An evolutionary game theoretic charging mechanism aimed at incentivizing charge sharing without any change in infrastructure

by

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A Thesis Submitted to the Academic Faculty in Partial Fulfillment of the Requirements for the Degree of

BACHELOR OF SCIENCE
IN
ELECTRICAL AND ELECTRONIC ENGINEERING

Department of Electrical and Electronic Engineering
Islamic University of Technology (IUT)
Board Bazar, Gazipur-1704, Bangladesh.
May, 2022

CERTIFICATE OF APPROVAL

The thesis titled, "**An evolutionary game theoretic charging mechanism aimed at incentivizing charge sharing without any change in infrastructure**" accepted as partial fulfillment of the requirement for the Degree of BACHELOR OF SCIENCE IN ELECTRICAL AND ELECTRONIC ENGINEERING of Islamic University of Technology (IUT).

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Declaration of Candidate

It is hereby declared that this thesis report is only submitted to The Electrical and Electronic Engineering Department. Any part of it has not been submitted elsewhere for the award of any Degree or Diploma.

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This thesis is dedicated to each of our family members, the constant support of whom have led us this far in life, and have also been partly responsible for the successful completion of our thesis.

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List of Abbreviations

CO_2	Carbon di-Oxide
DC	Direct Current
DSRC	Dedicated Short Range Communication
EGT	Evolutionary Game Theory
EU	European Union
EV	Electric Vehicle
EVCS	Electric Vehicle Charging Station
ICE	Internal Combustion Engine
NMVOC	Non-Methane Volatile Organic Compounds
NO_x	Nitrogen Oxide
OBU	On-Board Unit
P2P	Peer-to-Peer
PM	Particular Matter
RL	Reinforcement Learning
SO_2	Sulfur di-Oxide
SOC	State of Charge
V2V	Vehicle-to-Vehicle
WPT	Wireless Power Transfer
UI	User Interface

Acknowledgment

All praise and gratitude be to Allah, the most beneficent, the most merciful. We must first be grateful to Him only, because without His will, we would be lost.

We also express our dearest gratitude to our thesis supervisor Dr. Khondokar Habibul Kabir, Professor, Department of Electrical and Electronic Engineering, Islamic University of Technology (IUT). Beginning from our first interaction in the Data Communication and Networking course, down until this way, Dr. Kabir has been nothing but a path-finder for us. It would be wrong of us not to attribute the entirety of the thesis to his name. Worth mentioning that, Dr. Kabir was our first ever exposure to concepts like Evolutionary Game Theory and Replicator dynamics, theory we do not study within the walls of the classrooms.

We must also thank each of our parents and family members. The successful completion of our degree can only be attributed to the financial and mental support the three of us got from our respective homes. Had they not been as strong as they are, we might have not been in this place at this instant.

Finally, we would like to thank the entire department of Electrical and Electronic Engineering. We have constantly been supported by every single faculty member, by our honourable Head of the Department, by our respectable Dean, and by each of our course instructors from diverse cultures within this Islamic institution. We also thank the honourable Vice Chancellor for his spotless authority during this time coming out of a pandemic.

Abstract

This thesis presents a novel mechanism for charge sharing in between Electric Vehicles or EVs. Electric vehicles face some obstacles in the face of adoption over conventional cars. Electric vehicles (EVs) have a limited driving range due to battery limits. EV charging stations are also sometimes rather far apart, and they are not widely available in many areas. Battery depletion entails traveling to remote places or even taking detours, both of which increase the total driving time of EVs. Under the proposed network design, an EV that does not have enough energy to finish its route can ask for energy. Other EVs close to it may respond. It is to be kept in mind that every EV is selfish about its own charge. The model utilizes Evolutionary Game Theory (EGT) and replicator equation on graphs. The EV that needs extra energy and makes the initiative to ask for such is the *receiver*. The respondents may either be *givers* or *non-givers*. *Givers* choose to share their energy, whereas *non-givers* don't. *Givers* get a fixed incentive that topples the potential cost of driving to the *receiver*, whereas *non-givers* neither gain or lose anything. In the model proposed in this thesis, an attempt is made to control this incentive, thus controlling the total number of *givers* in the world. The results show that an equilibrium can be established in a system where *givers* are consistently created. This balance is achieved by altering the incentive provided by EVs with decreased energy levels. Thus, an effective energy sharing system is proved to be sustainable utilizing a theoretical and numerical approach as well as a simulation model to substantiate the theoretical model.

Chapter 1

Introduction and Background

Traditional vehicles are a major contributor to global warming, greenhouse gas emissions, health risks, and pollution. To address the accompanying disadvantages, many countries, including China, the European Union, and the United States, have dramatically shifted away from conventional energy and toward renewable energy in the past decade [4]. A reduction in greenhouse gas emissions by making big changes to the transportation sector through the use of solar energy and the deployment of electric vehicles (EV) can have a widespread positive impact on the environment. Batteries are a low-cost, dependable energy storage medium. Countries that want to transition to 100% renewable energy are replacing internal combustion engines with green transports such as e-bikes, e-cars, hybrid automobiles, hyperloops, and so on [5]. To address the climate crisis, the mass scale adoption and deployment of Electric vehicles (EVs) is of paramount importance. Among the industries contributing significantly to global greenhouse gas emissions, the transportation industry stands out. [6]. It is so significant that road transport by itself accounts for almost 72 percent of this industry's emissions [7]. Hence, the mass usage of electric vehicles are likely to play a crucial part in reducing greenhouse gas emissions. However, there remains significant impediments to the extensive use of EVs in day to day life.

In this chapter, a brief of the problem and the steps for its solution would be provided. The chapter is structured as such: the problem statement is pondered upon in Section 1.1, and then the research objectives are elucidated upon in Section 1.2. Section 1.3 expands upon what are expected off this research, and Section 1.4 speaks of how the thesis differs from previously established works. Finally, Section 1.5 offers a prelude to the proposed model in this research.

1.1 Problem Statement

Energy systems throughout the world are undergoing rapid transformations that will have a significant impact on how vehicles are fueled, homes are heated, and industries are powered. The energy crisis is caused by the insufficient use of alternate energy sources and fossil fuels. The planet is being harmed by an unbalanced energy mix. Because of the insatiable reliance on fossil fuels, which will continue for the next two decades, fossil fuels will soon get depleted. A worldwide energy crisis is impending as a result of global population expansion, increased consumption, and reliance on fossil-based fuels for the purpose of generation. It is commonly believed that rises in greenhouse gas concentration levels, if not reduced, will result in dramatic changes in global climate, with significant consequences for both the society and the economy [8].

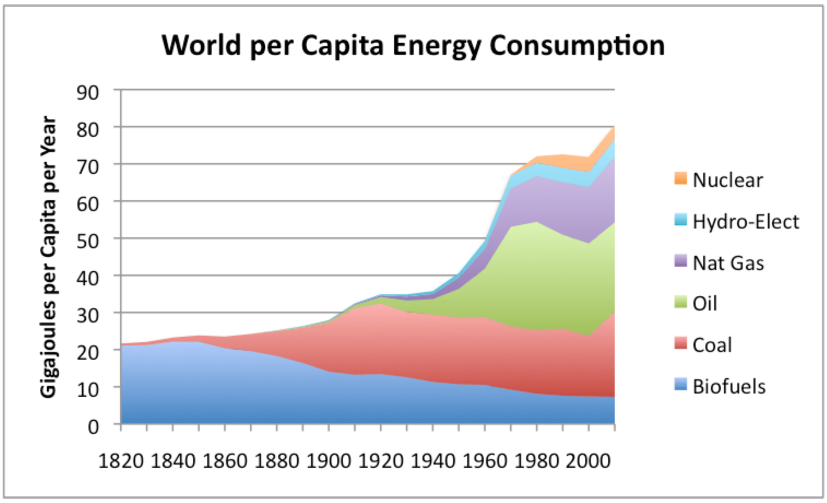

Figure 1.1: Energy Consumption per capita from 1820-2000 in the world. [1].

According to the graph above, the world's energy consumption is at an all-time high. To meet this increasing demand, fossil fuel usage has also reached its peak capacity. This has long-term hazardous effects to both the climate as well as the ecological balance of our planet. Furthermore, it has been stated that the demand for energy would only rise in the near future. This can be seen in Figure 1.2.

To combat this reliance on fossil fuels, electric vehicles are viewed as a more environmentally friendly alternative to traditional fuel-consuming automobiles. Electric vehicle adoption increased by 11 percent in the United States between 2011 and 2015 [9]. However, some critical obstacles are impeding the growth of EV adoption.

1.1.1 Problem Identification

Consumers have certain obstacles when it comes to EV adoption. Firstly, an EV's current battery limits the distance it can drive without stopping. When compared to regular vehicles, this significantly reduces the distances that an EV can go. A reduced driving range leads to increased visits to Electric Vehicle Charging Stations (EVCS) in order to recharge the battery's low charge levels. This results in higher travel distances, which disincentivizes people from switching from standard autos to EVs.

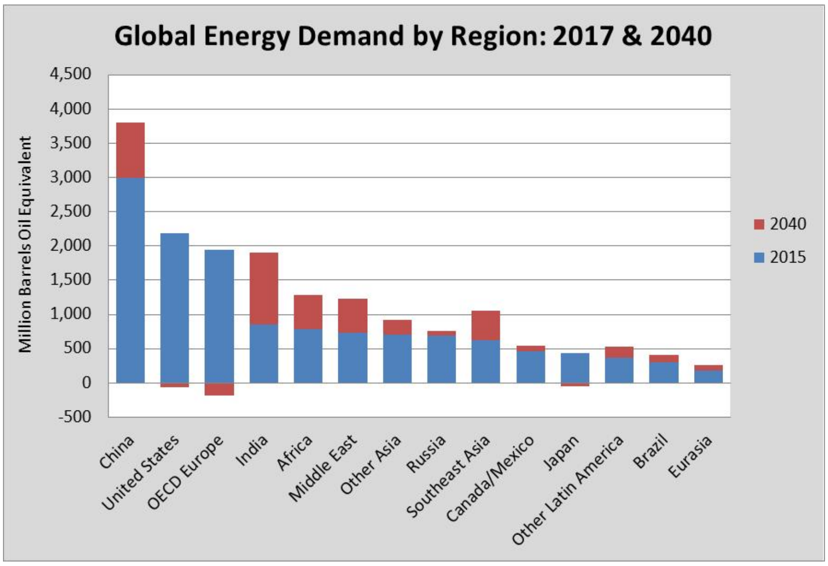

Figure 1.2: Future energy demand trend upto 2040 [2].

Secondly, infrastructure constraints such as limited EVCSs contribute to the general public's reluctance to EVs [7]. These stations are typically sparse and are great distances apart. The concern of reduced range of driving is worsened by the scarcity of these EVCSs in the drivers' immediate proximity. This difficulty is exacerbated when charging stations go out of service or are not working properly. Consequrntly, EVs are forced to traverse large distances to reach other charging stations, resulting in longer trip lengths. Long lines at scarcely available charging stations can also result in longer charging times.

1.1.2 Research Motivation

The following are the motivation towards our research:

- EVs have relatively high charging costs and waiting times, which decreases consumer satisfaction,
- in developing countries, there is a lack of suitable charging infrastructure,
- providing an incentive to switch from conventional to electric vehicles,
- inadequate management of storage systems, charging stations, and battery supply management systems.

1.1.3 Scope of the Research

The above-mentioned problems are solved by proposing an effective energy sharing mechanism to increase the popularity of EVs while also reducing automobile emissions. The electric vehicles in the system under consideration are assumed to be entirely autonomous or semi-autonomous. The proposed strategy is derived from an approach which is dependent on evolutionary game theory. The system objectives include the designing of a system that is stable and perpetual. It has to be such that whenever an EV requests charge from EVs in its vicnity it can obtain it. When the charge level drops below a threshold, the EV can transmit requests using standard communication networks. Henceforth, this EV which is requesting charge is designated as a *receiver*.

1.2 Research Objective

The research goal of the proposed methods is:

- enhancing EV range, and
- decreasing journey durations.

The goal is to shorten journey durations by not deviating from the intended path to reach an EVCS. In cases with no EVCSs in the nearby area, this proposed system can bring even more benefits to the locality. A corollary benefit of this sytem is that it does not require drastic changes to the infrastructure in the area. Thereby, helping to bypass the need for increased cost and bureaucracy. A cluster is created around the *receiver* EV which forms the environment of the game. There can be cases of heightened trip times where an EVCS is not in the destination route. If no EVCSs are located within the cluster, the situation is compounded. This highlights the need for EVs to share energy. A difficulty is that all vehicles have selfish characteristics and thus are unlikely to cooperate without an added incentive. To enable cooperation, a system is presented that *a) chooses a giving EV to meet with and share its charge with the seeking (receiver) EV,* and *b) takes into account the vehicle's selfishness*. There must be no human intervention in the system.

1.3 Research Outcome

The anticipated results from above objectives are:

- establishing an automated system where energy sharing takes place spontaneously,
- ensuring that incentives are always greater than cost for an individual EV,
- simulating the mathematical model for further justification.

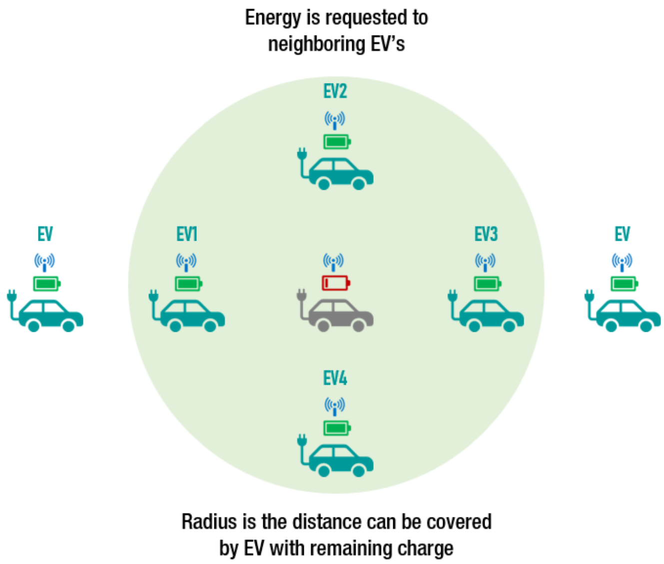

Figure 1.3: Proposed Scenario.

1.4 Novelty of the Research

This thesis takes Vehicle-to-Vehicle (V2V) energy-sharing to a new dimension with the addition of Evolutionary Game Theory (EGT). The way this research differs from previous works are mentioned below:

- The research uses EGT to make decisions based on the selfishness of the EVs.
- Vehicles can receive energy on multiple occasions throughout their journey.
- The work does not propose any changes to the existing infrastructure.

Previously completed works, as will be described in Chapter 2, have all proposed certain infrastructures. The problem with this is that, all of this necessitates a long-term investment, and will take long to implement. The reason for this is that, the infrastructure first has to be established. We propose a scheme that can work on the existing infrastructure. We create this with the help of EGT. Furthermore, for the sharing of charge, we have used a bidirectional DC-DC converter technology [10]. We have considered each EV to be a node in an EGT model. Because these vehicles are selfish in nature they are going to want to conserve their own State of Charge (SOC). The *receiver* EVs will therefore need to provide an incentive in order to get charged from another EV. In order to turn the other EVs into *givers*, EGT is used. This substantiates that each EV may take part in the game multiple times, thus having the potential to get charged multiple times.

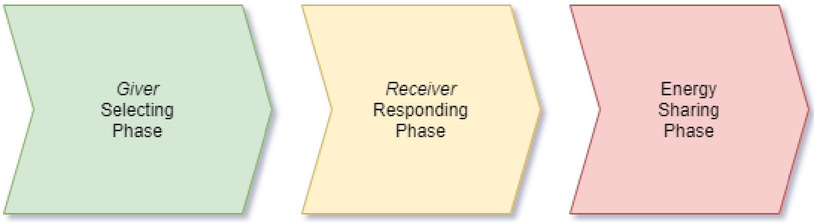

Figure 1.4: The three phases EVs must adopt for the game.

1.5 Overview of the Methodology

This research proposes an automated method aimed at enhancing EV trip range and decreasing journey durations. The goal is to shorten journey durations by not deviating from the intended path while going to an EVCS. The system benefits the community by not necessitating changes to public infrastructure. It keeps drivers' trip times lower by not having to go to far off EVCSs. This is possible due to EV energy sharing. However, the difficulty is that all these EVs are greedy and are unlikely to share energy in an act of selflessness. Therefore, a method is presented that *a) finds a giving EV that meets and distributes its energy with the asking (receiver) EV*, and *b) takes the vehicle's selfishness into account*. There should be no human intervention in the system. In this case, each individual EV in the population develops a plan for itself. Every round of the game, an EV chooses one of two different strategies: *to give* or *not to give*. This evolution can be seen using replicator dynamics on graphs [**?**, 11–14]. Replicator dynamics on graphs is an important tool used in our research and it is a derivation of the replicator dynamics employed for populations which are finite. The widespread adoption of a certain strategy by EVs in the system is dependent upon the payoff that these EVs can obtain by the utilisation of that particular strategy. This forms the basis of replicator dynamics in this case. In this scenario, the members of the EV population are the vertices of a regular graph. The EVs from the cluster that choose to give their charge to the *receiver* EV are called *giver* EVs. The two strategies which are allowed in the population of vehicles in this system are *Giving* and *not giving*. The following three stages must be repeated in order for this modeled game to be adopted:

1. Giver Selection Stage: Individual EVs decide to be a *giver* or a *non-giver* based on contacts with other EVs in the cluster.

2. Receiver Responding Stage: Once all of the EVs in the cluster have been selected, all of the EVs contact the *receiver*, and the *receiver* then meets for exchanging charge with the *givers*.

3. Energy Sharing Stage: Givers meet with the *receiver* and share their energy. The EVs which choose a strategy of *non-giving* don't take part in energy sharing.

These three stages encompass one round of the game. The duration of every round is assumed to be fixed with every vehicle being aware of it. Every individual round is determined by the quantity of energy consumed by the *receiver* due to the last phase being *energy sharing stage*. All the EVs are made aware of the round lengths using their connected communication networks. The model being proposed is inspired from the self-organised data aggregation technique presented in [15].

The concept that underpins the scheme is that EVs are selfish and requires incentives to prod them into exchaging their charge. In every round, the *giver* is given a form of gift to entice them, which plays the role of the incentive. Immediately two challenges rise up: *1) How is it possible to choose givers among selfish EVs? 2) Is it possible to limit the number of people who give?* In this case, the application of this type of evolutionary game theory can help in resolving these issues because it takes into consideration the various effects created by the mutual interactions of the EVs.

This chapter offered a brief introduction of the work done in this thesis. Chapter 2 will delve into the established work, and more into history, future and significance of EVs, in order to explain the importance of our work.

Chapter 2

Literature Review

Chapter 1 delved into an idea and procedures of our novel work. The work will further be explained in upcoming chapters. This chapter will talk more about EVs in general.

Nowadays, a great many research is being conducted in the field of vehicle-to-vehicle (V2V) energy exchange. One such work concentrates in the domain of V2V Wireless Power Transfer (WPT) where issues of scheduling, routing and matching vehicles are concentrated upon and various solution strategies are posited [16]. Inductive power transmission schemes for charge sharing are being proposed as well. Such research works proposed unique schemes to alternative ways inductive charging can be deployed [17, 18].

Research is ongoing to develop a cost-effective energy exchange framework. There are studies which take an all-inclusive view of energy management. One such study integrates wide ranging of issues of administration in a charge sharing model. [19]. Fog computing has also been considered for charge sharing in a V2V scenario. Works in these areas have dived into assuring security of transactions, utilizing blockchain techniques in order to create a strong network of EVs [20]. Ideas [21] proposing wireless charging of EVs while traveling on the road have also been heavily investigated. Nonetheless, systems involving charging via roads necessitate replacing existing roads and other structures thereby posing significant costs.

The chapter is broken down as follows: Section 2.1 talks about the history of EVs, and Section 2.2 about the future. Finally, Section 2.3 delves into the correlation between EVs and the power sector.

2.1 History of EVs

Electric vehicles were debuted more than a century ago, and at a point in time, they comprised a massive one-third of the entire car fleet. Users favoured electric vehicles because they were completely silent and did not burn petrol. However, by 1935, EVs had vanished from the market, owing in part to improved infrastructure, and an increased number of gas stations. Furthermore, EVs constantly suffered from range anxiety, and their charge would easily be depleted before completing journey. Infrastructural advancements enabled longer-distance travel, and for this reason, EVs are currently unable to compete with gasoline-powered vehicles. When the price of gasoline rose in 1970, electric vehicles (EVs) reappeared in the market. However, it was not until the beginning of 2000 that EVs achieved a tipping point and the actual development of EVs began. Previously, the golf range of EVs had been limited. Tesla Motors, a geographical area startup, announced the creation of an EV with a practice range of 200 miles in 2006. This, along with a variety of other factors including environmental benefits, helped in the introduction of EVs in existing established automobile manufacturing enterprises [22].

2.2 Future of EVs

The EV30@30 initiative offers the opportunity to simplify the transition to a completely renewable energy grid by electrifying transportation. According to the IAE 2018, a collaborative objective has been established that by 2030, 30 percent of all global automotive sales must be electric vehicles. In Sweden, a member of the EV30@30 movement established a goal of reducing emissions in the domestic transportation sector by at least 70% by 2030 compared to 2010. To achieve the stated purpose, Fortum Charge & Drive collaborated with Swedenergy to create The Almedalen Manifesto 2016. The Manifesto outlines how electric vehicles and charging infrastructure should be pushed in order to achieve the suggested aim of the Cross-Party Committee on Environmental Objects. According to the Manifesto, the technical advancement of electric vehicles and charging infrastructure has reached a point where an introduction to the larger market is viable. As a result, the Manifesto proposes a target of two million EVs in Sweden by 2030 in order to achieve the required decrease.

2.3 Importance of EVs in Power Sector

Road cars are a major contributor to global warming, greenhouse gas emissions, health risks, and pollution. To combat the associated disadvantages, many countries, including China, the European Union, and the United States, have dramatically shifted gears from conventional to renewable energy in the last decade [6]. Clean alternative energy (e.g., solar, wind, biomass, biofuel, etc.) and nuclear power are the dissolute energy sources, with both growing at a rate of 2.5 percent per year [7]. Reduced greenhouse gas emissions from substantial changes in the transportation sector, such as the use of solar energy and the deployment of electric vehicles (EV), can have a widespread positive impact on the environment.

Chapter 3

Background Study

In the previous chapter, the pre-existing work on the topic being discussed have been mentioned. Let us take this opportunity to delve into some new theory that will prove to be relevant to our topic. Set aside the model, Section 3.2 talks about Evolutionary Game Theory (EGT). Section 3.3 is an important section, in the sense that it talks about non-cooperative game theory, a game theoretic model in which individuals are selfish in nature. Finally, Section 3.4 delves into replicator equation on graphs.

3.1 Peer to Peer Energy Sharing

As more distributed generation is installed on the demand side, a growing number of consumers become prosumers. Numerous peer-to-peer (P2P) energy sharing models have been proposed to reduce prosumers' energy bills by encouraging energy sharing and demand response [23].

The foundation of energy sharing programs are energy sharing models, which outline how prosumers share and barter energy with one another. Many studies have been conducted in this topic. The studies can be classified into three types: *1) energy sharing performed by a single centralized authority; 2) energy sharing accomplished through the interaction of an operator (price-maker) and a group of prosumers (price-takers);* and *3) energy sharing accomplished by the interaction of a group of prosumers, i.e. P2P energy sharing* [24].

3.2 Evolutionary Game Theory

The two fundamental concepts of game theory, strategy and payoff, must be reinterpreted in the perspective of evolutionary biology. A strategy is an inheritable property, not a purposeful path of action; the outcome is Darwinian fitness (average reproductive success). The "players" are individuals of a population who are all striving for a larger part of the population.

If numerous variants of a trait exist in a population, natural selection causes the frequency of those variants with greater fitness to grow. If the success of a characteristic is not determined by its frequency, the best variation will eventually be fixed. However, if the success of a characteristic is frequency-dependent, its rise may result in a population composition in which alternative variants perform better; this can be examined using game theory [25].

3.3 Non cooperative Game Theory

For a precise formulation of a non-cooperative game, we must specify: (i) the number of players, (ii) the possible actions available to each player, and any constraints that may be imposed on them, (iii) the objective functions that each player attempts to optimize (minimize or maximize, as the case may be), (iv) any time ordering of action execution if the players are allowed to act more than once, and (v) any information acquisition that takes place.

As a result, we consider an N-player game, where $N := 1, \ldots, N$ denotes the Players set. Player i's decision or action variable is denoted by x_i, where x_i represents player i's action set. The action set could be finite (such that the player only has a finite number of actions), infinite but finite-dimensional (such as the unit interval, $[0, 1]$), or infinite-dimensional (such as the space of all continuous functions on the interval $[0, 1]$). Let x symbolize the N-tuple of all players' action variables, $x := (x_1, \ldots, x_N)$. Allowing for possibly coupled constraints, we define x as the game's constraint set, where x is the N-product of $x_1, \ldots, x_N$; hence, for an N-tuple of action variables to be feasible, we need x [26].

3.4 Replicator equation on graphs

A vertex of the graph represents each player. Who meets whom is indicated by the edges. A player can choose from n different strategies. Interaction with all of the players' immediate neighbors are taken into consideration for the formulation of the payoff. We look at three different types of update rules: "birth–death," "death–birth," and "imitation." In this model, a fourth update rule called 'pairwise comparison' is demonstrated to be comparable to birth–death updating. On regular graphs of degree k, we use pair approximation to characterize the evolutionary game dynamics. We can derive a differential equation that captures how the average frequency of each method on the graph evolves over time in the case of weak selection. This equation is a replicator equation with an altered payout matrix, which is remarkable [12].

Chapter 4

Proposed Model

Until this chapter, the study comprised of the prerequisites to our model. Chapter 3 discussed necessary concepts required to understand the model. This chapter delves deeper into the model. This chapter will only contain the mathematical model. The simulation analysis will be provided from Chapter 6.

Section 4.1 will provide an overview of the model and Section 4.2 will discuss the happenings of the game.

4.1 Overview of Model

The system proposed in the model works in and of itself without any external influence. We are to make each individual EV driver relax on the concern related to the running out of charge before a journey is completed. When the State of Charge (SOC) goes down, EVs look for Electric Vehicle Charging Stations (EVCS). Our claims might feel like we propose complete infrastructural change, but we assure you, that is not the case. Instead, our game considers the existence of clusters of EVs around the *receiver*.

As we are soon to find out in Section 4.2, each EV in the cluster can choose one of two strategies, *to give* or *not to give*. Each EV is considered to have chosen a strategy, or at least be able to choose a strategy. The strategies may or may not change each round of the game. These changes are modeled through replicator dynamics on graphs [11–14, 27]. Replicator dynamics on graphs, as found from studies, is a manipulated version of the actual replicator dynamics.

The three steps for this modeled game are as follows (see Figure 1.4):

1. Giver Selection Stage: Each EV interacts with every other EV in the cluster and then chooses to either be a *giver* or a *non-giver*.

2. Receiver Responding Stage: The *givers* then communicate with the *receivers* and then they travel to the *receiver* expending credit c (details: Chapter 5).

3. Energy Sharing Stage: The *giver* EVs get paid back with an incentive b from the *receiver*. The *non-giver* EVs neither gain nor lose anything.

All these three steps constitute a round. When these three steps finish, a round commences, and the next round starts, unless the game is stopped and no other EVs are requesting for energy. The cars are supposed to have the capability of communicating amongst themselves in order to ensure mutual interaction. The EVs are also cognizant of the duration of each round, and also the payoff it might derive given the neighbors choosing their respective strategies from the choice pool. The EVs however, do not know the strategies their neighbors are likely to play. Each EV knows how far it is to travel and the energy required to travel that length. The amount of energy required by the *receiver* determines the round. The EVs transmit the round's length, which can be changed if necessary. This model is based on a self-organized data aggregation technique described in [15], and it is a variation of EGT.

4.2 Selection of Givers

The cars in the cluster are reliant on the other members of the cluster. Each node is expected to communicate with its nearby *receivers* before deciding whether to be a *giver* or a *non-giver* based on the prospective rewards.

We consider a variable c which will be the charge-equivalent credit expended for a *giver* traveling to the *receiver*. This causes the reduction of SOC in the giver. Let b be the amount of incentive supplied by the *receiver*, i.e. the improvement in SOC it can get utilizing the credit gain. This means that, if an EV chooses to be a *giver*, then it spends c credits and achieves b credits.

The b amount of credit implies the amount of charge the EV will not need to pay for at an EVCS. *Non-givers* spend no energy, however, this strategy may not already be called a dominant strategy. This is because, *non-givers* also do not earn b. The gains and losses of both *givers* and *non-givers* can be represented as in the Figure 4.1.

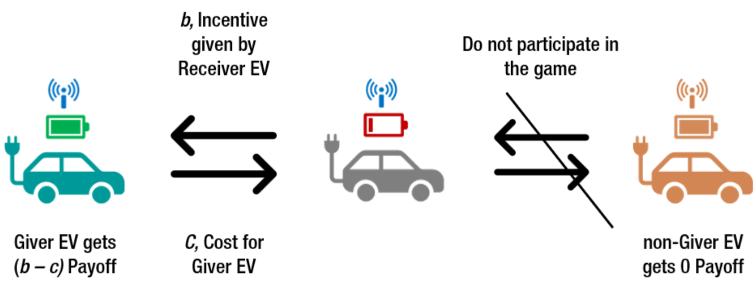

Figure 4.1: Payoff for *giver* and *non-giver* EV [3].

It is to be burnt to the back of our minds that EVs are naturally selfish about their SOC. This means that the incentive b has to be large enough so that some EVs choose to be *givers* despite the potential cost of travel c. This means that, $b > c$. On the surface, it appears that the value of b maybe increased without bounds in order to increase the ratio of *givers*. However, such is not the case. b will not be increased without bounds as the incentive gets divided among more *givers*, causing the impact of b to decrease. This means that if b is increased without bounds, more *givers* are formed, causing the incentive b from the *receiver* to be divided among more EVs, causing b to not be able to offset anything, causing the ratio of givers to fall back down. This will be clearer from Figure 4.2 and the simulation analysis in Chapter 6.

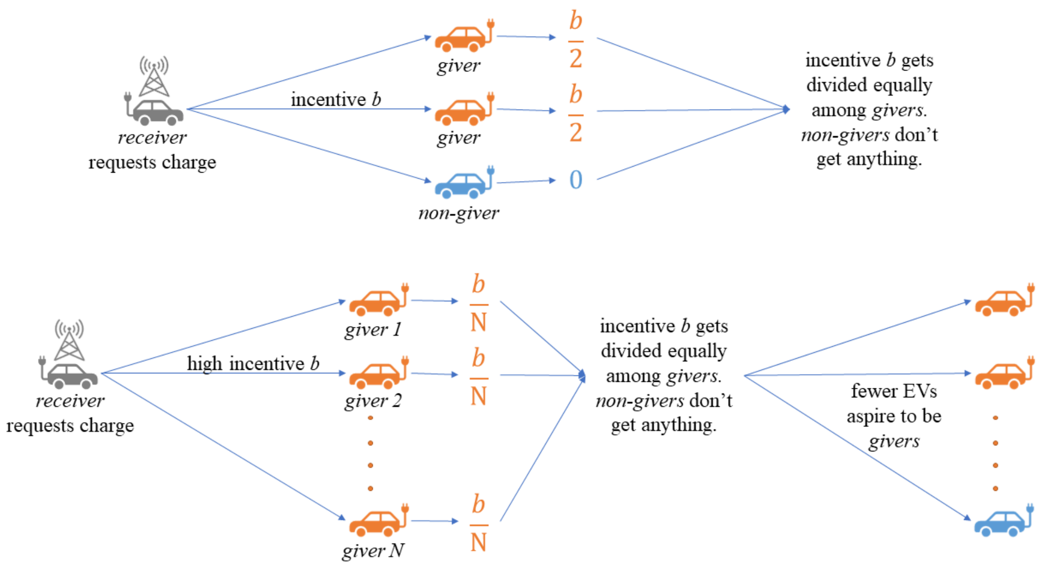

Figure 4.2: The *receiver* distributes b among *givers*. If b is too high, more EVs will want to be *givers*. As a result, b will be shared by more EVs. An individual EV can earn a maximum payoff of $\frac{b}{N}$, where N is the total number of EVs. The higher the value of N, the lower is the gain for each individual EV. So, EVs lose incentive to be *givers*. So, our model is an autonomous one.

This is not only able to control the ratio of the *givers*, but also the ratio of the *non-givers*. The receiver is only able to offer incentive b, no more, no less. And the incentive cannot be changed mid-round. The selection of this incentive b maybe theorized as a bargain between two EVs in the language of EGT. Two permissible roles exist among the population:

- *Giver*: agrees to share energy, and
- *Non-giver*: disagrees to share energy.

Amongst all kinds of combinations possible between two players picking either strategies, the payoff matrix can be represented as in the Table 4.1.

Table 4.1: 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	$0, b - c$	$0, 0$

Without knowing the specific plans of other players, each EV knows how much it stands to gain given the other EVs choose different respective strategies. An EV that results in the maximum possible return is likely to choose a giver strategy. Each EV is aware of the potential payoff if the competitor EV follows the same or a different approach. The highest possible payoff is found when one EV chooses to be a *giver* and the other chooses to be a *non-giver*. This means that the Nash Equilibrium persists along the diagonal of the payoff matrix.

If the only other EV chooses to *not give*, the *receiver* offers the whole incentive to the *giver*. When neither of the EVs chooses to share their energy, i.e. when they both opt to be *non-givers*, they incur no net loss, but they also miss out on the potential profit that sharing their energy could have brought them. In the event that both neighboring EVs elect to become *givers*, the *receiver* meets with both vehicles to share energy. As a result, each car's incentive is cut in half ($\frac{b}{2}$). After that, Table 4.1 can be abstracted into Table 4.2.

Table 4.2: 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

$T > R$ and $S > P$ are the values in the abstracted payoff matrix. Every vehicle is encouraged to become a *giver* in this scenario because $T > R$. The greater the b, the better. As a result, the *receiver* EV can regulate the production of *givers* by modifying the value of b. Furthermore, if both EVs considered opt to be *givers*, the *receiver* can draw energy from both EVs, resulting in a half-incentive. Furthermore, the requirement $T + S > R + P$ makes it easier to choose an evolutionary stable role [28].

Let us now assume, that the Nash Equilibrium has been achieved. Our system, therefore, will obviously reach a stable state. This means that both *givers* and *non-givers* in this state exist as is, without being influenced to further change their strategies [27].

The selections are fully reliant on the mutual interactions among the cars, taking into consideration each player's selfishness, which is a distinguishing feature of this model. During each encounter, the time it takes to charge is believed to remain constant. This is based on the fact that the EVs under consideration are homogeneous, and hence the *giver* and the *receiver* sides' latency is believed to be consistent across the system.

Chapter 5

Analytical Results

The previous chapter dealt with an overview of the analytical model. This section will deal with the mathematical results that we obtain from our model. The next chapter will discuss the simulation results.

This section employs replicator dynamics on graphs to establish an analytical relationship between the ratio of givers and the payoff matrix parameters [12, 14]. The interactions with all of its neighbors generate a payout for each EV. Following that, a comparison is made between the obtained payment and a randomly picked neighbor. The replicator equations on graphs are defined, as well as a detailed explanation of the analytical conclusions achieved.

5.1 Replicator Equation on Graphs

We are to begin the derivation of the replicator equation using graphs [27]. Consider x to be the ratio of *giver* EVs to total EVs. The ratio of *non-giver* EVs to total EVs, on the other hand, is $(1-x)$. The predicted fitness f_1 and f_2 are calculated as follows:

$$
\begin{aligned}
f_1 &= x(\frac{b}{2} - c) + (1-x)(b-c), \\
f_2 &= 0.
\end{aligned}
\tag{5.1}
$$

Here k denote the number of EV neighbors, often referred to as graph degree [13]. Although the analysis presented is focused on the k-regular graph [13], the method may also be extended to non-regular graphs such as unit disk graphs [12, 13]. On graphs, we can observe how the total number of EVs in a cluster influences the percentage of givers at a certain incentive level. The modified reward matrix for evolutionary game theory on graphs is the sum of the original payoff matrix and a modifier matrix [27]. Table 5.1 shows the modifier matrix.

Table 5.1: Modifier matrix between two EVs.

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

$$m = \frac{(k+3)(\frac{b}{2}-c)+3(b-c)}{(k+3)(k-2)}, \quad \forall k > 2. \tag{5.2}$$

m represents the local competition among strategies (as shown in Table 5.1). The gain of one approach is the loss of another, and local competition between identical methods delivers nothing. The predicted payoffs for *giver* and *non-giver* local competitions g_1 and g_2 are

$$\begin{aligned} g_1 &= (1-x)m, \\ g_2 &= -xm. \end{aligned} \tag{5.3}$$

Consequently, the two strategies' total average payoff is

$$\phi = x(f_1+g_1)+(1-x)(f_2+g_2). \tag{5.4}$$

Taking the values from Equations (5.1) and (5.3) and plugging them into Equation (5.4),

$$\phi = x[x(\frac{b}{2}-c)+(1-x)(b-c)]. \tag{5.5}$$

The replicator equation on graphs [27] is found to be for $k > 2$ using Equations (5.1), (5.3) and (5.5).

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

From this, we can derive

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

The derivative of x is represented by $\dot{x}$. As a result, $\dot{x} = 0$ is chosen to attain the maxima of x. As a result, $x^* = 0, 1$ and

$$x^* = \frac{2}{b}[(b-c)+\frac{k(b-c)+4.5b-6c}{(k+3)(k-2)}], \quad \forall k > 2. \tag{5.6}$$

This works for $0 < x^* < 1$. Applying this condition into Equation (5.6),

$$\frac{c(k^2+2k)}{k^2+\frac{3k+9}{2}-6} < b < \frac{2c(k^2+2k)}{k^2+2k+3}, \quad \forall k > 2 \tag{5.7}$$

If we simplify Equation (5.7), and manipulate it a little, this is what we will be left with

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

in which $b > c$ .The next section uses figures to build on the numerical results. such that $b > c$. The following part expands on the numerical results with the use of figures. The equilibrium found in Equation (5.6) is critical for regulating this model. Finally, the effects of the various factors and their interrelationships are addressed.

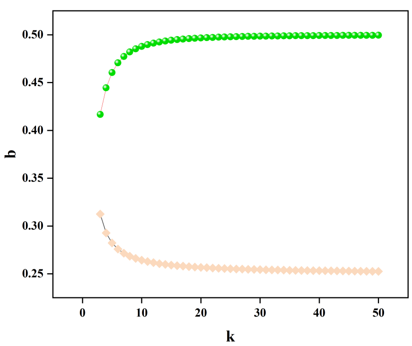

Figure 5.1: The supremum and infimum of b with k.

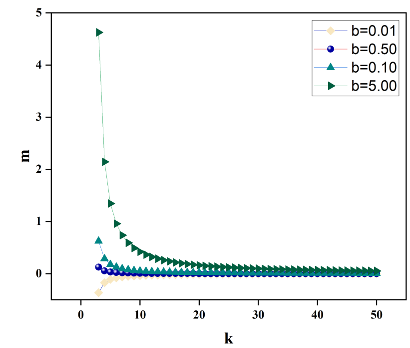

Figure 5.2: Modifier m controlling b.

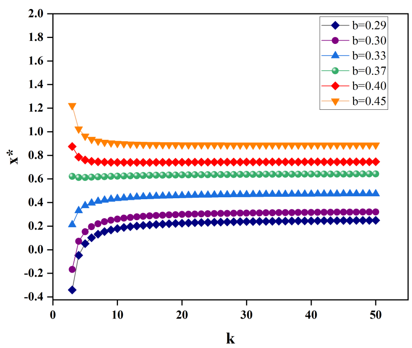

Figure 5.3: x^* controlled with b.

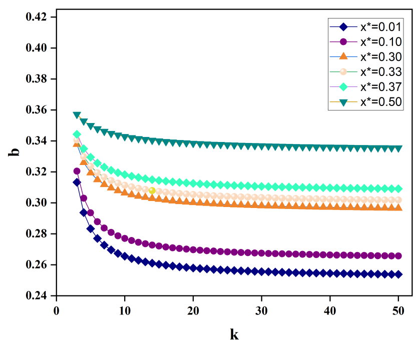

Figure 5.4: b controlled with x^*.

5.2 Numerical Results

The model is dependent on three variables: b, c, and k. The value of x is affected by the values of these variables. In this method, c is a very important variable in all of the graphs generated by replicator dynamics. We assumed that c was equal to 0.25 units for this analysis, but c can be any value depending on how far a giver needed travel to maintain this model. The value was maintained low enough to make the calculation simple. All of the following graphs have been extrapolated keeping this assumption in mind without losing generality. The units of b and c must be the same. In addition, the value of c would change depending on the price structure. To put it another way, the value of c in our work is purely speculative. It isn't applicable to everyone. And this number, as well as its unit, has an impact on the entire system, which includes b and x^*.

As seen in Figure 5.1, Equation (5.7) produces the supremum and infimum of b. Even in the worst-case situation, the value of b cannot be smaller than c, proving that $b > c$ is a cornerstone of this research. It's also worth noting that $2c$ is the largest value of b. This proves that the *givers* are not going to lose. This also explains why the *givers* cannot demand an exorbitant amount of credit, as the saturation of b for greater numbers of EV in the radius prevents this. Figure 5.2 displays the local rivalry for electric vehicles. The modifier equation is represented by Equation (5.2). With large k values, the modifier graph converges to 0 for a wide range of b values, meaning that the chances of EVs all using the same approach are slim.

The fluctuation of the value of x^* for modifying the value of b is also shown in Figure 5.3. Depending on b, x^* can be any value between $[0, 1]$ for a fixed amount of EVs. Because m equals zero for a limiting value of k, it may be concluded that x^* does not change as k grows for a given b.

x^* has various features depending on b for lower values of k, such as less than 15. As a consequence, our model is valid since altering b affects the system's x^* ratio. In the same way that x^* can be controlled by b, b can be controlled by x^*. This is seen in Figure 5.4. In reality, this means that the more *givers* in a given region, the more the *receiver* will have to pay, until the value of b is saturated by an excess of EVs.

Chapter 6

Simulation

Our work was conducted on the basis of Agent-based Dynamics. Respectively, we have conducted our work on *NetLogo* [29], the multi-agent simulation platform. For a decision criteria, we have used the *better possess chance* strategy. The entire work related to the simulation of the world will be discussed in this chapter. The chapter will be divided into two sections. Section 6.1 will contain the steps that made this simulation possible. It will therefore contain discussion upon the platform, the world, chosen strategies and working procedures. Section 6.2 will contain the observations, and what the conclusions are. It is to be proved that the optimum number of givers x^* in our world can be controlled based on the incentive b being provided.

6.1 Simulation Setup

This subsection will contain information on the platform used and the steps of simulation. This is to mention the name of the platform used, its benefits, the strategies adopted and the course of actions that led to our conclusion.

6.1.1 The Platform

The simulation was conducted on *NetLogo*, the agent-based modeling platform deviced by Uri Wilensky from the Northwestern University in 1999 [30]. The platform allows the creation of a world for simulation based on parameters selected by the user. *NetLogo* operates on the basis of agents. These are of four types, viz. patches, turtles, links and the observer.

6.1.2 The World

For this work, a (64×16) world was considered with the cursour at the center. The patch size and the font size have both been taken to be 10. Payoff updates were taken

Figure 6.1: NetLogo 4.1.3.

each tick. Tick is the *NetLogo* unit for time. It represents the shortest time in which an update can be recorded.

The world was set up by coloring all patches grey. Then the center of the y-axis was taken and alternating yellow squares were added to represent a divider. We have taken only one form of turtle, and that is "car". In the code, we have mentioned that the *giver* cars are to be painted red and the *non-giver* cars are to be painted blue (default turtle colour). The cars represent EVs traveling along a one-lane highway.

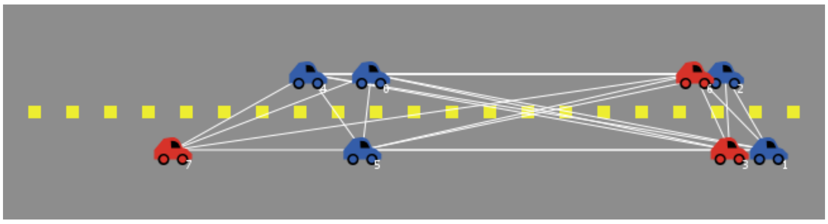

Figure 6.2: The World.

6.1.3 The Parameters

The topology of *unit-disk graphs* were considered for our purpose. For our range of view, the setup designed allows the consideration of a maximum of 4 km road. We considered a 1.6 km one. Furthermore, we have considered each *giver* and *non-giver* EVs to be communicating over a Dedicated Short-Range Communication (DSRC) network [31].

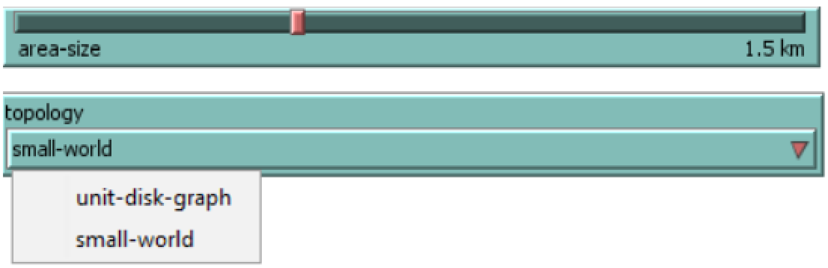

Figure 6.3: Total length of road being considered and the topologies being used.

Dedicated Short-Range Communication: The EVs are installed with an On-Board Unit (OBU) into their dashboards. When two such EVs are traveling towards each other at speeds of 55 mph, they are seen to have a transmission range of 466 m. Again, when traveling away from each other, the OBU has a lot more obstructions to overcome, like the length of the vehicle and everything that resides inside it. This is because, the OBU is stationed in the forefront. So, when traveling away from each other, the cars have a transmission range of 327 m. We have taken 327 m as our simulation parameter, as this represents the least possible transmission range with this speed.

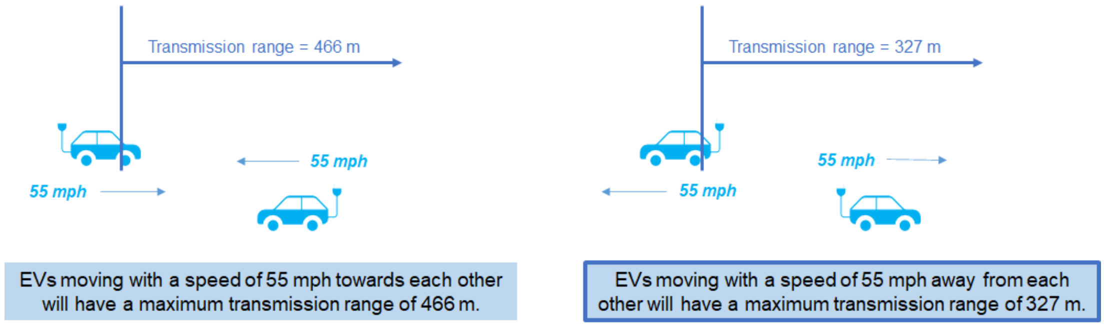

Figure 6.4: Transmission range if the EVs are traveling at a speed of 55 mph.

Furthermore, a separate set of simulation results have been derived, considering the EVs to be traveling at 70 mph. It has been found out that when traveling towards each other, the EVs have a transmission range of 401 m, which falls down to 170 m when they are traveling away from each other. Because 170 m represents the worst case scenario for this case, we consider this as our other simulation parameter.

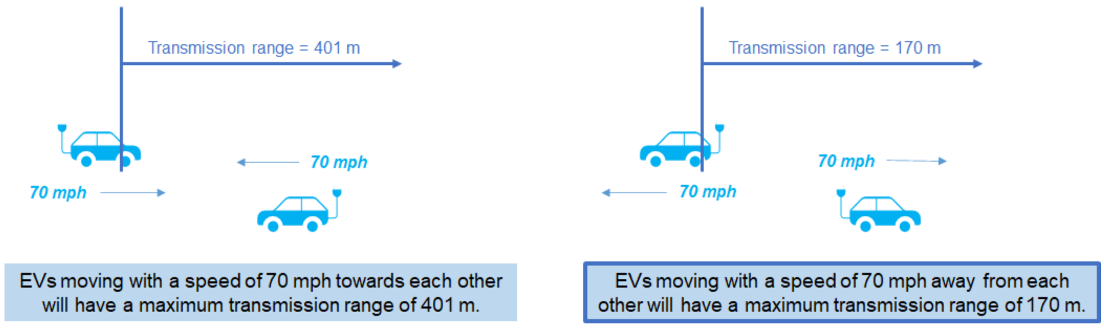

Figure 6.5: Transmission range if the EVs are traveling at a speed of 70 mph.

In the designed simulation User Interface (UI), we also had the freedom to choose a maximum of 200 EVs, represented as the variable "num-nodes" in the compiler. For the simulation, however, only 7 nodes were considered since it is highly unlikely that there would be any more EVs in our fixed length of 1.5 km. It is to be kept in mind that the number of nodes cannot be less than 2, as then the network can never be created. We have initiated the "giver-ratio" at 0.5. This means that the initial x is 50%. This is done to simulate the probability of a coin toss, so that neither strategy gets an advantage.

The world will initially have 3 or 4 *giver* EVs. As mentioned in Section 5.2, the cost c has been fixed at 25%. The benefit is considered to be variable, and it is changed according to necessity. The number of rounds was fixed at 100, as it is highly unlikely that an EV would have to play this game more than that in its lifetime. However, our immaculate code allows us to vary it till 9000 rounds and consider the results.

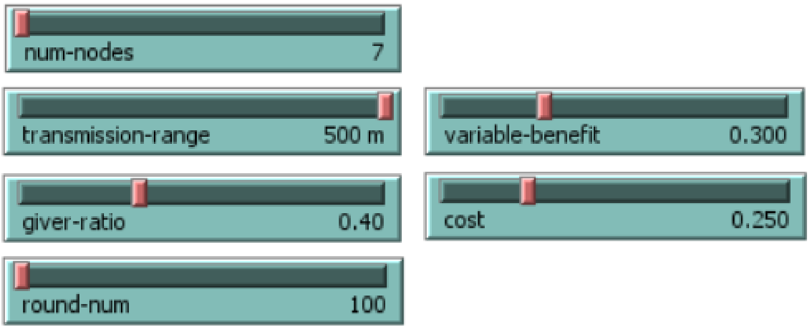

Figure 6.6: A few sliders mentioned in discussion.

In the UI, we can fix these parameters and observe how the ratio of *giver* EVs are changing with respect to the total number of EVs. The strategy we have chosen for our nodes to judge their payoffs against each other is "better possess chance". Because of its significance, this strategy will be elaborated on in the next subsection.

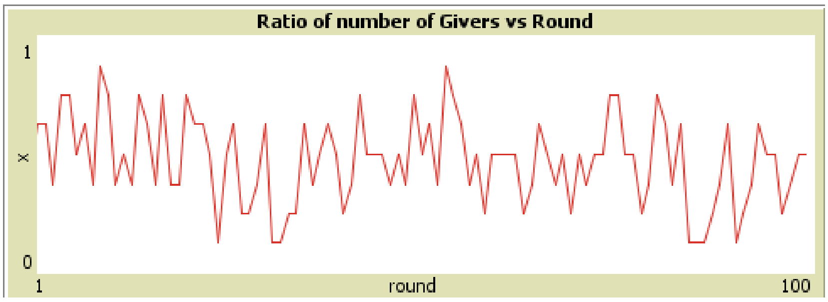

Figure 6.7: The ratio of *givers* changing in the NetLogo UI.

6.1.4 The Strategy

The strategy used is *"better possess chance*. It is a strategy where an individual Electric Vehicle compares its own payoff with its neighbor's payoff. In order to attain the probability of a vehicle to switch strategy, the probability would be this divided by maximum difference between payoffs [32, 33].

$$H(u,v) = \frac{Q_v - Q_u}{T - P}$$

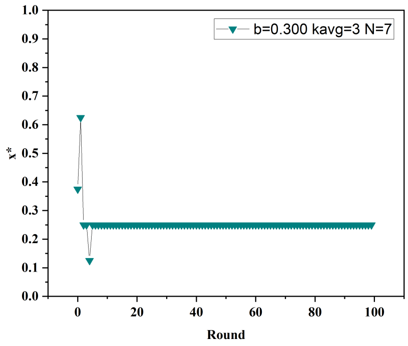

Figure 6.8: x^* with range 327 m and b 0.3.

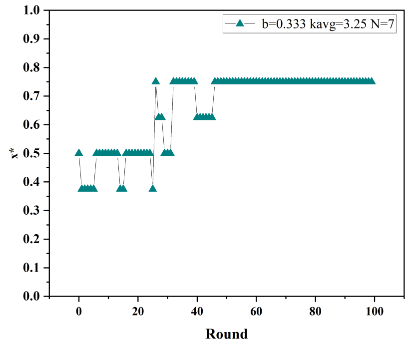

Figure 6.9: x^* with range 327 m and b 0.333.

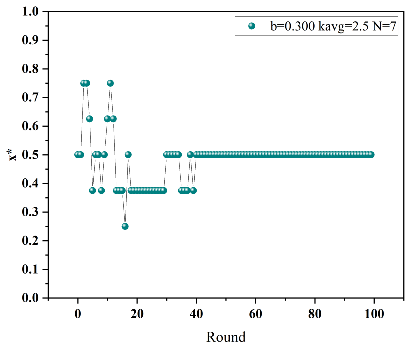

Figure 6.10: x^* with range 170 m and b 0.3.

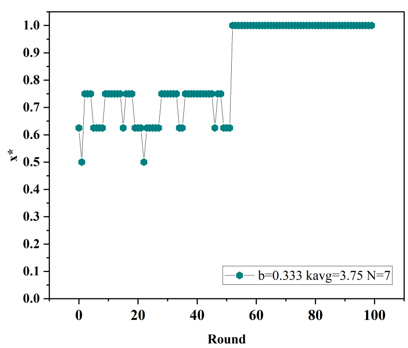

Figure 6.11: x^* with range 170 m and b 0.333.

6.2 Simulation Results

We have considered *unit-disk graphs* For this topology, two scenarios were considered: one in which the EVs have a transmission range of 327 m, and another in which it is 170 m. The world consisted of 7 EVs. Cost c was kept constant at 25%, and only benefit b was varied from 0.3 to 0.333. A description of the topologies and the observations are discussed below.

Unit disk graphs

Unit disk graphs are basically formed through the mutual intersections of equal-sized circles on a single plane. Unit disk graphs have already been used in studies [34] in order to describe the topographical context of broadcast networks.

When we considered the transmission range to be 327 m and $b = 0.3$, it was observed that the average degree of the graph, $kavg$ was 3, where as in the case of $b = 0.333$, it was 3.25. It was observed that the value of x^* is more for the higher b value for respective rounds. This can be observed from Figures 6.8 and 6.9.

Next, the same scenarios were considered for a 170 m long transmission range. This time at $b = 0.3$, the obtained $kavg$ was 2.5. This value increased to 3.75 for $b =$

0.333 It was observed that the value of x^* is more for the higher b value for respective rounds, for this small transmission range as well. This can be seen in Figures 6.10 and 6.11.

The results seem to be converging at a value for the ratio of *givers* for larger values of k. This means that the simulation world eventually achieves evolutionary stability. Upon observation of the results, we can conclude that, by controlling the value of incentive b, we can control the most optimized ratio of givers x^*.

Chapter 7

Conclusion

With the use of evolutionary game theory, a design model is proposed in which electric vehicles share energy among themselves, resulting in an efficient system. As a result, the title has been justified.

7.1 Achieving Expected Outcomes from the Objectives

The successful energy sharing and incentive transactions among electric vehicles can be seen in both simulation and analytical findings, and the decisions were made using evolutionary game theory. The following are the thesis's objectives and observations that support its conclusion.

1) Establishing an automated system for spontaneous energy sharing:
The simulation model supports the analytical method by demonstrating that each round generates a new set of *giver* and *receiver* EVs, and energy is shared simultaneously in each cluster.

2) Ensuring that incentives are always greater than cost for an individual EV:
We would never see a scenario of a giver EV in our simulation model or mathematical model if incentives are smaller than cost. As a result, it is reasonable that incentives always outweigh costs.

7.2 Limitations and Future Work Recommendations

The limitation of this work is that it depends heavily on the availability of EVs in the vicinity. In a scenario where enough EVs do not exist, no incentive would be high enough to make the EVs participate in the game. This means that in such scenarios, the SOC of the *receiver* would be depleted anyway.

There are a few major ideas for further development on this concept. Reinforcement Learning (RL) can be used among the cars so that one player can learn the techniques of other players more effectively. Where choosing the sharing option is extremely rewarding and refusing to share is punishing, resulting in a model for spontaneity.

In our mathematical model, the latency of energy exchange between two vehicles could be examined, with time as a variable. Within the limitations of our existing technology, the mode of energy sharing can also be investigated.

APPENDICES

A Replicator Equation in Evolutionary Game Theory

The replicator equations are the cornerstones of EGT. EGT presupposes the existence of a species, the survival of which depends on the fitness of the strategy of the species. The fitness is the payoff in this case. All species are mutually dependent, and the dominance of a strategy is determined by the distribution of strategies [35–38].

The goal is to first formalize a common case for two players with n number of strategies. All possible pairs of strategies of an $n \times n$ is represented as $A = [a_{ij}]$. $i, j = 1, 2, 3, \ldots$. Each entry of the payoff matrix, a_{ij} denotes the comparative payoff that can be obtained from strategy i when player is competing against strategy j.

x_i is considered to be the relative frequency of each strategy. From this assumption, we can make the following conclusion.

$$\sum_{i=1}^{n} x_i = 1. \tag{A.1}$$

If f_i is the expected payoff, then the following equation can be written, according to the Equation (A.1).

$$f_i = \sum_{j=1}^{n} x_j a_{ij}. \tag{A.2}$$

Again, the average payoff of the population is seen to be

$$\phi = \sum_{i=1}^{n} x_i f_i. \tag{A.3}$$

From Equations (A.2) and (A.3), the standard replicator equation is determined.

$$\dot{x}_i = x_i(f_i - \phi). \tag{A.4}$$

$\dot{x}$ represents the derivative of x with respect to time. According to Equation (A.4), the higher is the difference between the expected payoff of strategy i and the average payoff, the more strategy i is chosen. This equation applies only when a diverse and mixed population is available to participate in the game [38].

The difference of EGT [11,12,14,27,39,40] from regular game theory is that EGT assumes a finite population. Each player can be taken as a node on a graph. For the purpose of this work, the *unit-disk graph* topology was considered. In this topology, the the nodes are assumed to remain on the periphery of a circle, and the entire population is considered to create a disk. The average order $kavg$, in this case, does not remain in our control. Each player determines a payoff based on its interactions with its neighbours. Then it randomly chooses a neighbour. This neighbour will be the opponent. If the player's payoff is better than the opponent's, the player keeps its strategy. If not, however, the player imitates/takes up the strategy of the opponent. This rule is termed as the *imitation updating rule*.

The $n \times n$ payoff matrix A is expected to be sufficiently large if the population n is large enough. Therefore, in its totality, matrix A is unworthy of being represented here. Another $n \times n$ matrix $M = [m_{ij}]$ is considered to be the modifier matrix. The modified payoff matrix, $A' = [a_{ij}]$ will therefore be the summation of A and M.

$$a'_{ij} = a_{ij} + m_{ij}. \tag{A.5}$$

If the value of $k > 2$, then from [11],

$$m_{ij} = \frac{(k+3)a_{ii} + 3a_{ij} - 3a_{ji} - (k+3)a_{jj}}{(k+3)(k-2)}. \tag{A.6}$$

Since the gain of one strategy would mean the loss of another, the expectation is, $m_{ij} = -m_{ji}$. This criteria is satisfied by Equation (A.6). In other words, M should be a symmetric matrix. Again, local competition with the same strategy should return 0. For this reason, the diagonal elements, m_{ii} would also return 0. Let g_i be the expected payoff for local competition with strategy i. Therefore,

$$g_i = \sum_{j=1}^{n} x_j m_{ij}. \tag{A.7}$$

Since the sum of the average payoff of the local strategies should be 0, therefore,

$$\sum_{i=1}^{n} x_i g_i = 0. \tag{A.8}$$

Thus, the average payoff ϕ of the population on graph can be determined to be

$$\phi = \sum_{i=1}^{n} x_i(f_i + g_i) = \sum_{i=1}^{n} x_i f_i. \tag{A.9}$$

This is the same as the Equation (A.3). So, the replicator equation on graphs would look like the following [11–13]:

$$\dot{x}_i = x_i(f_i + g_i - \phi), \tag{A.10}$$

where, the values of f_i, g_i and ϕ are obtained from Equations (A.2), (A.6) and (A.8).

Note here that, Equation (A.10) simplifies to Equation (A.4). Remember that in order to obtain Equation (A.4), we basically substituted $[a_{ij}]$ for $[a_{ij} + m_{ij}]$. Therefore, for the case of EGT, this transformed payoff matrix $[a_{ij} + m_{ij}]$ is important for analytical purposes. The more the value of k increases, the more the contribution of g_i decreases, and the value of f_i dominates the equations. That is to say, for the case $k \to \infty$, Equation (A.4) boils down to Equation (A.4). So, for a highly connected graph, the replicator equation converges to a standard replicator equation [12].

B NetLogo UI and codes

User Interface

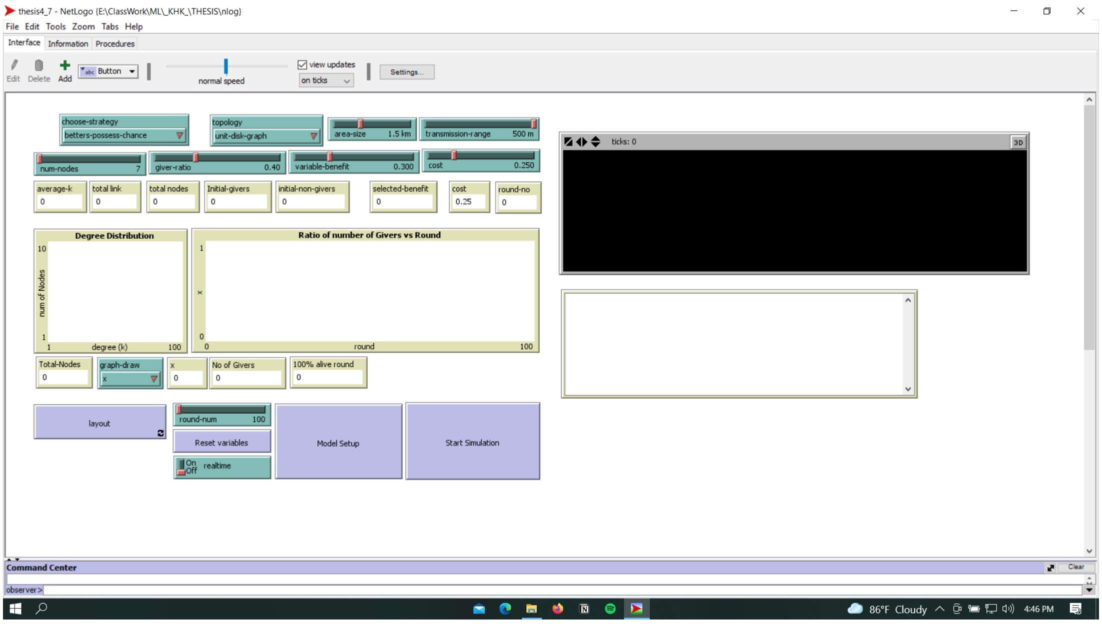

Figure B.1: User Interface built over NetLogo 4.1.3.

Setup

```
to setup
  clear-all

  set infinity 99999
  set seed-n 1

  ;; scaling from real values to virtual values
  set scaling-factor (max-pxcor - min-pxcor + 1) / (area-size * 1000)
  set scaled-transmission-range transmission-range * scaling-factor

  ;if save-data = "file-save" [simulation-output]
  ;random-seed count links
  draw-road  ;;;;;;;;;;; Setting up the world.
  set-default-shape turtles "car"
  while [count nodes < num-nodes] [ make-node ]  ;; for all topologies

end
```

World Setup: Road

```
to draw-road
  ask patches
  [
    set pcolor grey
    if ((pycor = 0) and ((pxcor mod 3) = 0))
    [ set pcolor yellow ]
  ]
end
```

World Setup: Cars

```
to make-node
  create-nodes 1 [
    set new-node self
    set-payoff-matrix
    setxy random-xcor * 0.95 3
    set color blue
    set label who
  ]

  create-nodes 1 [
    set new-node self
    set-payoff-matrix
    setxy random-xcor * 0.95 -3
    set heading 90
    set color blue
    set label who
  ]

  ask nodes [
      set shape "car"
      set size 3
  ]
end
```

Setting the Payoff Matrix

```
to set-payoff-matrix
  let N num-nodes
  set c  cost
  set ss ratio_e * cost

  set b variable-benefit
  set R (b / 2 - c)
  set S (b - c)
  set T (0)
  set P (0)

  set benefit b  ;; to display benefit value
end
```

Unit Disk Graphs

```
to make-unit-disk-graph ;; make a unit disk graph
 ask nodes [
  set shape "car"
  set size 3
 ]

 ask nodes [
  ask nodes in-radius (scaled-transmission-range * 2) [
   if who > [who] of myself [

     if realtime [ layout ]

    create-link-with myself
   ]
  ]
 ]
end
```

Small World Networks

```
to small-world-network ;; for SWN
  ask links [
   ;; whether to rewire it or not?
   if (random-float 1) < random-probability
   [
    ;; "a" remains the same
    let node1 end1
    ;; if "a" is not connected to everybody
    if [ count link-neighbors ] of end1 < (count turtles - 2)
    [
     ;; find a node distinct from node1 and not already a neighbor of node1
     let node2 one-of turtles with [ (self != node1) and (not link-neighbor? node1) ]
     ;; wire the new edge
     ask node1 [ create-link-with node2 [ set color red set rewired? true ] ]
     set number-rewired number-rewired + 1 ;; counter for number of rewirings
     set rewired? true
    ] ]
   if realtime[ layout]
  ]
 end
```

Certain user-defined yet self-explanatory functions have not been provided.

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Conference Publication

Md. R. Kabir, Md. M. Muhaimin, Md. A. Mahir, K. H. Kabir, "Design and Analysis of an Efficient Energy Sharing System among Electric Vehicles using Evolutionary Game Theory", 2022 International Conference on Artificial Intelligence in Information and Communication (ICAIIC), February 21-24, 2022, IEEE Communications Society, pp. 411-416, IEEE.
DOI: 10.1109/ICAIIC54071.2022.9722684