).

Additionally, a two-stage simulation-based heuristic for the EVRP is proposed by (Keskin et al., 2021), which determines EV routes in the first stage by considering the expected waiting time at the charging stations, while the second stage corrects the infeasible solutions by penalizing the time-window violations and late returns to the depot.

Also, simulation tools are today largely used to assess and optimize the trip of conventional and EVs. One example is SUMO (Simulation of Urban Mobility), a microscopic, open-source traffic simulation software that can simulate individual vehicle movements and their interactions within a road network (Behrisch et al., 2011).

This paper starts with the smart charging strategies to address the EVRP for logistics applications developed in the previous work of (del Cacho et al., 2022), which determines the optimal routing for an EV fleet while considering customer demand and power grid requirements. The network comprises customer nodes serviced by connected EVs and several charging points. Each EV can be charged or discharged during the trip based on the battery level and requirements of the grid. An intelligent charging approach is used, in which an EV is charged when its SoC is inadequate to reach the next node and discharged when the power grid requires it. In order to validate the solutions obtained in (del Cacho et al., 2022), this paper presents a real case study using SUMO, which addresses the complexities of the problem by incorporating various features like road and traffic conditions.

In the proposed model, EVs possess various properties, including energy capacity, charging rates, and cargo capacities. There are many categories of clients with differing delivery schedules and load weights. In addition, the charging and discharging schedules of EVs are subject to time-varying power rates. In addition, charging stations have a maximum amount of energy they can deliver over a specific time. Furthermore, the charging stations belong to distinct energy districts with varying maximum energy values they may deliver over a certain time. By addressing these complexities, the proposed method offers a more comprehensive and realistic solution to the EVRP problem for logistics applications.

The paper is structured as follows. Section II literature review Section III recalls the optimization model, and Section IV provides the real case study modelled on SUMO. Finally, Section V is the results section, and Section VI provides the conclusions and highlights future work.

2. Literature Review

Several studies have focused on optimization and simulation approaches to tackle the challenge of optimizing the routing of EV fleets engaged in delivery operations while considering charging and discharging costs and power grid constraints. Notably, (Lee C., 2020) addresses EVRP considering nonlinear charging time. The study aims to minimize travel and charging times by developing an algorithm that accurately accounts for the nonlinear charging time function. The approach involves segmenting the vehicle tour and constructing an extended charging station network.

Simulation tools like SUMO have been widely employed to validate and enhance optimization solutions. These tools allow researchers to model and simulate the EVRP under various traffic scenarios and road topologies. Combining optimization techniques and simulation enables the assessment of system performance metrics, such as travel time, and identifying potential modifications to the routing strategies.

Prominent literature in this field includes the works of (QIN et al.,2021, Shuai Zhang et al.,2020, Afroditi et al., 2014, Xiao et al., 2021, and Moghdani et al., 2021). These studies provide comprehensive reviews on the EVRP, highlighting different models, algorithms, and future research directions to optimize EV fleet routing strategies and promote sustainable logistics operations.

Researchers have been using SUMO to study various aspects of EVRP, such as optimizing charging station locations and developing efficient routing algorithms. For example, (Xu et al., 2022), the authors proposed a new algorithm to optimize the locations of charging stations by simulating vehicle movements and analyzing the charging demands of the vehicles.

In recent years, researchers have extended the capabilities of SUMO to include modelling electric vehicle charging behavior and integrating renewable energy sources into the charging infrastructure. For instance, (Canizes et al., 2019), the authors developed a framework for simulating the charging behavior of electric vehicles in a public transportation system using SUMO. These studies demonstrate the versatility of SUMO as a platform for testing different routing algorithms.

3. EVRP Model Description

The EVRP involves finding the optimal route for a fleet of EVs that depart from a depot and must fulfil customer demands. The goal is not only to determine the most efficient route in terms of distance travelled but also to establish a connection between the EV and the customer. Each EV in the set $K = \{1, \dots, N_K\}$ departs from the Depot Node (D) with full cargo and a fully charged battery. The EV travels across different nodes until it reaches its destination. The goal of the EV is to reach its destination while delivering goods to customers through the shortest path. The battery can be charged or discharged at charging points during the journey if required.

In the set of Customer Nodes (CN) $N = \{1, \dots, N_N\}$, each element denotes the node to which EVs supply goods. When an electric vehicle (EV) needs to recharge or discharge energy, it approaches one of the Charging Points (CP) in the set $S = \{N_N + 1, \dots, N_S\}$. The set $P = \{1, \dots, N_P\}$ includes districts. The routing problem is addressed by considering a daily timeslot forming the set $T = \{1, \dots, N_T\}$.

To model and elaborate the EVRP problem, a graph depicts a network of points that consists of the nodes in the set $U = D \cup N \cup S$ as shown in Figure 1. This network defines a departure node (depot), customer nodes, and charging/discharging points. The nodes are linked by bidirectional arcs. The goal is to determine the optimal routes for the fleet of electric vehicles to meet customer demand while implementing an intelligent charging strategy to manage battery charging/discharging during the journey. Each EV in the fleet has a cargo capacity and is employed to service customers while participating in the charging/discharging strategy. The charging/discharging technique respects the power grid requirements, such as power balancing and not exceeding the maximum allowed demand peak. The energy demand constraints issue is addressed at the charging station and district levels. The optimization model determines the best charging/discharging approach for each EV on the trip while ensuring sufficient autonomy is maintained to complete the journey. In the proposed scenario, the weight of each arc between nodes represents the shortest path distance between nodes in kilometers.

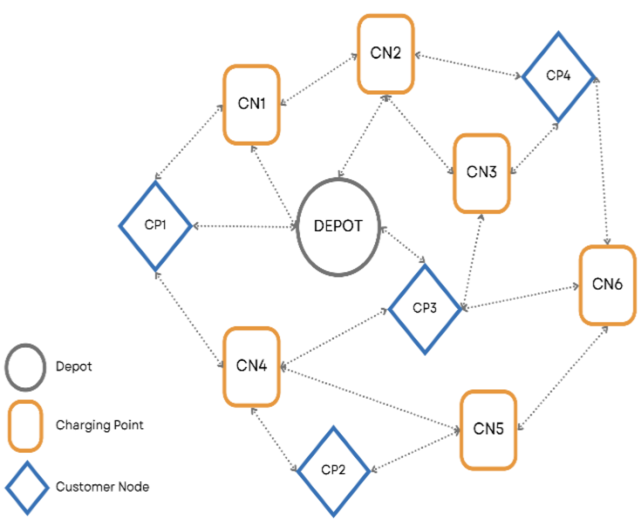

Figure 1. Example of nodes network

4. EVRP optimization model

The EVRP is modelled as an ILP problem as presented in (del Cacho et al., 2022) and recalled in this work. Some necessary parameters and notations are described and then the ILP problem is formulated. The considered sets of the ILP problem are:

$N = \{1, \ldots, N_N\}$	Set of customer nodes $N \in \mathbb{N}$
$S = \{N_N + 1, \ldots, N_S\}$	Set of charging station nodes $S \in \mathbb{N}$
$D = \{0\}$	Depot node
$U = D \cup N \cup S$	Set of nodes $U \in \mathbb{N}$
$T = \{1, \ldots, N_T\}$	Set of time slots $T \in \mathbb{N}$
$K = \{1, \ldots, N_K\}$	Set of EVs $K \in \mathbb{N}$
$P = \{1, \ldots, N_P\}$	Set of districts $P \in \mathbb{N}$.

The paraments are:

$td_{ij} \in \mathbb{R}^+$	Distance to travel from node i to node $j, i, j \in U$ [km]
$tt_{ij} \in \mathbb{R}^+$	Time to travel from node i to node $j, i, j \in U$ [h]
$Q_k \in \mathbb{R}^+$	Battery capacity of EV$k \in K$ [kWh]
$V_k \in \mathbb{R}^+$	Amount of time to fully charge EV $k \in K$[h]
$pr_t \in \mathbb{R}^+$	Unit electricity buying price during time slot $t \in T$ [€/kW]
$pd_t \in \mathbb{R}^+$	Unit electricity selling price during time slot $t \in T$ [€/kW]
$end_k \in U$	End node of EV $k \in K$
$e_i \in \mathbb{R}^+$	Open hour to start service allowed at node $i \in U$ [t]
$l_i \in \mathbb{R}^+$	Latest time to start service allowed at node $i \in U$ [t]
$C_k \in \mathbb{R}^+$	Cargo capacity of EV $k \in K$ [kg]
$q_i \in \mathbb{R}^+$	Demand of customer $i \in N \cup S. q_{i \in S} = 0$ [kg]
$s_i \in \mathbb{R}^+$	Time required by the customer for delivery at the node$i \in N$ [h]
$\delta \in \mathbb{R}^+$	Time slot duration [h]
$Pre_{kt} \in \mathbb{R}^+$	Cost of charging EV $k \in K$ during time slot $t \in T$ [€/kW]
$Pdis_{kt} \in \mathbb{R}^+$	Cost of discharging EV $k \in K$ during time slot $t \in T$ [€/kW]
$P\delta_i \in \mathbb{R}^+$	Power that charging station $i \in S$ can provide at time slot$t \in T$
$emax_i \in \mathbb{R}^+$	Maximum energy that charging station $i \in S$ can provide in each time slot [kWh]
$emaxD_p \in \mathbb{R}^+$	Maximum energy that district $p \in P$ can provide in each time slot [kWh]
$dt_{pi} \in \{0,1\}$	Binary parameter equal to 1 if charging station $i \in S$ belongs to district $p \in P$; 0 otherwise.

The decision variables are the following:

$y_{ij}^k \in \{0,1\}$	Binary decision variable equal to 1 if EV $k \in K$ travels from node i to node $j(td_{ij} > 0)$. 0 otherwise.$i, j \in U$
$r_{itk} \in \{0,1\}$	Binary decision variable equal to 1 if EV $k \in K$ charges its battery at node $i \in U$ at time slot $t \in T$;0 otherwise.
$d_{itk} \in \{0,1\}$	Binary decision variable equal to 1 if EV $k \in K$ discharges its battery at node $i \in U$ at time slot $t \in T$;0 otherwise.
$\tau_{ki} \in \mathbb{R}^+$	Arrival time of EV $k \in K$ at node $i \in U$ [h]
$u_{ki} \in \mathbb{R}^+ \cup \{0\}$	Remaining cargo in EV $k \in K$ upon arrival to node $i \in U$ [kg]
$v_{ki} \in \mathbb{R}^+$	SoC (autonomy) in terms of time in EV $k \in K$ upon arrival to node $i \in U$ [h]

The EVRP objective function aims to minimize the EVs travel distance, using the shortest route, and the total cost of the route. The objective function is described as follows:

$$f(y_{ij}^k, r_{itk}, d_{itk}) = \sum_{i\in U}\sum_{j\in N\cup S}\sum_{k\in K} td_{ij}\cdot y_{ij}^k + \\ + \sum_{k\in K}\sum_{i\in S}\sum_{t\in T} \delta\cdot\left((r_{itk}\cdot Pre_{kt}) - (d_{itk}\cdot Pdis_{kt})\right) \tag{1}$$

The problem is defined as follows:

$$\min_{y_{ij}^k, r_{itk}, d_{itk}} f(y_{ij}^k, r_{itk}, d_{itk})$$

s.t.

$$\sum_{k\in K}\sum_{j\in N\cup S} y_{ij}^k = 1 \qquad \forall i\in N,\ i,j\neq end_k,\ i\neq j,\ tt_{ij}>0 \tag{2}$$

$$\sum_{j\in N\cup S} y_{0j}^k = 1 \qquad \forall k\in K,\ j\neq end_k,\ tt_{0j}>0 \tag{3}$$

$$\sum_{i\in N\cup S} y_{i,end_k}^k = 1 \qquad \forall k\in K,\ i\neq end_k,\ tt_{iend_k}>0 \tag{4}$$

$$\sum_{i\in D\cup N\cup S} y_{ij}^k = \sum_{i\in N\cup S} y_{ji}^k \qquad \forall j\in N\cup S,\ i,j\neq end_k,\ i\neq j\ \forall k\in K \tag{5}$$

$$e_i \le \tau_{ki} \le l_i \qquad \forall i\in U,\ \forall k\in K \tag{6}$$

$$r_{itk} + d_{itk} \le 1 \qquad \forall i\in S,\ \forall t\in T,\ \forall k\in K \tag{7}$$

$$\sum_{i\in N\cup S}\sum_{j\in N\cup S} q_i\cdot y_{ij}^k \le C_k \qquad \forall k\in K,\ tt_{ij}>0 \tag{8}$$

$$\tau_{kj} \ge \tau_{ki} + \\ + \left((tt_{ij}+s_i)\cdot y_{ij}^k\right) - \\ -M\cdot(1-y_{ij}^k) \qquad \forall i\in N,\ \forall j\in N\cup S,\ \forall k\in K,\ td_{ij}>0 \tag{9}$$

$$\tau_{kj} \ge \left(\begin{matrix}\delta\cdot t\cdot\\ (r_{itk}+d_{itk})\cdot y_{ij}^k\end{matrix}\right) + \\ +(tt_{ij}\cdot y_{ij}^k) - \\ -M\cdot(1-y_{ij}^k) \qquad \forall i\in S,\ \forall j\in N\cup S,\ \forall t\in T,\ \forall k\in K,\ td_{ij}>0 \tag{10}$$

$$u_{k0} \le C_k \qquad \forall k\in K \tag{11}$$

$$v_{ki} = V_k \qquad \forall k\in K,\ i=0 \tag{12}$$

$$\tau_{ki} - (t-1)\cdot\delta \le \\ \le M\cdot(1-d_{itk}-r_{itk}) \qquad \forall i\in S,\ \forall t\in T,\ \forall k\in K \tag{13}$$

$$u_{kj} \le u_{ki} - (q_j\cdot y_{ij}^k) + \\ +M\cdot(1-y_{ij}^k) \qquad \forall i,j\in N\cup S,\ \forall k\in K,\ td_{ij}>0 \tag{14}$$

$$v_{kj} \le V_{ki} - (tt_{ij}\cdot y_{ij}^k) + \\ +M\cdot(1-y_{ij}^k) \qquad \forall k\in K,\ \forall j\in N\cup S,\ td_{ij}>0 \tag{15}$$

$$v_{kj} \le v_{ki} + \sum_{t\in T}\delta\cdot r_{itk} - \\ -\sum_{t\in T}\delta\cdot d_{itk} - (tt_{ij}\cdot y_{ij}^k) + \\ +M\cdot(1-y_{ij}^k) \qquad \forall k\in K,\ \forall i\in S,\ \forall j\in N\cup S \tag{16}$$

$$\sum_{t\in T}\delta\cdot r_{itk} \le V_k - v_{ki} \qquad \forall k\in K,\ \forall i\in S \tag{17}$$

$$\sum_{t\in T}\delta\cdot d_{itk} \le v_{ki} \le V_k \qquad \forall k\in K,\ \forall i\in S \tag{18}$$

$$0 \le v_{ki} \qquad \forall k\in K,\ \forall i\in N\cup S \tag{19}$$

$$v_{kj} \le V_k\cdot\sum_{i\in D\cup N\cup S} y_{ij}^k \qquad \forall k\in K,\ \forall j\in N\cup S \tag{20}$$

$$\sum_{k\in K} P\delta_i\cdot(r_{itk}-d_{itk}) \\ \le emax_i \qquad \forall i\in S,\ \forall t\in T \tag{21}$$

$$\sum_{k\in K} P\delta_i\cdot(r_{itk}-d_{itk})\cdot dt_{pi} \\ \le emaxD_p \qquad \forall i\in S,\ \forall t\in T,\ \forall p\in P \tag{22}$$

Constraints (2) through (5) handle controlling the flow of electric vehicles, ensuring they follow a single route and terminate at the arrival node, and connecting customer nodes with charging stations. Constraints (6) and (13) controls that the EV does not exceed its maximum cargo capacity. Equations (7), (8), and (9) are used to control the travel time of EVs, taking into account battery charging and discharging. Constraints (12) controls that all customers demand are satisfied. Constraints (10), (11) and from (14) to (20) focus on controlling all aspects related to the EVs batteries. Finally, constraints (21) and (22) ensures that the maximum energy peak is not exceeded in order to balance the network.

The more detailed meaning of the constraints is reported in paper (del Cacho et al.,2022).

5. EVRP Simulation model in SUMO

The described system is simulated by SUMO tool. Using Open Street Maps data sources, SUMO can model the roadways, traffic signals, demand, and infrastructure of large-scale locations. In addition, SUMO can provide a more extensive road structure, generate massive traffic scenarios, and simulate intelligent transportation systems under various situations. Therefore, we use SUMO to simulate a real case study in Apulia region (Italy), to validate the proposed optimization approach for EVRP. To this aim we imported OpenStreetMap data of the Apulia region and obtained a simulation map in SUMO.

The final map findings are displayed in Figure 2.

Furthermore, we have created a SUMO model of the nodes network and routes.

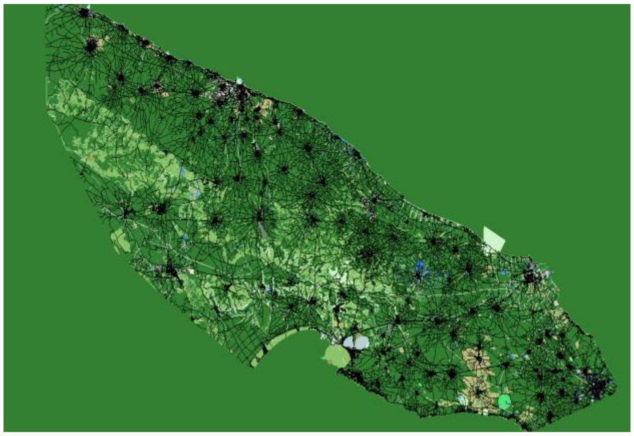

Figure. 2 Apulia region map in SUMO.

6. Case Study

6.1. Description of the simulation model

In the previous work (del Cacho et al.,2022), a real case study of a network of customer nodes located in the Apulia region is presented. The EVRP ILP was solved using CPLEX considering the distance between each node regardless road conditions.

In this study, we simulate the same scenario in microscopic traffic simulation considering the same traffic conditions; each vehicle is explicitly described, has a unique route, and travels independently across the network according to EVRP ILP road conditions. Additionally, we explore the impact of traffic volume on travelling time by adding different traffic levels to the simulation.

The SUMO simulation graphic interface is shown in Figure 3. There are four components depicted: the depot of the vehicles (light green color), the customer nodes (CN) which are shown in blue color, the charging points (CP) represented in yellow color, and the EVs, which are depicted in different colors. The node network shown in Figure 3 comprises one Depot Node (from which all EVs leave), NN= 15 customer nodes of set N = {CN1,..., CN15}, and NS = 5 charging points for EVs of set S = {CP1,...,CP5}.

The EVs begin their path from the Depot Node and travel through the nodes of N and S before arriving at the destination, which is included in the set N. The distance in km between the connected pairs of nodes is shown in Table 1.

It should be noted that two districts, namely P={1,2}, are taken into consideration based on the configuration of the electric power grid. The charging points CP1 and CP2 are located in district 1, whereas CP3, CP4, and CP5 are located in district 2.

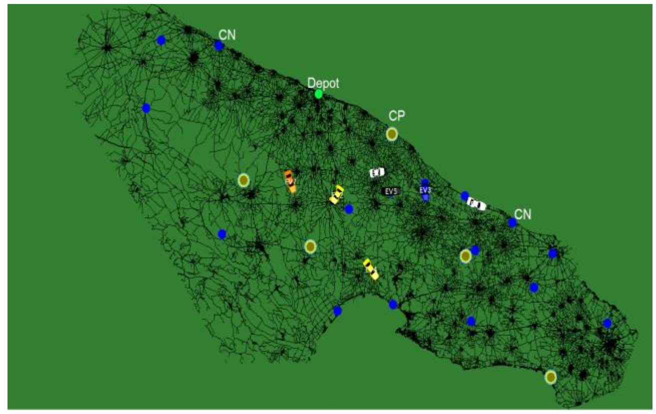

Figure.3 SUMO Simulation view.

Table 1 Distance Between the Connected Nodes

	td_{ij} [km]					
CN1	CN7 22	CN13 59				
CN2	DEPOT 38	CN5 49	CP2 21			
CN3	DEPOT 72	CP3 63	CP4 48			
CN4	CN14 29	CP3 31				
CN5	CN2 49	CN14 27	CP2 53			
CN6	CN12 51	CP4 19	CP5 63			
CN7	DEPOT 64	CN1 22	CP2 38			
CN8	DEPOT 59	CN9 53				
CN9	CN8 53	CN15 32				
CN10	DEPOT 41	CP4 67	CP5 21			
CN11	DEPOT 61	CN13 97	CP1 51			
CN12	CN6 51	CP3 38	CP4 59			
CN13	DEPOT 103	CN1 59	CN11 97	CP1 73		
CN14	CN4 29	CN5 27				
CN15	CN9 32	CP1 66	CP5 73			
CP1	CN11 51	CN13 73	CN15 66			
CP2	CN2 21	CN5 53	CN7 38			
CP3	CN3 63	CN4 31	CN12 38	CP4 68		
CP4	DEPOT 73	CN3 48	CN6 19	CN10 67	CN12 59	CP3 68
CP5	DEPOT 51	CN6 63	CN10 21	CN15 73		

The problem involves satisfying the customers' requests using a set K= {EV1,...,EV7} of NK=7 EVs characterized by the parameters shown in Table 2. In addition, it is assumed that all the EVs in the fleet travel at an average speed of 100 km/h.

Table 2 Electric Vehicles Data

	Electric Vehicles						
	EV1	EV2	EV3	EV4	EV5	EV6	EV7
B_k	3.8	5.5	4.4	2	3.4	3.3	8.3
C_k	300	350	400	250	450	600	300
Q_k	58	100	80	52	52	60	100
g_k	43	22	22	22	43	22	43
end_k	CN1	CN15	CN6	CN12	CN4	CN14	CN7

The network model is developed to consider a 12-hour time horizon divided into 20-minute time slots, resulting in 36 time slots (3 per hour). Within each time slot, both recharging and discharging battery prices are taken into account for the charging points. Additionally, there are specific time windows defined for both the customers and charging points to start their services. The customers are also expected to provide information on their freight demand and the duration of the service required at their node.

The first 4 columns of Table 3 report for each vehicle EVi∈K the routes obtained by the ILP solution in (del Cacho et al., 2022), the travelled distances and the corresponding travel times, respectively.

6.2. Test results

Now, we perform the simulation test in SUMO environment by associating to the EVs the paths obtained by the ILP optimization results of (del Cacho et al.,2022).

The simulations are performed by an Intel processor I9 up to 5.20 GHz, a DDR4 64GB RAM and GPU RTX 3090 24G and simulation goes to an end in about 2 hours in the worst case.

To simulate the travel of EVs in the studied scenario, various parameters such as energy consumption, battery SoC, and delivery schedules are considered into the SUMO simulation model. The EVs follow the paths shown in Table 3 to reach the CNs and deliver their cargo. At the same time, they must consider their energy usage and charging needs at the CPs located along their routes. Furthermore, EVs can maintain energy usage within the district and CP limits, ensuring that energy demand does not exceed supply.

Even if the traveled distances are the same in the two cases, i.e., ILP solution and SUMO simulation, there are some differences in the obtained travel times since the simulation considers the topology of the routes and the traffic conditions. Indeed, the results in the 5th and 6th columns of Table 3 compare the travel times in the optimization and in the simulation (named Scenario S0), when only the topology of the roads are considered without traffic. In such a case the travel time values are very similar. Moreover, three traffic scenarios are simulated considering different traffic conditions obtained by randomly assigning vehicles to the routes: light traffic (scenario S1 with 1000 vehicles), medium traffic (scenario S2 with 2000 vehicles), and intensive traffic (scenario S3 with 5000 vehicles). Then results show that scenario S1 leads to an increase of 11% on average in travel time compared to scenario S0. As traffic volume increases, the travel time also increases, scenario S2 exhibits a higher travel time than S1 and scenario S3 the travel time increases up to 20% for EV7 compared to S0.

Summing up, the results show the basic importance of the simulation to test and evaluate the solutions obtained by optimization models. Indeed, the topology of the roads and the traffic conditions could modify the results and require more realistic route planning strategies.

Table 3 Electric Vehicles Optimal Paths

			Travel distance [km]	Travel time [minutes]				
EV	Intermediate nodes	end_k	ILP/ SUMO	ILP	S0	S1 (1000 vehicles)	S2 (2000 vehicles)	S3 (5000 vehicles)
EV1	CN7	CN1	86	51	50	56	57	61
EV2	CN10 – CP5	CN15	135	100	104	111	113	122
EV3	CP4	CN6	92	75	71	74	78	85
EV4	CN3 – CP3	CN12	173	123	124	131	139	144
EV5	CN2-CN5-CN14	CN4	143	85	88	115	118	127
EV6	CP4-C26-CN12-CP3-CN4	CN14	241	243	249	254	268	297
EV7	CN8-CN9-CN15-CP1-CN11-CN13-CN1	CN7	439	382	385	394	405	428

7. Conclusions

This paper presents optimization and simulation approaches to address the problem of optimizing the routing of the EVs fleets that must perform delivery operations. The optimization problem was formulated and solved in a previous paper by an ILP problem (del Cacho et al., 2022) with the objective of minimizing the travel distance. Charging and discharging costs for the EV logistics fleet are considered also imposing power grid constraints. In particular, the EVs must deliver freight to customers and their energy demand must not exceed imposed bounds at district and charging point levels.

In this paper, we model and simulate the EVRP by using SUMO software and we validate and compare the optimization solution with the results of the simulation. A real case study in the Apulia Italian region is considered and different traffic scenarios are performed in SUMO. The results show that the traffic and the topology of the road can impact on the performance of the system in terms of travel time. Moreover, the results highlight the methodology's scalability and flexibility, as SUMO simulation model effectively handles larger areas and bigger fleet sizes in varying real-world conditions. On the contrary, ILP optimization can solve systems of limited dimentions (maximum 100 nodes of the considered graph). The limitation of the optimization model can be solved by proposing heuristic algorithms able to find solutions for large e complex transportation systems.

Future work will study the route planner of electric vehicles by simulating traffic conditions, accidents, and weather. To this aim SUMO will be used with Traffic Control Interface (TraCi) (Wegener et al., 2008).

Funding

This work is a part of the eCharge4Drivers project. This project has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No 875131. This content reflects only the author's view, and the European Commission is not responsible for any use that may be made of the information this publication contains. The research is also supported by the Italian project POR Puglia FESR 2014-2020 Research for Innovation (REFIN), grant number 8473A73.

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