Design and Analysis of an Efficient Energy Sharing System among Electric Vehicles using Evolutionary Game Theory

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***Abstract*—Electric Vehicles (EV) are limited to a short driving range owing to battery constraints. The charging locations of EVs also tend to be quite distant from one another and often times they are not available in many places. The combination of these two problems lead to longer trip durations for an EV since the depletion of the battery requires travelling to distant locations or even taking detours to reach the charging stations. In the proposed network scheme, an EV that lacks energy to complete its trip can request for energy from EVs in its vicinity. The model proposed is based on a variant of evolutionary game theory. This model is premised on the selfishness of each individual EV and is expanded upon using replicator dynamics on graphs. The EV which is requesting charge, known as a *receiver*, offers an incentive to attract other EVs, known as *givers*, to share their energy. The model outlines the procedure by which the regulation of the incentive contributes to a change in the ratio of *givers* in the model. The results demonstrate that an equilibrium can be established where there is the consistent creation of *givers* in the system. This equilibrium is attained by varying the incentive offered by EVs with depleted energy levels. Thus, using a theoretical and numerical approach it is demonstrated that an effective energy sharing system is sustainable.**

***Index Terms*—Electric vehicle, evolutionary game theory, replicator dynamics, bi-drectional DC-DC conversion**

I. Introduction

Electric vehicles (EVs) and their widespread use are a major tool in humanity's arsenal to fend off the climate crisis. The transportation industry, in general, stacks up a significant share of the greenhouse gas emissions around the world [1]. Road transport alone contributes approximately 72% of the emissions from this industry [2]. As a result, EVs are likely to play an essential role in curbing greenhouse gas emissions. There is a major hindrance, however, to its adoption in everyday life and global coverage.

Firstly, the distance that can be traversed seamlessly by an EV is circumscribed by its current battery limitations. This drastically reduces the distances that can be travelled by an EV compared to traditional vehicles. A shorter driving range leads to a much more frequent need to visit Electric Vehicle Charging Stations (EVCS) to restore depleted energy levels of the battery. This leads to increased trip durations, consequently, disincentivising consumers from switching to EVs from traditional vehicles.

Secondly, infrastructure issues in the form of limited EVCSs add to the aversion of EVs among the general populace [2]. These stations tend to be few and far apart. The problem of limited driving range gets exacerbated with a paucity of these EVCSs in the vicinity of the drivers. This challenge gets compounded when such public infrastructure is out of service or malfunctioning. As a result, EVs are forced to travel to distant charging locations which leads to extended trip durations. Long queues at sparsely available charging sites can lead to longer charging times as well.

To boost the popularity of EVs- curbing emissions from vehicles in the process- an efficient energy sharing scheme is being propounded in this study. The EVs in this system are either autonomous or semi-autonomous. The bedrock of the scheme being proposed is a variant of an evolutionary game theoretic approach. In addition to the design of a stable and perpetual system, the aim is to establish automation in this system such that any EV with depleted charge levels can collect charge from surrounding EVs upon request. When the energy level drops below a designated threshold, the EV sends out requests using existing communication networks. The EV with depleted energy can be labeled as the *receiver*.

Fig. 1 below illustrates the proposed scenario where a *receiver* in its journey to its destination engages in an energy sharing scheme with other EVs. The EV which accepts the request and takes upon the role of sharing energy with this *receiver* is labeled as *giver*. The request sent out using communication networks reaches to all the EVs which are connected to the network. The distance that an EV can travel with its remaining charge is used to form a circular cluster around it with other EVs along the cluster's radius becoming participants in the game. This game-initiating EV ensures that minimum energy is expended in suit of this energy collection purpose by traveling the shortest path. Owing to the autonomous selection of *giver* EVs in the cluster by local interactions among them, the goal of the scheme is fulfilled.

Due to its logical, strategic decision-making features, the evolutionary game theoretic method is one of the most suited techniques for achieving such a system. It takes into account the process of natural selection which is advantageous in dealing with selfishness among the EVs. It uses a mathematical model called replicator dynamics to characterize it [3].

All participants are assumed to be homogenous agents as EVs with same charging port, equal battery capacity etc. All

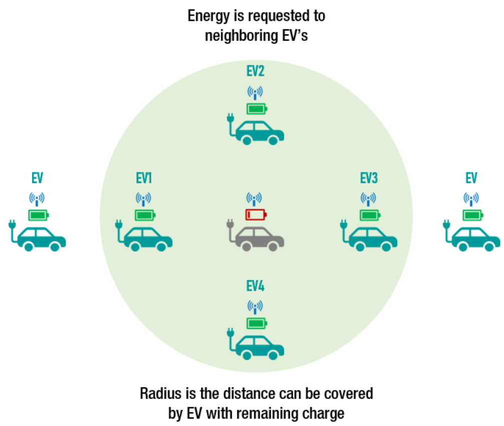

Fig. 1: Proposed scenario.

the EVs along form Internet of things (IoT) devices which communicate with each other on existing networks. Charge transfer occurs using bidirectional DC-DC converter technology using a wired setting. It is heavily employed already in the domain of stored energy systems. This converter technology is nowadays demonstrated to be effective at the transfer of charge between vehicles. Bidirectional DC-DC technology leads to an increase of 1% SOC in 1 minute 8 seconds [4]. The change in SOC is interpreted by the *receiver* and *giver* EVs in terms of the cost per unit they are expending or in terms of the incentive being provided to them. This is further elaborated upon in sections below. This also helps to validate the repetitive nature of the game as every time the *receiver's* charge is depleted, it requests for charge and the game is re-initiated. It is noted that all the EVs and their batteries are part of a vehicle-to-energy network supported via the Internet of Things (IoT)

This process continues till the receiver can reach its destination. Other technologies such as battery swapping and V2G (Vehicle to Grid) charging are also prevalent in the EV charging technology domain. In light of the proposed scheme which requires vehicles to exchange their energy and then continue in their respective journeys, each EV is fitted with this converter technology and its component devices [5], [6]. Afterwards the applicability and suitability of this energy-sharing scheme is discussed where section II ponders upon other studies conducted in relevant fields, section III describes the proposed scheme, section IV demonstrates the numerical results and section V concludes this study.

II. Related Works

Vehicle-to-vehicle (V2V) energy sharing technology is becoming increasingly popular. There is research which focuses on the challenge of routing, scheduling, and matching vehicles in a V2V Wireless Power Transfer (WPT) medium on an energy-time extended network, and provides a dynamic programming solution approach to solve it [7]. Other researchers are positing charging sharing schemes among EVs (V2V) which employs inductive power transfer. Those works posited novel solutions into different ways inductive charging can be deployed which are not yet practically implementable [5], [6]. Research is going on to develop a cost-effective energy-sharing framework for electric vehicles. In one such energy-sharing model, the study offers a comprehensive approach to energy management, integrating the applicability and existence of grids, thus taking a holistic view of energy management [8]. Other works have focused on V2V energy sharing using fog computing. Those works have delved into ensuring security in such transactions using blockchain methods to enable a robust network of EVs [9]. There are other research proposals which suggest the charging of EVs while driving on the road wirelessly [10]. However, such systems entail the overhaul of current infrastructure which can be extremely costly. The advantage of the scheme proposed in this paper is that it does not impose onerous restrictions on the type of infrastructure needed for implementation. The following section dives into the details of the proposed scheme.

III. Proposed Scheme

The discussion in this section encompasses the formulation of the game to be modeled, the various components of the game and its implementation in the system. The relationship between the EVs in this system is thoroughly outlined alongside the different roles they might play in the game. It is noted that all the EVs and their batteries aided by IoT is the vehicle to energy networking.

A. Overview

This paper suggests an automated system which aims at increasing the range of EVs and reducing trip durations. The objective is to reduce trip durations by not having to divert from the route of the destination to reach an Electric Vehicle Charging Station (EVCS). In cases where there are no EVCSs in the vicinity, this approach can help the community even more. The design of the system is such that it does not necessitate changes to public infrastructure and bypasses all the bureaucracy and cost its change entails.

The cluster formed around the *receiver* EV dictates the environment of the game. If an EVCS is far away, even within this cluster, and takes the *receiver* farther from its desired route, trip duration can increase. The problem is exacerbated if no EVCSs are found within the cluster. This brings forth the need for energy sharing emong EVs. However, the challenge is that all vehicles are potentially selfish and are unwilling to share their energy. As such, a system is proposed that *a)* selects a *giver* EV that rendezvous and shares its energy with the requesting (*receiver*) EV and *b)* takes the vehicle's selfishness into account. The system must not have any form of human intervention.

Here, every individual EV in the overall population formulates a strategy for itself. The strategy that gets chosen by an EV changes in every round of the game. This change can be visualised with the help of replicator dynamics on graphs [11], [12], [13], [14], [15]. Replicator dynamics on graphs is a derivative of the original replicator dynamics in the case of a finite population. According to replicator dynamics, the prevalence of a particular strategy being adopted by EVs in the system is dependent upon the payoff that those EVs can attain from that strategy. The members of the population of EVs in this case represent the vertices of a regular graph. The utilisation of the scheme allows the selection of certain EVs in a cluster referred to as *giver* EVs which are willing to share their energy with the *receiver* EV. For this work, *giving* and *not giving* are the two allowed strategies in the population upon the *receiver* requesting energy.

To adopt this modeled game, there needs to be the recurrence of the following three stages:

1. Giver Selecting Stage: Every individual EV chooses to be a *giver* or a *non-giver* depending on mutual interactions with other EVs in the cluster.

2. Receiver Responding Stage: When the selection is complete among the EVs in the cluster, all the EVs communicate with the *receiver* and the *receiver* responds to rendezvous for energy sharing.

3. Energy Sharing Stage: Each *giver* meets and shares energy with the *receiver*. *Non-giver* EVs do not meet with any EV and do not take part in energy sharing.

A *round* of the game is defined as the repetition of these three stages which is undergone by the system. It is assumed that all the vehicles synchronise with each other and are cognizant of the duration of the round. The amount of energy intake by the *receiver* and the amount it further needs to reach its destination determines every individual round. The length of the round is communicated among the EVs and can be updated if necessary. This model is a variant of evolutionary game theory based on a self-organized data aggregation technique described in [16].

The fundamental theme propelling this scheme is that EVs are selfish about their energy. As a result, an *incentive* is needed to prod them to share their energy. The *giver* in every round is imparted with a type of benefit to attract them which serves as the *incentive*. This brings forth two challenges: *1)* How can the selection of *givers* be done automatically under situations where all EVs are potentially selfish? *2)* Is it possible to control the number of *givers*? Here, the application of this variant of evolutionary game theory can assist in resolving these since it takes into account the different influences caused by the mutual interactions among the EVs.

B. Selection of the Givers

The vehicles in the cluster are under mutual dependency with other cluster members. It is assumed that each node communicates with its neighboring *receivers* and then determines to be a *giver* or a *non-giver* based on the potential benefits it can reap. In this system, let c be the equivalent amount of credit that is expended as a *giver* travels and consumes battery energy to meet, i.e. equivalent to the decrease in SOC, with a *receiver* for energy sharing purposes. Let, the amount of incentive offered by the *receiver* be b, i.e. equivalent to the increase in SOC it can attain using that gain in credit. This is the energy equivalent amount of credit that the *givers* are to be provided if they expend c amount of energy equivalent credit to service the request of *receivers*. The EVs can utilise this b amount of credit automatically at any EVCS to get recharged by the energy level afforded by b without any additional payments. However, since the *non-giver* EVs are not traveling in the quest of sharing energy, they are also not spending energy for the cause. So, *non-givers* are neither losing nor consuming any energy in order to service the request of the *receiver*. Fig. 2 above illustrates the *giver* selection and the corresponding payoff received when the other EV chooses to be a *non-giver*.

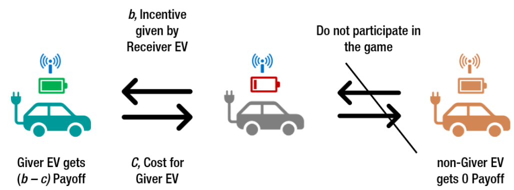

Fig. 2: Selection of *giver* EVs.

Since the EVs are selfish in nature it must be ensured that their energy expenditures are offset by subsequent incentives. Hence, the incentive offered by the *receiver* needs to be a level of b such that $b \geq c$. Intuitively, it can be asserted that larger the b being offered, the more the number of *givers*. This condition also helps to subdue the number of *non-givers* in a system. This incentive b can only be offered by the *receiver* which allows it to regulate the number of *givers* created in the system.

Initially, the bargain among vehicles is modeled as a game between two neighboring EVs, i.e. players in evolutionary game theory. There are two roles (strategies) for each player: *giver* (shares energy with the *receiver*) and *non-giver* (declines to share energy with the *receiver*). Table I below illustrates the possible combinations among the two players in this game.

TABLE I: The payoff matrix in between two EVs.

EV 1 \ EV 2	Giver	Non-Giver
Giver	$\frac{b}{2} - c$, $\frac{b}{2} - c$	$b - c$, 0
Non-Giver	0, $b - c$	0, 0

The ensuing payoffs for all of the individual scenarios can be modeled by taking the credit offered by the *receiver* and the equivalent credit of the energy consumed by the EVs into account. An individual EV knows its own payoffs in light of the possible strategies of other players, without knowing the exact strategies. A *giver* strategy is likely to be preferred by an EV which results in the highest possible payoff. Each EV is cognizant of the payoff it can receive when the competing EV chooses the same or different strategy.

In a case where one of the EVs is a *giver* with the other being a *non-giver*, the largest gain is by the *giver* whereas the *non-giver* remains at a net neutral point with no loss or profit.

The *receiver* offers the full incentive to the giver ($b-c \geq 0$) for this scenario since other EV chooses to become a *non-giver*.

In the case where none of the EVs choose to share their energy, i.e. both choose to be *non-givers*, they encounter no net loss but they also do not get the potential profit that sharing their energy could have reaped.

In the case where both the neighboring EVs decide to become *givers*, the *receiver* meets with both the vehicles for energy sharing. As a result, the incentive offered to each car is halved ($\frac{b}{2} \geq c$). Afterwards, it is possible to abstract Table I into Table II.

TABLE II: The abstracted payoff matrix in between two EVs.

EV 1 \ EV 2	Giver	Non-Giver
Giver	P, P	T, S
Non-Giver	S, T	R, R

In the abstracted payoff matrix, $T > R$ and $P > S$. In this proposed scenario every vehicle is incentivised to become a giver as $T > R$. The larger the b, the greater is the incentive. Resultantly, this proves that the *receiver* EV can change the value of b to control the creation of *givers*. In addition, if both EVs taken into consideration choose to be *givers*, the *receiver* can take energy from both the EVs offering half the incentive.

Furthermore, the condition $T + S > R + P$ facilitates the selection of a role which is an evolutionarily stable strategy [17]. The most preferred role is the case where a player can get the highest reward for sharing their energy while the other player does not wish to share their energy. In conjunction with the payoff matrix and evolutionary game theory, when every EV undertakes appropriate strategies to maximise its own payoff, then the system reaches a fully stable situation where both *givers* and *non-givers* stably coexist [13]. A distinguishing characteristic of this model is that the selections are entirely dependent on the mutual interactions among the vehicles by taking into account the selfishness of each player. The time it takes for charging during each interaction is assumed to be constant. This is predicated upon the homogenous nature of the EVs considered and hence, the latency of the giver and receiver side is also assumed to be constant throughout the system.

IV. Analytical Results

In this section, the relationship between the ratio of *givers* and the parameters of the payoff matrix is derived analytically with the aid of replicator dynamics on graphs [12], [15]. Each EV derives a payoff from the interactions with all of its neighbors. Afterwards, a comparison is performed in terms of the obtained payoff with a randomly chosen neighbour. The replicator equations on graphs are delineated upon along with a thorough elucidation of the anaytical results obtained. Furthermore, the future scope of this research which can further validate this work is also expanded upon.

A. Replicator Equation on Graphs

In order to start the derivation of replicator equation on graphs [13], consider the ratio of *giver* EVs to the total number of EVs as x. On the other hand, $1 - x$ is the ratio of the *non-giver* EVs to the total number of EVs. The expected fitness f_1 and f_2 are given by

$$\begin{aligned} f_1 &= x(\frac{b}{2} - c) + (1 - x)(b - c), \\ f_2 &= 0. \end{aligned} \tag{1}$$

Let k denote the number of neighbors of each EV, called degree of graph [14]. Despite the fact that the analysis given is based on the k-regular graph [12], the method may also be applied to non-regular graphs, like unit disk graphs [12], [14]. This allows us to visualise on graphs how the total number of EVs in a cluster can affect the ratio of *givers* at a certain incentive level. The sum of the original payoff matrix and a modifier matrix is the modified payoff matrix for evolutionary game theory on graphs [13]. The modifier matrix is given as Table III.

TABLE III: Modifier matrix between two EVs.

EV 1 \ EV 2	Giver	Non-Giver
Giver	0, 0	m, $-m$
Non-Giver	$-m$, m	0, 0

$$m = \frac{(k+3)(\frac{b}{2} - c) + 3(b - c)}{(k+3)(k-2)}, \quad \forall k > 2. \tag{2}$$

The local competition among the strategies is denoted by m (as shown in Table III). Each tactic's gain is another's loss, and local competition between the identical strategies yields zero. The expected payoff for the local competition g_1 and g_2 of *giver* and *non-giver* are

$$\begin{aligned} g_1 &= (1 - x)m, \\ g_2 &= -xm. \end{aligned} \tag{3}$$

Consequently, the average payoff consisting of the two strategies becomes

$$\phi = x(f_1 + g_1) + (1 - x)(f_2 + g_2). \tag{4}$$

Putting the values from Eqns. (1) and (3) into Eqn. (4),

$$\phi = x[x(\frac{b}{2} - c) + (1 - x)(b - c)]. \tag{5}$$

From Eqns. (1), (3) and (5), the replicator equation on graphs [13] is found for $k > 2$ to be

$$\dot{x} = x(f_1 + g_1 - \phi).$$

This can be manipulated to

$$\dot{x} = x(1-x)[-\frac{xb}{2} + (b-c) + \frac{k(\frac{b}{2} - c) + 4.5b - 6c}{(k+3)(k-2)}], \quad \forall k > 2.$$

$\dot{x}$ represents the derivative of x. Therefore, in order to obtain the maxima of x, $\dot{x} = 0$ is taken. Therefore, $x^* = 0, 1$ and

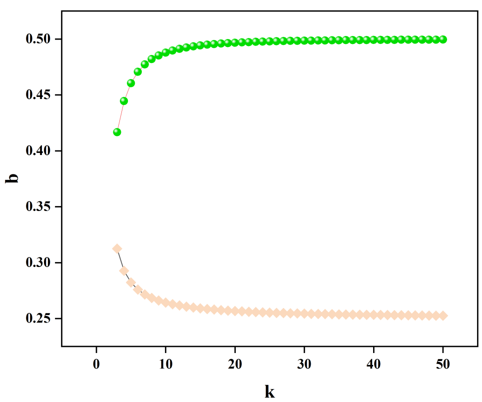

Fig. 3: The supremum and infimum of b varying with k.

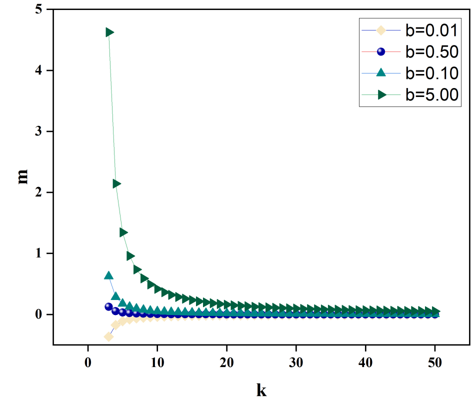

Fig. 4: Modifier m controlled by changing the value of b.

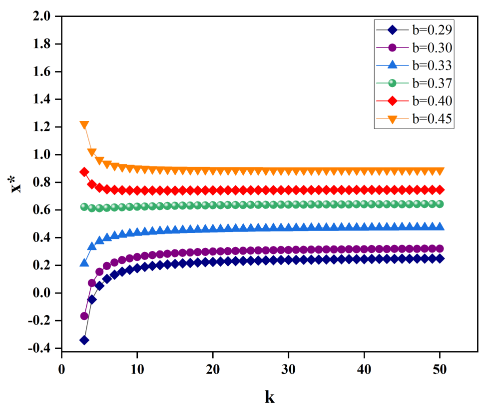

Fig. 5: The value of x^* controlled with the value of b.

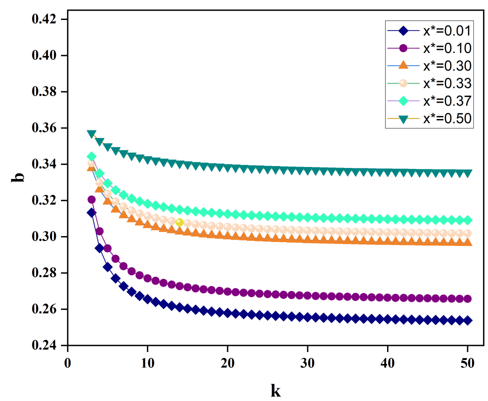

Fig. 6: The value of b controlled with the value of x^*.

$$x^* = \frac{2}{b}[(b-c) + \frac{k(b-c)+4.5b-6c}{(k+3)(k-2)}], \qquad \forall k > 2. \qquad (6)$$

Now, this is feasible for $0 < x^* < 1$. So, from Eqn. 6,

$$\frac{c(k^2+2k)}{k^2+\frac{3k+9}{2}-6} < b < \frac{2c(k^2+2k)}{k^2+2k+3}, \qquad \forall k > 2 \qquad (7)$$

It is found

$$0 < \frac{c(k^2+2k)}{(k^2+\frac{3k+9}{2}-6)} < \frac{2c(k^2+2k)}{(k^2+2k+3)}, \qquad \forall k > 2$$

such that $b > c$. The numerical results with the aid of figures are expanded in the following section. The equilibrium achieved in Eqn. (6) plays a vital role in controlling this model. The impacts of the different variables and their inter-relationship is discussed in the end.

B. Numerical Results

The three variables that the model depends on are b, c and k. The values of these variables affect the value of x. In this scheme, c is a very prominent variable in the case of all the graphs obtained from replicator dynamics. For the purpose of this study, we have considered c to be equivalent to 0.25 units but c can be chosen as any value depending on how far a *giver* needs to travel for upholding our model. We have kept the value sufficiently small for the ease of calculation. All the following graphs have been extrapolated keeping this assumption in mind, without loss of generality. The units of b and c must be the same. Also, the value of c would change according to the pricing scheme. In short, the value of c in our work is just an assumption. It is not universal. And this value and its unit impacts the entire system comprising of b and x^*.

Fig. 3 demonstrates the supremum and infimum of b as satisfied by Eqn. 7. It is observed that even in the worst case, the value of b cannot be less than c, which satisfies a cornerstone of this work stating that $b \geq c$. Furthermore, it is observed that the maximum value of b results in $2c$. This substantiates the model because it proves that the *givers* will not lose. This also clarifies that the *givers* cannot demand an unreasonable amount of credit, since this is controlled by the saturation of b for higher numbers of EV in the radius.

Afterwards, Fig. 4 represents the local competition among the EVs. The modifier equation is represented from Eqn. 2. The modifier graph converges to 0 for different values of b with large k values which implies that the likelihood of EVs all choosing similar strategies is minimal.

Further, the variation of the value of x^* for the controlling of the value of b is also evident from Fig. 5. Here, x^* can be any value in between 0 and 1, depending on b for a fixed number of EVs. It can be deduced that for a specific b, x^* does not change when k becomes large owing to the fact that for limiting value of k, m tends to zero as illustrated in Fig. 4. On the other hand, for relatively smaller values of k, for instance, less than 15, x^* shows different characteristics, depending on b. With decreasing values of b, the value of x^* decreases and vice versa. Therefore, our model is valid since the changing of incentive b affects the ratio of *givers* x^* in the system. As x^* can be controlled by b, similarly, b can also be controlled by x^*. This is evident from Fig. 6. In essence, this means that, the more the number of *givers* in the vicinity, the more the *giver* will have to pay, unless the excessive amount of EVs has already saturated the value of b.

C. Future Scope

Future works can be directed at further validating this model with the aid of agent-based dynamics to conduct micro level experiments. These experiments are to be worked on to ensure these mathematical models are elaborated upon. It can allow the model to be viewed from a micro level perspective in contrast to the macro level perspective present here. Micro level considerations can be included in these studies ranging from time, distance and the relative velocity of the EVs. Since in this analysis time is assumed to be constant, future work can include the factor of time and thus form a dynamic game. A dynamic game can further be executed with the aid of Reinforcement learning (RL). It can then elucidate the latency of the *giver* and *receiver*. Varying latencies of *giver* and *receiver* can be investigated. These considerations can reinforce the robustness of this proposed model.

V. Conclusion

Widespread acceptance of EVs as viable alternatives is stunted by many impediments. The main reason for this is range anxiety. The objective of this study is reduce trip durations for EVs by providing charging sources where there are no charging stations nearby, whittling down trip durations in the process. This is achieved by the design of an efficient model to share energy among EVs which is conducted autonomously with the aid of a variant evolutionary Game Theory. It paves the way for the creation of a system where an EV can collect energy from other EVs by touting an incentive. The level of incentive offered by *receivers* is used to control and induce the creation of *givers*, thereby, formulating an automated system of EVs connected in a network to share energy amongst themselves. The elucidation of the model using replicator dynamics on graphs in conjunction with the numerical results allows the comprehensive analysis of this proposed framework. The theoretical and numerical approach employed here substantiates the equilibrium of *givers* and the corresponding incentives that regulate this equilibrium. In this way an efficient energy sharing scheme among electric vehicles can be established.

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