Sustainable Suburban Mobility: Shared Autonomous Electric Vehicles Day-Ahead Transit and Charging Optimization Using TOU Rates and Renewable Energy

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Abstract

Shared Autonomous Electric Vehicles (SAEVs) offer a transformative solution to bridge the mobility gap in suburban regions where public transportation means are scarce. Integration of SAEVs into the current electrical grid system poses operational challenges due to the anticipated surge in electricity demand for their charging. This paper proposes a strategy based on the Vehicle Scheduling Problem (VSP) for SAEVs to fulfill passenger travel demand and provide optimal charge scheduling such that electric grid constraints are satisfied. A significant portion of this study also investigates the fiscal benefits of utilization of local renewable energy for charging SAEVs. A multi-objective function to minimize charging costs, mobility costs and waiting time for passengers is formulated using mixed-integer linear programming (MILP). The proposed strategy is simulated and analyzed on a coupled traffic and low voltage suburban power grid of the French region considering coordinated charging strategy in the presence and absence of renewable energy. The comparison of results shows that the algorithm optimally schedules charging to maximize the utilization of renewable energy while serving passenger requests.

Keywords: Active distribution networks; Autonomous electric vehicles; renewable energy; charge scheduling; vehicle scheduling problem

1. Introduction

1.1. Motivation and relevant background

Electric mobility is a multifaceted concern encompassing societal, environmental, political and industrial dimensions. Given the projected growth in transportation demand, achieving the Net Zero Emissions by 2050 Scenario requires a substantial reduction in emissions from the transportation sector by 2030 [1]. This reduction can be effectively realized through the electrification of existing transportation modes and the implementation of policies that promote the utilization of renewable energy sources (RES) for electric vehicle charging.

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Nomenclature

Sets	
O	Origin Depot
F	Final Depot
N	Set of all transportation nodes
V	Set of all vehicles
S	Set of all charging stations
H	Set of all time blocks
R	Set of all requests
Decision Variables	
$x_{i,j}^{v}(h)$	1 if vehicle v moves from node i to j during time block h
T_i^v	Service starting time at node i for vehicle v
B_i^v	Battery capacity of vehicle v at node i (kWh)
$\tau_s^v(h)$	Time of charging at station s for vehicle v during time block h
Parameters	
$t_{i,j}(h)$	Travel time between nodes i and j during time block h
e_i	The earliest time for the start of service at node i
l_i	Latest time for the start of service at node i
B^{max}	The total battery capacity of all vehicles
B_o^v	The initial battery capacity of vehicle v
P_s^{rate}	Charging rate at station s (kW)
$P_{load}^{b}(h)$	Power consumption of non-EV load at bus b (kW)
$P_{EV}^{b}(h)$	Power consumption of EV load at bus b
k_i	The number of passengers at node i
$b_{i,j}(h)$	Required battery capacity for travel between i and j during time block h
$C_{i,j}(h)$	Travel cost between node i and j during time block h (€/min)
$C_s(h)$	Charging cost at station s during time block h (€/kWh)
β	Congestion coefficient
α	AEV efficiency (kWh/km)
H_{ij}^{h}	Lower time index of time block h in minutes
H_{ij}^{h+1}	Upper time index of time block h in minutes
B_i^{close}	Battery required to move from node i to the closest charging station

Operating any vehicle requires formal training. However, due to human negligence, many road accidents occur annually which also result in increased traffic congestion. Major corporations worldwide are conducting extensive research to replace human drivers with autonomous vehicles. Currently, autonomous electric vehicles (AEVs) are under development for fleet applications due to low maintenance costs [2] and the ability to cut down mobility costs [3]. In a suburban context, by efficiently pooling passengers, SAEVs can significantly enhance suburban mobility by providing cost-effective and accessible transportation. It is suggested to pilot projects in rural areas before moving into the urban environment [4] because the traffic situation is simpler than in cities and it will be easier for market corporations to build consumer confidence and acceptance of the new technology. Penetration of SAEVs will speed up as a result. Corporations can then take that experience and apply it in cities, always remembering that they will need to adjust their business model in line with the different demands and infrastructure. Partnerships and collaborations will be the name of the game here, enabling the provision of total mobility solutions and the full exploitation of transportation synergies.

However, the widespread deployment of Autonomous Electric Vehicle (AEV) fleets in suburban areas presents a noteworthy challenge. It imposes an added electrical load on a low-voltage distribution network originally not designed to accommodate the daily operational charging needs of such a fleet. To effectively address this issue, a viable scientific approach involves the integration of local renewable energy sources within the AEV charging infrastructure [5]. The AEV fleet operation consists of satisfying passenger requests, reducing their waiting time, and navigation of individual AEVs to an optimal charging location such that operational costs are minimized while simultaneously satisfying the electrical distribution and transportation network constraints.

In this context, numerous studies have been conducted on charging navigation of electric vehicles considering transportation and power systems separately or on coupled power and transport systems. [6] proposes a charging navigation strategy for coupled power and transportation systems incorporating the empty-load ratio and dynamic electricity prices. This strategy utilizes a 'four networks and four flows' model to analyze the intricate dynamics between electric vehicle charging demand, information networks, traffic networks, and the power grid. [7] investigates the potential of SAEVs in urban transport and grid integration. A simulation framework was established to examine SAEV dynamics including size and battery capacity and tested on the transportation demands of Tokyo concluding that even a fleet as small as 10-14% of private cars can provide similar transport services cost-effectively. [8] explores the strategic integration of electric mobility services within Local Energy Communities by leveraging renewable energy sources. Using a mixed-integer linear programming model, the research applies this methodology to a university campus in Italy, aligning mobility assets with end-user needs showing that the bike-sharing service is about three times profitable than car sharing in small geographical areas.

Numerous studies have also been dedicated to using classical transportation problems for solving electric vehicle routing and charge scheduling. [9] transforms the classical Dial-a-ride problem (DARP) for AEVs that encompasses battery management, charging station logistics, and depot selection. DARP was solved to minimize passengers travel costs and waiting time while considering an ideal distribution grid. [10] proposes location routing problems for electric vehicle fleets with time windows and partial recharging. Multi-objective functions, including minimizing total traveled distance and optimizing vehicle and charging station quantities, are explored while integrating routing decisions and charging station siting. Similarly, [11] explores the electric vehicle routing problem with time windows. Unlike conventional models that mandate full recharging, this research permits partial recharging, mirroring real-world EV charging scenarios with shorter durations. The problem was formulated as a 0-1 MILP and computational experiments demonstrate the effectiveness of the proposed approach, demonstrating significant route improvements when partial recharging is incorporated. The literature on DARP for electric vehicles [9] – [11] although can schedule charging and transportation demand simultaneously, neglects the distribution grid constraints and solely focuses on an uncoordinated charging strategy i.e. assuming that AEV is charged as soon as it arrives at a charging station.

While a number of studies have investigated conventional charging infrastructure for (SAEV) fleet systems, others have focused on the use of battery swapping and mobile charging stations to meet charging requirements. [12] addresses the Dial-a-Ride Problem with Electric Vehicles and Battery Swapping Stations (DARP-EV), a practical challenge involving scheduling electric vehicles to serve transportation requests while allowing for battery swaps at recharging stations. The study introduces three Evolutionary variable Neighborhood Search algorithms and highlights the importance of EV technology in practical applications like booking travel requests for patients. [13] introduces a novel mobile charging service for battery electric vehicles (BEVs), aiming to alleviate range anxiety and provide flexibility to BEV drivers. The mobile charging service operator receives booking reservations, including electricity requirements, locations, and time windows and dispatches mobile charging vehicles (MCVs) to perform charging, offering an alternative to fixed charging facilities.

Incorporating both transportation and charge scheduling in a scientific model is complex since constraints from both power and transportation networks need to be satisfied. [14] explores the potential benefits of optimizing trip and charge scheduling for commercial electric vehicle fleets, particularly in the context of Vehicle-to-Grid (V2G). Coordination of trips and charge scheduling can result in increased grid stability. The study presents a mathematical framework for optimal trip scheduling as a mixed-integer linear program. [15] presents a resilience enhancement strategy for networked microgrids (MGs) by incorporating both electricity and transport aspects. The proposed approach addresses high-impact and low-probability events that can disrupt the power system. It employs a hierarchical control approach based on a detailed AC Optimal Power Flow (OPF) algorithm, enabling accurate modeling of technical constraints such as voltage, angle, and power loss, as well as precise power exchange solutions between Micro Grids (MGs). [16] introduces a comprehensive charge scheduling strategy that encompasses factors such as driver preferences, road traffic dynamics, charging station loads and grid efficiency. Utilizing simulation platforms, the research demonstrates that this strategy offers multiple advantages, including reduced local traffic congestion during peak hours, improved safety and economics of power networks, and enhanced charging infrastructure efficiency.

The potential of EVs as a shared mode of public transportation has led to numerous studies on the optimal operation of shared EV fleets. [17] presents an innovative approach to efficiently manage the overnight charging of electric bus fleets. The method optimizes the charging strategy to minimize battery aging costs, a key economic factor for electric bus deployment. The optimization process integrates electro-thermal and aging models of lithium-ion batteries. [18] explores the synergistic potential of SAEVs and renewable energy sources within a grid-connected Virtual Power Plant (VPP) and an isolated microgrid. A sophisticated optimization methodology was devised to manage vehicle charging and discharging efficiently, aiming to minimize overall system costs. The findings, based on scenarios and data from the Tokyo region, demonstrate that optimized SAEV charging substantially reduces costs within the VPP context. [19] presents a practical and scalable approach for optimizing SAEV operations, including smart charging based on real-time electricity prices. Combining independent optimization modules with a simulation model, this framework overcomes complexity and scalability challenges. [20] introduces a novel Dynamic Pricing Scheme (DPS) tailored for a large-scale Electric Vehicle (EV) sharing network, addressing vehicle unbalancing and promoting Vehicle-Grid-Integration (VGI) services while maximizing the system operator's profit. The DPS formulation involves two Price Adjustment Levels (PAL) for each origin-destination station pair, influencing EV-sharing demand and travel times. The model incorporates operational constraints and utilizes data-driven graph filters to improve station-level demand prediction. The proposed studies [17]-[20] explore the interaction between power grid and transportation systems. However, the utilization of local renewable energy sources is not studied in great detail as it can provide a comprehensive solution to grid instability caused by additional AEVs charging load demands.

The use of renewable energy in the context of both shared and conventional EVs has been shown to reduce the additional load demand on the power grid along with the utilization of dynamic pricing and eco-routing strategies for charge scheduling and navigation. This has been investigated in a few studies, although not specifically in the context of SAEVs. [21] presents an optimal siting and sizing of charging stations for the operation of the AEV fleet using local renewable energy generation. [22] presents a multi-criteria framework for managing the charging behaviour of Plug-in Hybrid Electric Vehicles (PHEVs) within renewable-based energy hubs. The framework considers the interests of both PHEV owners and energy hub operators. It optimizes PHEV charging patterns by balancing owner convenience, energy hub profit, and technical grid performance criteria. [23] presents an optimization algorithm for intelligent EV charging to mitigate net-load variance in the presence of an increasing EV and Photovoltaic (PV) penetration, aiming to enhance grid stability. The approach is formulated as a quadratic programming problem, allowing for Vehicle-to-Grid (V2G) charging and considering various constraints such as EV availability, owner charging requirements and voltage stability. [24] introduces a Time-of-Use (TOU) pricing strategy for managing EV clusters through a demand response program. The model optimizes pricing and load patterns to induce demand modifications in response to wholesale prices and user behaviours. [25] addresses the Electric Vehicle Routing Problem (EVRP), focusing on minimizing energy consumption. EVs have limited battery capacity and need to visit recharging stations en route, making conventional vehicle routing schemes unsuitable. The EVRP formulates a mathematical model to minimize energy consumption, considering various constraints related to vehicle and battery capacity, recharging, and energy consumption calculations. The paper introduces an ant colony (AC) algorithm-based meta-heuristics as the solution method for the EVRP.

1.2. Scientific Contribution

The existing literature on this topic primarily focuses on the traditional Pickup Delivery Problems (PDPs) and does not consider the constraints posed by the distribution grid. Alternatively, some studies have solely concentrated on the charging demands of AEVs at charging stations while disregarding the travel requests of passengers. In this paper, we propose a novel framework for the optimal transport and charge scheduling of AEV fleets in a Day-Ahead context, considering the TOU price of electricity to account for peak demand hours and distribution grid constraints. The framework considers a coupled power and transportation network in a sub-urban region as shown in Fig. 1. More clearly, we extend the VSP to incorporate:

- The TOU price of electricity
- The distribution grid's power capacity limit
- Passenger travel requests within specified time windows
- The integration of local renewable energy sources (PV arrays) alongside distribution grid for charging

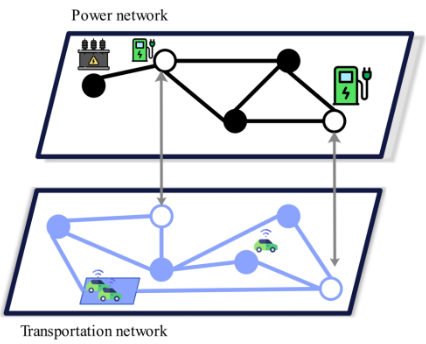

Fig. 1. Coupled Power and Transportation Network.

The rest of this paper is organized as follows. In Section 2, the extended VSP for AEVs is explained. Section 3 provides the mathematical formulation along with constraints. Moving forward, the case study is presented along with results in Section 4. Finally, the conclusions and limitations of the model are discussed in Section 5.

2. Shared Autonomous Electric Vehicles Transportation and Charging Navigation Model

2.1. Model Framework

To formulate an optimal transportation and charging navigation strategy, a comprehensive approach encompassing the power grid, transportation network, information flow, and value flow is devised. The core of this complex model is the AEV fleet manager, which acts as an intermediary, facilitating the interactions among the five main stakeholders, as depicted in Fig. 2. The passengers provide trip requests and preferred pick-up windows. The charging stations provide information regarding charging prices and current grid congestion status. This information is relayed to the AEV fleet manager in a day-ahead manner who then generates an optimal schedule for charging and transportation of passengers.

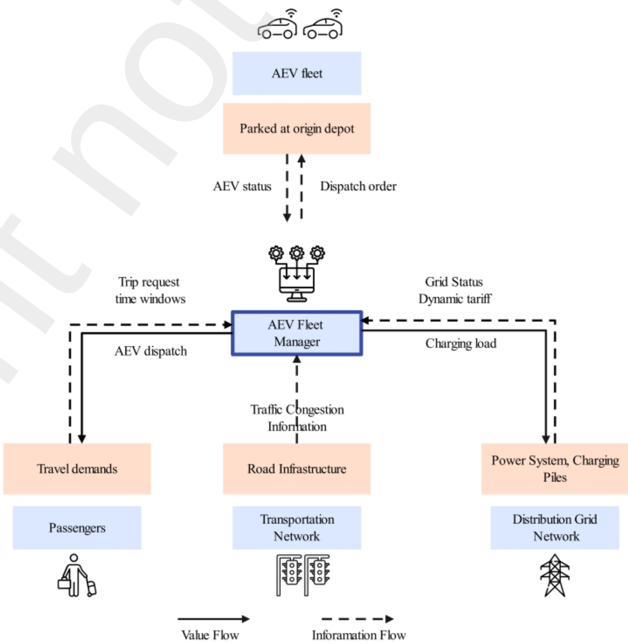

Fig. 2. Transportation and Charging Navigation Model

2.2. Vehicle Scheduling Problem for SAEV

Let's consider a set of n trip requests by passengers denoted as $\{R_1, R_2, ..., R_n\}$ where each request R_i associated with a specific time window during which the corresponding must be picked up. The $[e_i, l_i]$ represents the earliest and latest time for passenger request R_i to be assigned to an AEV. $t_{ij}(h)$ is the time taken during time block h if vehicle fulfills R_j directly after R_i. O and F represent the origin and final depots respectively. Depots are the locations with parking spaces where AEVs are positioned at the beginning and end of the optimization process. Each AEV fulfill certain number of trips when it leaves the origin depot and at the end of the day moves to the final depot. When the battery of any AEV is low, it can move to an optimal charging station S_i among the available total charging stations s in $\{S_1, S_2, \ldots, S_s\}$. Note that each charging site has multiple charging piles depending on the available parking space. For congestion control of AEVs at each individual charging station, power flow constraints are utilized. The maximum power that can traverse through the LV bus at each charging station is known. Hence, the simultaneous charging of AEVs at each charging station should not exceed the number of available parking spaces and maximum power capacity as explained in the following section. Each day is divided into 24 time blocks where each block is represented by h. Let N be the set of trips represented as nodes defined as N = {0} ∪ {1, 2, ..., n+s} ∪ {n+s+1} represent all the trips that could be made including passenger requests and trips to charging station where {n+s+1} represents the final depot. The travel cost between two consecutive nodes which varies based on road congestion during different times of the day can be represented as $C_{ij}(h)$. $C_{ij}(h)$ depends on the travel time between two nodes which is then multiplied by average cost of an uber ride in euro/min to convert it into cost. Considering Day Ahead, the travel time is known in advance. Similarly, the charging cost at charging site s at any time block h can be represented as $C_s(h)$.

Each request and charging station are modelled as a node as shown in Fig. 3. The optimization algorithm determines the optimal time block to visit each node (fulfill request or charge) to minimize charging costs, travel costs and waiting time for passengers while considering distribution grid constraints.

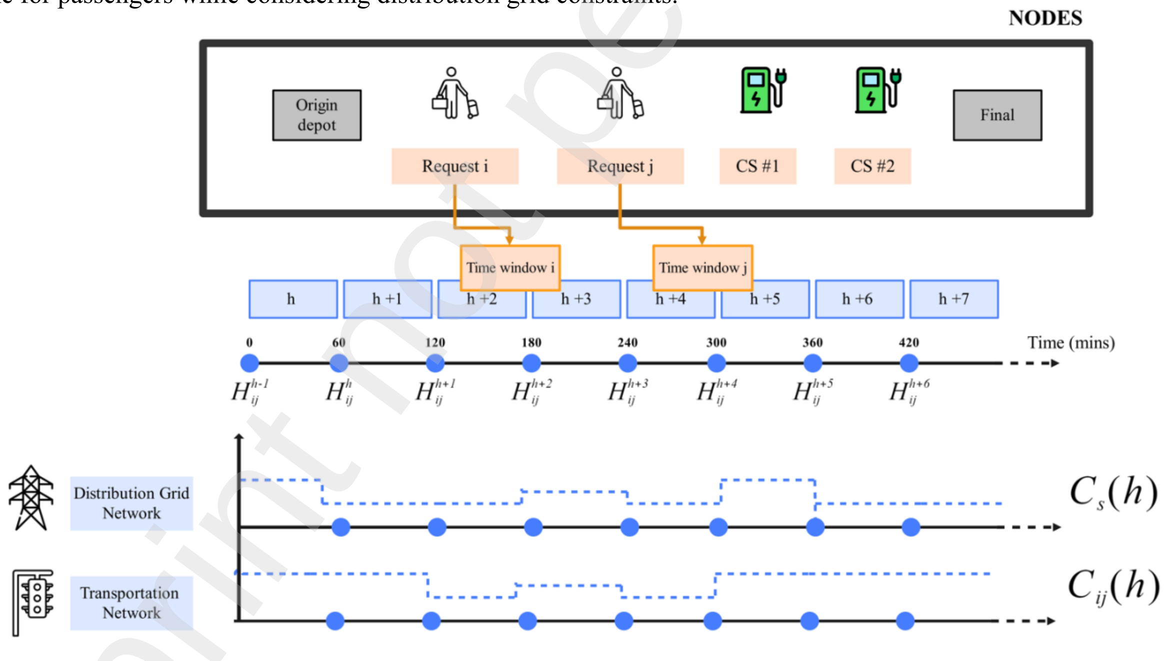

Fig. 3. Request based model of optimization algorithm.

3. Mathematical Modeling

This section presents the detailed mathematical formulation. The optimization problem formulation is introduced at first along with the relaxations needed to make the formulation suitable for MILP optimization [26]. Then, the multi-objective function is provided.

3.1. Optimization Problem Formulation

3.1.1. AEV Flow Constraints

These constraints guarantee the optimal flow of individual AEVs to their respective locations within each time block. The binary decision variable $x_{i,j}^{v}(h)$ equals one when a vehicle is scheduled to move from node i to j during time block h. Each vehicle must leave the origin depot and either pick up the passenger, proceed to a charging station or move to the final depot during the optimal time block h as described in Equation (1). Each AEV should return to the final depot at the end of the day, as stated in Equation (2). A key aspect of vehicle movement is that any vehicle entering a particular node should also leave it, as indicated in Equation (3). Equation (4) ensures that all the requests must be fulfilled.

$$\sum_{h\in H}\sum_{j\in R\cup S\cup F} x_{O,j}^{v} = 1 \qquad \forall v\in V \tag{1}$$
$$\sum_{h\in H}\sum_{i\in R\cup S\cup O} x_{i,F}^{v} = 1 \qquad \forall v\in V \tag{2}$$
$$\sum_{h\in H}\sum_{j\in N} x_{i,j}^{v} - \sum_{h}\sum_{j\in N} x_{j,i}^{v} = 1 \qquad \forall v\in V, i\neq j \tag{3}$$
$$\sum_{v\in V}\sum_{h\in H}\sum_{j\in N} x_{i,j}^{v} = 1 \qquad \forall i\in R \tag{4}$$

3.1.2. AEV Battery Constraints

Equation (5) initializes each vehicle's battery state to its maximum capacity at the beginning of the optimization. Equation (6) ensures that AEVs have sufficient battery capacity to reach nearest charging stations. The battery capacity update during travel between nodes is governed by Equation (7), (8) where b_{ij} (h) represents the required capacity to move from node i to j other than station nodes. M is a big constant used for linearization purposes. Equation (9), (10) ensures that the battery level of an AEV is updated according to the time spent at charging station.

$$B_O^v \leq B^{max} \qquad \forall v\in V \tag{5}$$
$$B_o^v \geq B_i^{close} \qquad \forall v\in V, i\in N \tag{6}$$
$$B_j^v \geq B_i^v - b_{ij}(h) - M\left(1-x_{ij}^v(h)\right) \qquad \forall v\in V, i,j\in N\backslash S, h\in H, i\neq j \tag{7}$$
$$B_j^v \leq B_i^v - b_{ij}(h) + M\left(1-x_{ij}^v(h)\right) \qquad \forall v\in V, i,j\in N\backslash S, h\in H, i\neq j \tag{8}$$
$$B_j^v \geq B_s^v - b_{sj}(h) - M\left(1-x_{sj}^v(h)\right) \qquad \forall v\in V, j\in N, s\in S, h\in H, j\neq s \tag{9}$$
$$B_j^v \leq B_s^v - b_{sj}(h) + M\left(1-x_{sj}^v(h)\right) \qquad \forall v\in V, j\in N, s\in S, h\in H, j\neq s \tag{10}$$

3.1.3. Temporal Constraints

Equation (11) ensures that each passenger request is met within its specified time window. Equation (12), (13) sets lower and upper bounds for starting the service at node j after departing from node i while considering the travel time between nodes respectively. When a vehicle is scheduled to serve a node during time block h, Equations (14) and (15) dictate that the service commencement should align with the limits of that time block. After visiting a charging station, Equation (16), (17) sets the minimum starting time for service at node i. Furthermore, Equation (18) defines an upper bound for charging time when a vehicle starts its service at station s at T_s^v, as shown in Fig. 4.

$$e_i \leq T_i^v \leq l_i \qquad \forall v\in V, i\in R \tag{11}$$

$$T_j^v \geq T_i^v - t_{ij}(h) - M\left(1 - x_{ij}^v(h)\right) \qquad \forall v \in V, i,j \in N \backslash S, h \in H, i \neq j \tag{12}$$
$$T_j^v \leq T_i^v - t_{ij}(h) + M\left(1 - x_{ij}^v(h)\right) \qquad \forall v \in V, i,j \in N \backslash S, h \in H, i \neq j \tag{13}$$
$$T_j^v \geq H_{ij}(h) - M\left(1 - x_{ij}^v(h)\right) \qquad \forall v \in V, i,j \in N, h \in H, i \neq j \tag{14}$$
$$T_j^v \leq H_{ij}(h+1) + M\left(1 - x_{ij}^v(h)\right) \qquad \forall v \in V, i,j \in N, h \in H, i \neq j \tag{15}$$
$$T_j^v \geq T_s^v + \tau_s^v(h) + t_{sj}(h) - M\left(1 - x_{sj}^v(h)\right) \qquad \forall v \in V, j \in N, s \in S, h \in H, j \neq s \tag{16}$$
$$T_j^v \leq T_s^v + \tau_s^v(h) + t_{sj}(h) + M\left(1 - x_{sj}^v(h)\right) \qquad \forall v \in V, j \in N, s \in S, h \in H, j \neq s \tag{17}$$
$$\tau_s^v(h) \leq H_{ij}(h+1) - T_s^v + M\left(1 - x_{sj}^v(h)\right) \qquad \forall v \in V, j \in N, s \in S, h \in H, j \neq s \tag{18}$$

3.1.4. Power Flow Constraints

These constraints guarantee that the AEV flows are consistent with the network's physical limitations. The active powers at each bus are defined as follows:

$$P_b(h) = P_{PV}^b(h) - P_{load}^b(h) - P_{AEV}^b(h) \times x_{ib}^v(h) \qquad \forall v \in V, i \in N, b \in S, h \in H, i \neq b \tag{19}$$

where $P_b(h)$ is the active power of Bus b, at time block h. Reactive power flows are modelled similarly. The total power at Bus b, at instant time block h, is equal to the sum of the injected PV power $P_{PV}^b(h)$, the drawn load power $P_{load}^b(h)$, and the EV power. Term $P_{AEV}^b(h)$ is the expected day-ahead active power for the AEV connected to charging station at Bus b. The linearized power flow equations are given as follows [27]:

$$P_{ab}(h) = G_{ab}\left(V_a(h) - V_b(h)\right) + B_{ab}\left(\theta_a(h) - \theta_b(h)\right) \tag{20}$$
$$Q_{ab}(h) = B_{ab}\left(V_a(h) - V_b(h)\right) + G_{ab}\left(\theta_b(h) - \theta_a(h)\right) \tag{21}$$

where the conductance and susceptance values of the electrical line between Buses a and b are denoted by G_{ab} and B_{ab}, respectively. $V_a(h)$ and $V_b(h)$ represent the voltages at Bus a and b, while θ_a and θ_b are the respective phase angles. Additionally, it is assumed that the per unit values of the voltages are approximately equal to 1 (i.e., $|V| \approx 1$).

Active power, reactive power, and bus voltage at each bus should remain within specified limits. Furthermore, there is a maximum current limit for electrical lines, denoted as I_{ab-max}. These constraints are stated in Equations (22)-(25).

$$P_{a,min} \leq P_a(h) \leq P_{a,max} \tag{22}$$
$$Q_{a,min} \leq Q_a(h) \leq Q_{a,max} \tag{23}$$
$$V_{a,min} \leq |V_a(h)| \leq V_{a,max} \tag{24}$$
$$|I_{ab}(h)| \leq I_{ab,max} \tag{25}$$

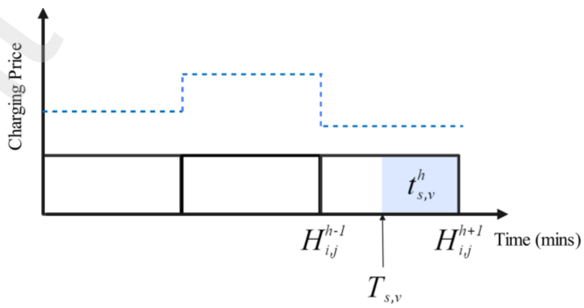

Fig. 4. Charging during time block h

3.2. Multi-Objective Function

A multi-objective function is defined to minimize charging costs, travelling costs, and passenger waiting time. The charging rate of all charging stations remains constant. The cost of charging is determined by the duration spent at the charging station $\tau_s^v(h)$ as expressed in the following equation

$$Obj_1 = min \sum_{h\in H} \sum_{v\in V} \sum_{i,s\in N} (P_s^{rate} - P_{PV}^s(h)) \times \tau_s^v(h) \times C_s^v(h) \times x_{i,s}^v(h) \quad (26)$$

The travelling cost between two nodes during time block h is denoted as $C_{ij}^v(h)$. For AEV fleet manager, it is important to travel at most suitable time when costs are minimal.

$$Obj_2 = min \sum_{h\in H} \sum_{v\in V} \sum_{i,j\in N} C_{ij}^v(h) \times x_{i,j}^v(h) \quad (27)$$

A small penalty cost ƛ in euros per min is added for ensuring the quality of service of passengers. The wait time of passenger is calculated as $(T_i^v - l_i)$.

$$Obj_3 = min \sum_{h\in H} \sum_{v\in V} \sum_{i,j\in N} \left(\max 0, (T_i^v - l_i\right) \times ƛ) \quad (28)$$

Different weights are assigned to each objective based on the scenarions considered in the case study.

$$Obj_{min} = w_1 Obj_1 + w_2 Obj_2 + w_3 Obj_3 \quad (29)$$

4. Case Study

4.1. Transportation Network

A traffic road network of French suburban area of 25 km^2 is selected. This network encompasses five small communes located in France including Forest-sur Marque, Gruson, Chéreng, Willems, Baisieux and Tressin. Based on typical weekly traffic patterns from [28], the parking lots nearest to traffic-intensive roads were selected. The parking location and space were acquired from Open Street Maps [29]. 30 transportation nodes were selected that which people can travel via an AEV. During data preprocessing, the provided origin-destination pairs from passengers are systematically transformed into a trip-based model, as depicted in Fig. 5. Subsequently, these structured trips can be reverted to their respective initial geospatial coordinates or locations in post-processing. This is done to represent the origin and destination as a single node to reduce complexity. Locations of charging stations were distributed across nodes 26, 27, 28, 29. The parking lots with the highest parking capacity were considered as the origin and final depots. Due to the low grid capacity of suburban networks, Level 2 chargers are considered. The detailed parameters of each charging station can be found in Table 1.

4.2. Distribution Grid

A small-scale suburban low-voltage distribution network is modelled [30] using data on the location and length of overhead LV lines [31]. A graphical representation of the coupled network is shown in Fig. 6. This rural network consists of 95 single-phase households with four public charging locations.

Table 1. Parameters of each charging station

Charging Station Number	**CS1**	**CS2**	**CS3**	**CS4**
Number of Charging Piles	4	5	5	3
Charging Power (kW)	7.4	7.4	7.4	7.4
Charging efficiency (%)	92	92	92	92

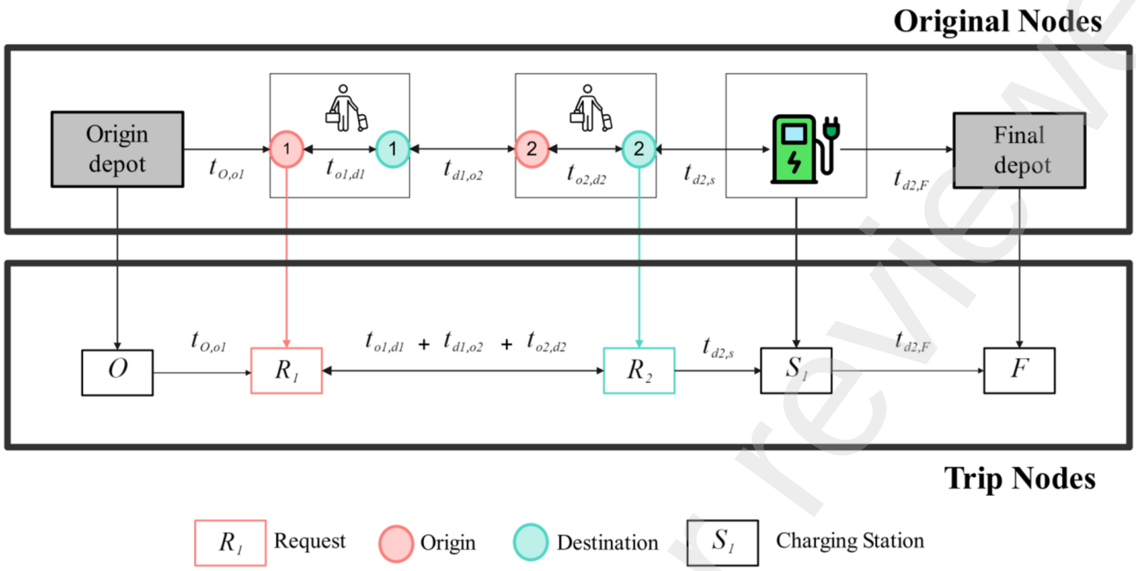

Fig. 5. Trip-based model generation

4.3. AEV model

It is assumed that there are 50 AEVs at the origin depot to provide passenger services. For this suburban AEV fleet, the battery capacity is relatively low compared to its urban counterparts. It is assumed that all AEVs have a battery capacity of 15kWh and an efficiency of 0.25 kWh/km. The battery level required to travel between two nodes is calculated based on this efficiency. The average speed of all AEVs is assumed to be 40 km/hr. To introduce traffic congestion, a congestion parameter β is introduced, which directly impacts the average speed and travel time between nodes. Consequently, the cost of travel also increases during congestion hours. The average speed during congestion hours is calculated by dividing 40 km/hr by the congestion coefficient. The congestion coefficient during different hours is provided in Table 2.

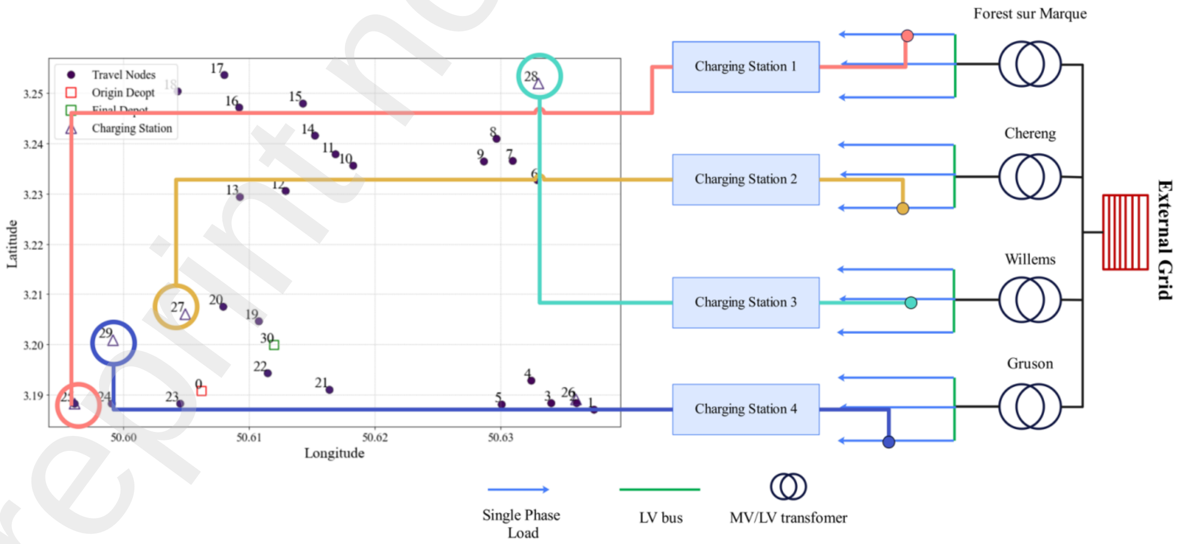

Fig. 6. Line diagram of the studied distribution network

Table 2. Congestion Coefficient for different road conditions

Traffic Conditions	Smooth	Slightly congested	Congested
Congestion coefficient	1	1.5	2
Average speed	40	26.67	20
Hours	[0-6] [16]	[10-15]	[7-9] [17-20]

4.4. Data Sets

The data on typical aggregated non-EV load demand at buses connected to charging station nodes in July were selected from Ausgrid [32], as shown in Fig. 7a. The TOU price data from EDF [33] is selected as charging costs. Based on the occurrence of load demand peaks at buses where public charging stations are connected, the TOU peak, off-peak, and mid-peak price data is set as charging costs as shown in Fig. 7b. To study the impact of renewable energy specifically on charging navigation, it is assumed that each charging station is integrated with local PV panel of a size equivalent to average parking space of a car i.e. 16 meters square. Considering efficiency “þ” of 15% for PV panels and using the solar irradiance “*ķ*” in W/m^2 from [34], the typical PV production during a sunny day in July is calculated using Equation (30) and shown in Fig. 8.

$$P_{PV}^{s}(h) = \text{ķ} \times 16 \times \text{þ} \tag{30}$$

4.5. Analysis of simulation results

4.5.1. Charging and transport navigation of AEVs

To assess the effectiveness of the AEV guidance strategy, three schemes are established:

- Scheme 1: Charging stations are selected according to the lowest charging costs. For this purpose, the objective function associated with charging costs receives the highest weightage.
- Scheme 2: Select the closest charging station. In this case, the objective function associated with travel costs is given the highest weightage.
- Scheme 3: Improved Quality of Service. This scheme gives the highest weightage to minimize the waiting times for passengers. A penalty cost of ƛ = 0.3 euros/min for waiting time is set.

The MILP was solved using CPLEX python on an intel core i-7 with 16 GB memory. A fleet of 50 AEVs are selected for simulation. For transport navigation, the list of requests along with their respective time windows are provided in Fig. 9. Out of the 50 AEVs, 35 AEVs are considered out of service due to their low battery capacity of 30 percent. For base case, we solve the optimization model from 6:00 in the morning to 12:00 in the afternoon without renewable energy. For studying charging navigation, the 35 AEVs are also optimized to charge up to 50 percent of their maximum battery capacity.

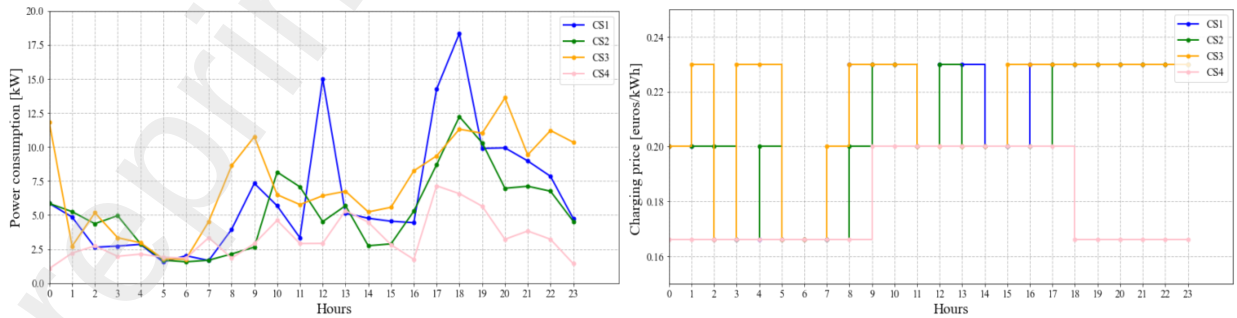

Fig. 7. a) Non-EV load distribution b) Charging costs

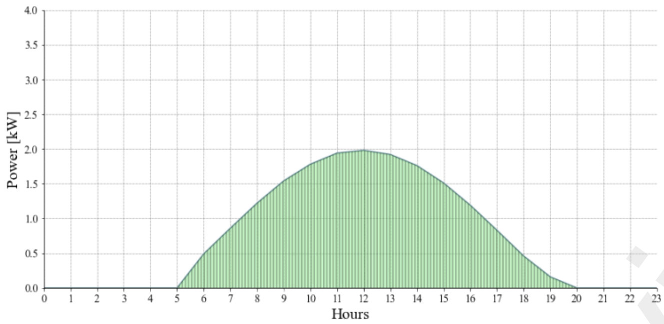

Fig. 8. Typical sunny day solar PV production

The efficiency of each individual scheme is evaluated based on five key performance indicators (KPIs) and results are provided in Table 3.

- Total charging costs of the system: C_{cg}
- Total travel costs of the system: C_{tr}
- Total costs of the system: C_{total}
- AEV load demand during peak hours (6-9 hr): $P_{AEV-peak}$
- Quality of service (passengers served within their preferred their time windows): Q_{OS}

From Table 3, it can be concluded that the proposed strategy gives optimal results as scheme 1 has the least charging cost among all the other schemes. Similarly scheme 2 has the least travel cost. However, scheme 2 and scheme 3 have similar results for all KPIs. It is because both schemes emphasize on the movement of AEVs rather than charging. Scheme 1 has the highest total cost because while finding the charging station with the lowest price, the AEVs tend to travel to the farthest charging station increasing the travel cost. Hence a balanced approach is required to minimize the costs.

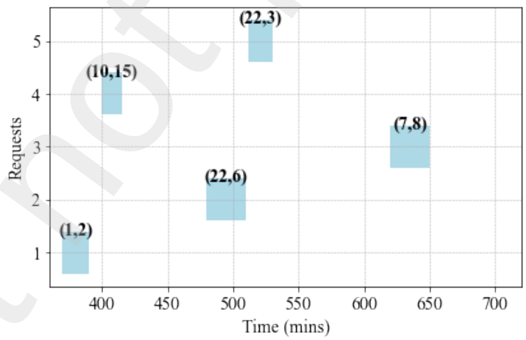

Fig. 9. Passenger requests with time windows

Table 3. Charging and transport navigation analysis

Charging Strategy	Scheme	Weight distribution (w_1, w_2, w_3)	C_{cg} (euros)	C_{tr} (euros)	C_{total} (euros)	$P_{AEV-peak}$ kW	Q_{OS} %age
TOU price of charging	Scheme 1: Least expensive to charge	1000, 1, 1	26.674	150.90	177.574	155.4	100
	Scheme 2: Least travel expense	1, 1000, 1	29.665	141.59	171.255	88.88	100

	Scheme 3: Highest quality of service	1, 1, 1000	29.44	141.88	171.38	88.8	100

Fig. 10 provides the hourly charge requests at each charging station for each scheme. For scheme 1, charging station 1 and 4 serve 33 charging requests. Note that an individual AEV can have multiple charging requests at different stations. This is because charging station 2 is the closest charging station to the depot as shown in Fig. 2 and has low charging prices as compared to other charging stations during hour 7, 8 and 9. The second most utilized charging station for scheme 1 is 4. It is because it has the least charging price as shown in Fig. 7a. Scheme 2 has similar charging requests pattern to scheme 3. It can be concluded that scheme 1 outperforms scheme 2 and 3 in regard to charge scheduling. The pickup times for passenger requests for all schemes are provided in Table 4.

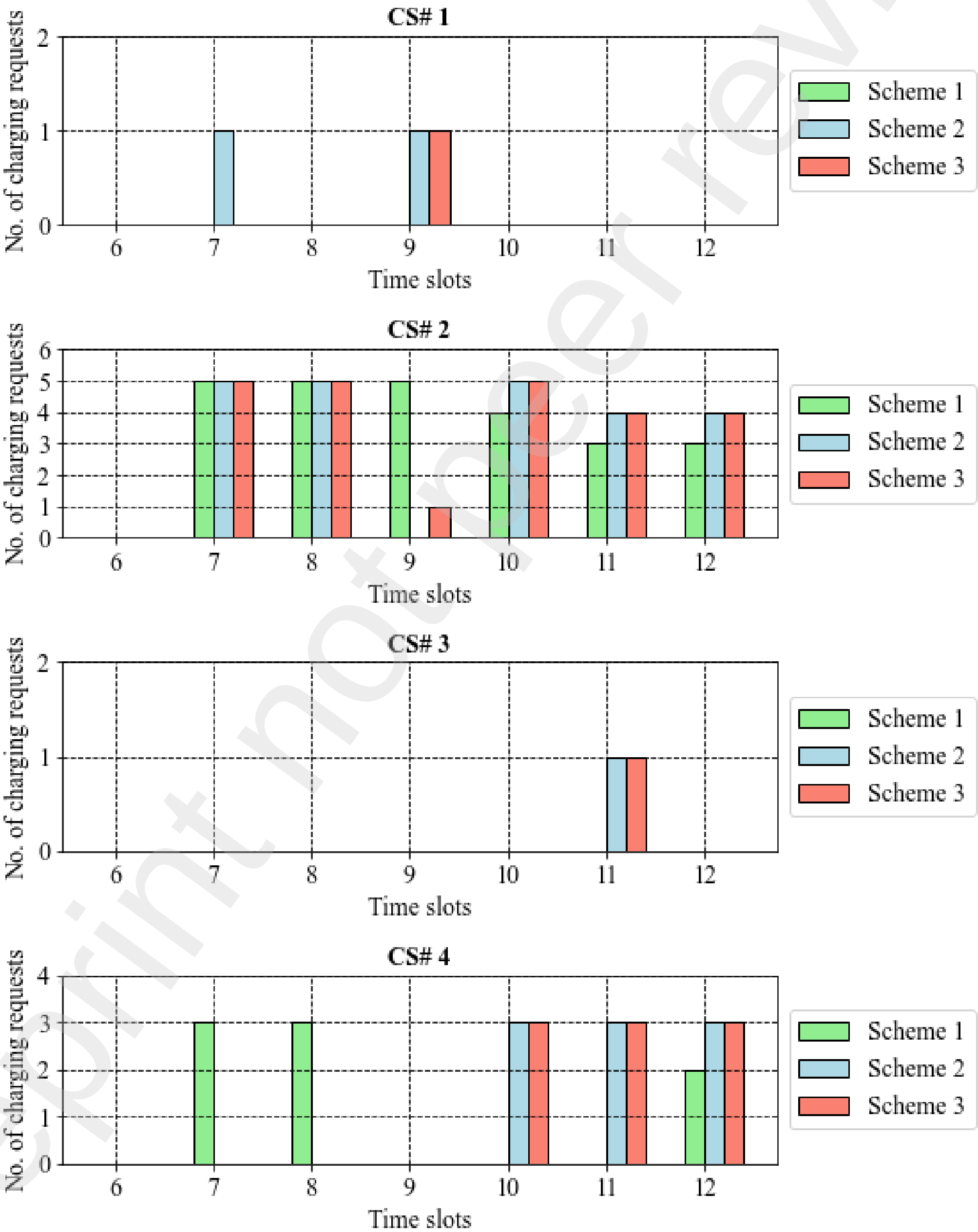

Fig. 10. Hourly charge requests at charging stations

Table 4. Optimal passenger pickup time

Request	Earliest pickup time	Latest pickup time	Optimal pickup time		
			Scheme 1	**Scheme 2**	**Scheme 3**
1	370	390	377.5	370	377.55
2	480	510	480	480	491.099
3	620	650	625	635.27	649.875
4	400	415	405	400	400
5	512	530	516.2	512	512

It is concluded from Table 4 that the quality of service remains one hundred percent for all schemes. An interesting observation is made that during Scheme 1 and Scheme 2, the passengers are serviced earlier than in scheme 3. However, it has no impact on the quality of service.

4.5.2. Impact of renewable energy on distribution grid

Renewable energy plays a crucial role in reducing charging costs as well as additional load demand on low-voltage distribution grid. Based on KPIs defined in previous section, results are obtained while assuming the PV production as shown in Fig. 8. Table 5 provides comprehensive analysis for different schemes in the presence of renewable energy. It is concluded that the charging costs are significantly reduced when compared to Table 4 for all schemes. Renewable energy helps in reducing 44% peak load AEV demand during scheme 3 as well. Since charging station 2 is the most utilized charger due to its close proximity to origin and final depot, the AEV load demand under scheme 1 and 2 with PV production for charging station 2 are shown in Fig. 10.

During scheme 1, it is observed that optimization solver selects peak sunlight hours 10:00 -12:00 to charge AEVs when PV production is considered as compared to prior solution of hours 9:00 – 11:00 when no PV was considered. The same pattern is repeated for scheme 2 as well where optimization solver selects hours 9:00 -12:00 instead of 6:00 - 9:00 hours for charging AEVs.

Table 5. Charging and transport navigation analysis with RES

Charging Strategy	Scheme	Weight distribution (w_1, w_2, w_3)	C_{cg} (euros)	C_{tr} (euros)	C_{total} (euros)	$P_{AEV-peak}$ kW	Q_{OS} %age
TOU price of charging with RES	Scheme 1: Least expensive to charge	1000, 1, 1	20.97	153.99	170.2	155.4	100
	Scheme 2: Least travel expense	1, 1000, 1	22.480	141.59	164.07	88.88	100
	Scheme 3: Highest quality of service	1, 1, 1000	22.240	141.88	164.07	44.44	100

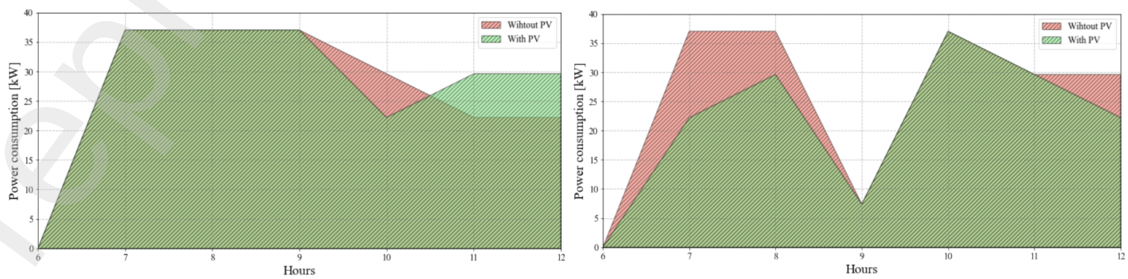

Fig. 11. AEV load demand at charging station 2 under a) Scheme 1 b) Scheme 2

5. Conclusion and future work

This paper proposes a novel framework to optimize the transportation and charge scheduling of Shared Autonomous Electric Vehicle Fleet, considering coupled power and transportation networks. Passenger requests are modelled as trips with specified time windows, extending the classical vehicle scheduling problem to incorporate autonomous electric vehicles. A multi-objective function was implemented using MILP to minimize charging costs, travel costs, and passenger waiting time, applying it to a suburban area in France. The case study investigates a coordinated charging strategy for a fleet of 50 AEVs in the presence and absence of PV under different charging and transportation navigation schemes. The result shows:

(1) The proposed strategy can effectively service passenger requests and schedule charging while considering grid congestion.
(2) Integrating PV arrays with charging stations reduces the charging costs and increases renewable energy utilization significantly.
(3) Giving preference to an objective function regarding charging costs or travel costs may reduce these costs but result in higher total costs. A balanced approach is needed for optimal solutions.

Through the analysis of integration of renewable energy, it can be seen that the charging decision made by optimization solver can be sub-optimal if there is uncertainty in the decision-making progress. In further research stochastic modelling of uncertainties regarding PV arrays, residential load demand and passenger arrival times will be introduced.

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