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Agent Based Aggregated Behavior Modelling For Electric Vehicle Charging Load

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***Abstract*—Widespread adoption of electric vehicles (EVs) would significantly increase the overall electrical load demand in power distribution networks. Hence, there is a need for comprehensive planning of charging infrastructure in order to prevent power failures or scenarios where there is a considerable demand-supply mismatch. Accurately predicting the realistic charging demand of EVs is an essential part of the infrastructure planning. Charging demand of EVs is influenced by several factors such as driver behavior, location of charging stations, electricity pricing etc. In order to implement an optimal charging infrastructure, it is important to consider all the relevant factors which influence the charging demand of EVs. Several studies have modelled and simulated the charging demands of individual and groups of EVs. However, in many cases, the models do not consider factors related to the social characteristics of EV drivers. Other studies do not emphasize on economic elements. This paper aims at evaluating the effects of the above factors on EV charging demand using a simulation model. An agent-based approach using NetLogo is employed in this paper to closely mimic the human aggregate behaviour and its influence on the load demand due to charging of EVs.**

***Index Terms*—Agent based model, electric vehicles, complex systems, load modelling, charging stations.**

I. Introduction

The resurgence of electric vehicles (EVs) provides an opportunity to address prevailing concerns such as scarcity of energy resources, increasing fuel prices, air pollution and global warming. EVs are known to be more energy efficient when compared with internal combustion engine vehicles (ICEVs) [1]. The total cost of EV ownership can be lower when compared with ICEVs. Globally, a growing number of people are considering purchasing EVs. In this context, [2] revealed a 42% yearly increase in EV sales. The 21^{st} century has seen growing interest in EVs due to advances in battery technology and greater emphasis on renewable energy [1]. With greater EV penetration expected in the near future, the demand for electricity is bound to increase as EVs require electrical energy for charging their batteries. The authors of [3], [4] stated that large scale adoption of EVs may help in improving transportation sustainability. However, increased EV adoption brings with it several challenges for grid planners. Apart from the construction of charging infrastructure, system operators need to plan for an increase in electricity demand. Household electricity consumption can increase by up to 50% with the addition of a single EV. The authors of [5], [6] proposed the use of energy storage. However, due to a rapid rise in the demand for EVs, many challenges are bound to arise with the extensive deployment of charging infrastructure. These challenges, among others, include developing an appropriate number of charging stations to cater to the large number of EVs and optimizing the locations of these charging stations. In this context, the charging behaviour of EV drivers is an important parameter to be considered in the implementation of a well planned charging infrastructure. Understanding the factors which influence this charging behaviour is crucial in developing strategies which promote efficient utilization of the charging infrastructure.

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A. Objective of this study

The objective of this study is to provide both qualitative and quantitative insights into the charging behaviour of EV users. It aims at creating a model which examines factors influencing charging behaviours and predicts the charging demand of different types of EVs under various circumstances. The end result will facilitate an efficient process of identifying optimal locations for charging stations thereby ensuring maximum utilization of the charging infrastructure.

The rest of this paper is organized as follows: A review of existing approaches is presented in Section II. Section III describes the EV load model along with the details of micro-level and macro-level parameters which influence EV charging. Section IV explains the setup of the simulation platform using NetLogo. Results obtained from the simulation study are discussed in Section V followed by conclusions in Section VI.

II. State-of-art

Various studies have been performed to assess the impact of EVs on the grid [7], [8]. Several reliable and accurate models have been developed to examine the complex charging behaviours of EVs. A probabilistic constrained load flow was proposed in [9] with the inclusion of wind energy in the power system. In [10], two different algorithms were proposed to address the issue of overwhelming peak load and its impact on grid stability. The authors of [11] proposed the use of the Monte Carlo method to model temporal and spatial transportation behaviours. The authors of [12], [13] used a bottom-up approach for modelling EV load while the authors of [14], [15] employed a top-down approach. The bottom-up approach in simulation models allows the analysis to begin from individual elements and subsequently progress to the entire system.

Though many studies in literature have considered mobility patterns and electricity prices for EV load modelling, the power demand required for charging EVs also depends on other factors such as the initial State of Charge (SOC) of the EV battery, charging duration, location of the charging station, charging start time, peak hours, previous charging records, type of charging i.e. fast or slow, and driver experience. Hence, predicting the charging demand of EVs is a non-trivial problem. Various studies such as [16] and [17] have considered charging processes and EV model characteristics. However, the location of charging stations and driver's experience were neglected while simulating the EV charging load.

Among the different approaches available for EV load modelling, short period models (SPM) have been widely used in literature. In SPM, charging behavior is modelled with the help of fixed scenarios such as uncontrolled charging [18], delayed charging or smart charging using charge scheduling algorithms [19]. The major drawback of these models is that they yield predetermined results of charging demand. This means that the accuracy of results due to the incorporation of certain charging strategies and policies is presumed during modelling. Instead, modelling should be explicit to test the effectiveness of different charging strategies or policies.

Furthermore, a failure to consider travel patterns in these models results in randomness not being captured which reduces model flexibility and responsiveness to various policies. The authors of [20] used the 'Feathers' software for an activity based model to generate 24h charging demand. For this, the authors assigned a capacity equivalent to internal combustion engines (ICEs) to their agents and mapped the energy consumption equivalent to it. However, this model is not sensitive to electricity prices because the travel schedules are generated from independent ICEVs. The analysis presented does not evaluate the effect of charging strategies on travel patterns and vice versa.

Agent-based modelling (ABM) has been used in many power system applications. The authors of [21] modeled distributed renewable energy generation and demand as different agents. The energy transaction mechanism in power markets was extended for these agents. The approach reduced energy purchase costs by tracking the forecasted energy consumption and generation. In [22], each distributed energy storage (DES) was modelled as an agent. The communication between these agents was implemented through the dynamic average consensus method to retrieve the average SOC of DES. In [23], the authors developed a price based demand response procedure for day-ahead planning and decision-making in retail electrical energy markets using an agent-based framework. Here, the ABM approach was used to address issues of interoperability and data privacy in retail power markets. The ABM approach provides scope to add different charging behavior preferences due to various policies and facilitates a study on the effect of such policies on charging demand and charging station planning.

A. Major Contributions

The major contributions of this paper may be summarized as follows:

1. This paper proposes an ABM approach for predicting the electricity demand for EV charging. Various factors including initial State of Charge (SOC), charging duration, charging station location, charging start time, peak hours, previous charging records, varying electricity prices, types of charging, and driver experience are considered while developing the model. Unlike previous studies, the model captures human behavioural tendencies in the context of an EV owner's decision making process regarding charging location. Finally, the model also accounts for the complex inter dependencies which exist between these factors. The different modelling parameters are stochastic in nature which allow the model to account for unpredictable charging behaviour.
2. The model proposed in this paper provides a framework to analyze the effects of varying EV charging demand due to different charging strategies and policies. This framework would, among others, help in planning optimized locations for EV charging stations.
3. A good charging demand forecast is the bedrock on which several power system analyses can be based. The authors have performed some preliminary power system analysis by linking the proposed agent environment with an optimal power flow problem using a modified IEEE 14-bus network. This link opens up several possibilities to study economic grid operation, charging strategies, congestion analysis, identification of overloads in the system etc. Strategies aimed at mitigating these issues can also be studied in depth using this platform.

III. System Model

In this paper, the ABM approach is used to model the charging demand of EVs. It aims at assessing the behaviour of the system as a whole. Agents are autonomous, able to interact with each other and react to stimuli to achieve their goals. The functioning of the system is not determined by design. Instead, it is the result of the spontaneous and natural conduct of agents in the environment [24]. The final aim of the ABM approach is to find explanatory insights through the assessment of the collective behaviour of agents in their natural environments rather than finding practical solutions or solving engineering problems by designing agents in a deliberate manner. The spontaneous nature of the ABM approach allows the prediction of human charging behaviour based on the different parameters assigned. The model simulates and defines each EV through its charging characteristics, mobility pattern and vehicle type. This creates an interactive environment where decision making and dissimilar circumstances are inculcated to produce a realistic model that predicts charging demands of individual as well as groups of EVs.

In this paper, the model is simulated using the NetLogo software package [25] which is well suited for complex systems analysis as it allows interactions among agents. Thousands of agents can receive instructions simultaneously and operate independently. The connections between macro and micro mobility patterns that emerge from agent interactions can be used for understanding EV charging behavior thereby leading to the development of a hybrid modelling approach. With the inclusion of a proper setup and all the factors which influence the load model, it allows the charging demand to be analyzed. This paper uses data and statistics in the context of Singapore to test the proposed modelling approach.

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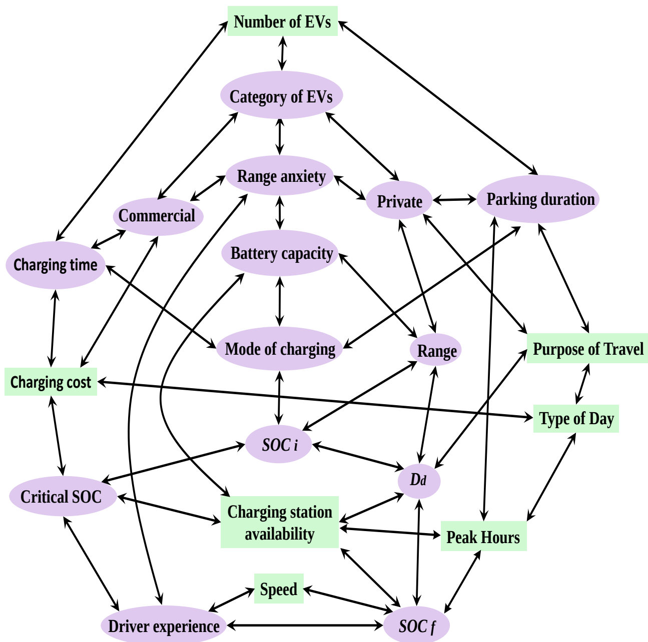

Fig. 1: Interdependency of EV charging system parameters

A. *Type of model*

Aggregate modelling has become an effective tool to simulate aggregate movement and behaviour in real life. Many researchers have used microscopic and macroscopic modelling approaches for dynamic environments. The macroscopic model focuses on the overall pattern behaviour of the whole human aggregate and increases simulation efficiency while the microscopic method focuses on characteristics of individuals such as decision making and captures the accuracy of individualistic behaviours [26]. In NetLogo, it is possible for these two models to co-exist in order to leverage on the individual strengths of both models. The agents (EVs) in this model have their own specifications and make decisions based on their objectives. For instance, the EV starts to look for charging stations whenever the SOC of its battery falls below 25% (a variable in the model whose value can be changed to carry out detailed analysis). This demonstrates the microscopic nature of the model as EVs act individually and make decisions based on their own specifications. On the other hand, this behaviour is constrained by the overall movement of the human aggregate. For example, an EV user cannot charge at a charging station if it is fully occupied. The parameter 'Charging station availability' is determined by the presence of other EVs at the charging station. If all chargers at a particular charging station are fully occupied, EV users can either decide to queue and wait or find other charging stations. This would further reduce the SOC of their batteries. These EVs would not only influence and add to the load at other charging stations but also increase the amount of energy required for their charging and charging duration. These two parameters would then influence the 'Charging station availability' parameter for other EVs at various charging stations. This chain effect is triggered by the action of a single EV and affects other EVs in its vicinity. Another example would be during the night when most private cars are parked overnight instead of being driven on the roads. Such behaviour is considered on the macro level as the EVs account for the presence of other EVs; interact with each other and behave on a large scale. This discussion emphasizes the need for this study as the usage of the proposed model enables a comprehensive coverage of factors at individual/micro and macro levels.

Fig. 1 shows the micro level decision variables in 'circles' and macro level decision variables in 'squares' along with their inter dependencies in decision making for charging EVs by the owners.

B. *Micro level parameters*

These parameters are associated with the individual behaviour of each EV and its driver.

1) Category of EV: The EVs are classified into two categories - private and commercial. Private EVs are similar to personal vehicles while commercial EVs mainly comprise electric taxis [27]. Such a categorization is necessary to distinguish between different behaviors exhibited by vehicles in each category. Private EVs can be modelled using trends of office hours and carpark statistics at residential complexes and shopping malls. Electric taxis tend to operate for 24h with different shifts. Hence, private EV models cannot be used for modelling electric taxis.

2) Range anxiety and battery capacity: The battery capacities of EVs affects the range anxiety as larger battery capacities enable EVs to travel longer distances without quickly depleting their batteries. This gives greater assurance to the driver since the chances of quickly running out of energy decreases with an increase in battery capacity. The results in [28] show that there is an inverse relationship between range anxiety and battery capacity.

3) Initial SOC, (SOC_i): Assuming that the same charging power is used, charging duration naturally increases with a lower SOC_i. EV owners would normally prefer to charge their batteries to at least 80% SOC before leaving the charging station. Thus, with a lower SOC_i, a longer duration is required for EVs to complete charging. In this simulation study, SOC_i is initially allocated as a random value following a normal distribution between 50% to 90%.

4) Final SOC (SOC_f): SOC_f depends on the type of EV and total distance the EV owner intends to travel before the next charging event. It is assumed that commercial EVs will always attempt to get a full charge in minimum time. For private EVs, the distance travelled by an EV after the last charge is estimated based on a typical probability density function (PDF) with an average travel distance of 50km and standard deviation of 10km. An average travel distance of 280km and standard deviation of 50km are considered for commercial EVs [29]. EV users can also enter the desired SOC_f in the simulation platform in real-time.

The SOC of an EV SOC^{ev} varies from the SOC after it leaves a charging station at the end of one charging event (denoted by SOC_{f}) to the SOC when it reaches a charging station for the next charging event (denoted by SOC_{i}) based on the speed and acceleration of the EV as described in the following paragraphs.

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TABLE I: Mechanical parameters for EV discharge power calculation [30]–[34]

M_{i3}	1415 kg	A_{i3}	2.8 m^2	$C_{\text{d,i3}}$	0.29
M_{Leaf}	1500 kg	A_{Leaf}	2.74 m^2	$C_{\text{d,Leaf}}$	0.28
M_{Soul}	1580 kg	A_{Soul}	2.51 m^2	$C_{\text{d,Soul}}$	0.35
ρ	1.196 kg/m^3	C_{r}	0.025	α	0
P_{Aux}	700 W	η_{b}	90%	η_{m}	93%

Based on the road forces acting on the EV, the mechanical power required by the EV P_{m}^{ev} in Watt can be calculated as follows [30]:

$$P_{\text{m},k}^{\text{ev}} = M_j a_k \mathcal{V}_k + M_j g(\mathcal{V}_k \sin\alpha + C_{\text{r}} \cos\alpha) + \frac{1}{2} C_{\text{d},j} A_j \rho \mathcal{V}_k^3 \tag{1}$$

where M_j represents the mass of an EV (kg) of type j, $\mathcal{V}$ represents the speed of the EV (m/s), a represents the acceleration of the EV (m/s^2), g represents gravitational acceleration (9.8 m/s^2), $C_{\text{d},j}$ represents the aerodynamic drag coefficient of an EV of type j, A_j represents the frontal area of an EV of type j (m^2), ρ represents air density (kg/m^3) and C_r represents the coefficient of rolling resistance for a tarmacadam road [30]. Further, α represents the gradient of the road whose value is taken as 0 in this work. In other words, the roads considered in this work are assumed to have zero gradient. The road gradients at different locations can be easily modified subject to availability of data from the relevant authorities. Table I provides the values of all the parameters used in (1) for the 3 types of EVs considered in this work - BMW i3, Nissan Leaf and Kia SoulEV. All the time varying variables are denoted using $(\cdot)_k$ during minute k.

Based on the mechanical power required, the following equation calculates the electric power to be provided to the EV's electric motor (P_{e}^{ev}) by factoring in the motor efficiency (η_{m}), EV auxiliary power requirement (P_{Aux}) and battery efficiency (η_{b}):

$$P_{\text{e},k}^{\text{ev}} = \frac{P_{\text{m},k}^{\text{ev}}}{\eta_{\text{m}}} + P_{\text{Aux}} \tag{2}$$

$$SOC_k^{\text{ev}} = SOC_{k-1}^{\text{ev}} - \frac{P_{\text{e},k}^{\text{ev}}}{\eta_{\text{b}} B_{\text{ev}}.60} \tag{3}$$

$$\Delta SOC_k^{\text{ev}} = \frac{P_{\text{e},k}^{\text{ev}}}{\eta_{\text{b}} B_{\text{ev}}.60} \tag{4}$$

$$SOC_{\text{i}} = SOC_{\text{f}} - \sum_{k=0}^{N} \Delta SOC_k^{\text{ev}} \tag{5}$$

where N represents the number of samples during the total duration of the trip.

The energy consumed (E^{ev}) per unit kilometer distance (d) travelled by the EV during its last trip can be calculated in kWh/km as follows:

$$E^{\text{ev}} = \frac{1}{60000} \frac{\sum_{k=0}^{N} P_{\text{e},k}^{\text{ev}}}{d\ \eta_{\text{b}}} \tag{6}$$

5) Mode of charging: In the proposed model, EVs can choose between fast charging or slow charging depending on the category of EV as well as the distance and time remaining to reach the destination.

6) Charging time: A longer charging duration results in the charging slot being occupied for a longer period of time. Other EVs that intend to charge may in turn re-route or travel longer distances in search of charging stations with vacant charging slots. This causes a further reduction in their SOC_i values. The charging time parameter acts at both microscopic and macroscopic levels. Three different types of EVs are used in the proposed model and their details are provided in Table II.

The open circuit voltage (OCV) of the battery pack was obtained from the standard battery models available in MATLAB-Simulink [35] and curve fitting (smoothing spline) was used for deriving a relationship between OCV and SOC.

$$V_{\text{OCV,SOC}} = f(SOC) \tag{7}$$

where f is given by,

$$\arg\min f, f = \sum (V_{\text{OCV}} - f(SOC))^2 + (1-p) \int \left(\frac{d^2(SOC)}{df^2} \right)^2 d(SOC) \tag{8}$$

where p represents the smoothing factor. p can be varied between 0 and 1 for varying the smoothness of the fit wherein 0 results in a linear fit and 1 results in a piece-wise cubic polynomial fit. Furthermore, p can also be selected as $\frac{1}{\left(1+\frac{h^3}{6}\right)}$ where h represents the average difference between the data points.

Let I_{cc} be the current required in constant current (CC) mode. $P_{\text{cc,SOC}}$, which represents the power required in CC mode (for a particular SOC) is given by the following equation:

$$P_{\text{cc,SOC}} = V_{\text{OCV,SOC}} \cdot I_{\text{cc}} \tag{9}$$

The charging current in constant voltage (CV) mode at time instant n is given by the following equation:

$$I_n = I_{n-1} - I_{\text{slope}} \tag{10}$$

where I_{slope} represents the slope of current decrements in the CV mode. I_{slope} is calculated from the time required in the CV region for each EV (a fixed value determined based on the EV characteristics [31]-[33]). The charging power required in CV mode is calculated as follows:

$$P_{\text{cv,SOC}} = V_{\text{OCV,SOC}} \cdot I_n \tag{11}$$

The charging power at any time instant n is given by the following equation:

$$P_n = \frac{P_{\text{b},n}}{\eta_{\text{c}}} \tag{12}$$

where P_n represents the AC power supplied and η_{c} represents the converter efficiency (considered as 0.95). $P_{\text{b},n}$ can be either $P_{\text{cv,SOC}}$ or $P_{\text{cc,SOC}}$ depending on the status of the EV battery.

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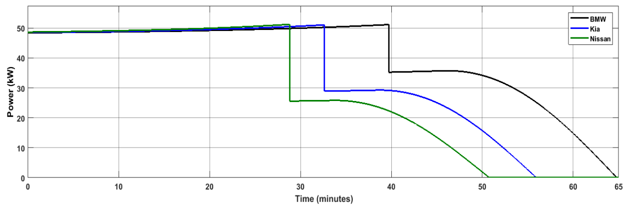

Fig. 2: Fast charging characteristics of EV batteries

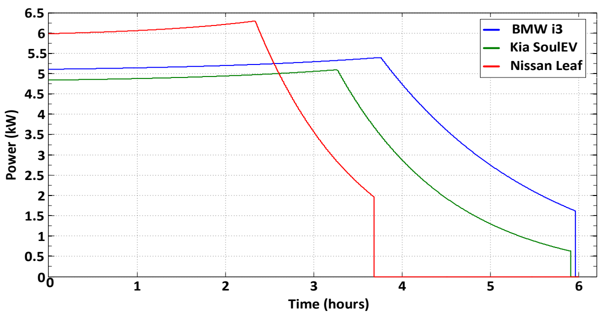

Fig. 3: Slow charging characteristics of EV batteries

The SOC increment is calculated using the following equation:

$$SOC_n = SOC_{n-1} + \left[\frac{P_n}{P_{1c}.60}\right] \tag{13}$$

where SOC_n represents the increased SOC; SOC_{n-1} represents the SOC before supplying P_n and P_{1c} represents the power at 1C with one minute resolution.

Using the above equations, the charging curve of an EV can be generated and the charging time can be determined based on the number of samples. For fast charging, typical charging powers and charging times are shown in Fig. 2 for the three types of EVs considering SOC_i as 20%. For slow charging, the typical charging powers and charging times are shown in Fig. 3.

7) Parking duration: This parameter varies based on different scenarios such as: i) the office carpark is occupied during office hours ii) shopping mall and restaurant carparks are occupied during evening hours and iii) residential carparks are occupied during night hours. An example of real-time carpark statistics in a Singapore shopping complex is shown in Fig. 4 [36]. This parameter provides a more realistic perspective of EV usage behaviour. If an EV is parked for a longer duration, it may prefer to charge in slow charging mode instead of fast charging mode. This could reduce the peak demand as well as enable cost savings through better utilization of off-peak electricity prices.

Fig. 4: Carpark occupancy in shopping mall, Singapore [36]

TABLE II: EV Battery specifications [31]–[33]

EV Model	**Battery Capacity** B_{ev}	P^{ev} **(Fast)**	P^{ev} **(Slow)**
BMW i3	18.8 kWh	35.89 kW	5.4 kW
Nissan Leaf	24kWh	38.76 kW	6.3 kW
Kia SoulEV	27kWh	39.1 kW	5.1 kW

8) Range anxiety and driver experience: Range anxiety refers to the fear of not reaching the destination before the EV's battery gets depleted. As the driver's experience with the EV grows, it results in a reduction in the overestimation of range requirement [37]. This means that drivers become more experienced in predicting the EV's range in relation to their range requirements thereby leading to a reduction in range anxiety.

During the modelling process, the critical SOC is defined as a new parameter which refers to the lowest permissible SOC of the EV. Below this SOC, the driver will choose to enter the charging station to charge the EV. It is directly affected by range anxiety as a higher range anxiety usually results in a higher critical SOC. The authors of [37] also demonstrated that range anxiety has a direct relation to charging behaviour as EV drivers have a tendency to charge very frequently and to charge longer than required. This mindset indirectly leads to higher critical SOC levels as drivers charge unnecessarily most of the time. In the simulation model described in this paper, the driver's experience varies with respect to a normal distribution with μ=7 and σ=3 among the total number of EVs in the model. The experience level 10 (highest) defined in the model means that the driver will only search for a charging station when SOC approaches 25%. This percentage has been increased in steps of 5% with each level of decrease in driver experience, up to level 1 (lowest).

C. Macro level parameters

These parameters are associated with the group behavior of EVs and their drivers. The presence of EVs at one location will influence the behavior of other EVs present in their vicinity. This aggregated behavior is implemented using the following parameters.

1) Availability of slots in charging stations: Before EVs enter a charging station, the availability of vacant charging slots is checked. If there are no vacant slots, the EV will not enter. Thus, it can be seen that EV behaviour is not only affected by its own characteristics but is also dependent on the other EVs around it. This affects the SOC_i of the EV as the charging event gets delayed while the SOC continues to deplete.

2) Speed of EVs: The speed of an EV changes according to the vehicles that are around it. It accelerates whenever there are no vehicles ahead of it and only decelerates when the speeds of the cars ahead are lower. It stops when the speed of the car ahead is zero. Another situation where speed is important is when EVs move backwards, either out of charging stations or parking lots. In such cases, EVs check for other cars to avoid any accidents. Therefore, speed is another factor which largely depends on the interaction of an individual EV with EVs other than itself. It has a direct relationship with the SOC of EVs since the calculation of SOC accounts for the physical

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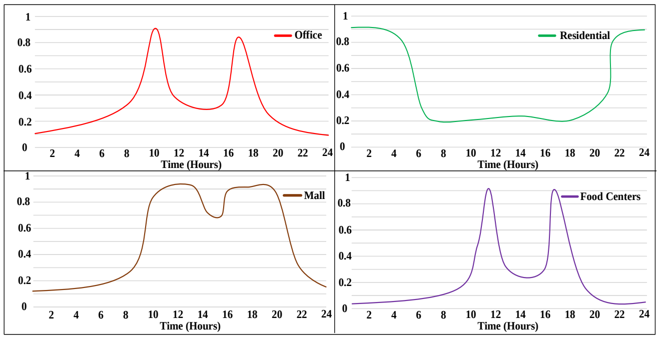

Fig. 5: Typical probability distribution of EV charging

distance travelled which involves the speed factor.
Each patch, which is a unit of distance in the simulation platform, is converted into km with respect to the duration of movement of EVs and the speed setting of EVs in the simulation platform. The speeds of EVs can be observed in real time during simulation.

3) Number of EVs: This parameter is critical for deploying EVs. The number of residential and office places as well as the number of charging stations in a particular region can only accommodate a certain number of EVs. Beyond this threshold, charging stations will be overburdened and EVs would start queuing up for empty slots thereby causing further charging delays. Hence, while planning the number of charging stations in any area, it should be ensured that the maximum number of EVs serviced by each charging station is below this threshold value.

4) Type of Day: EV usage patterns are different on weekdays and weekends. On weekdays, the usage of private EVs is mainly governed by office hours. On the other hand, during weekends, shopping malls and residential carparks show maximum activity [36].

5) Purpose of travel: This determines the selection of charging stations located en route to the destination. The daily commute to the workplace might result in charging near office charging stations while weekend activities might result in charging either at food centres, shopping malls or residences.

6) Charging cost: Peak hour periods affect the price of charging indirectly. They do not directly alter the price of charging but rather cause a change in the mindset of drivers. During peak hours, drivers tend to disregard the charging price since they are more concerned with getting an empty slot in the charging station. This relationship demonstrates the social aspect of the model as human behaviours are incorporated into it.

7) Peak Hours: During peak hours, there is a reduced price barrier since people normally disregard the price as getting a charging slot becomes priority. Critical SOC increases as drivers hold less regard for their SOC and prioritize getting a charging slot during peak hours. Typical peak hours used in the model are as follows:

- The standard office peak hours are 8am-10am and 5pm-7pm on weekdays. This is in accordance with the daily office shift timings in Singapore which are usually from 08:30am - 05:30pm. EVs start looking for offices and office carparks once office peak hours begin.
- The standard mall peak hour period is set between 11am-10pm on weekends. Data from [36] shows that there is a sharp decrease in the number of available parking slots in most malls between 11am-2pm and 7pm-10pm. Hence, this period is chosen as the standard peak period for malls. As the price barrier decreases, critical SOC increases and EVs start looking for malls during this period.
- Residential peak hours are set as 10pm-7am on weekdays. Usually, prices for residential charging stations are lower than commercial charging stations.
- The peak hour periods for food centres are set between 12pm-2pm and 6pm-8pm on both weekdays and weekends.

TABLE III: System parameters

Electricity price	\$0.20 /kWh	Charging station peak hours	
Number of EVs	120	Office	μ = 9, σ = 2 μ=17, σ = 2
Private EVs	70%	Mall	μ = 20, σ = 3
Commercial EVs	30%	Food center	μ = 12, σ = 2 μ=20, σ = 2
Driver experience	(Level 7) μ = 7, σ = 3)	Residential	μ = 2, σ = 4
Fast charging EVs	50% of total EVs	Type of Day	Weekday

For all four types of places i.e. office, mall, residential and food centre, the peak timings can either be typical standard timings as mentioned above and shown in Fig. 5 or can be manually changed within the simulation platform based on the requirements of any condition. This provides a greater scope to analyze the impact of varying peak timings on the EV charging load demand.

IV. Simulation Platform Setup

All macro level and micro level parameters are simulated using the NetLogo software package [25] to emulate real life human decisions by incorporating human behavioral tendencies towards EV charging. The simulation platform developed in this paper is shown in Fig. 6. The model consists of a 6X6 grid i.e., 36 blocks. Each block can be selected to function as a residential charging station (RCS), office charging station (OCS), food centre charging station (FCS), shopping mall charging station (MCS), carpark (CP) or residential block ('None'). The user interface is designed to allow users to select parameters based on statistical data for any region under consideration. This data represents various probabilities and proportions of decision variables in the macro and micro level operation of EVs as mentioned in Table III.

In this model, charging stations equipped with 10 chargers are located at the following blocks (R-Row, C-Column):
OCS @R3C3; FCS @R4C4; RCS @R1C1 and @R6C6 and Carparks at @R2C1, @R1C2, @R2C2, @R3C2, @R4C2, @R4C3, @R3C4, @R3C5, @R4C5, @R5C5, @R6C5, @R5C6. The remaining blocks are set as housing blocks i.e. 'None'.

The path tracing algorithm is designed such that when the EV decides to charge its battery based on the SOC, driver

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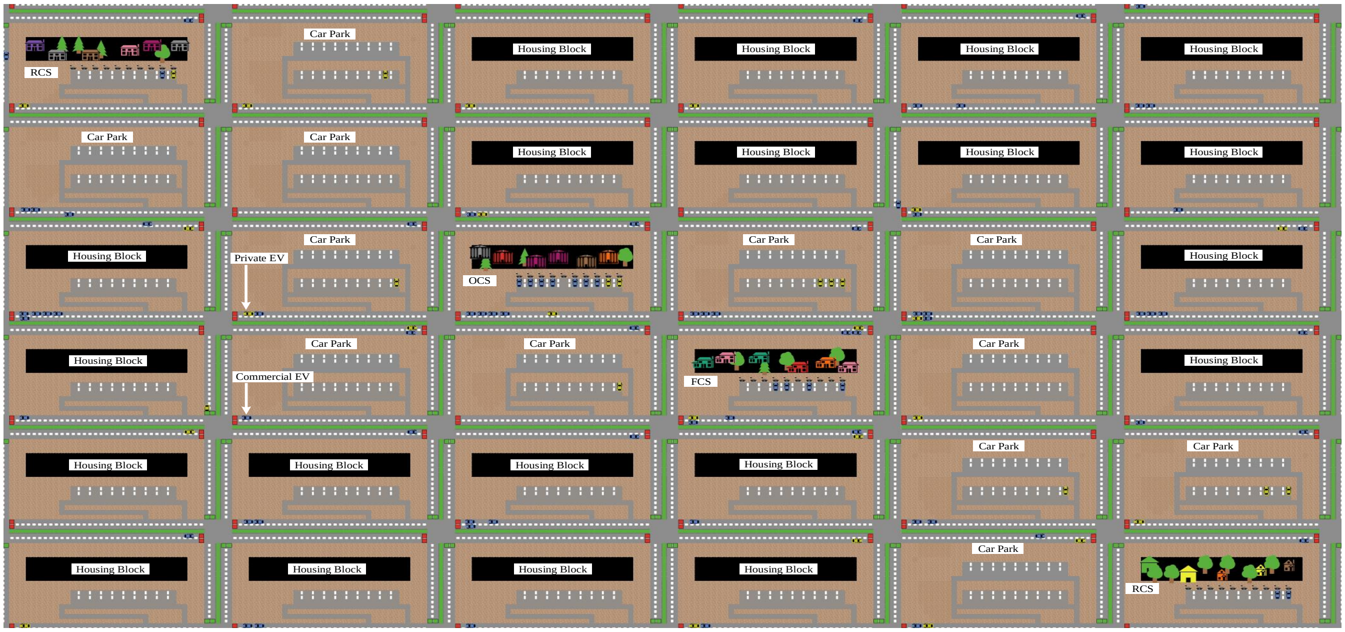

Fig. 6: Overview of EV charging system using NetLogo

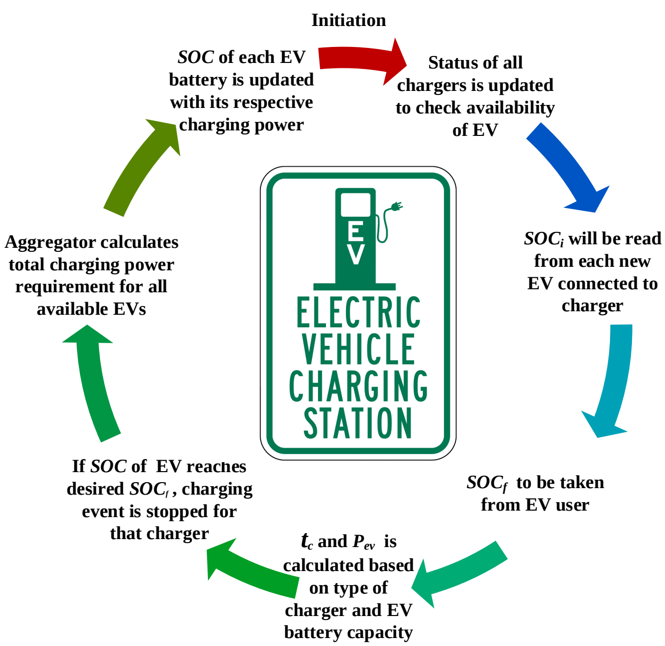

Fig. 7: Load calculation process at EV charging station

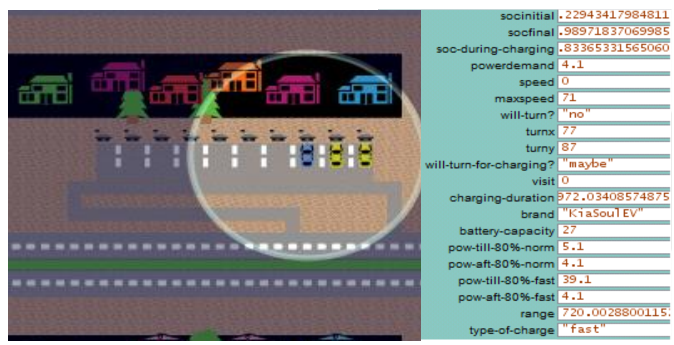

Fig. 8: Typical EV characteristics in model

experience etc., the minimum distance to reach all charging stations is calculated based on the current location of EV and the locations of all nearby charging stations. Among all the charging stations, the EV moves towards the nearest charging station which is analogous to a real world scenario wherein refueling stations are chosen based on navigation devices. If the charging station is found to be fully occupied upon arrival, the EV cannot wait or queue up. The distances to the nearest charging stations are calculated again and the EV moves towards the next charging station located at minimum travel distance. This ensures that the EV battery does not get depleted completely.

Private EVs charged in OCS will get parked in office carparks during office hours (8:30am-5:30pm). The private EVs charged at RCS during the night remain parked in residential carparks during the night. On the other hand, commercial EVs are restricted from parking at office and residential carparks after charging at OCS and RCS respectively. They continue to operate for 24h in different shifts. This provision avoids a situation of private EVs being unnecessarily driven on the roads thereby creating a more realistic EV mobility pattern.

The load modelling process at each charging station is illustrated in Fig. 7. The charging load at each charging station is calculated and each EV charger's status is updated every 3 seconds.

The model is developed with the following provisions to make it adaptive for generating EV charging load demand for any region and situation:

- Number of EVs and ratio of private EVs to commercial EVs can be set manually.
- Driver experience levels, EV models and ratio of fast chargers to slow chargers can be defined based on the demographic projections of any region.
- Battery charging characteristics of different EVs can be

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added.

- Function of each block in the grid can be defined based on the geographical map of any city. The entire grid is scalable. Hence, the proposed model is well suited for large scale EV modelling applications.
- Peak and off-peak periods can be defined for various charging stations based on local requirements and site conditions.
- Electricity prices can be set at individual charging stations to study the effects of varying electricity prices on EV charging behavior.
- Each EV can be observed individually for its path tracing, energy consumption as well as charging preferences and battery characteristics. This enables a precise extraction of the mobility pattern. Fig. 8 shows the details of a typical EV's characteristics which can be monitored during simulation.

V. Results

The proposed model is simulated for several days over a 24h time period from 12 midnight to 11:59pm. After the agents

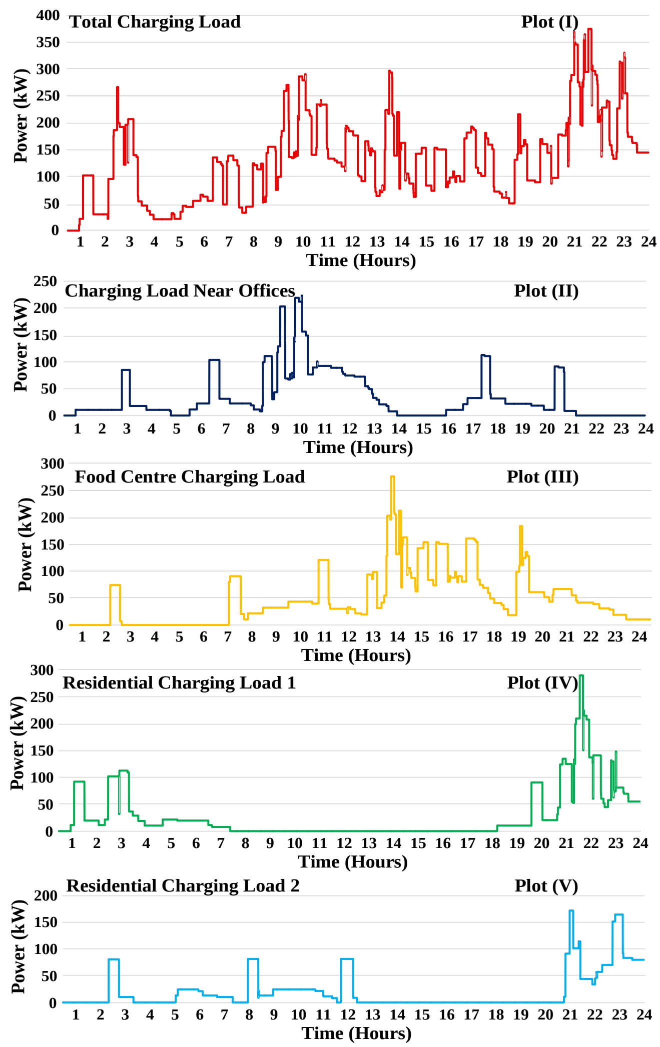

Fig. 9: EV charging load- Plot(I) Total charging load, Plot(II) Charging load near offices, Plot(III) Food Centre Charging Load, Plot(IV) Residential charging load 1, Plot(V) Residential charging load 2

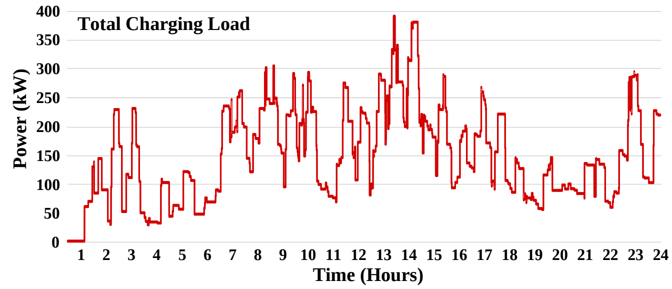

Fig. 10: Total charging load for 80% Commercial EVs and 20% Private EVs

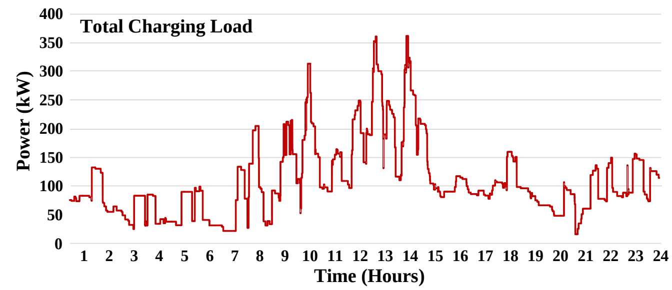

Fig. 11: Total charging load for least EV driver experience

started following the charging process routine, the results were extracted and plotted as shown in Fig. 9. This procedure is used to eliminate errors arising from the initialization of system parameters. The total power demand due to the charging process of all EVs considering all charging stations in the system is shown in Plot(I) of Fig. 9. The overall charging demand from office charging stations is shown in Plot(II) whereas Plot(III) of Fig. 9 shows the charging demand from residential charging stations. It is observed from Fig. 9 that the ABM approach for determining the EV charging demand generates results which are close to reality.

1. The charging load near offices is higher during office hours since EVs are charged at residential charging stations during the night.
2. Residential EV charging starts after office hours at approximately 8pm and decreases close to the beginning of office hours on the next day i.e. at 8am.

Electricity prices are considered to be the same for all charging station during this simulation. The key inference from the simulation is that when human behaviour is included while predicting EV charging demand, the peak demand occurs between 12:00 noon and 2:00pm. However, the predicted charging demand of EVs depends on the choice of parameters as shown in Table III. For example, with all other parameters remaining the same, if the ratio of private to commercial EVs is changed to 20% of private EVs and 80% of commercial EVs, the total charging demand will change significantly as is shown in Fig. 10. The EV charging demand is spread across the day. It is observed that the ratio of private to commercial EVs has a significant impact on the EV charging demand pattern. The influence of driver experience on the total EV charging demand and its pattern is shown in Fig. 11. It can be observed that with all other parameters kept the same, if the driver experience is changed to the lowest level i.e. Level

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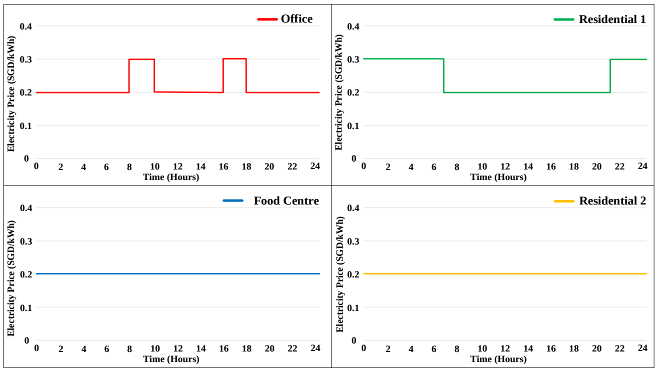

Fig. 12: Electricity price profiles of charging stations

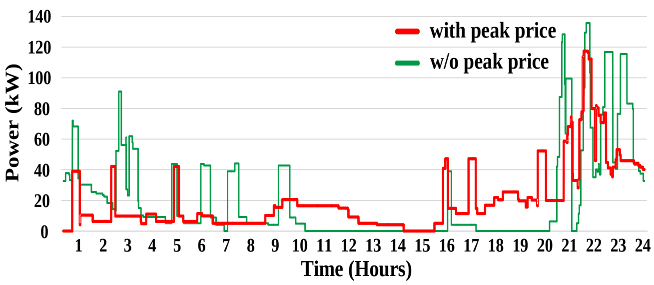

Fig. 13: Effect of rise in price during peak hours at RCS

1, the charging demand and the charging pattern changes. Occurrence of demand peaks increases with a decrease in driver experience.

To assess the impact of peak pricing on charging load at various charging stations, all other conditions in Table III are retained and electricity prices are varied as shown in Fig. 12 for different charging stations. A localized peak price of 0.30 SGD/kWh is imposed during hours when the respective charging stations encounter peak charging demand. For example, from Fig. 12, it is evident that the OCS imposes peak prices during times of maximum load demand during morning and evening hours. The study, while not necessarily fully consistent with electricity market principles, provides insights into how EV owners could behave when localized peak prices are charged and how it could impact their decisions regarding preferred charging locations and charging times. Fig. 13 shows the charging power requirement at RCS with and without peak hour pricing. It can be observed that a significant portion of the charging load at RCS has been shifted to off-peak hours. The inference from this observation is that EV users prefer not to charge during high price hours and prefer to charge their vehicles during off-peak hours. It can also be observed that the average peak power has reduced from 33.51 kW to 20.98 kW. Hence, the two-tier pricing has a considerable impact on the behaviour of EV drivers in RCS. Similarly from Fig. 14, a reduction in the peak power requirement at OCS can be observed and the charging demand is distributed more uniformly than without peak power pricing. Furthermore, a significant reduction in peak power from 44.69 kW to 29.68 kW can be observed from Fig. 14. It may be inferred that the EV charging demand is influenced by electricity prices and EV users prefer to charge at charging stations with

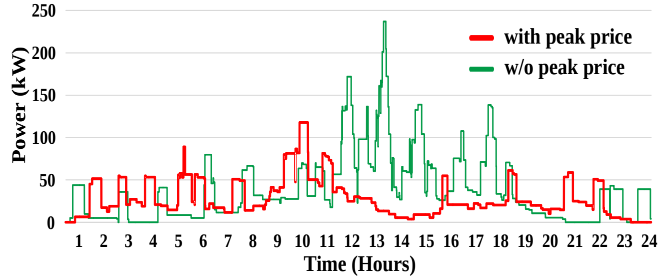

Fig. 14: Effect of rise in price during peak hours at OCS

lower prices. This analysis not only helps in identifying the loading requirements of charging stations but also has other applications. For example, based on the predicted behaviour, appropriate demand response strategies could be designed. Another application of this study is in the sizing of renewable energy sources and stationary energy storage systems (ESS) which could provide support to the distribution grid in case of overloading caused by a particular charging station. Each of these applications is interesting in its own right and merits thorough investigation which is outside the scope of this paper.

It is pertinent to mention at this juncture that in all the above cases, both micro and macro level parameters are taken into consideration.

A. Application in ESS sizing

The results obtained from the simulation platform may be extended for various applications such as RES sizing and ESS sizing. Here, the case of ESS sizing is presented as an application of the extended results.

The PV system in this case-study is of 75 kW_{peak} rated capacity and is selected based on the guidelines issued by Singapore's Land Transport Authority (LTA) [38] for an area required for 20 parking lots. Figs. 15 and 16 show box-plots of the energy required at the OCS and energy generated by the PV system respectively. It may be noted that Fig. 15 is obtained from NetLogo simulations performed over a period of time and Fig. 16 is obtained from real solar irradiance data [39] by using the formulation mentioned below.

The power output from a PV system at the j^{th} interval in a given day is calculated as follows:

$$P_j^1 = P_{pv,peak} . \frac{SI_j}{1000} . [1 - \beta_{pv}(T_{amb,j} - T_{amb,rated})] \quad (14)$$

$$P_j = \eta_{conv} . \delta_{PV} . \eta_{MPPT} . P_j^1 \quad (15)$$

where SI_j is the measured solar irradiance during the j^{th} time interval; β_{pv} is the coefficient of temperature for the module's efficiency; $T_{amb,j}$ is the measured ambient temperature during the j^{th} time interval; $T_{amb,rated}$ is rated ambient temperature (30^oC) and $P_{pv,peak}$ is the maximum power generated under standard test conditions [40]. P_j^1 is the power output from the solar PV system during the j^{th} interval before considering power conversion efficiency and P_j is the power output after considering power conversion efficiency. η_{conv}, δ_{PV} and η_{MPPT} represent the efficiency of converter, de-rating

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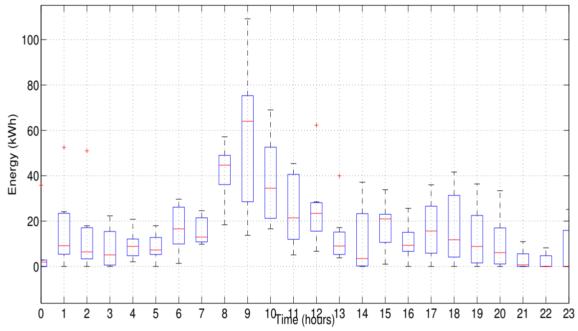

Fig. 15: Box-plot for EV Load at OCS

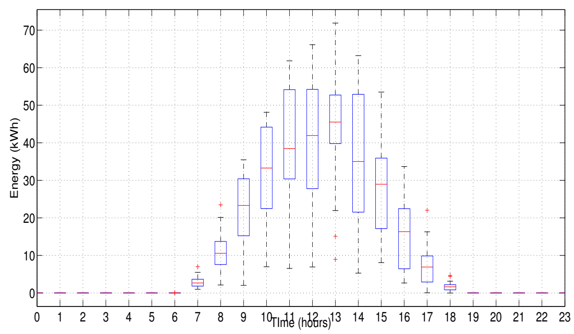

Fig. 16: Box-plot for PV output at OCS

factor for PV panels and efficiency of maximum power point tracking (MPPT) respectively. The value of $\eta_{conv}.\delta_{PV}.\eta_{MPPT}$ is considered to be 0.85 [40].

The objective chosen for sizing the energy storage system is to avoid a condition where the solar PV generation is higher than the total EV load and the ESS capacity is not sufficient to store the surplus energy. This is a realistic condition wherein the charging station operators would prefer some flexibility to charge/discharge the ESS based on market conditions. The ESS designed for such conditions will cater for worst case scenarios. However, the operation can be optimized using methods such as the one proposed in [6]. The size of the ESS is given by the following equation:

$$Size_{ESS} = \sum_{i=1}^{24} E_{PV,j}^{max} - E_{EV,j}^{min}, \forall E_{PV,j}^{max} - E_{EV,j}^{min} > 0 \quad (16)$$

For this application, the ESS capacity is given by the area under the curve shown in Fig. 17 for $E_{PV,j}^{max} - E_{EV,j}^{min} > 0$ and it is calculated to be 419 kWh.

B. Electrical Grid Mapping

In this section, the authors map the agent environment to an exemplar electrical grid to demonstrate the practical applicability of the charging demand prediction model developed in this paper. A modified IEEE 14-bus system is chosen as the exemplar electrical grid in this study. It is assumed that residential charging stations are located at buses 2 and 9; office charging station is located at bus 3 and food centre charging station is located at bus 4. It is assumed that EV charging loads constitute 5.2% of the total system

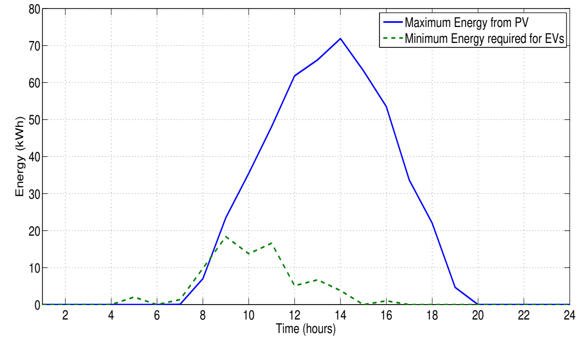

Fig. 17: Energy Storage requirement at OCS

TABLE IV: Diesel Generator Parameters

Gen	Bus	a ($)	b ($/kW)	c ($/kW^2)	P_{min} (kW)	P_{max} (kW)
1	3	80	0.03	0.000001	100	3000
2	8	200	0.06	0.000002	100	3000

load demand [41]. The charging stations are located at buses which have a relatively larger connected load. To make the network more suitable to be used as distribution grid, the line resistance values were increased to 5 times the standard p.u. values provided in the MATPOWER [42] case files. The line reactance p.u. values were left unchanged. The total system load was divided among the buses in the same ratio as the original MATPOWER case file. The modified 14-bus network is operated as a microgrid with some embedded generation present in the microgrid as well. It is assumed that bus 1 has a point of common coupling (PCC) with the main utility grid with a maximum real power exchange capacity of 1MW; buses 2, 3, 4 and 9 have solar PV power plants with capacities of 150kW, 75kW, 75kW and 150kW respectively; buses 3 and 4 have energy storage systems with capacities of 420kW and 300kW respectively. Diesel generators of 3MW capacity were placed at buses 3 and 8 respectively. The base value for the simulation was considered as 8000kVA. The parameters of the diesel generators are provided in Table IV [43]. In Table IV, a, b and c are fuel cost curve coefficients while P_{min} and P_{max} are minimum and maximum powers produced by the diesel generator respectively.

The MATPOWER package is used in Octave to solve the optimal power flow (OPF) problem for this network. Charging load demands generated by the agents in Netlogo are provided as inputs for solving the OPF problem. The OPF problem was solved for different kinds of system loads ranging from high charging load to low charging load. For the network configuration mentioned in the previous paragraph, it was observed that the OPF converged without any difficulty. Moreover, no voltage overloads were observed at any of the buses. The network configuration especially the placement of generators was however finalized after extensive trial and error attempts using MATPOWER. Techniques such as the Jump and Shift method described in [43] may be used to combine the scheduling (unit commitment) and OPF problems to verify the feasibility of scheduling results.

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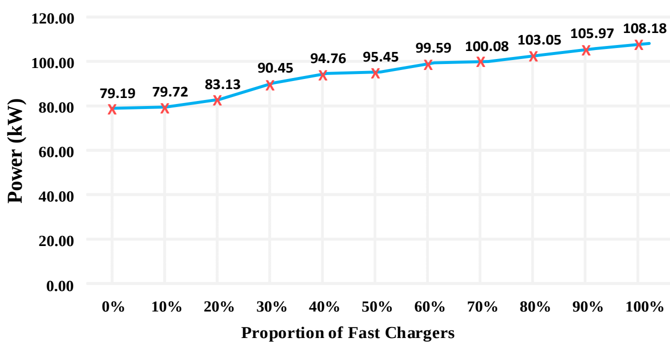

Fig. 18: Sensitivity analysis for type of charging

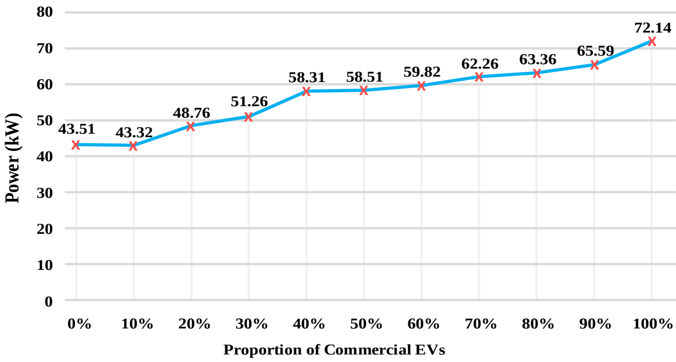

Fig. 19: Sensitivity analysis for proportion of commercial EVs

C. Sensitivity Analysis

Three important parameters - charging type, driver experience and ratio of commercial to private EVs were used to perform sensitivity analysis on the model developed in this paper. The results of the analysis are presented in Figs. 18, 19 and 20. From Fig. 18, it is observed that the daily average charging load demand increases with an increase in the proportion of fast chargers in the system. This is intuitive since the power drawn by fast chargers is more when compared with slow chargers. Moreover, from Fig. 19, it is observed that the daily average charging load demand also increases with an increase in the proportion of commercial EVs in the system. This is also quite natural since commercial EVs are assumed to operate 24h hours a day in shifts as opposed to private EVs which operate only for a limited number of hours every day. The average energy consumed by commercial EVs is therefore higher when compared with private EVs. On the flip side, from Fig. 20, it is observed that the daily average charging load demand decreases when driver experience goes up since EV users are more aware about their vehicle range and do not resort to panic charging before battery SOC drops to its critical level. Overall, the sensitivity analysis reaffirms the hypotheses presented earlier in the paper regarding the influence of various parameters on EV charging load demand.

VI. Conclusion

In this paper, a simulation model to predict the charging demand of EVs based on various essential parameters was proposed. The results emphasize the practical applicability of the ABM based approach to predict the charging demand of EVs. The ABM approach accounted for various aspects of EV

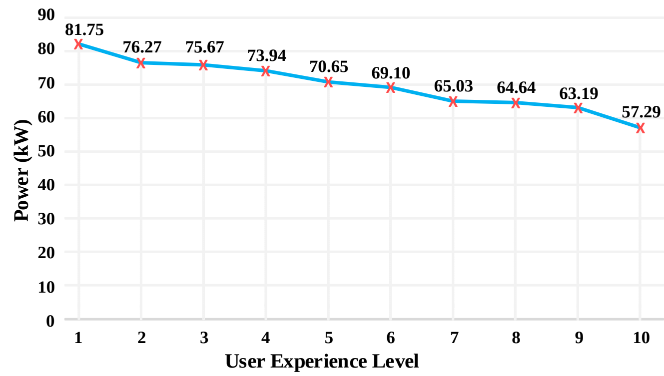

Fig. 20: Sensitivity analysis for driver experience

charging including technical, social and economic parameters to ensure reliable results. The simulations were carried out for a 24-hour period over several days. Individual and total power demands were determined for various scenarios to enable further analysis in real world situations. Furthermore, the proposed model also facilitated the analysis of both commercial EVs and private EVs by accounting for their respective usage patterns. The model developed in this paper was used for sizing RES and ESS. The agent environment was also linked with the electrical network by solving the optimal power flow problem for an exemplar power system. Hence, the model presented in this paper overcame various disadvantages inherent in existing models by accounting for the influence of human aggregate behaviour on the overall charging demand of EVs. In future, the approach presented in this work can be validated using measured data from government agencies such as Singapore's Land Transport Authority or private charging station operators and EV fleet owners. Three important parameters were selected in this paper for performing sensitivity analysis. In future, a comprehensive sensitivity analysis can be performed by considering a wider selection of variables. For sensitivity analysis, fuzzy membership functions can be used to represent the different variables being studied.

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