EV-Connect: Energy Efficient & Incentive Cost Based Model for Range Anxious EVs with Multi-Hop Socially Assisted V2V Charging

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Abstract: With an increasing demand for a sustainable environment, there has been a rapid shift from internal combustion engines (ICEs) to battery-powered engines (BPEs), which are installed in electric vehicles (EVs). With the increasing need and demand for electric vehicles (EVs), the need for charging stations (CS) is also increasing. However, the paradigm shift is slow regarding CSs because of their high installation costs. Thus, there is still the non-ubiquity of CSs in cities, highways, and remote areas, which causes EV users to experience range anxiety. In this context, vehicle-to-vehicle (V2V) charging could be a promising solution recently gaining prominence. In this paper, we have proposed the incentive-based socially connected V2V charging model for EVs where the excess charge of EVs acts as an alternate charging option for other EVs. We have used the maximum bipartite matching algorithm to map the EVs experiencing range anxiety with available CSs and other EVs with surplus charge. The results of our model have shown the trend that the number of EV users who were experiencing range anxiety is less than the only CS-dependent users. Also, the trend of results indicates that there could be a significant reduction of load on the power grid in that particular area, especially during peak hours.

1 INTRODUCTION

In recent years, there has been continuous demand to lower the emission of greenhouse gases (GHG), which has raised the widespread adoption of EVs. Gasoline-powered vehicles alone are responsible for 40% of CO_2 emissions and 70% of the other GHG gases (Frade et al., 2011). In contrast to them, EVs are more environmentally friendly, energy-efficient, and quieter. As evident from Fig.1, we can see that these factors have led to a tremendous increase in the sale of EVs.

Because of the mentioned advantages of EVs over gasoline-powered vehicles, many countries such as China, the United States, and some European countries are promoting the adoption of EVs.(International Energy Agency (IEA), 2023). By 2040, there is expected to be a complete transition from traditional vehicles to EVs, with the number of EVs exceeding more than 250 million. This large-scale adoption of EVs will reduce the emission of CHG significantly, but it will also lead to a substantial increase in electricity demand (International Energy Agency, 2019). This surge in electricity demand could pose the challenge of overloading the power grid, especially during peak hours (Lopes et al., 2011).

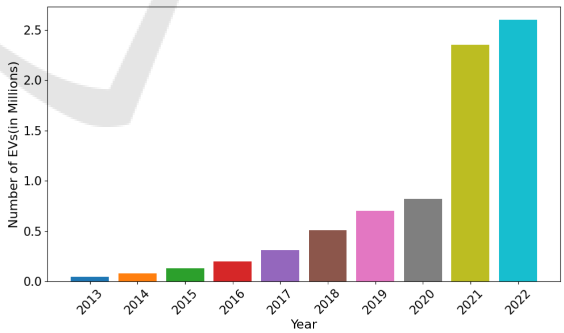

Figure 1: Rise of EVs: Global Trend (International Energy Agency, 2019).

Another challenge for the widespread adoption of EVs is the gradual and non-ubiquitous deployment of CSs. The current ratio for the number of EVs on each CS is 135:1 (Bolt Earth, Year). With the increasing number of EVs, the number of CSs to meet the demand of EV users is very low, and this uneven ratio of EVs to CS has led to anxiety among EV users, which is popularly known as range anxiety. Range anxiety

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concerns EV users about the possibility that the vehicle may run out of charge before reaching the nearest CS or final destination. The range anxiety particularly increases among EV users in areas where there is limited availability of CSs, such as highways and remote locations, or even at CSs having longer queues (Kester et al., 2020), (Xiong et al., 2018).

EVs, also functioning as mobile energy storage units, give rise to new concepts of energy transfer such as Vehicle-to-Grid (V2G), Vehicle-to-Home (V2H), and Vehicle-to-Vehicle (V2V), which are evolving due to the advent bi-directional chargers (Ucer et al., 2019). The concept of V2V charge exchange enables EV users to alleviate range anxiety by transferring surplus charge from one EV to another with a charge deficit. (Liu et al., 2013), (Dhungana and Bulut, 2019). It allows EV users to get charged by other EV users, especially during peak hours, when charging demand is high. Thus, V2V charging can be exploited to reduce the load on the power grid in that area.

In the latest developments in the V2V charging framework, some efficient matching algorithms such as stable-matching (Zhang et al., 2017), (Wang et al., 2018), and maximum-matching (Zhang et al., 2019) have been used to map the consumer EVs with provider EVs. Apart from this, in (Bulut and Kisacikoglu, 2017), a social model system has been proposed, where an EV is mapped with either CS or with another EV, having a surplus charge. They have used the maximum weighted bipartite matching algorithm. In (Zhang et al., 2019), (Shurrab et al., 2022b), and (Shurrab et al., 2022a), authors have proposed the charge sharing models that are cost-effective and user satisfaction-based for EV users. Authors in (Kim et al., 2018) have considered a dynamic pricing scheme for off-peak and on-peak load time and proposed a matching theory based on the charge requested by an EV. Also, in (Bulut et al., 2019), authors have proposed the probable trip-based EV charging where consumer EV detour cost has been minimized. Considering the high demands of EVs, authors in (Yuan et al., 2022) have proposed an auction framework to promote EVs to sell their excess energy, as CSs often pose a threat to satisfy these demands. Despite all these advancements, some constraints, such as trust, still make EV users hesitate to request the charge from anonymous users.

Considering the trust constraints, we have proposed the socially connected V2V charge-sharing framework, which provides a trustworthy connection. The incentive-based model offers a cost-effective solution for anxious EVs. It is also an effective solution to reduce the load on the power grid.

2 SYSTEM MODEL

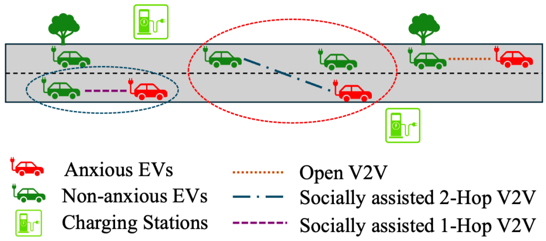

Figure 2: System model consisting of the anxious EVs, non-anxious EVs, and CSs.

As shown in Fig. 1, our system model consists of N number of EVs, including both anxious and non-anxious EVs, and C number of CSs. Here, anxious EVs are charge deficient and experiencing range anxiety, denoted as N_i^A, i = 1, 2,.., N^A; and non-anxious EVs have a surplus charge to provide the charging to anxious EVs in return for some incentives, which are are denoted as N_j^N, j = 1, 2, ...,N^N, and N^N = (N − N^A). Expanding the current V2V charging framework, we have included a social metric among EVs to establish a charge-sharing framework. Social V2V charging is defined as V2V charging where social connection is established if EVs are connected through some social networking platform (Foursquare, 2024) such as Twitter, Facebook, etc. We assume that the EVs are connected socially; based on that, anxious EVs can request the charge from other non-anxious EVs. We have defined a set of socially connected anxious and non-anxious EVs as N_s^N.

The range (Rg) of an EV is defined as the maximum distance it can travel in a specific amount of charge. We have considered the EV user's daily trip distance as (D_t) and an extra distance that an EV user may travel additionally, (D_a). Apart from this, the range anxiety (RA) can be defined as:

$$RA = SoC - \varepsilon \tag{1}$$

where, we have assumed ε is the threshold value and State of Charge (SoC) is the current battery charge of EV, which can be calculated as:

$$SoC = Rg - D_t - D_a \tag{2}$$

Based on the evaluated value of RA an EV user can be classified as anxious EV if it's value is less than zero; otherwise, they are classified as non-anxious EVs.

To minimize the number of anxious EVs experiencing range anxiety, we have constructed a bipartite graph to attain an optimal matching among EVs and CSs. In this graph, vertices (V) represent EVs or CSs, while the edges (E) represent the connection between anxious EVs and CSs or between anxious and non-anxious EVs. More formally,

$$|V| = (|N^A| \cup |N^N| \cup |N_s^N| \cup |C|), \text{ where} \tag{3}$$

N^A is the set of all anxious EVs , N^N is the set of all non-anxious EVs, N_s^N is the subset of all non-anxious EVs having social relationship with anxious EVs, and C is the set of all CSs . The total set of edges for socially connected anxious vehicles with CSs (e_C) and with non-anxious vehicles (e_s^N) is defined as:

$$e = (e_C \cup e_s^N) \tag{4}$$

2.1 Charging Framework

In our proposed charging framework, we have considered the serviceable charging radius (SCR), within which any charge deficit EV can obtain a charge from any CS or from socially connected EV through V2V charge sharing. The charging services for each anxious EV are based upon its minimum detour distance (additional distance traveled to reach a point off the original route). The mapping of anxious EVs for our charging framework is classified into the following cases:

- ***For CS:*** Based on the mapping of anxious EVs with CS within its SCR, the edges of bipartite graph are defined as: $\forall j \in N_A, \forall k \in C$

$$e(j,k) = \begin{cases} 1 & \text{if } RD(j) \geq \text{dist}_j^k \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

  Where, RD(j) represents the remaining distance of j^{th} anxious EV, and the $dist_j^k$ is its trip distance with k^{th} CS.

- ***CS with V2V(CS+V2V):*** In contrast to CS, where anxious EVs rely solely on CSs to get their required charge, we facilitate V2V charging here, enabling them to obtain charge from other non-anxious EVs. Non-anxious EVs with excess charge will act as charge providers for anxious EVs. By incorporating V2V charging, the number of anxious EVs is expected to reduce as the available charging options increase.

$$e(j,k) = \begin{cases} 1, & \text{if } RD(j) \geq \text{dist}_j^k \\ & \quad \text{and} \\ & RqD(j) \leq RD(k) - 2 * \text{dist}_j^k \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

$$\forall j \in N^A, \forall k \in C \cup N^N$$

  Here, RqD is the amount required distance demanded by anxious EV user.

- ***For Socially Assisted 1-Hop/2-Hop V2V:*** By integrating a social factor, this scenario expands upon the CS with the V2V approach. Incorporating this social factor allows anxious EVs to be mapped to non-anxious EVs based on their social relationships.

$$e(j,k) = \begin{cases} 1, & \text{if } RD(j) \geq \text{dist}_j^k \\ & \quad \text{and} \\ & RqD(j) \leq RD(k) - 2 * \text{dist}_j^k \\ & \quad \text{and} \\ & \quad X_{j,k} \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

$$\forall j \in N^A, \forall k \in C \cup N_S^N$$

$$\text{where } X_{j,k} = \begin{cases} 1, & \text{if } j \text{ and } k \text{ are friends} \\ 0, & \text{otherwise} \end{cases}$$

Where $X_{j,k}$ is defined as a social tie between EVs, with a value of 1 if j and k are directly connected (1-hop V2V) or indirectly connected (2-hop V2V) and 0 otherwise (Li et al., 2014).

Our aim is to maximize the matching among anxious EVs with both non-anxious EVs and CSs. The optimal matching for anxious EV is achieved if it gets mapped with at most one socially connected non-anxious EV or CS. We have calculated the weight of matched edges as:

$\max \sum_{\forall i} Q_i \qquad s.t.$

$$Q_i = \sum_{\forall j \in N^N \cup C \cup N_s^N} k_{im}, \forall i \in N^A \tag{8}$$

$$\sum_{\forall m \in N_{NA} \cup C \cup N_s^N} k_{im} \leq 1, \forall i \in N^A \tag{9}$$

$$\sum_{\forall i \in N^A} k_{im} \leq 1, \forall m \in N^N \cup C \cup N_s^N \tag{11}$$

$$k_{im} = \begin{cases} 1, & \text{if } i \text{ is assigned to } m \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

2.2 Total Energy Consumption

Considering the total battery capacity of the EV as B^{EV} in KWh, and the required energy of an anxious EV is E^A (KWh). The E^A depends upon the anxious EV's SoV and its mileage (Mil^{EV}) in (Km/KWh) of the anxious EV given as:

$$E^A = SoV/Mil^{EV} \tag{13}$$

We have also assumed that the power transfer efficiency for V2V and V2CS is η. Thus, the maximum energy an anxious EV can receive (ρ^A) is given as:

$$\rho^A = \eta * E^A \tag{14}$$

The above mentioned equation evaluates the ρ^A for each anxious EV. Thus, the total energy consumed (ρ_T^A) by the mapped anxious EVs can be formulated as:

$$\rho_T^A = \sum_{\forall i \in N_A} \rho_i^A \tag{15}$$

The total energy for mapped anxious EVs with CSs is given as: (ρ_{avCT}^A), with open V2V as (ρ_{avVT}^A) and with socially connected EVs as (ρ_{avST}^A). Thus, the total average energy consumed by anxious EV for the case of mapping with CS and socially connected V2V can be determined as follows:

$$\rho_{avCT}^A = \sum \rho_C^A / N_C^A \tag{16}$$

$$\rho_{avVT}^A = \sum \rho_V^A / N_V^A \tag{17}$$

$$\rho_{avST}^A = \sum \rho_S^A / N_S^A \tag{18}$$

The evaluation of the power grid load depends on the number of EVs fulfilling their charging requirements through CSs. The higher the number of anxious EVs getting with CSs, the greater the load on the power grid will be. Our proposed socially (1-hop/2-hop) assisted V2V charging framework could be potentially helpful in distributing the load solely from the power grid, and it can be evaluated by using the factor named reduction of load (ROL). ROL is the difference between the total energy consumed from the power grid in the case of only CSs based framework and Socially assisted charging framework, formulated as:

$$ROL = \rho_{CT'}^A - \rho_{CT}^A \tag{19}$$

Where, for our socially assisted model it is represented as ρ_{CT}^A and for only CS case it can be represented as $\rho_{CT'}^A$.

2.3 Average Cost per EV

In our proposed cost model, we have defined the two types of costs: Standard Price (SP^A) and Incentive Price (IP^A). Both are priced at what anxious EVs must pay to buy the charge. Also, both costs depend upon the energy consumed by an anxious EV. The price set by the grid to buy the surplus charge from non-anxious EVs is prominently lower than the price they will get from anxious EVs (Tushar et al., 2015). Both the costs are defined and formulated as below:

2.3.1 Standard Price (SP^A)

It refers to the unit price or actual price which is offered by CSs to EVs ($/KWh). Thus, the average cost per anxious EV with CSs (C_{CS}) is given as:

$$C_{CS} = \rho_{CT}^A * SP^A \tag{20}$$

2.3.2 Incentive Price (IP^A)

It refers to the discounted price offered to an anxious EVs by non-anxious EVs. The incentive is determined based on the social and non-social relationship between anxious and non-anxious EVs. Thus, the IP^A is defined as follows:

$$IP^A = (SP^A - x\% of SP^A) \tag{21}$$

Where x% is the percentage of discount offered on the SP^A, which will vary for V2V charging framework basd on open V2V and social-V2V (1-hop/2-hop) for anxious EVs. Thus, the incentive-based cost for charging the anxious EV can be computed as:

$$C_{EV} = \rho_{ST}^A * IP^A \tag{22}$$

where, ρ_{ST}^A is the average energy received by each anxious EV from non-anxious EV during V2V charging.

3 PROPOSED APPROACH

In our proposed model, we construct a bipartite graph comprising the set of vertices defining the anxious, non-anxious, and CSs. An edge between the vertices is established if the charge is shared between anxious EV and CS or anxious and non-anxious EV. The maximum weighted bipartite matching algorithm is applied to discover the most optimal match (Kingsford, 2019). The energy-cost model can be used for mapped anxious EVs that are socially connected to non-anxious EVs and for mapped anxious EVs with CSs in a bipartite graph. The average energy the anxious EVs receive is determined for the cases (i). When only CSs are present, (ii). When CS + open V2V is present and (iii). When CS + socially connected V2V charging option is also available. For open V2V and socially assisted V2V charging, the evaluation involves the same number of mapped anxious EVs as in the case of only CSs. Still, due to the availability of V2V charging, there will be a lesser number of anxious EVs getting mapped with CSs.

4 SIMULATION RESULTS

4.1 Simulation Parameters

In this section, we evaluate the effectiveness of our results, comparing them with the traditional V2V charge-sharing framework (Bulut and Kisacikoglu, 2017). We have conducted our simulations in Java

Data: Set of demanding EVs (N^A), set of provider EVs (N^N), set of CSs (C)
Result: The optimal matching for demanding and provider EVs.
for $j = 1$ ***to*** $|N^A|$ **do**
  Calculate **SoV** and **RA** based on Equations (1), (2);
  for $k = 1$ ***to*** $|C|$ **do**
    Establish bipartite graph G_1 for set N^A and C;
    if $(RD(j) > dist_j^k)$ **then**
      Establish E in G_1 // Construct the edge set E;
    end
  end
  for $k = 1$ ***to*** $|C \cup N^N|$ **do**
    Establish bipartite graph G_2 for N^A and $C \cup N^N$;
    if $(RD(j) > dist_j^k)$ ***and*** $(RqD(j) \leq RD(k) - 2 * dist_j^k)$ **then**
      Establish E in G_2 // Construct the edge set E;
    end
  end
  for $k = 1$ ***to*** $|C \cup N^N \cup N_s^N|$ **do**
    Friends$[j][k] \leftarrow 1$ if j and k are friends, else -1;
    Establish bipartite graph G_3 for set N^A and $C \cup N^N$ // Initially empty;
    if $(RD(j) > dist_j^k)$ ***and*** $(RqD(j) \leq RD(k) - 2 * dist_j^k)$ ***and*** $X_{j,k}$ **then**
      Establish E in G_3 // Construct the edge set E;
    end
  end
end
while G_1, G_2, G_3 **do**
  Find perfect matching **M** using maximum bipartite matching;
end
for $j = 1$ ***to*** $|M|$ **do**
  Compute ρ^A;
  Compute ρ_C^A using ρ_S^A **and** η;
  Compute Total Energy ER_{CT}^A **and** ER_{ST}^A;
  Calculate ROL according to Equation 19;
  Calculate average cost C_{CS} and C_{EV} according to Equations 20, 22;
end

Algorithm 1: Mapping of anxious EVs to non-anxious EVs and CSs based on matching of maximum weighted bipartite graph.

using a custom discrete event simulator. We consider a stochastic model for EVs where they can choose either the nearest CS or V2V charging to get charged. We evaluate the overall energy consumption and cost for anxious EV users. The simulations study various cases: *Case 1:* Comparing mappings of anxious EV users with CSs, V2V charge sharing, and multi-hop socio V2V charge sharing. *Case 2:* The effect of variation of social factor (%) on mapping of anxious EV users with multi-hop socio V2V charge sharing. *Case 3:* The total average energy consumption by anxious EV users. *Case 4:* Total average cost of buying the charge for anxious EV users. All the simulations are performed for 20 iterations and are averaged for validating our proposed model and also to obtain the uniformity in the result for randomly moving EV users in our scenarios.

Table 1: Simulation Parameters.

Metric	Value	Unit
RNG	Uniform distribution from 90 - 100	km
T_d	Uniform distribution from 60 - 90	km
E_d	Uniform distribution from 10 - 25	km
ε	25	km
S^f	0-100	%
RD	Random distribution from 20 - 35	km
SP^A	Random Distribution from 10 - 20	$
x	5 - 20	%
η	0.85 and 0.90	%
N	[30, 60, 90, 120, 150, 180]	-

To mitigate the range anxiety among EV users, we evaluate the effect of having V2V charging along with CSs. The performance of our approach is measured in terms of anxious EV users mapped. In our simulations, we vary number of vehicles (V) from 30 to 180, with a step size of 30. There are 1/V CSs that are randomly located in our scenario. Based on the value of RA, as described in equation 3, we get our anxious and non-anxious EV users.

1. *Mapped Anxious EVs Comparison*: In Fig. 1, we performed the simulation where we considered anxious and non-anxious EVs, and CSs. We compare our proposed multi-hop-socially assisted V2V charging with the traditional V2V charging framework. The figure shows that if we consider V2V charge sharing along with CSs, the number of mapped anxious EV users increases compared to when only CSs are present.
2. *Anxious EVs Blocked*: From Fig. 1, we can conclude that more anxious EVs can be mapped after incorporating V2V charging and CSs. Fig. 2 shows the number of blocked EVs, i.e., the vehi-

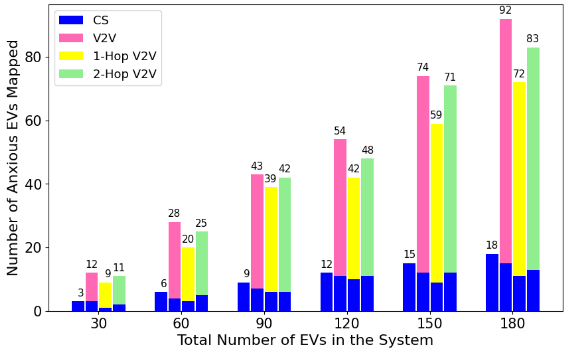

Figure 3: Number of Consumer EVs Mapped to Provider EVs and CSs.

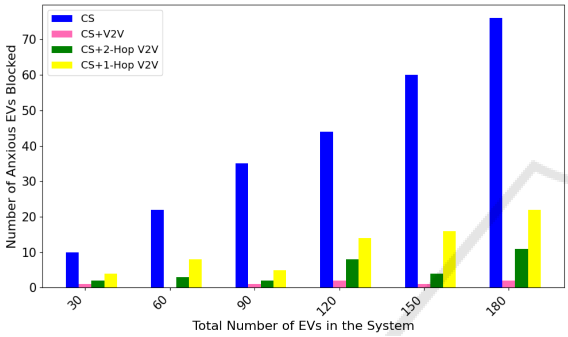

Figure 4: Number of Consumer EVs Mapped to Provider EVs and CSs.

cles that could not get the required charge. We can see from the figure that the maximum number of anxious EVs who could not get the necessary charge are in the case when only CSs are available. However, as we incorporate V2V charging, the blocked number of EVs decreases, which means that more anxious EVs can get the required charge. The minimum number of blocked EVs occurs when both CSs and V2V charging are available. This is followed by 2-hop socially assisted V2V charging, as EV users have more charging options compared to 1-hop socially assisted V2V charging.

3. *Average Energy Consumption by Anxious EVs*: The average energy consumption for mapped anxious EVs is calculated considering the value of B^{EV} to be 75KWh, allowing the vehicle to travel up to 250Kms on a single charge. Thus, the Mil^{EV} is calculated to be 3.33 km/kWh. The value of E^{A} can easily be found using equation 13 considering the value of SoV and Mil^{EV}, which falls in the range of 27.03KWh to 30.03KWh.

   Due to some power loss for charging the EV from CS and V2V, the efficiency for power transfer is not ideally 1, but it is considered to be 0.9 for CS and .85 for V2V. Thus, the maximum value of ρ^{A} falls from 22.97KWh to 24.327KWh for CS and 25.25KWh to 27.07KWh for V2V for each anxious EV. The minimum value of ρ^{A} is evaluated when the range anxiety has been triggered in the anxious EV, i.e., at ε = 25Km, assessed in a range of 5.75KWh to 6.76KWh. From the total number of mapped anxious vehicles, the total average energy consumed is evaluated for the following two cases:

   (a) *With V2V charging framework*: Fig. 4 shows the total average energy consumption from CSs for V2V, and our social-assisted charging framework falls in the range of 27 KWh to 235KWh. With the increase in area and the number of vehicles, most of the charging requirement is accomplished by the V2V charging framework. Thus, the minimum value of the load on the power grid $\rho^{A}_{CT'min}$ is 27KWh for the case when CS=3 and the total number of EVs = 30. The maximum value of the load on the power grid or the value of $\rho^{A}_{CT'max}$ is 235KWh for the case when CS=18 and the total number of EVs = 180.

   (b) *Wihout V2V charging framework*: From Fig. 4, the precise observation can be made that with only CS possibilities, the minimum value of ρ^{A}_{CTmin} is 278KWh for CS=30 and a total number of EVs= 30 to meet the demand of exact number of anxious EVs through CS only. The maximum value of ρ^{A}_{CTmax} is 1335KWh for CS=180, and the total number of EVs=180 for the same number of anxious EVs through CS only.

   Thus the minimum value of ROL for total number of EVs to be 30 is 251Kwh. And the maximum value of ROL for the total number of EVs to be 180 is 1100KWh. And it can be concluded that our model helped significantly in reducing the load on grid along with secure charge sharing framework.

4. *Average Cost for Anxiuos EVs*: We have considered the SP^{A} for charging the anxious EVs through CSs and the IP^{A} for charging the anxious EVs through V2V charging infrastructure which is categorized into the three cases based on the relation they maintain either open V2V or they are socially connected. All the three cases are mentioned as below:

   (a) Open V2V charging- For V2V charging framework, the anxious EVs are offered with the discount (x) ranging from 5% to 10% on the (SP^{A}).

   (b) 2-Hop socially assisted V2V charging - So-

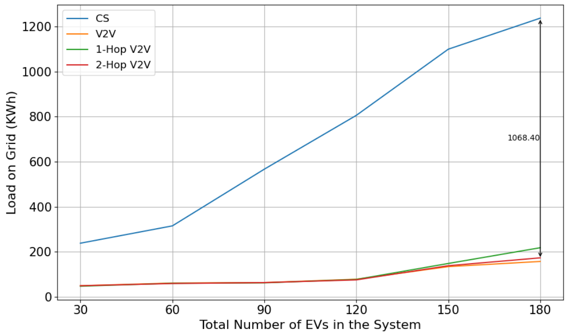

Figure 5: Average energy consumption by mapped anxious EVs to CS (KWh).

cially assisted charging framework allows the EV users of having higher discounts in comparison to open V2V, thus resulting in the lower average cost. Here, anxious EVs will be offered a discount (x) ranging from 10% to 15% on the SP^A.

(c) 1-Hop socially assisted V2V charging - In this case, anxious EVs are offered with maximum discount (x) ranging from 15% to 20% on the IP^A. The discount is maximum as compared to other charging options as they share the direct social relationship.

Fig. 6 shows that incentive based average cost framework for 1-hop, 2-hop and V2V is significantly lower as compared to standard average cost for only CS based cost framework. Thus, for socially assisted 1-hop V2V charging framework the value ranges from \$17.51 to \$ 113.29, for 2-hop \$19.57 to\$134.56, for open V2V \$29.78 to \$174.53 and for only CS based charging framework it ranges from \$38.05 to \$197.94.

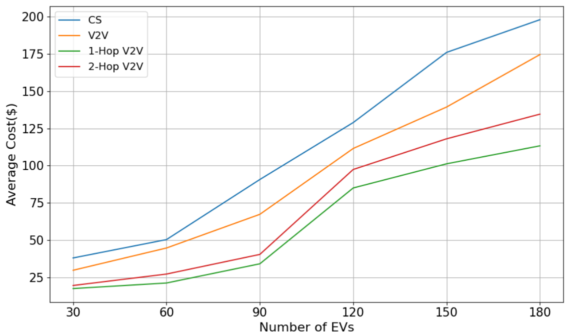

Figure 6: Average cost($).

5. *Impact of Social Factor (S^f)*: To analyze the effect of socially connected EVs on range anxiety, we have considered three cases such as 1-hop, 2-hop, and open V2V charge-sharing framework. And the value of S^f is varied from 0 to 100%. We can see from Fig. 7 that as the S^f increases for 1-hop and 2-hop, more anxious EVs are getting mapped to non-anxious EVs and the results aligns with the open V2V charging framework, which validates our socially assisted charging framework and additionally giving the secure charging framework.

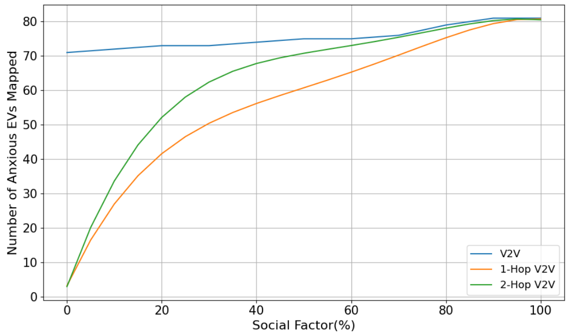

Figure 7: Mapped anxious EVs with increase of social factor.

5 CONCLUSION

In this paper, we presented the cost-aware socially connected V2V charging framework for addressing the range of anxiety in anxious EVs by enabling them to buy energy from other non-anxious EVs with surplus charge on discounted price.

We performed simulations for various cases with and without V2V charging to assess the system's performance. The proposed social charging system grants EV drivers complete control over their charging needs while safeguarding their privacy. After closing analyzing the mapping of lesser anxious EVs to CSs gave the insight that socially assisted V2V charging framework also significantly reduces the load on the power grid. It establishes a mutually beneficial environment for EV energy sellers and buyers. As part of our future work, we plan to investigate the impact of other simulation parameters on the system's outcomes. Additionally, we will explore pricing mechanisms, such as auctions, within social market scenarios for this charging system.

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