Semi-stochastic load model for heavy goods electric vehicles depot charging considering the potential for demand side management

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Semi-Stochastic Load Model for Heavy Goods Electric Vehicles Depot Charging Considering the Potential for Demand Side Management

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***Abstract*— Research and development on the electrification of road vehicles have been dominated by light-duty passenger vehicles and vans. Recent developments in Electric Vehicle (EV) technology, however, are bringing attention to the electrification of heavy-duty vehicles and raising questions about fleet charging profiles and related implications for power networks. In this paper, a semi-stochastic model is developed for the simulation of Heavy Goods Electric Vehicle (HGEV) depots' charging demand profiles. The modelling of daily fleet charging profiles, managed and unmanaged, are addressed in this paper to investigate the characteristics of the typical load profile and the potential of the demand side management in response to price signals. Issues of charging constraint and optimal depot charging, from a power network perspective, have been applied to understanding how the fleet demand is met. The findings of this work pavs the way to study the impacts of heavy-duty vehicle electrification on the network and the maximum power demanded from the grid based on the charging strategies taken. Adoption of flexibility programs or network reinforcement plans around sites of fleet charging can be informed by this study - helping to mitigate the overall stress that the grid could face due to increasing future demands.**

Keywords*— *Electric Vehicle, Charging Station, Load Modelling, Demand Side Management.

I. Introduction

Road transport in the UK remains largely based on fossil fuels and accounts (pre-Covid) for over 70% of all transport-related energy consumption. Of this, Heavy Goods Vehicles (HGV) energy use accounts for 17% and has demonstrated a long-term upward trend (growth) in energy consumption since the 1970s. More recently, the impact of Covid on road transport has shown a less pronounced impact on HGV and Light Goods Vehicles (LGV) use than that on cars [1]. These trends highlight challenges of emission reduction associated with HGV transportation and the need to deal with this growing and seemingly critical demand. The electrification of transport, here fuelling HGV powertrains with electric batteries and electricity derived energy vectors such as hydrogen and ammonia, is promoted as an important development in addressing Green-House Gas (GHG) emissions [2].

It is anticipated that transport electrification will bring challenges to the electricity network. The severity of the implications is a complex phenomenon that mainly depends on the capacity of existing infrastructure, demand level and the charging methods adopted by the fleet operators. An invaluable amount of analytical data and collective experience, both in industry and academia, have been acquired since the commencement of the electrification of light-duty vehicles (including passenger cars and vans). However, the electrification of heavy-duty vehicles is less developed due to the challenges of power and range performance of battery technology but has started to get wider attention.

One of the few works on heavy goods electric vehicles from a power grid perspective, which considers load/demand characteristics, has been conducted by the USA National Renewable Energy Laboratory (NREL) [3]. The main concern of this research was the grid impact analysis of Heavy Goods Electric Vehicle (HGEV). Regarding the Tesla HGEV productions, the authors assumed that the long-haul trucks with high battery capacities provide an average rate of 375 miles on a charge available. As a result, it is stated that charging the high-capacity batteries required extremely fast chargers to reduce the charging time. It might lead to adding a multi-megawatt very high loading to the network. This loading is consistent with a public charging station that provides the capacity of parallel charging of HGEV at the same time. In reference [3], an agent-based modelling approach has been used to model the load profile of charging stations. These stations are facilitated by DC fast-charging system, which has been analysed earlier in [4].

In [3], it is also highlighted that the performance of electric vehicles (heavy or light) and the related charging stations modelling is dependent on determining defined properties. The property set is introduced in [5] and include battery capacity, arrival time, initial State Of Charge (SOC), final desired SOC or energy demand and a power acceptance curve. Reference [5] defined arrival time and SOC as random variables governed by probability distributions obtained in this research via a combination of real telemetry data analysis and EV systems. Reference [3] also emphasised that the charging demand curve of a vehicle and its battery pack is a chemistry-dependent process and affected by the complex control algorithms of Battery Management Systems (BMS). Sample demand profiles of the stations are determined assuming the availability of various HGEV charging ports (1, 5 & 10) with traffic of 30 vehicles per day.

In [6], the authors investigate the electrification of land transport in a fully renewable, complex electricity network. This work is developed for the national electricity market of Australia (on an hourly energy balance scale) with full uptake

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of electric vehicles for land transport (except trains). Train demand is calculated from the average daily travelling distance and the energy consumption per distance travelled along with energy losses. The land transport modes involved in this research were categorised as rail, non-freight carrying trucks, rigid trucks, buses, motorcycles, articulated trucks, light commercial vehicles, and passenger vehicles. The charging strategies were categorised into flat (uniform charging load 24 h per day), daytime charging (charges during daytime e.g. day 08 -17), peak-low rate charging (charges during the evening peak, e.g. 4-21, at a low-power rate), night time (charges during the night after the evening peak period, e.g. 21-09), end of the trip (charges as soon as the trip finishes) and pick high rate charging (charges during the evening peak, e.g. 16-21 at a high-power rate).

The competitiveness of electric vehicles is evaluated in [7] using the advantage of a new cost-benefit for everyday usage compared to other options. In [8], the authors argue that little attention is drawn to the study of topological characteristics of traffic networks, although this is highly likely to have a great influence on the macroscopic characteristics of the electric vehicle group. Therefore, the research applied a typical approach study on the impact of the traffic network and charging profiles of large-scale electric vehicle groups. Tempo-spatial distribution of this group of electrical vehicles is employed via a multi-agent technique to model adaptive systems considering the electric vehicle group, traffic network and charging stations. Their findings illustrate the charging power of regional HGEV follows a logarithmic normal distribution while the mathematical expectation of probability density deliver a periodic performance.

There are gaps in understanding of both deployment of the emerging HGV technologies and the interaction with the power network. Questions arise concerning the energy demand level expected from heavy-duty vehicle fleets and the difference between their charging behaviours and light-duty vehicles. For the HGV operators, there will be a significant choice to be made between on route charging and depot-based charging. Solely depot-based options will only suit some fleets. Where depot-based charging is viable, and vehicles have material idle time at the depot there will be opportunities to manage to charge to minimise fuel cost and network impacts simultaneously. A range of approaches have been adopted in the literature to simulate charging loads [9-14]. Broadly these can be grouped into three main categories, the deterministic, stochastic and artificial intelligence-based approaches. As expected, each of them considers various sub-methods. Depending on desire, further details are available in [15, 16].

The HGEV depot and the fleet charging have similarities with the light vehicle and public station, although remarkable differences. As with light vehicles and public charging stations, HGEV fleet charging is influenced by some key stochastic variables, e.g. daily travelling distance. However, the management rules of HGEV depots change the nature of some parameters commonly deemed stochastic variables in public station modelling to parameters that can be deemed effectively deterministic, e.g. the state of charge and starting time of charging/time of arrival. Therefore, addressing the gap, this work benefits the advantage of a new semi-stochastic approach to model HGEV depot charging demand and evaluate the capacity of demand side management in the case.

Furthermore, considering the remarkable differences between the HGEV and light EVs in battery capacity and consequently the required time of charge, as well as considering the rating power of chargers commonly used for this task, make it severe required to specify research on analysing HGEV charging demand separately. The time schedules are common in the operation of the depots emphasises this necessity which is answered in this research. Also, the central management system of depots makes them highly capable of demand-side management. Therefore, evaluating the capacity of price-based management in HGEV depots is the other question that is answered in this research. Having managed and unmanaged HGEV load profiles available is also required to evaluate the grid impacts of HGEV electrification in the future research.

II. Overview of the Proposed Analysis

In order to develop the modelling approach, a typical case is presented in this research which represents a fleet with a clear working day and overnight off-duty period. This can be expected to be one of the cases with the greatest opportunity for taking advantage of charging management. As evidenced earlier, the charging demand profile of a fleet of vehicles depends on many factors, including the size of the fleet, distance travelled, specific energy consumption, battery capacity, charge point power, environmental factor, and the charging strategy. Here, it is assumed that the fleet returns to the depot at the end of its duty, and the vehicle batteries are fully recharged over the night to be ready for the next daily operation.

To quantify the capacity of the demand side management of the fleet, model has been developed with the consideration of two charging strategies: managed and unmanaged charging. In the first (unmanaged) strategy, the model considers the main parameters of the fleet and the depot along with the start and end times for the charging events. These times are set considering the State Of the Charge (SOC) of the fleet and the available charging power at the depot. Demand profiles for individual vehicles and the total demand of the fleet, which is covered by the network during the recharge time of the fleet, are determined. In the managed strategy the half-hourly electricity market price index has been used as a control signal to coordinate the recharge of the fleet to minimise electricity cost assuming access to dynamic Time of Use (ToU) pricing.

It is worth mentioning that the 'state of charge' function produces the SOC vector based on the distance travelled, and the specific energy consumption of a typical vehicle as in Fig.1. The generated SOC vector is stored in an Excel file to be used in the vehicle charging function.

Fig. 2. shows the structure of the depot load profile modelling. It is comprised of the main controller and the parts function with their specific roles.

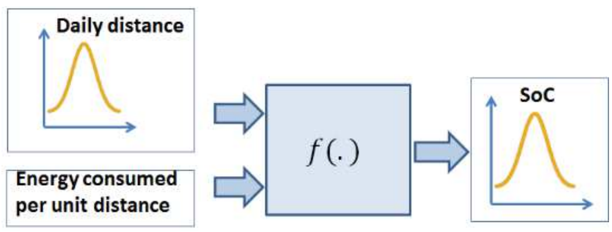

Fig. 1. State of charge for a given fleet size

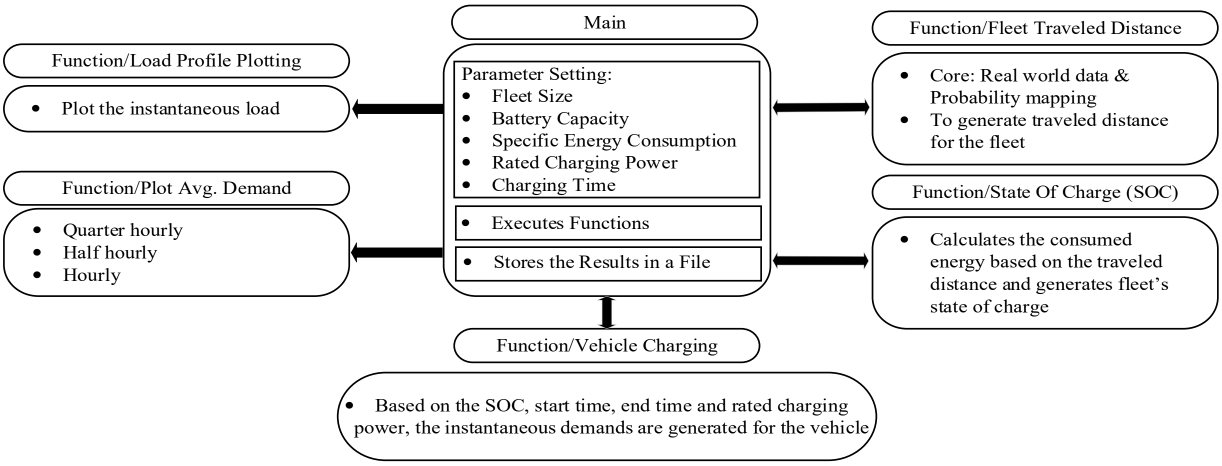

Fig. 2. Structure of the proposed depot charging model.

The "fleet travelled distance" block functions stochastically to produce a set of travelled distance values equal to the fleet size using the daily travelled distance distribution. The output of this function is a vector with the same size of the fleet that gives the distances travelled by the vehicles in completing their daily operations since the time they depart the depot until they return to the depot.

The specifications for the electric trucks in this research are assumed considering values reported by vehicle manufacturing companies [17-21]. The 'load profile plotting' function generates the instantaneous load of the fleet demand based on the input parameters and the averaged consumptions (according to the desired average demand type).

The "vehicle charging function" models the load profile of the fleet based on the SOC of the fleet, the charging power of the depot, and the allocated charging time. The depot's charging capacity is the total power of parallel charging points available at a station. In the current approach, it is defined as the multiple of the fleet's vehicles, the rating power of the charging points and a coefficient identified here as the depot factor. For example, if this is the case that the depot has enough electrical capacity for the whole fleet's vehicles to be plugged in and charged simultaneously, then the depot factor is equal to '1'. While, for the case that the depot does not have enough capacity for recharging the whole fleet simultaneously, the depot factor is less than '1'. Fig. 3. illustrates the flowchart of the depot charging model.

III. Price Based Charging Optimisation

Large scale electrification of the transport sector will bring challenges to the grid in terms of the demand level and capacity limitation of grid infrastructure. A general view has been seen that the current electricity grid has sufficient spare capacity to accommodate the demand from transport sector electrification with only local exceedance. However, this capacity is available at off- peak times, when the demand arising from other sectors is lower. This represents an opportunity, with the price of electricity and the charge for grid use of being lower in off-peak times. To benefit from this, the fleet operator would need to have optimising measures in place to minimise their total cost of electricity use. There are various methods ranging from linear programming, dynamic programming to the application of machine learning techniques that have been discussed in the literature for vehicle charging optimisations [22-33]. In what follows, it is sufficient to use a linear optimisation technique, at this stage, for the cost minimisation of fleet charging at depots, and the objective function is given as:

$$min \sum_{v=1}^{V_{max}} \sum_{s=1}^{T} P_c \pi_s \delta_s \quad (1)$$

Subjected to the following constraints:

$$N_s P_c \leq P_{lim} \quad (2)$$

$$E_v = E_{full}, \quad v \in \{1,2,3, \ldots V_{max}\} \quad (3)$$

$$\sum_{v=1}^{V_{max}} E_v = E_{total} \quad (4)$$

$$t_{start} \leq t \leq t_{end} \quad (5)$$

where:

π_s: electricity price in time slot s
N_s: number of vehicles being charged in each time slot
δ_s: charging time slot
P_c: charging power
P_{lim}: depot power limit
E_{full}: Vehicle full energy
E_v: required energy by each vehicle
E_{total}: total energy required by the fleet
V_{max}: the size of fleet
t_{start}: start of charging event
t_{end}: end of charging event

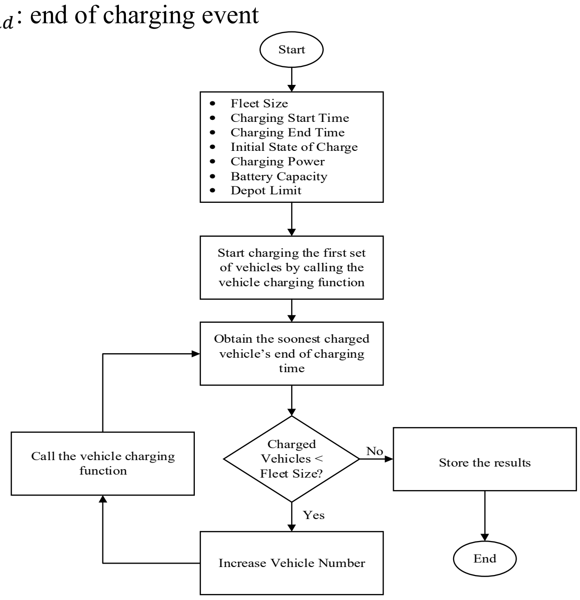

Fig. 3. Depot fleet charging flow chart.

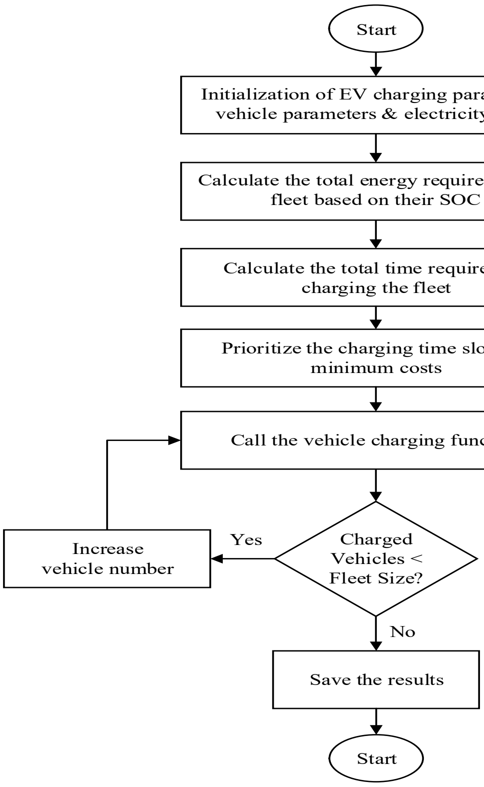

Fig. 4. Price minimised fleet charging flow chart.

The algorithm starts by assigning the initial values of the parameters and variables such as rating power of the charging points, the depot capacity, the start and stop time of the charging event, the vehicle battery capacity, the price vector, and the state of charge (SOC) of the vehicles. The required energy of the vehicles is obtained based on the battery capacity of the vehicles and the SOC of the vehicles when they arrive at the depot. Then the algorithm follows the charging cost minimisation principle, as given above, to find the minimum charging cost of each vehicle and the fleet. This process is repeated according to the number of the vehicles in the fleet as shown in Fig. 4. to complete the recharging of the whole fleet to be ready for the next daily operation according to the time and depot capacity constraints.

IV. Simulation Studies

In this chapter, the simulation studies considering the evaluated case study, the planned operating scenarios, and comparative analysis of determinate demand characteristics have been presented in detail.

A. Case Study

Fleets of 25 and 50 heavy vehicles with a battery capacity of 400 kWh (for each) have been analysed in this research. It is consistent with the Volvo trucks' specifications have an average battery capacity among the products of different companies. Based on the case, the power of charging points is assumed to be 25 or 50 kW, and the depot factors are 0.5, 0.7 and 1.0, which means the depots have enough electrical capacity to simultaneously charge 50%, 70% and all the vehicles, respectively.

Sample "fleet travelled distance" which is applied in this research is given in Fig. 5. [34]. In this modelling all the vehicles in the fleet are assumed of similar specifications i.e., having similar battery capacity without any loss of generality as the vehicles returning to the depot (or arriving at the stations).

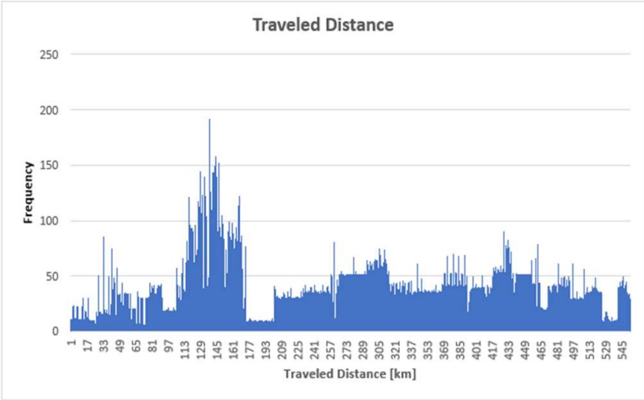

Fig. 5. Daily travelled distance [34]

The output of this function is a list of travelling distances with the same size of the fleet for the vehicles in completing their daily operations since the time they depart the depot until they return the depot. The model produces the power demand profile, energy profile, and the SOC profile as shown in Fig. 6.

The adopted approach, as explained in the methodology, is to obtain the power demand profile based on the arrival SOC of the vehicle, the time of charging (controlled by the fleet operator), and the specifications of the vehicle. In this modelling - for the sake of simplicity- the charge acceptance of battery is considered as a linear function; in practical cases depending on the battery construction and its constituting materials it would be a nonlinear phenomenon.

B. Operating Scenarios

The model is simulated for two plausible (unmanaged and price optimised) scenarios; in both, the SOC of the fleet vehicles are kept the same to analyse the performance of the model and the potential of the demand side management within various cases. Also, during this comparison, the vehicles have similar characteristics, and the fleets have the same depot factors for each case study.

Based on the first strategy and with due attention to the electrical capacity of the depot, the algorithm takes place by dividing the vehicles into two sets. The first set of vehicles are charged simultaneously, and with the time as any vehicle from the first set completes charging, its place (electrical port) is freed to be occupied by a vehicle from the second set. This process goes on until the charging of the rest of the vehicles in the second set has been completed. Fig. 7. show the charging demands in an unmanaged approach for fleets with 25 vehicles.

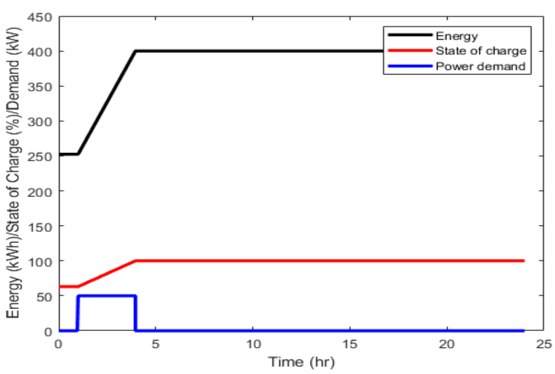

Fig. 6. Charging load profile of a vehicle.

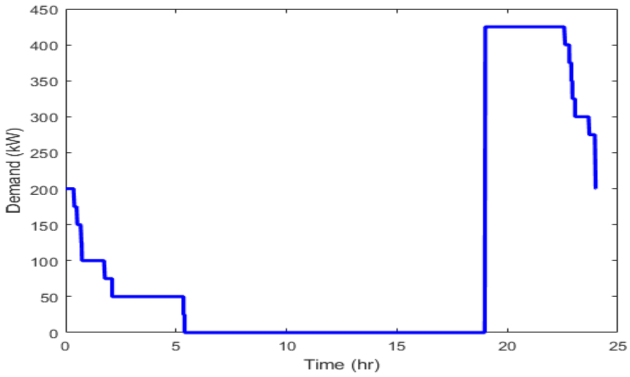

Fig. 7. Unmanaged charging demand profile

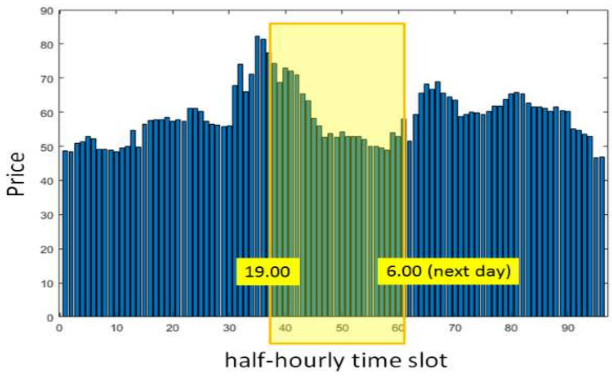

Fig. 8. Electricity prices (half-hourly) for two consecutive days.

In the second strategy, the same parameters and initial values have been considered as in the first. But, there is a prioritisation to be considered in the model in facing total price minimisation problem scenarios, as explained earlier. A list of time slots is determined that have been picked by the algorithm, pursuing the price minimisation along with fully charging the fleet within the given time window. Since the fleets in both cases have similar SOC, approximately the same length of time (number of time slots) is required to fully charge the fleets. However, due to the depot's capacity restriction in the second case, the optimised times slots are different when compared to those of the first case. Fig.8. illustrates the prices of electricity for two consecutive days in the UK.

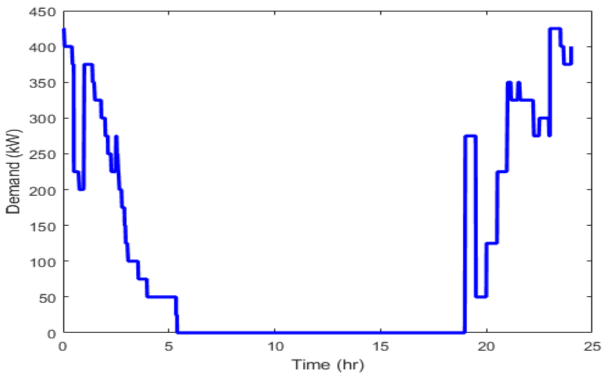

Fig. 9. Managed (cost optimised) charging demand for a fleet of 25 vehicles

According to the domain of the time slots – the time window to charge the fleet: 19:00 to 6.00 (next day) – the algorithm optimally selects the time slots that lead to minimum charging cost while making sure that the vehicles are fully charged by 6.00 (next day) and be ready for daily operation. Fig.9. illustrates sample of the minimum cost load profile of a fleet of 25 vehicles (with battery capacity of 400 kWh); the power of charging point is 25 kW and the depot factor of 0.7

Results obtained via the application of the proposed load modelling system for the various HGEV depots charging using both (unmanaged and managed) strategies are given in Table I. The potential of the demand side management is released as the capacity of the cost reduction and the potential for peak period overlapping reduction; it is a projection of the capability of load shifting to the off-peak time and determined within the cases.

V. Conclusion

In this paper, a semi-stochastic HGEVs depot charging model is proposed based on various essential parameters. The suggested model is applied successfully to determine the load profiles of the HGEV depots, and the results emphasise the practical applicability of the model. The simulations are carried out for 24 hours period over several case studies with different characteristics and operating using unmanaged and price-based management strategies.

TABLE I. Comparative Results of the Proposed Model Application for Various Depots

Fleet Size	**Charger Power**	**Depot Factor**	**Max. Demand**	**Total Daily Price of Energy**		**Cost Reduction [%]**	**Peak Period Overlapping**		**Overlapping Reduction [%]**
				Unmanaged	***Managed***		***Unmanaged***	***Managed***	
25	25	1.0	625	14588	13583	06.89	13.82	0.00	100.0
25	25	0.7	425	13440	11239	16.38	09.97	0.00	100.0
25	25	0.5	300	16304	11213	31.23	08.44	0.00	100.0
25	50	1.0	1250	13190	10258	22.23	32.08	0.00	100.0
25	50	0.7	850	14065	10064	28.45	21.12	0.00	100.0
25	50	0.5	600	11772	10571	10.20	17.64	0.00	100.0
50	25	1.0	1250	27996	20034	28.45	14.56	0.00	100.0
50	25	0.7	875	27237	23177	14.91	10.15	0.01	94.29
50	25	0.5	625	25495	21773	14.60	07.32	0.01	88.01

• Prices are in penny and power and loads are in kW • Overlapping are in percentage

• Period of peak consumption consistent with UK typica daily load is defined between 16:30 and 19:30 [35]

The analysis of the charging demand profiles of both unmanaged and price-optimised strategies show how the fleet demand can be spread across the off-peak time under the managed strategy; and that, the total cost of charging incurred under this strategy is lower than the unmanaged strategy; up to 31.23% less than total cost based on a UK typical daily tariff variations. From a network perspective, the overlapping of the charging profiles with the peak period of energy consumption is also evaluated for both unmanaged and managed strategies. The findings of this step reveal the potential of demand side management over HGEV depots which can be a value of 88.01% to fully mitigate this conformity depending on the fleet size and the depot characteristics.

The findings confirm Depot Factor (DF), as the ratio of the number of available charging ports to the fleet size, along with chargers' power rating are parameters that play leading roles in this field and consequent energy price reduction capacity and the potential for the demand side management. In future, the determined load profiles using this approach can be updated depending on the case and incorporated into network analysis, e.g. power flow and time sweep, to evaluate the impacts of HGEV depots electrification upon available power systems.

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