Master Thesis

Designing Social Systems based on GA-Driven Massively Multi-Agent Simulations

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Abstract

A modern city is a large-scale complex system composed of various social systems, which makes it difficult to predict dynamic changes. It is difficult for humans to design urban systems to provide people with comfortable living environment and make society more efficient. Multi-Agent Simulation (MASim) has been studied to deal with the difficulties.

We model actors, such as humans and organizations, as agents in MASim. Accumulation of interaction among agents represents the whole society. That allows us to deal with complex systems. Moreover, to design optimal social systems, problems in social institution design should be recognized in advance by using MASim.

We need to define parameters to run simulations. Parameters define social systems in simulations. A parameter set corresponds to a candidate design for a social system. When we design new social systems, an outline of systems is often decided. However, clear guidelines are not found since it is ambiguous what parameters we should use and set. In massively MASim, the number of parameters increases and phenomena become more complicated because of decisions of agents and interactions among agents. The number of simulation patterns increases, and full search is not realistic. Therefore, this study aims to get a semi-optimal design in designing new social systems by using massively MASim, even if proper parameter sets are not clear, and full search is difficult within a realistic time because of large search space.

For achieving this objective, this study addresses the following issues.

Search for a semi-optimal solution Exhaustive search is necessary to obtain a semi-optimal design by analyzing structure of social systems and improving understanding. However, computational complexity necessary to run one simulation is very high, and combinations of parameters needed to search exhaustively are massive because of an increase of parameters and elaborated models. Therefore, frameworks to run exhaustive simulations efficiently have been demanded.

This research uses Genetic Algorithm (GA) and proposes a GA-driven approach to achieve a semi-optimal design. Multipoint search is a characteristic of GA, which

gives GA the ability to reach global optimization and makes parallel implementation of GA easy. Therefore, this research considers the approach to search solutions efficiently and to get a semi-optimal solution in a short time in designing complex social systems.

The proposed approach treats parameter sets of social systems as chromosomes in GA. A social system is expanded on the basis of design information contained in a chromosome, and MASim is executed. The proposed approach evaluates results of the simulation on the basis of a social indicator and treats the evaluation value as a fitness value of the individual with the chromosome. New individuals are generated by selection, crossover, and mutation based on GA. This research searches a semi-optimal solution by iterating similar processes. This research uses distributed GA, which has high parallel efficiency, and improves search efficiency.

This research treats an integrated system composed of traffic system and power system as a target for designing social systems. More specifically, EVs transport surplus power generated by PV generation, and people share power through power exchange stations located in various places. Four parameters are defined as a chromosome. These parameters are participation rate of system, acceptable range of the distance to station, the number of stations, and station placement pattern. A better system is defined as a system to create a better balance between suppliers' amount of discharge and consumers' amount of charge in power exchange stations. Fitness value is defined on the basis of above evaluations. In experiments with 9000 agents, the proposed approach obtained the semi-optimal solution with the second best fitness value in approximately three days. It takes approximately fifteen days to execute full search. The derived solution achieved approximately 3% power saving as compared to other solutions. Therefore, it is believed that the proposed approach can search a semi-optimal solution in the target social system in this study.

This research makes a contribution as follows.

Proposal and analysis of the method for designing social systems This study proposed a method for getting a semi-optimal design by using GA-driven search algorithm, even if computational complexity to search fully is high since the social system is complex. It was found that the proposed approach can search a semi-optimal solution in the target social system in this study.

GA 駆動の大規模マルチエージェントシミュレーションに基づく社会システムのデザイン

十見 俊輔

内容梗概

現代の都市は，多種多様な社会システムが複合した大規模複雑系であり，動態の予測は困難である．人々に快適な生活環境を提供し，社会をより効率的にするための都市規模のシステムデザインは人手での計算能力を超えている．この課題に対して，マルチエージェントシミュレーション (MASim: Multi-Agent Simulation) を利用した研究が行われている．

MASim では，人間などの行動主体をエージェントとしてモデル化し，それらの相互作用の集積として社会といった全体が表現される．それにより，人間社会における複雑な現象を取り扱うことが可能である．そして，社会制度設計を行う際に社会シミュレーションを用いて事前に問題点を把握し，最適な制度設計を予見的に行う社会デザインが可能になると期待されている．

シミュレーションを実行するためには扱うパラメータを決定しなければならない．そのパラメータにより対象となる社会システムが規定され，あるパラメータセットはひとつのデザイン案に当たる．新たな社会システムを設計する際には，そのシステムの大枠が決定されていることは多い．しかし，具体的にどのようなパラメータを扱い，その値をどのように設定すべきか曖昧で，明確なガイドラインは見当たらない．また，大規模な社会シミュレーションともなると，扱うパラメータの増加，個々のエージェントの判断やその相互作用により，現象が複雑化していき，パターンそのものも増大する．そのため，シミュレーション 1 回の計算量は大きく，網羅するパラメータの組合せも膨大になり，全探索は現実的ではない．そこで本研究では，妥当なパラメータセットが不明瞭であり，探索空間が広大で全探索が現実的には困難な状況下でも，準最適なデザイン案を得ることを目的とする．

この目的を達成するために，本研究では以下の課題に取り組む．

準最適解の探索　対象となる社会システムの構造や性質を分析して理解を深め，準最適なデザインを獲得するには，網羅的な試行が必要となる．しかし，大規模シミュレーションではモデルの精緻化やパラメータの増加により，単体のシミュレーション実行時間と網羅すべき組合せは膨大になってしまう．

そのため，網羅的試行を効率的に実行し，少ない計算時間で探索を可能とするフレームワークが必要である．

この課題に対し，本研究では遺伝的アルゴリズム (GA: Genetic Algorithm) を利用し，準最適なデザインを獲得する手法を試みる．GA は多数の解を同時に探索点として持ち，大域的最適化能力だけでなく並列実装を容易にする．そのため，複雑な社会システムデザインにおいても効率よく探索を行い，少ない計算時間で準最適解を求めることができると考える．

提案手法では，デザイン案である社会システムを規定するパラメータセットを GA における染色体とする．その染色体が内包するデザイン情報を基に社会システムが展開され，MASim が実行される．その結果をある社会指標に基づいて評価し，その評価値を対応する染色体を持つ個体の適合度とする．そして，GA に則った選択，交叉，突然変異によって，新たな染色体が生み出される．同様の処理の繰り返しによって，評価値の高い準最適なデザインを探索する．GA には並列化効率の高い分散 GA を用い，探索効率が良くなるようにする．

また本研究では，デザインする社会システムの対象として，交通流と電力流通の複合システムを扱う．具体的には，太陽光発電による余剰電力を電気自動車により運搬し，各地に設置された車載電力交換ステーションで電力を共有するシステムである．染色体に使用するパラメータセットとして，システム参加率，立ち寄り許容距離，車載電力交換ステーション設置数，配置パターンの 4 つを設定した．また，車載電力交換ステーションにおける供給者の放電量と需要者の充電量のバランスが良いほど優れたシステムであるとし，適合度を定義した．エージェント数 9000 の実験では，全探索に約 15 日かかるところ，約 3 日間で全解中 2 番目に適合度が高い準最適解を導出した．また，得られた近似解は他の解と比べ，約 3%の節電が実現された．これらにより，本研究で対象としたシステムでは準最適な解が探索できていると考えられる．

本研究における貢献は以下の点である．

GA 駆動 MASim による社会システムデザイン手法の提案と分析　対象となる社会システムが複雑で，探索空間が広大で全探索には計算量が膨大になってしまう状況下でも，GA 駆動の探索アルゴリズムにより準最適なデザインを探索する手法を提案した．提案手法により，本研究で対象としたシステムでは準最適な解が得られたことが分かった．

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Contents

Chapter 1 Introduction

A modern city is a large-scale complex system composed of various social systems, which makes it difficult to predict dynamic changes. It is difficult for humans to design urban systems to provide people with comfortable living environment and make society more efficient. Multi-Agent Simulation (MASim) have been studied to deal with this difficulties [1].

We model actors, such as humans and organizations, as agents in MASim. Accumulation of interaction among agents represents the whole society. That allows us to deal with complex phenomena in human society. Moreover, to design optimal social systems, problems in social institution design should be recognized in advance by using MASim [2]. For example, we apply MASim to traffic phenomena [3], power distribution phenomena [4], and disaster evacuation phenomena [5, 6]. Therefore, Results of simulations help us understand, predict, and verify phenomena.

However, there are some problems. First, it is difficult to directly implement optimal social policies predicted by simulation results, since there are interests among parties, emotional issues, feelings of resistance to changes in convention, occurrence of unexpected events. Therefore, it is difficult to calculate an "optimal" solution by simulating only once and force the solution on society simply [7]. Thus, processes for reconsidering simulation results by humans and running simulations reflecting results of reconsideration.

The second problem is related to defining parameter sets of simulations. We need to define parameters in order to run simulations. Parameters define social systems in simulations. In other words, a parameter set corresponds to one candidate design for a social system. When we design a new social system, an outline of the social system is often determined. However, clear guidelines are not found since it is ambiguous what parameters we should use and set. Therefore, methods for defining parameter sets in simulations largely depend on researchers' experience and knowledge [8].

The last problem is related to computational complexity necessary to run simulations and to search an optimal solution. In massive social simulations, the number of parameters increases, and phenomena become more complicated because of decisions of agents and interactions among agents. Thus, the number of simulation patterns increases. Moreover, the amount of data necessary to manage increases when we attempt exhaustive simulations for structure analysis and identification of target social systems. Therefore, computational complexity necessary to run one simulation is very high, and execution time is very long. Exhaustive search is difficult within a realistic time since combinations of parameters needed to search exhaustively are massive. Accordingly, we need to take advantage of computational resources of super computers, such as K computer, to run massively complex simulations. Furthermore, frameworks to run exhaustive simulations efficiently have been demanded [9].

The objective of this study is to obtain a semi-optimal design in designing new social systems by using massively MASim, even if proper parameter sets are not clear, and exhaustive search is difficult within a realistic time because of large search space. For achieving this objective, this research uses Genetic Algorithm (GA) that is one of evolutionary computation and proposes a GA-driven approach to achieve a semi-optimal design. The greatest characteristic of GA is having many solutions as search points at the same time. This characteristic not only gives GA a ability to reach global optimization, but also makes parallel implementation of GA easy [10]. Therefore, this research considers the approach to search solutions efficiently and to get a semi-optimal solution in a short time in designing complex social systems.

The proposed approach treats parameter sets defining social systems, candidate designs, as chromosomes in GA. A social system is expanded on the basis of design information contained in one chromosome, and MASim is executed. The proposed approach evaluates results of the simulation on the basis of a social indicator and treats the evaluation value as a fitness value of the individual with the chromosome. New individuals are generated by selection, crossover, and mutation based on GA. This research searches a semi-optimal solution with a high evaluation value by iterating similar processes. This research uses Distributed Genetic Algorithm (DGA) [11, 12], which is one of GAs and has high parallel efficiency, and improves search efficiency.

Meanwhile, what kind of social systems is needed to be considered in this study? Energy is necessary for every social activities. New energy and methods for introducing into society have been searching around the world in recent years. Every social activities are driven by traffic, which is generated from comings and goings of humans, things and information by consuming energy. Examinations regarding energy and traffic systems are necessary when we design future society [13]. Society becomes environment-oriented, and Photovoltaic (PV) power generation systems, and Electronic Vehicles (EV) spread among people. The diffusion brings a situation that PV's general users become to generate energy, and EV's general users become to transport and stock energy by using EV batteries.

This research treats a integrated system composed of above traffic system and power system as a target for designing social systems. More specifically, EVs transport surplus power generated by PV generation, and people share power through power exchange stations located in various places. The power exchange station is a place with infrastructure facilities to charge power. People with surplus power generated by home PV generators provide surplus power in power exchange stations. In the other hand, people who don't have PV generators at home and surplus power charge power in power exchange stations. In this social system, each person changes behavior depending on both traffic flow and power distribution. As for traffic flow, people change behavior depending on daily traffic situations and remaining battery capacity of EVs. As for power distribution, people change contribution to power distribution since each power condition, such as power consumption and remaining battery capacity of an EV, changes depending on changes in traffic behavior. This social system exhibits complex behavior based on the interaction between traffic flow and power distribution.

This research applies the proposed approach to the integrated system composed of traffic system and power system, and designs the new social system composed of various existing systems. This research conducts two types of experiments. One is in 9000 EVs, and the other is in 20000 EVs. Thereby, this research examines whether search efficiency could be improved by changes in the number of agents or not. This research also examines how the nature of the problem is changed by the number of agents. Moreover, this research verifies the proposed approach by analyzing search time, convergent trend and simulation results of obtained candidate designs.

The rest of the thesis is organized as follows. In Chapter 2, related work on GA and social system design based on MASim is shown. Diffusion and impact of EV and PV, which are related to the design target in this study, are described, too.

Chapter 3 describes the integrated system composed of traffic system and power system. Next, Chapter 4 describes a simulation platform to simulate the social system. Chapter 5 proposes a social system design method based on GA-driven MASim, and then Chapter 6 discusses results of experiments with the proposed approach. Finally, Chapter 7 presents the conclusion.

Chapter 2 Related Work

First, this chapter describes social system design based on MASim, which is background of this research. Secondly, this chapter describes GA, which is used in order to get a semi-optimal design in the proposed method. Finally, present situations of EV and PV are shown. EV and PV in the integrated system composed of traffic system and power system are simulated in this study.

2.1 Social System Design based on Multi-Agent Simulation

Much attention has been paid to Multi-Agent Simulation (MASim). MASim describes diversity of actors' behavior and allows observation for each of actors and analysis [14]. We model actors, such as humans and organizations, as agents in MASim. Accumulation of interaction among agents represents the whole society. That allows us to deal with complex systems. Moreover, to design optimal social systems, problems in social institution design should be recognized in advance by using MASim [2].

Previous studies have proposed new social systems and mechanisms by using artificial intelligence, and verified the systems by simulations. In many of these studies, researchers design new social systems and use simulations for advance verification of the systems.

[3] is a research on traffic flow. They pointed out that researches on autonomous vehicles proceeded, however existing intersection management system is wastefulness in autonomous vehicles since the management system is for humans. Therefore, they suggested an alternative mechanism for coordinating the movement of autonomous vehicles through intersections. In the mechanism, autonomous vehicles can move efficiently and safely. Drivers and intersections in the mechanism are treated as autonomous agents in a multi-agent system. Vehicles can pass through interactions without traffic lights since intersections use a new reservation-based approach built around a detailed communication protocol in this multi-agent system. Moreover, they tested the management system in simulations and presented experimental results that strongly attest to the efficacy of the approach.

[4] is a research on power distribution. They proposed a power management

system when power storage devices are installed into every homes in the future. If micro-storage devices are all charged at the same time using power from the electrical grid, it means a higher demand and, hence, requires more generation capacity, results in more carbon emissions, and, in the worst case, breaks down the system due to over-demand. To alleviate such issues, they presented a novel agent-based micro-storage management technique that allows all storage devices in the system to converge to profitable, efficient behavior. Furthermore, their solution shows that, in the UK electricity market, it is possible to achieve savings of up to 13% on average for a consumer in simulations.

In these researches, methods for determining parameter sets in simulations largely depend on researchers' experience and knowledge. There are limitations to think of designs of new social systems by humans.

On the other hand, it is important in designing social systems not to predict behavior social systems accurately, but to verify whether behavior of social systems fall with in a assumed range or not. Thus, we aim to create frameworks to investigate models of social systems exhaustively by simulations [8].

Exhaustive simulations are starting to be used to verify emergency evacuation plan and traffic flow navigation. In [5], they proposed the one-dimensional pedestrian model, which simplifies the obstacle avoiding algorithm and the interference between pedestrians for high-speed calculation. They developed evacuation simulator NetMAS with the one-dimensional pedestrian model. The validity of the model was confirmed by comparing simulation results with data observed from an actual evacuation drill. As application of their simulator, they took up the evacuation in a large-scale commercial complex, and verified the effective factors on the efficiency of evacuation. In [6], they verified traffic flow navigation by using the one-dimensional pedestrian model and PRACTIS(Pedestrian Rapid Aggregation Control Town-wide Integrated Simulator). PRACTIS is a simulation controller, which verifies or evaluates exhaustive simulations. They investigated characteristics of congestion occurrences by running exhaustive simulations for various patterns. More specifically, they confirmed an effective traffic flow control method for Sumida fireworks festival by using PRACTIS and executing 1500 patterns of simulations.

[9] proposed a method for search parameters of simulations efficiently and ex-

haustively. In massive social simulations, the number of parameters increases and phenomena become more complicated because of decisions of agents and interactions among agents. Thus, the number of simulation patterns increases. Moreover, the amount of data necessary to manage increases when we attempt exhaustive simulations for structure analysis and identification of target social systems. Therefore, they pointed out that a method for executing exhaustive simulations efficiently is necessary. They proposed shifting iterate design of experiment, which is based on design of experiment, to search exhaustively combinations of parameters efficiently. They also proposed a method for searching parameters by using analysis of variance contribute to find sensitive combination of parameters. Furthermore, They verified these methods. They treated n-prisoners' dilemma as a example. Future work is to increase the size and complexity of problems and verify the large-scale complex problems.

It is difficult to run simulations exhaustively and seek a precise optimal solution since the design target in this research is a new integrated social system composed of various social systems. For this issue, this research attempts to search a semi-optimal solution by approximate search method based on GA, which is one of evolutionary computation. There are other methods for search optimal solution. However, society originally have a nature of remaining better things and improving bad things, and it seems that the nature could be applied in designing social systems. As the Section 2.2 shows, the greatest characteristic of GA is having many solutions as search points at the same time. This characteristic not only gives GA a ability to reach global optimization, but also makes parallel implementation of GA easy. Therefore, this research considers GA can search solutions efficiently and get a semi-optimal solution in a short time in designing complex social systems. That is why this research employs GA.

2.2 Genetic Algorithm

Holland, J. H. proposed Genetic Algorithm (GA) [15], and D. E. showed various expansions and a direction of development [16]. GA is a field of research that has advanced in expansions and development the most widely in evolutionary computation. GA is inspired from evaluation of population of organisms. A set of solutions

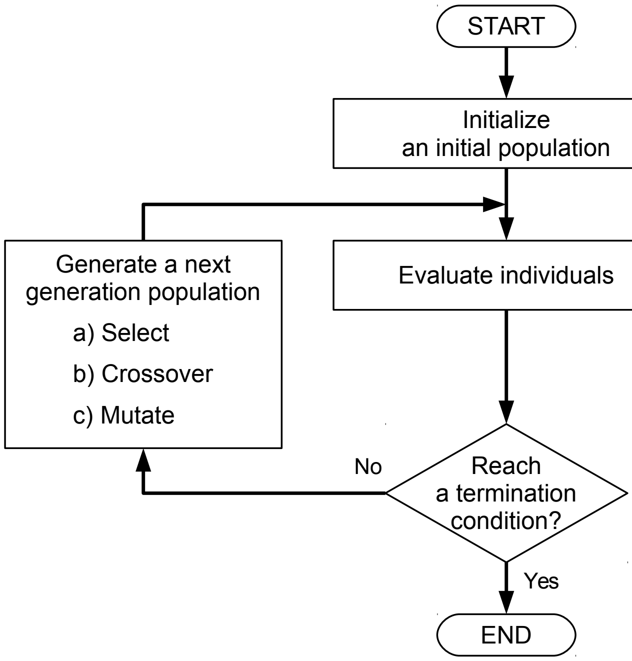

Figure 1: Flowchart representing simple GA

for an optimization problem corresponds to a population in GA. Population for the next generation is generated from the current population by using genetic operations such as crossover and mutation. At this time, by using a mechanism similar to natural selection, a relatively good solution in the current population is selected as the parent to generate a solution for the next generation. New solutions generated constitute the population for the next generation. By iterating this generation update, population is expected to gradually evolve into a set of good solutions. Even if improvement of solutions at between individual generations are very small, an optimal solution or a good approximate solution close to the optimal solution are obtained as a result of evolution in the long term by the accumulation of improvement by generation updates. This is the basic search mechanism in GA, and improving solution set corresponds to the evolution of population of organisms. Moreover, GA is also applicable to an optimization problem in which the objective function is not expressible in strictly mathematical expression. Therefore, GA is effective when an evaluation value of solutions is given by simulations [10].

Figure 1 shows a flowchart of simple GA, and the general procedure for GA is described as follows:

1. Generate initial population.
2. Evaluate each individual in the population.
3. Confirm whether termination conditions are met or not. Terminate if conditions are met, otherwise go to the next step.
4. Repeat the following steps to produce a child population. Choose individuals included in the population for the next generation from the child population.
   (a) Select parent individuals.
   (b) Apply crossover operation to the selected parent individuals.
   (c) Apply mutation operation to the child individuals applied crossover operation.
5. Go back to 2.

The greatest characteristic of GA is having many solutions as search points at the same time. This characteristic not only gives GA a ability to reach global optimization, but also makes parallel implementation of GA easy. For this reason, many parallel models of GA have been studied. Even among those, Distributed Genetic Algorithm (DGA) [11] has not only high parallel efficiency but also superior search performance relative to others [12]. Therefore, DGA is expanded to various ways as a search algorithm.

DGA divides a population into some sub populations. DGA is called island model since a sub population is also called an island. In each sub population, genetic operations such as selection, crossover, and mutation are applied independently of other sub populations as in Figure 1. In DGA, migration operation, which exchanges searching information between sub populations, is added. Figure 2 shows the schematic of migration in DGA. There are a synchronous model and an asynchronous model. These are different from time to apply migration operation. A synchronous model migrates among all sub populations synchronously. An asynchronous model migrates partly between sub populations.

When implementing DGA in parallel computers, we assign a processor to each sub population. Most of calculations are performed within each processor, and DGA has high parallel efficiency since genetic operations are executed independently except migrations. Selection locality improves convergence within each sub population because searching in some sub populations. Furthermore, indigenous evolution in

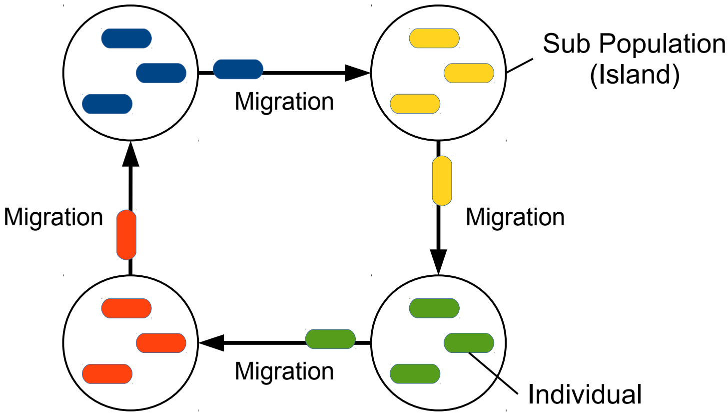

Figure 2: Schematic of migration in DGA

each sub population can keep diversity in whole population [10].

In DGA, there are parameters relating to migration as follows:

Number of islands The number of sub populations. This number and population size decide each sub population size.

Migration interval Interval of generations to migrate.

Migration rate Percentage of migrants to all individuals in a sub population. The product of sub population size and migrate rate decides the number of migration individuals.

Migration topology Migration path. Individuals migrate from which sub population to which sub population.

Method for selecting migrants How to select migrants.

Proper parameter settings differ with a target optimal problem. In [17], they presumed the best parameters of DGA by using design experiment method. For the preliminary experiment, they studied 13 types of parameters of DGA by applying 4 numerical test functions. The parameters are classified into two groups; the parameters that are used in sub populations and the parameters that are concerned with the migration. From the numerical examples, the best values of parameters were derived. This study sets parameters that are concerned with GA on the basis of results of [17].

Table 1: Diffusion target of next-generation vehicles (reprinted from [18])

Vehicle type	2020	2030
Conventional vehicle (%)	50–80	30–50
Hybrid vehicle(%)	20–30	30–40
EV & plug-in hybrid vehicle (%)	15–20	20–30

Table 2: EV battery road map (created based on data from [20])

Indicators	2012	2020	2030
Mileage per charge (km)	120–200	250–350	500
Weight of battery (kg)	200–300	100–140	80
Electric energy of battery (kWh)	16–24	25–35	40
Energy density (Wh/kg)	60–100	250	500
Cost of battery (Millions of Yen)	1.1–2.4	0.5–0.8	0.4
Cost of EV (Millions of Yen)	2.6–3.76	2.0-2.3	1.9

2.3 Diffusion and Impact of EV and PV

Electric Vehicles (EV) enter the diffusion stage. Table 1 shows that diffusion target of EVs and plug-in hybrid vehicles is set between 20% and 30% [18]. EVs are likely to diffuse in the future because of high environmental performance of EV and a relationship with urban design policies, such as compact city. Then, the key of EV diffusion is to improve EV performance. Energy density in 2030 is predicted to approximately five times larger than in 2010 [19]. Table 1 shows mileage per charge in 2012 is between 120 km and 200 km, however one in 2030 is predicted to approximately 500 km [20]. Therefore, the problem of battery performance is expected to be solved.

On the other hand, diffusion of Photovoltaic (PV) generation is described as follows. Table 3 shows that installation target of PV generation in 2020 is set to twenty times larger than in 2009. Table 3 also shows that installation amount of electric power is predicted to 53 GW in 2030. As for PV performance and cost, Table 4 shows these targets. In 2012, additionally, Feed-In Tariff (FIT) was installed and

Table 3: Installation target of PV (created based on data from [21])

Indicators	2005	2020	2030
Electric power (GW)	1.4	28	53
(Crude oil equivalent (kL))	35	700	1300

Table 4: PV road map (created based on data from [23])

Indicators	2013	2020	2030
Cost of PV system (Thousands of yen/kW)	275	200	100
Cost of power generation (Yen/kWh)	23	14	7
Module conversion efficiency (%)	16	22	25
Rate of utilization (%)	13	15	15
Life of PV (years)	20	25	30

genuine diffusion of PV generation is expected [21]. However, improvement of PV diffusion exposes a problem of surplus power. Concentration of PV generation interconnection causes power to flow back to electrical grid, that is called reverse power flow, and worsens power quality [22]. Therefore, measures such as controlling PV generation output is necessary.

In prospect of the above diffusion of EVs in the future, connecting EVs to electrical grid, which is called Vehicle-to-Grid (V2G), has been studied [13, 24]. The objective of V2G is stable power supply and cost reduction in installing renewable energy. These researches postulate advantages of using EVs in order to cut peak power by using EV batteries as buffers and to stabilize unstable output of renewable energy. This study also assumes the existence of V2G and verifies that derivation and flow of renewable energy in V2G by using simulations.

In power distribution through EV batteries, people transport power, and distribution routes and distribution opportunities depend on humans' decision making. Therefore, behavior of power distribution system is not clear. In the environment where stable electrical grid diffuses like Japan, especially, power distribution through EVs is not necessary to provide power, and it is difficult to find new value in backup system. However, it is possible to find new value in PV power distribution system. In urban areas, where population concentration and aggregation of social functions progress, simultaneous diffusion of EV and PV allows people to generate and transport power on a large scale. Therefore, this research makes the concept of user participatory urban power distribution system to aggregate and distribute surplus PV power generated in distributed locations by using EV. The social system is design target in this research.

Chapter 3 PV Power Distribution System through EVs

This chapter describes the integrated system composed of traffic system and power system that is design target in this research. First, the outline of social system that is design target is described. Next, Models and simulation parameters defining the social system in MASim are described.

3.1 System Overview

This research tries to obtain a good design of the social system to distribute PV power in the urban traffic system. Therefore, this research models traffic generated by movements of EVs. Process for aggregating and distrusting PV power generated in distributed locations through EVs proceeds simultaneously with power consumption behavior of each human. This research verifies how PV power distribution system changes values concerned with power distribution, such as the amount of power leaded from electrical grid and the amount of power generated by PV and transported by EVs, by using MASim.

Figure 3 shows the outline of PV power distribution system through EVs. In this simulation, power use in homes and EV running are factors of power consumption. On the other hand, electrical grid and PV generations are power supply sources. Each EV determines an action plan every day and runs in accordance with the plan. Plans are based on each power demand, surplus power, and the Origin-Destination (OD) table. The OD table includes elements such as homes, offices, and supermarkets. Surplus PV power generated in various locations is distributed to other places through EVs.

More specifically, EVs with surplus power, which mean suppliers, and EVs with capacity to charge, which mean consumers, stop at power exchange stations. The power exchange station is a place with infrastructure facilities to charge batteries. People with surplus power generated by home PV generators provide surplus power in power exchange stations. In the other hand, people who don't have PV generators at home and surplus power charge power in power exchange stations. Charging and discharging through batteries at power exchange stations realize power transfer between suppliers and consumers. However, if batteries at power exchange stations

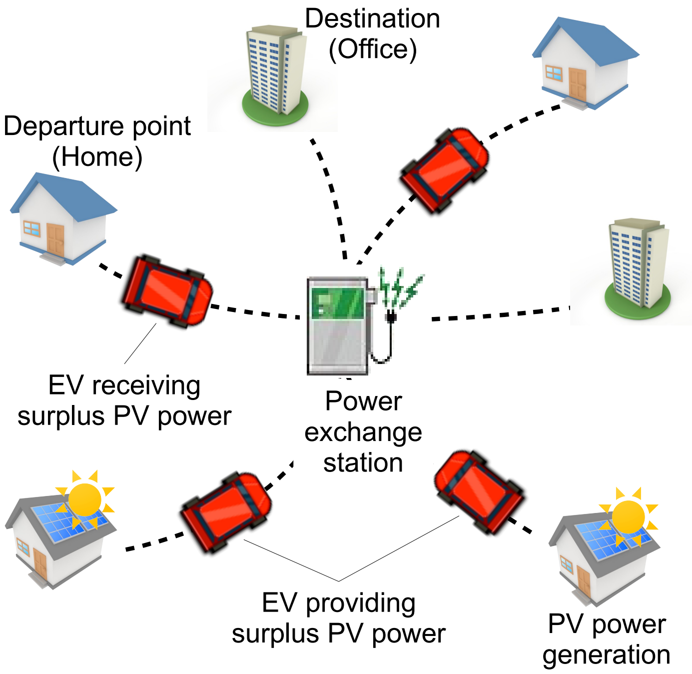

Figure 3: Schematic of PV power distribution system

don't have sufficient power, power exchange stations lead from electrical grid as well as normal charging stations.

Generally, if surplus PV power is expected to be generated, each home reduces the amount of PV generation or reverse power to electrical grid. Reverse power flow means power selling generally. However, reverse power flow should be inhibited since reverse power flow worsens power quality [22]. Moreover, since there are problems about PV power purchase and depreciation of PV power purchase price, it is necessary to consider methods for using surplus PV power. Therefore, this research considers sharing surplus PV power by humans participating this system worthy.

In this simulation, movements of EVs allow share of power among homes, which resolves uneven PV distribution. This research searches system requirements to create a good balance between suppliers' amount of discharge and consumers' amount of charge.

Finding a good design which is the combination of conditions is difficult since it is necessary to tune various conditions defining the system, such as power consumption in each home, boundary conditions of agents' behavior in providing surplus PV power, and ways for installing power exchange station. Therefore, this research ex-

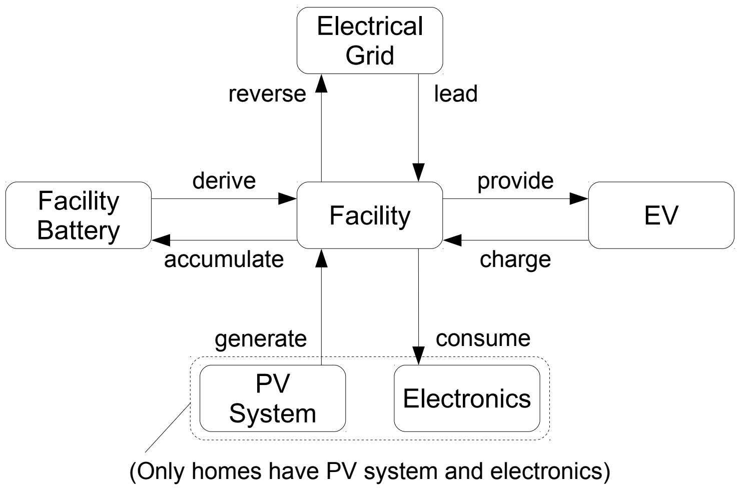

Figure 4: Facility (home or power exchange station) power model

amines a method for obtaining a better social system design by evaluating the social system in MASim, where agents simulate individual behavior, in order to design the social system in consideration of human daily behavior.

3.2 Definition of Models

Facility power model and EV power model in the PV power distribution simulation are defined as shown in Figures 4 and 5.

3.2.1 Facility Model

Figure 4 shows power input and output in facilities such as homes and power exchange stations. Facilities consume power by home electronics and feeding power to EVs. Facilities also get power by leading from electrical grid, generating by PV generators and deriving from EV batteries and facility batteries. Facilities can always lead from electrical grid as well as the actual world. Therefore, only PV power and power derived from EV batteries are charged into facility batteries. For feeding power to EVs and consumption by electronics, if storage amount of facility batteries runs out, facilities lead from electrical grid. Conversely, if surplus power is generated by PV generation, facilities charge surplus power into facility batteries. If more surplus power is generated and facility batteries are charged fully, facilities reverse power to electrical grid. However, power exchange stations don't have any electronics and PV generators. Thus, power exchange stations don't generate power and

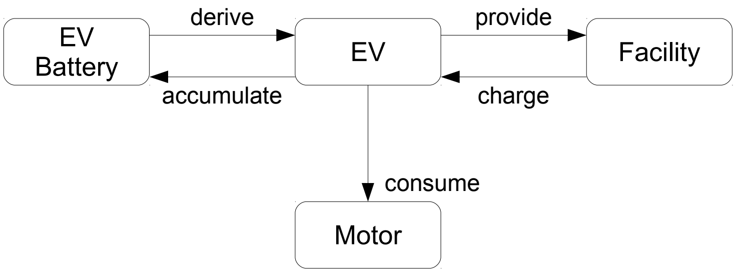

Figure 5: EV power model

consume power by electronics. In other words, only homes generate power by PV systems and consume power by electronics. Once surplus PV power beyond home consumption is charged into facility batteries at a certain point, facilities derive from facilities batteries when needed. That is, facility batteries perform as buffers in order to use PV power efficiently.

3.2.2 EV Model

First, power input and output in EVs are described. Figure 5 shows power input and output in EVs. EVs derive power from EV battery and consume power by motor when running. When EVs are parked in facilities, EVs charge power from facilities or provide power of EV batteries for facilities. Charge from facilities changes depending on remaining battery capacity of facilities. If facility batteries have sufficient power, EVs derive power from facility batteries. If facility batteries don't have sufficient power EVs derive power from facilities after facilities lead power from electrical grid. On the other hand, if EV batteries have sufficient power, EVs provide power of EV batteries for facilities.

Next, rules of power transfer of EVs are described in detail. In this simulation, each agent makes decisions individually in given simulation conditions and makes actions such as moving, power consumption, and power transfer. This simulation assumes that EVs are cooperative in power transfer on the presupposition that EVs ensure sufficient power to consume in running. More specifically, each EV agent has an action plan representing the EV agent moves from where to where. The EV agent estimates the amount of power required to run on the basis of the action plan. Each EV agent acts to always keep the amount of power that is sum of the estimated amount and an extra margin. Under the presupposition, EV agents with surplus power generated by home PV generators stop at power exchange stations and become suppliers providing power. On the other hand, EV agents that don't have PV generators at home and surplus power stop at power exchange stations and become consumers charging power. Then, EV agents that are consumers bring back charged power to home and consume.

Action rules of power transfer when EVs are parked in facilities are described as follows. When EVs are parked in facilities, EV agents change power transfer actions in accordance with the condition met first after checking the following conditions in order from 1.

1. **Condition** If an EV agent is parked in a power exchange station and home has surplus power and remaining battery capacity of the EV is sufficient,

   Action The EV agent becomes a supplier. The EV agent provides power of EV battery for battery of the power exchange station.
2. **Condition** If an EV agent is parked at home and remaining battery capacity of the EV is not sufficient,

   Action The EV agent derives power from home and charges EV battery.
3. **Condition** If an EV agent is parked at home and remaining battery capacity of the EV is sufficient,

   Action The EV agent provides power of EV battery for home.
4. **Condition** If an EV agent is parked at home and home has sufficient power and EV battery is not full,

   Action The EV agent derives power from home and charges EV battery.
5. **Condition** If an EV agent is parked in a power exchange station and home has sufficient power and remaining battery capacity of the EV is not sufficient,

   Action The EV agent becomes a consumer. The EV agent charges EV battery from the power exchange station.
6. **Condition** If an EV agent is parked in a power exchange station and home doesn't have surplus power and EV battery is not full,

   Action The EV agent becomes a consumer. The EV agent charges EV battery from the power exchange station.
7. **Condition** Otherwise,

   Action If the EV agent has a destination, the EV departs. If the EV agent has no destination, for example after getting home, the EV agent does nothing and stays.

The above action rules simply represent that EVs are cooperative in power transfer under the presupposition that EVs ensure sufficient power to consume in running. Under these settings, this simulation calculates the amount of power: power leaded from electrical grid, reverse power flow and power that suppliers provide and consumers charge in power exchange stations.

3.3 Simulation Parameters

This study treats PV power destruction system through EVs as a design target. The system is defined by some parameters concerned with social facilities at homes and human behavior. Parameters in this simulation are described below. Setting values and domain of parameters are also described. However, this simulation set parameters by assuming Kyoto City as a specific city. The urban space in the simulation is divided into three parts: inner city, peripheral part, and suburban. Three parts are allocated to three zones as a concentric circle based on the distance of the center of the city. Inner city, peripheral part, and suburban is hereinafter referred to as zone 1, zone 2, and zone 3 respectively. This research focuses on verification of PV power distribution through EVs. Therefore, this research assumes that a social environment where PV generation diffuses to a certain level, and where PV power can be distributed. This research uses parameter settings suitable for the social environment.

(1) Diffusion rate of PV generators

This parameter decides the number of homes with PV generators. The parameter also decides the amount of power provided for society. It is expected that diffusion rate of PV generation is 23% in 2025[1]. Therefore, this study sets diffusion rate at 25% because PV generation is assumed to diffuse as described above.

(2) PV generator placement pattern

This parameter represents the rate of PV generator placement in each city zone. The parameter decides the placement of PV power supply sources. We can

[1] Fuji Keizai: Research Series of Market by Demands 2013; Penetration Forecast Study of Residential Energy and Related Device by Area (2013)

consider the example placement that many PV generators are installed to a new residential area om suburban. For simplicity, however, This research installs PV generators to each zone in an unbiased way.

(3) Participation rate of PV power distribution system

This parameter decides the number of EV owners who participate in the PV power distribution system and provide power cooperatively. This parameter also decides the potential amount of PV power distribution. This study sets this parameter to 8 values: 20%, 30%, 40%, $\cdots$, 80%, 90%.

(4) Acceptable range of the distance to station

This parameter represents system participants' range of activities. In order to provide surplus power generated PV generators, EVs stop in power exchange stations deviating from the optimal original route. In this time, this parameter decides the upper limit of the distance to power exchange station. This study sets this parameter to 32 values: 50 m, 100 m, 150 m, $\cdots$, 1550 m, 1600 m.

(5) Number of power exchange stations

This parameter represents the number of power exchange stations to share surplus power. This parameter also decides the accumulation of surplus PV power. It is difficult to determine the standard value because power exchange station exist only in the system in this study. However, in the equipment vision of charging infrastructures in Kyoto[2)], Kyoto City plans to install approximately 150 charging infrastructures in Kyoto City. The upper limit of the parameter is set to about half of 150 because this simulation space is a part of Kyoto City. This study sets this parameter to 8 values: 20, 30, 40, $\cdots$, 80, 90.

(6) Power exchange station placement pattern

This parameter represents the placement rate of power exchange stations in each city zone. This parameter also decides the location of collection and distribution of PV power. The location of power exchange stations affects behavior of humans who participate in PV power distribution system. Therefore, this study considers the biased placement in each city zone. This study sets the ratio of zone 1 to zone 2 to zone 3 as 8 values: (2:1:1), (4:1:1), (1:2:1), (1:4:1), (1:1:2),

[2)] http://www.pref.kyoto.jp/denkizidousya/documents/visionlist.pdf

Table 5: Simulation parameters

Parameters		Ways	Domain of definition
(1)	PV diffusion rate (%)	1	25
(2)	PV placement pattern	1	equally installed by regions
(3)	Participation rate of new system (%)	8	20, 30, $\cdots$, 80, 90
(4)	Acceptable range of the distance to station (m)	32	50, 100, 150, $\cdots$, 1550, 1600
(5)	Number of stations	8	20, 30, 40, $\cdots$, 80, 90
(6)	Station placement pattern	8	(2:1:1), (4:1:1), (1:2:1), (1:4:1), (1:1:2), (1:1:4), (3:2:1), (1:1:1)

(1:1:4), (3:2:1), (1:1:1). Both (2:1:1) and (4:1:1) represent the inner-city concentration type. Both (1:2:1) and (1:4:1) represent the peripheral-part concentration type. Both (1:1:2) and (1:1:4) represent the suburban concentration type. Each value is different in the degree of concentration. (3:2:1) represents the inner-city concentration type, where stations gradually decrease towards suburban. (1:1:1) represents the even type.

Table 5 shows the above parameters.

It is possible to treat more parameters in MASim. However, technical devices are needed to search an expanded solution space. Therefore, this study focuses on investigating the possibility of the search method based on GA, and keeps down the number of parameters for simplicity. Similarly, this study uses not real-valued but discrete-valued parameters.

Chapter 4 Simulation Platform

This chapter describes the simulation platform to simulate the social system as described in Chapter 3.

4.1 Simulation Platform Overview

The simulation in this study is implemented as the integrated simulation composed of traffic simulator based on massively multi-agent simulator, MATSim [25], and power consumption simulator. Figure 6 shows the schematic of the simulator. Traffic simulator calculates traveling route including detours to power exchange stations, and reproduction of driving behavior for each EV agent [26]. Power consumption simulator calculates the amount of power leaded from electrical grid, the amount of PV generation, and the amount of power consumption of EVs and homes. Event Manager and Event Manager Connector act as intermediaries between traffic simulator and power consumption simulator. Simulation Controller integrates them, and the integrated simulation composed of traffic flow and power distribution is executed.

This simulation calculates traffic behavior and power consumption behavior for each unit time. By iterating the calculation, the simulation calculates each agent's behavior for a day. Behavior for each unit time is calculated iteratively until time becomes beyond 86400 seconds, because a day has 86400 seconds. This research sets a unit time as 5 seconds. Figure 7 shows a flowchart of the process.

First, this simulator receives a parameter set defining a social system as input, and initializes the simulation environment. Second, the traffic simulator calculates

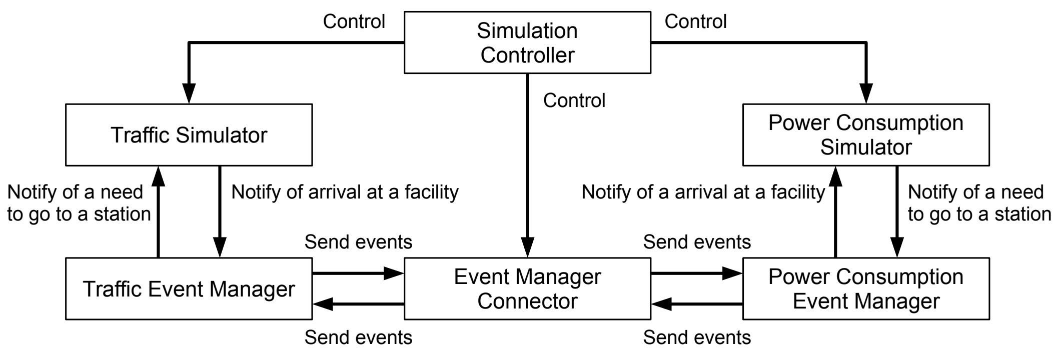

Figure 6: System diagram of simulation platform

traffic behavior in a unit time. Travel distance for each agent is determined by calculations of traveling routes and traffic behavior for each agent in a unit time. Third, the power consumption simulator calculates power consumption behavior in a unit time. The amount of power consumption in each home and the amount of PV generation are calculated on the basis of power information given in advance. The power information represents how much power each home consumes and generates at a certain period of time. For example, consumed power is 0.8 kW, and PV generated power is 7 kW between ten and eleven. The power consumption simulator determines whether a EV agent charges or provides power in the facility if the power consumption simulator receives an event of arrival at a facility. The power consumption simulator also calculates whether EV agents stop in power exchange stations deviating from the optimal original route or not. If an EV stops in a power exchange station, the power consumption simulator notifies the traffic simulator of an event that requires recalculations of the change of the destination and the traveling route in order to change the optimal original route. Event Manager and Event Manager Connector transfer events between the traffic simulator and the power consumption simulator. Each simulator notifies each Event Manager of events. Then, each Event Manager notifies the other simulator through Event Manager Connector.

4.2 Traffic Simulator

The traffic simulator conducts two types of calculations. One is the calculation of EV routing. The other is the calculation of traffic behavior in each unit time.

The traffic simulator calculates routing at the beginning of a day in a simulation. Each EV has an action plan representing the OD and the departure time. The traffic simulator calculates the traveling route on the basis of the action plan and Dijkstra's algorithm. The traffic simulator calculates the traveling rote so that the time distance is the shortest. The time distance that an EV travels on each link is calculated on the basis of the simulation results of the previous day. Each EV departs from its own departure place to its own destination at the departure time and runs on the selected route.

The traffic behavior is calculated in each unit time in a day in a simulation. To represent traffic behavior of each EV and traffic congestion simply, this research uses the car-following model. An EV agent presses the accelerator and the break so that the EV agent run at the desired speed. This research sets the desired speed as 30 km/h. If the speed is less than the desired speed, an EV agent presses the accelerator. If the speed is higher than the desired speed, an EV agent presses the brake. On the other hand, if there is another vehicle in front, an EV agent runs keeping a certain distance with the front vehicle. That is, if the speed is less than the desired speed and the distance between vehicles is less than a certain distance, an EV agent presses the brake. Pressing the accelerator and the brake determines the speed in a unit time.

After determining the speed in a unit time, the traffic simulator calculates the traveling distance in a unit time. An EV agent has location information: which link the EV runs on, and which point on the link the EV exists. The EV travels the distance based on the calculated speed from the point on the link. If the EV reaches the end point of the link, the EV moves the next link. Vehicle capacity is set for each link. If the number of EVs running on a link is more than the capacity, the EV trying to enter the link waits at the starting point of the link and cannot enter the link. That represents traffic congestion.

The traffic simulator iterating the above calculations in a unit time, each EV moves its own departure place to its own destination.

4.3 Power Consumption Simulator

The power consumption simulator calculates power consumption behavior of facilities and EVs in a unit time.

As described in Section 3.2.1, facilities are homes and power exchange stations. Homes consume and generate power basically. This research splits a day into 24 time slots, which means each time slot has one hour. The power consumption simulator is given power information about consumed power and power ratio to PV related power in each time slot. The amount of power consumption and the amount of generation are calculated on the basis of the power information. If the amount of power consumption is more than the amount of generation, the home derives power from the home battery or leads power from electrical grid. On the other hand, if the amount of generation is more than the amount of power consumption, the home accumulates power in the home battery. If the home battery is full, the home reverse power to electrical grid. Moreover, power exchange with the EV is based on the action rules in Section 3.2.2. By that means, the amount of power exchange with batteries, electrical grid, and EVs are calculated.

The amount of power in power exchange stations is calculated as with homes. Power exchange stations exchange power with EVs on the basis of the action rules in Section 3.2.2. If the amount of power provided by EVs is more than the amount of power charged by EVs, the power exchange station accumulates power in the facility battery. On the other hand, the amount of power charged by EVs is more than the amount of power provided by EVs, the power exchange station derives power from the facility battery or leads power from electrical grid as with homes.

EVs consumes power in running. EVs also exchanges power on the basis the action rules in Section 3.2.2. Consumed power in running, charged power, and provided power are set. On the basis of these power, the amount of power consumption in running, the amount of charging power, and the amount of providing power are calculated in a unit time.

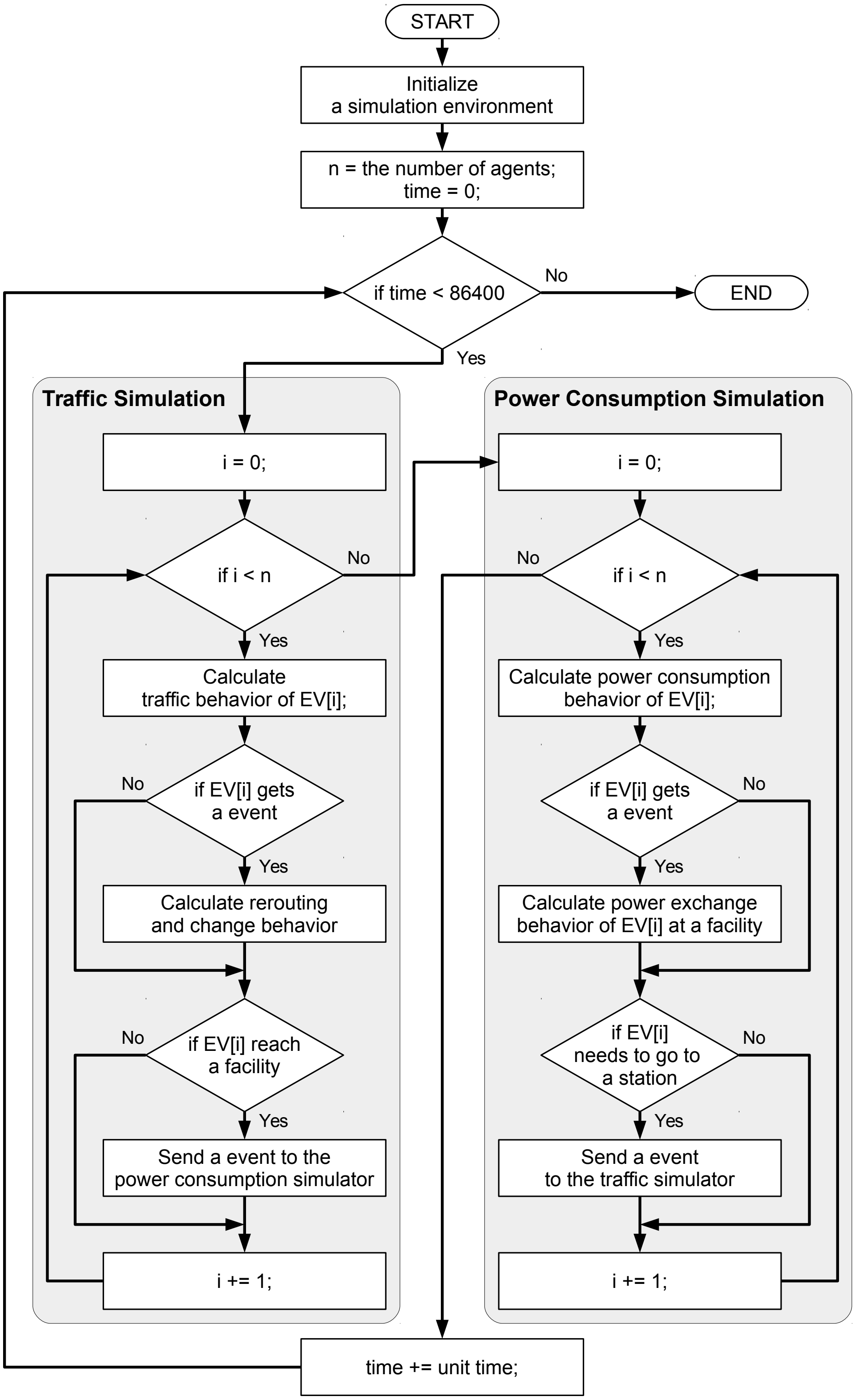

Figure 7: Flowchart representing the simulation process

Chapter 5 Social System Design based on GA-Driven Multi-Agent Simulations

This chapter describes the proposed method for designing semi-optimal social system.

It is difficult to determine the combination of conditions that define behavior of complex social systems by humans. This research aims to obtain a semi-optimal design by determining the combination of conditions. This research treats the combinations of conditions as parameters in MASim. The number of parameters becomes enormous, because urban social systems is massive and complex. Exhaustive search is necessary to obtain a semi-optimal design by analyzing structure of social systems in this situation. However, the number of parameters is enormous, and the search space is large. Thus, it is difficult to decide a combination of parameters to be next evaluated by MASim. Therefore, this research proposes the method for obtaining a semi-optimal design through the combination of MASim and GA, which is one of EC. By using the search algorithm of GA, the proposed method decides MASim to be next executed and controls a lot of MASim needed to be executed.

5.1 Approach Overview

Figure 8 shows the schematic of the proposed method. First, the proposed method models the target social system and defines the evaluation function. As for modeling, attribute variables and domains of the variables are determined. The attribute variables represent features of the social system. As for the evaluation function, the proposed method determines the function to calculate quantitative values representing desirability of the social system on the basis of results of the simulation. Generally, the desirability of the social system is determined on the basis of social indicator. The above settings are described as Initial settings in Figure 8 and are treated as input.

Secondly, as shown in the center of Figure 8, the proposed method iterates the following three steps:

1. Generate a parameter set, which is a candidate solution
2. Run a simulation based on the parameter set
3. Evaluate results of the simulation

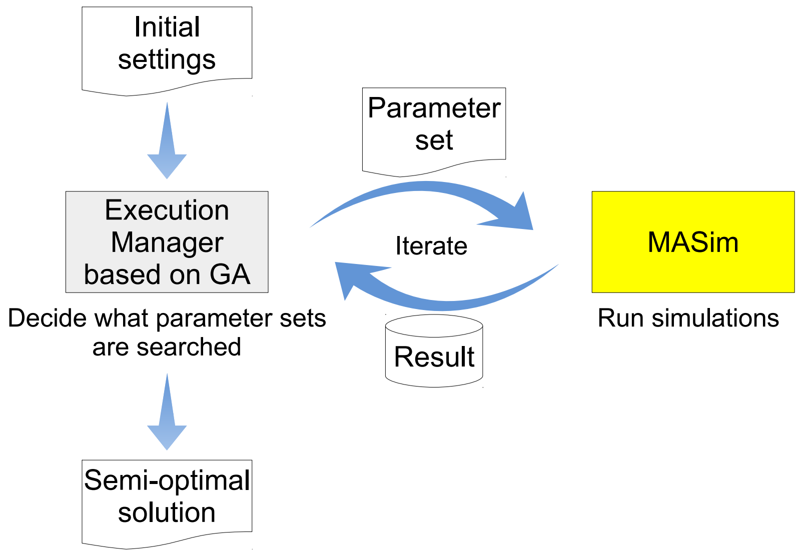

Figure 8: Schematic of solution process

The proposed method searches solutions with higher evaluation values by iterating the above steps.

The set of conditions defining behavior of the target social system is represented C. Each condition is also represented c_i. Each c_i takes arbitrary number of values and is referred to as $c_i = \{v_{i1}, v_{i2}, \cdots, v_{ij}\}$, which means the range of each condition. A parameter set, which is a candidate solution, is referred to as a vector $\vec{d} = \{v_m | v_m \in c_m, m = 1, 2, \cdots, |C|\}$, assigning a each value to a each condition. MASim calculates behavior of agents, receiving an arbitrary candidate solution $\vec{d_k}$ and a set of agents A as input. In other words, a simulation environment is set on the basis of $\vec{d_k}$, and a design of the social system is generated. In the generated virtual social environment, a agent $a_l \in A$ decides behavior and acts on the basis of its own behavior model. After the simulation, results of the simulation are evaluated on the basis of the evaluation function, and the evaluation value of the candidate solution $\vec{d_k}$ is determined. On the basis of the evaluation, the proposed method continues to calculate candidate solutions nearby $\vec{d_k}$. If the proposed method reaches a termination condition, the process of finding solutions stops. For example, termination conditions are defined as a limit number of evaluations of MASim or a target value of the evaluation value.

If a solution space is large and conditions defining behavior social systems are mutually dependent, calculating a precise solution difficult in general. Therefore, this research attempts to find solutions by using finding process based on GA, which is one of EC. The proposed method treats $\vec{d_k}$, a candidate solution of the social system, as a chromosome in GA. A social system is expanded on the basis of design information contained in one chromosome, and MASim is executed. Emergent phenomena in simulations and the evaluation value determine a fitness value of a individual with the chromosome. New individuals are generated by selection, crossover, and mutation based on GA. The proposed method obtains useful system designs for an arbitrary social indicator by iterating similar processes.

5.2 Process of Finding Semi-Optimal Design based on GA

The process of finding a semi-optimal solution by the combination of MASim and GA is described. This finding process is based on the search algorithm of GA. The process uses MASim as the function to calculate fitness values in GA. Thus, Evaluations of an arbitrary social system are conducted on the basis of accumulation of many agents' actions.

5.2.1 Encoding from Chromosomes to Parameter Sets

First, individuals used in GA are described. The proposed method encodes each parameter, as described in Section 3.3. Then an individual with a chromosome representing a design is generated. As described above, each parameter means a condition representing the social system. The objective of these calculations is to obtain a set of conditions that generate more desirable phenomena socially.

As described in Section 3.3, both parameters (1) and (2) are fixed. Therefore, this research treats parameters (3) – (6) as genes. Parameters (3), (5), and (6) contain 8 values respectively, which means 3 bits. Parameter (4) contains 32 values, which means 5 bits. That is, a parameter set is represented as a chromosome that is a sum of 14 bits in length. Thus, a 14-bit binary code is divided into 3 bits, 5 bits, 3 bits, and 3 bits, and each part is assigned to each parameter. For example, there is a chromosome referred to as "00111001100101". First, the chromosome is divided into "001", "11001", "100", and "101". Second, each part is decoded into each genotype, as "$\{(3), (4), (5), (6)\} = \{1, 25, 4, 5\}$". Finally, each genotype is encoded into each parameter on the basis of Table 6. The above example is encoded as follows: "$\{(3), (4), (5), (6)\} = \{30\%, 1300\text{ m}, 60, (1{:}1{:}4)\}$".

Table 6: Correspondence table between genes and parameters

	Genotypes					
Parameters	0	1	2	···	6	7
(3)	20	30	40	···	80	90
(5)	20	30	40	···	80	90
(6)	(2:1:1)	(4:1:1)	(1:2:1)	···	(3:2:1)	(1:1:1)

	Genotypes					
Parameters	0	1	2	···	30	31
(4)	50	100	150	···	1550	1600

(3) Participation rate of new system (%)
(4) Acceptable range of the distance to station (m)
(5) Number of stations
(6) Station placement pattern

5.2.2 Process of Finding Semi-Optimal Design

Figure 9 shows the flowchart representing the finding process based on GA. The finding process is described as follows.

1. Generate some individuals randomly, regard the individuals as an initial population. The chromosome of each individual contains design information of a social system.
2. Generate a environment for MASim from each individual. First, as described in Section 5.2.1, encode chromosomes into parameter sets. Then, initialize multi-agent simulators on the basis of information contained in genes on chromosomes. Environments surrounding agents and agents' range of actions are decides, but each agent's behavior model is not defined. Agents determine own behavior on the basis of behavior model, as described in Section 3.2.
3. Run MASim in social systems and simulation environments generated from individuals.
4. Evaluate results of simulations on the basis of a social indicator. Treat the eval-

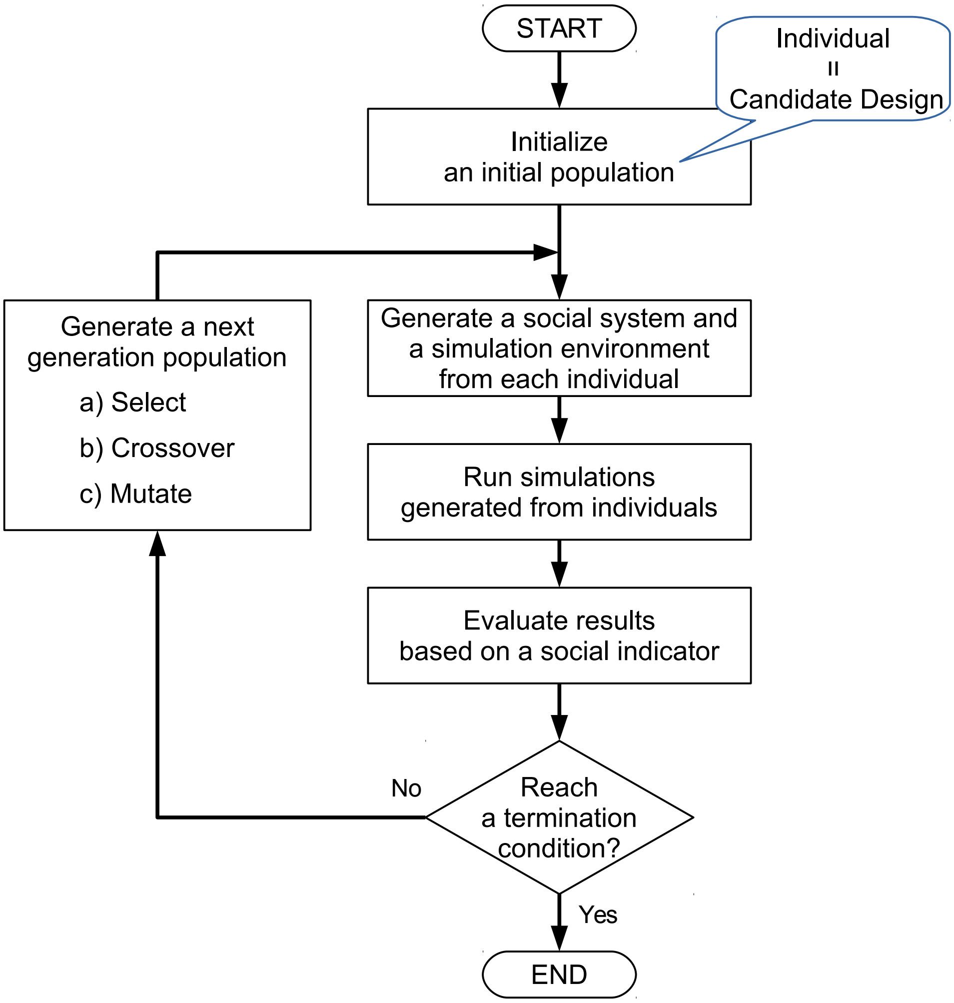

Figure 9: Flowchart representing search algorithm based on GA

uation values as fitness values F in GA. The evaluation function is described in Section 5.3.

5. Return the best solution at the time if a termination condition is reached. The solution is the design derived by the proposed method. For example, a termination condition is defined as a target value of fitness values F. Go to the next step if a terminal condition isn't met.
6. Repeat the following steps to produce a child population. Choose individuals included in the population for the next generation from the child population.
   (a) Select parent individuals on the basis of fitness values F.
   (b) Apply crossover operation to the selected parent individuals.

(c) Apply mutation operation to the child individuals applied crossover operation.

7. Go back to 2.

5.3 Evaluation Function

In this study, the fitness value F is higher if the social system creates a better balance in power transfer between suppliers and consumers in power exchange stations. This research considers that social utility is high and the system is good if surplus PV power are transferred in various locations, and PV power is aggregated and distribute in the PV power distribution system. This research also considers that the fitness value F is higher if the amount of reverse power flow decreases. However, this research considers it important not only that the amount of reverse power flow decreases, but also that aggregated PV power is distributed well. Thus, this research uses the evaluation function concerned with a better balance in power transfer. Therefore, the fitness value F is defined as above. More specifically, the fitness values F is described as follows.

$$F = \frac{C}{C - P}.$$

C : The total amount of power charged by EVs in power exchange stations.

P : The total amount of power provided by EVs in power exchange stations.

The total amount of power charged means the sum of power that all EVs charge in power exchange stations in a day. The total amount of power provided also means the sum of power that all EVs provide in power exchange stations in a day. It is quite unlikely that PV power covers all consumed power, and it seems that the total amount of power charged in power exchange stations is larger than that the one provided in power exchange stations. Therefore, this research assumes $P < C$. Since this assumption leads $0 < C - P$, both the numerator and the denominator of F are non-negative number. $F > 1$ holds because $C > C - P$ holds naturally. Accordingly, the closer $C : P$ is to $1 : 1$, the higher F is. That means the fitness value F is higher if the social system creates a better balance in power transfer between suppliers and consumers.

Chapter 6 Experiments

This chapter describes experiments that apply the proposed method to the PV power distribution system, the results, and the discussion.

This research performed two types of experiments. One was in 9000 EVs, and the other was in 20000 EVs. To verify the proposed method, this research conducted pre-analysis of the solution space in case of 9000 EVs, which was the small-scale problem. Then, discussion about results is described.

6.1 Settings

This section describes the settings of PV power distribution system and the settings of GA.

6.1.1 Settings of PV Power Distribution System

This research used the actual Kyoto City road network as the road network in simulations. This research generated the road network on the basis of the numerical map data of Zenrin Company. The road network has approximately 7000 links and 14000 nodes and is approximately ten kilometers square. This research ran agents simulating vehicles in the actual world on the road network. All vehicles were EVs in the experiments. This research performed two types of experiments: 9000 EVs and 20000 EVs.

This research assigned OD for each EV agents on the basis of a Person Trip Survey in 2000 [27]. Table 7 shows the number of vehicles which depart from one area O to another area D. For example, the (1, 2)-th entry means that 194 vehicles depart from Kita-ku to South Sakyo-ku. On the basis of percentage of total vehicles in Table 7, the number of vehicles departing from area O to area D is determined. Then, one node is selected from the road network representing area O randomly. The node of area O is the departure place. One node is also selected from the road network representing area D randomly. The node of area D is the destination. As a result, OD for an EV is determined. Table 8 shows the number of vehicles which depart from one area in a time slot. For example, the (1, 1)-th entry means that 275 vehicles depart from Kita-ku between 0:00 and 1:00. Similarly, on the basis of Table 8, the departure time for each EV is determined. This research fixes the random

Table 7: OD table (created based on data from [27])

Area ID		To						
		3111	3112	3121	3122	3123	3124	3151
	3111	875	194	186	165	104	23	145
	3112	186	748	140	152	111	54	81
	3121	197	142	230	130	98	44	111
from	3122	177	136	150	373	224	67	251
	3123	111	115	98	204	400	73	189
	3124	29	54	29	62	84	121	54
	3151	157	96	96	263	177	35	1059

Area ID	Name
3111	Kita-ku （北区）
3112	South Sakyo-ku （左京区南部）
3121	Kamigyo-ku （上京区）
3122	Nakagyo-ku （中京区）
3123	Shimogyo-ku （下京区）
3124	Higashiyama-ku （東山区）
3151	Ukyo-ku （右京区）

seed; therefore, all ODs are same in all simulations. Each EV agent has one departure place, such as home, and one destination, such as an office and an supermarket. The departure place is on the above node from area O, and the destination is on the above node from area D. First, each EV agent departs from its own departure place, and goes to its own destination. After arriving at the destination, each EV agent stays there for several hours. Then, each EV agent goes back to the departure place. That is, each EV agent moves twice. Each EV agent selects an arbitrary route and run along the route on the basis of its own assigned OD.

This research sets parameters of PV generators, batteries, and EV in reference to [20, 21]. PV generators is uniform in performance, and this research excluded weather conditions. PV generated power is 10 kW in this research because generated

Table 8: Time table for OD (created based on data from [27])

Time slot \ Area ID	3111	3112	3121	3122	3123	3124	3151
0:00 – 1:00	275	333	105	446	412	975	342
1:00 – 2:00	167	187	278	212	302	848	132
2:00 – 3:00	163	202	61	229	379	479	181
3:00 – 4:00	43	54	42	133	101	195	93
4:00 – 5:00	49	102	130	93	363	172	474
5:00 – 6:00	680	178	182	0	278	45	622
6:00 – 7:00	1526	1593	672	797	706	555	2835
7:00 – 8:00	5405	5837	3036	2939	2551	1154	10265
8:00 – 9:00	9990	7658	3801	4645	4269	1472	11664
9:00 – 10:00	6439	5844	3333	4398	4667	1868	7434
10:00 – 11:00	6571	6690	3733	7204	6021	1633	7109
11:00 – 12:00	5086	6579	4383	6556	5476	1788	8433
12:00 – 13:00	3978	4806	3300	4571	4142	1196	6693
13:00 – 14:00	5765	4919	3877	4660	6802	2607	7006
14:00 – 15:00	5456	5041	4348	6324	6643	1808	6035
15:00 – 16:00	5242	4491	3786	4761	7505	1508	6780
16:00 – 17:00	5992	5919	3191	5105	7101	2192	6880
17:00 – 18:00	7597	7386	5015	7242	7168	2547	10326
18:00 – 19:00	6297	7142	3791	6966	7517	2247	9299
19:00 – 20:00	4113	4006	2698	4464	5488	1240	6394
20:00 – 21:00	2504	3560	1599	3596	3309	1060	4120
21:00 – 22:00	1915	3576	1591	2994	2571	1168	2693
22:00 – 23:00	1258	1705	1051	2458	1455	1335	1970
23:00 – 24:00	913	848	843	2157	1316	817	934

power of PV generator for homes is defined as less than 10 kW in Feed-In Tariff and PV conversion efficiency is considered to be improved as described in Section 2.3. Power generation efficiency is the highest at noon in this research. Therefore, the amount of PV generation in a day is the same. More specifically, this research assumes weekday in summer and sets power ratio to PV related power in each time slot as shown in Table 9. For example, if PV related power is 10 kW, generated power is 7.5 kW between 12:00 and 13:00. Similarly, this research sets consumed power at homes in each time slot as shown in Table 10. For example, a home consumes 0.6 kW of power between 0:00 and 1:00. As for home batteries, only homes with PV generators have batteries. The home battery capacity is 5 kWh and the initial amont of home battery power is 0 kWh. As for EVs, there are three types of battery capacity of an EV: 20 kWh, 50 kWh, and 100 kWh. The initial amount of EV battery is the amount of full capacity. This research set the ratio of (the number of EVs with 20-kWh battery:the number of EVs with 50-kWh battery:the number of EVs with 100-kWh battery) as (1:3:1). For simplicity, power consumed of EVs is 0.75 kW; therefore, mileage per charge is 200 km if EVs with 20-kWh battery run at an average of 15 km/h.

Table 11 shows the above settings.

6.1.2 GA Settings

This research used DGA (island model), which is one of GA and has high parallel efficiency. This research reduced latency in migrations because DGA was an asynchronous model in this research. For the realization of asynchronous DGA, each sub population has a mailbox to receive immigrants. As for emigration, each sub population sends individuals to emigrated sub populations at migration intervals. As for immigration, each sub population checks its own mailbox at migration intervals. If the mailbox receives individuals, the individuals immigrate to the sub population. The above process realizes asynchronous migrations. At this time, this research set parameters of DGA on the basis of [17]. Table 12 shows parameters of DGA.

As described above, this research kept down the size of solution space. Therefore, this research set the limit number of generations to 100 generations, which was a termination condition. This research also set population size to 32. Since the number of islands is 4, each sub population size is $32/4 = 8$. It is considered that the optimal mutation rate is $1/L$, where L is chromosome length. Thus, this research set mutation rate to $1/L = 1/14 \approx 0.08$.

[17] describes that difference in selection methods is small. This research used

Table 9: Power ratio to PV related power in each time slot [3)]

Time slot	Power ratio (%)
0:00 – 1:00	0.0
1:00 – 2:00	0.0
2:00 – 3:00	0.0
3:00 – 4:00	0.0
4:00 – 5:00	0.0
5:00 – 6:00	0.0
6:00 – 7:00	0.06
7:00 – 8:00	0.03
8:00 – 9:00	0.47
9:00 – 10:00	0.64
10:00 – 11:00	0.73
11:00 – 12:00	0.77
12:00 – 13:00	0.75
13:00 – 14:00	0.70
14:00 – 15:00	0.56
15:00 – 16:00	0.41
16:00 – 17:00	0.23
17:00 – 18:00	0.06
18:00 – 19:00	0.0
19:00 – 20:00	0.0
20:00 – 21:00	0.0
21:00 – 22:00	0.0
22:00 – 23:00	0.0
23:00 – 24:00	0.0

tournament selection as a selection method. This research also used elitist strategy. In this research, one individual is handled over to the next generation.

[3)] Tables 9, 10 are created based on data from Advanced Technology Research Laboratories, Panasonic Corporation.

Table 10: Consumed power at homes in each time slot [3)]

Time slot	Consumed power (kW)
0:00 – 1:00	0.60
1:00 – 2:00	0.52
2:00 – 3:00	0.44
3:00 – 4:00	0.42
4:00 – 5:00	0.40
5:00 – 6:00	0.42
6:00 – 7:00	0.58
7:00 – 8:00	0.96
8:00 – 9:00	1.00
9:00 – 10:00	0.88
10:00 – 11:00	0.84
11:00 – 12:00	0.76
12:00 – 13:00	0.84
13:00 – 14:00	0.80
14:00 – 15:00	0.72
15:00 – 16:00	0.78
16:00 – 17:00	0.84
17:00 – 18:00	1.10
18:00 – 19:00	1.20
19:00 – 20:00	1.40
20:00 – 21:00	1.32
21:00 – 22:00	1.36
22:00 – 23:00	1.18
23:00 – 24:00	0.94

[17] also describes that random ring is good with regard to migration topology. For simplicity, however, this research used bi-directional ring. Furthermore, [17] describes that performance of method for selecting migrants depends on target problems. However, they claims that individuals with high fitness values should not be

Table 11: Settings of PV power distribution system

Parameters	Values
Road network	7000 nodes and 14000 links
Number of EVs	9000 or 20000
PV generation capacity (related power)	10 kW
Home battery capacity	5 kWh
EV battery capacity	20 kWh:50 kWh:100 kWh = 1:3:1
Consumed power of EVs	0.75 kW
Battery charge and discharge efficiency	1.0

replaced by immigrants. Therefore, this research used tournament selection to select emigrants as with normal selection method, and used random selection to select individuals replaced by immigrants.

6.1.3 Machine Specification

This research conducted experiments on the machine using Intel Xeon Processor: 2.67 GHz, 12 cores, and 24 threads. In the experiment with 9000 EVs, it takes approximately 15 minutes to run one simulation. In the experiment with 20000 EVs, it takes approximately 25 minutes to take run one simulation. This research allocated three cores to each sub population; therefore, it takes three times as long as running one simulation to run simulations in one generation. Since the termination condition is the number of generation reaches 100, to conduct the experiment with 9000 EVs takes

$$100 \text{ (generations)} \cdot 15 \text{ (minutes)} \cdot 3 = 4500 \text{ (minutes)} \approx 3.1\text{(days)}.$$

On the other hand, to conduct the experiment with 20000 EVs takes

$$100 \text{ (generations)} \cdot 25 \text{ (minutes)} \cdot 3 = 7500 \text{ (minutes)} \approx 5.2 \text{ (days)}.$$

6.2 Pre-Analysis of Solution Space

GA is a search method for getting a good approximate solution close to the optimal solution. However, it doesn't known how close the approximate solution is to

Table 12: GA settings

Parameters	Values
Chromosome length	14 bits (= L)
Population size	32
Number of islands	4
Limit number of generation	100
Selection method	Tournament selection
Tournament size	4
Crossover rate	1.0
Crossover method	One-point crossover
Mutation rate	0.08 (= $1/L$)
Mutation method	Bit string mutation
Migration interval	5
Migration rate	0.5
Migration topology	Bi-Directional ring
Emigrant method	Tournament selection
Immigrant method	Random

the optimal solution. Therefore, this research analyzed the solution space for PV power distribution system through EV. More specifically, this research conducted a full search for the solution space in the experiment with 9000 EVs. This research analyzed how close the derived solution is the optimal solution by the full search.

This research conducted the full search in 12 parallel on the machine using Intel Core i7-3960X Processor: 3.3 GHz, 6 cores, and 12 threads This research ran MASim for $2^{14} = 16384$ designs because chromosome length is 14 bits. Since it takes approximately 15 minutes to run one simulation, the full search takes

$$16384 \text{ (trials)}/12 \text{ (threads)} \cdot 15 \text{ (minutes)} = 20480 \text{ (minutes)} \approx 14.2 \text{ (days)}.$$

Tables 13, 14 show results of the full search. Table 13 shows four parameter sets: the worst fitness value, the median fitness value, the mean fitness value, and the best fitness value in all parameter sets. The parameter set with the best fitness value means

Table 13: Comparison of parameters in worst, median, mean, and best fitness in full search (9000 EVs)

	Parameters	Worst	Median	Mean	Best (Optimal)
(3)	Participation rate of new system (%)	20	60	90	90
(4)	Acceptable range of the distance to station (m)	50	1000	350	100
(5)	Number of stations	20	50	30	20
(6)	Station placement pattern	(1:2:1)	(3:2:1)	(1:1:2)	(1:1:2)
	Fitness	1.013	1.108	1.220	1.428

Table 14: Comparison of power data in worst, median, mean, and optimal fitness in full search (9000 EVs)

Total power consumption (MWh)	Worst	Median	Mean	Best (Optimal)
EVs provide for stations	0.06	6.15	6.05	2.73
EVs charge from stations	4.66	63.28	33.34	9.21
Stations lead from grid	4.37	41.97	9.44	2.68
EVs consume	3.632	3.89	3.74	3.66
Homes lead from grid	93.33	92.79	95.99	94.35
Homes reverse power	85.47	79.93	81.18	84.35

the optimal solution in all solutions. Table 14 shows each power data in parameter sets in Table 13.

Results of the full search show two trends. One is that the fitness value is high if the participation rate of PV power distribution system is high. The other is that the fitness value is high if acceptable range of the distance to station is short. As for acceptable range of the distance to station, the parameter in all solutions from the second best to the thirteenth best is 50 m, although the one in the optimal solution is 100 m. That is, the second best solution where the parameter is 100 m is the fourteenth best solution in all solutions. Thus, the solution space is not unimodal, but multimodal.

Moreover, the results show the fitness values in more than half of solutions are lower than the mean one because the median fitness value is lower than the mean one. Actually, the mean fitness value is the approximately 1000th best in all 16384 solutions. Many solutions have the low fitness values, and the number of solutions with high fitness values is small.

6.3 Results

Figures 10, 12, 14 and Tables 15, 17 show results in the experiment with 9000 EVs. Figures 11, 13, 15 and Tables 16, 18 show results in the experiment with 20000 EVs.

Figure 10 shows the transition of the best fitness values in all individuals in the population. Figure 11 shows the transition of the mean fitness values in all individuals in the population. In the experiment with 9000 EVs, an increase of fitness values stops around 20th generation. This means the convergence to a local solution. Then, fitness values escape from the local solution around 75th generation, and increase. In the experiments with 20000 EVs, fitness values converge around 10th generation. Subsequently, fitness values don't increase. Despite using elitist strategy, the best fitness value decreases at 11th generation. This means the best is replaced by immigrants accidentally when replaced individuals is selected randomly in the migration. For the same reason, the best fitness values decreases at 86th generation in the experiment with 9000 EVs. In both experiments, the mean fitness values are on upward trends.

Figures 12, 13 show the transition of the best fitness values in each sub population. Fitness values are on upward trends as well as Figures 10, 11. In the experiment with 9000 EVs, fitness values improve step by step in each sub population, and then good solutions are shared by migrations. By contrast, in the experiment with 20000 EVs, the solution with the high fitness value is found in Sub-Population2, and then the solution is shared amount other sub populations by migrations.

Figures 14, 15 show the transition of the mean fitness value in each sub population. In both experiments, the mean fitness values change significantly in each sub population. In early generations, fitness values improve significantly, and then remain unchanged. This results from natural selection, which is one of characteristics

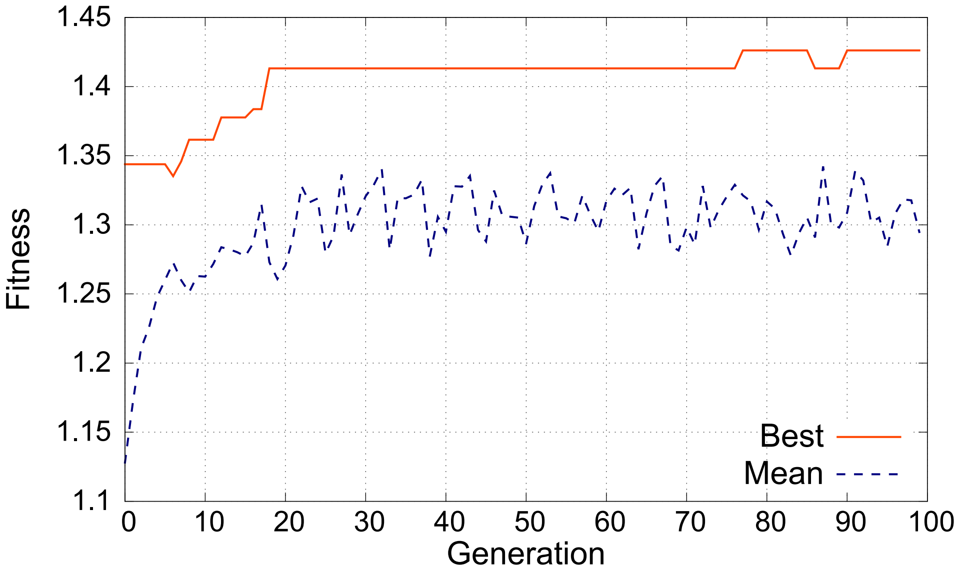

Figure 10: Fitness in each generation (9000 EVs)

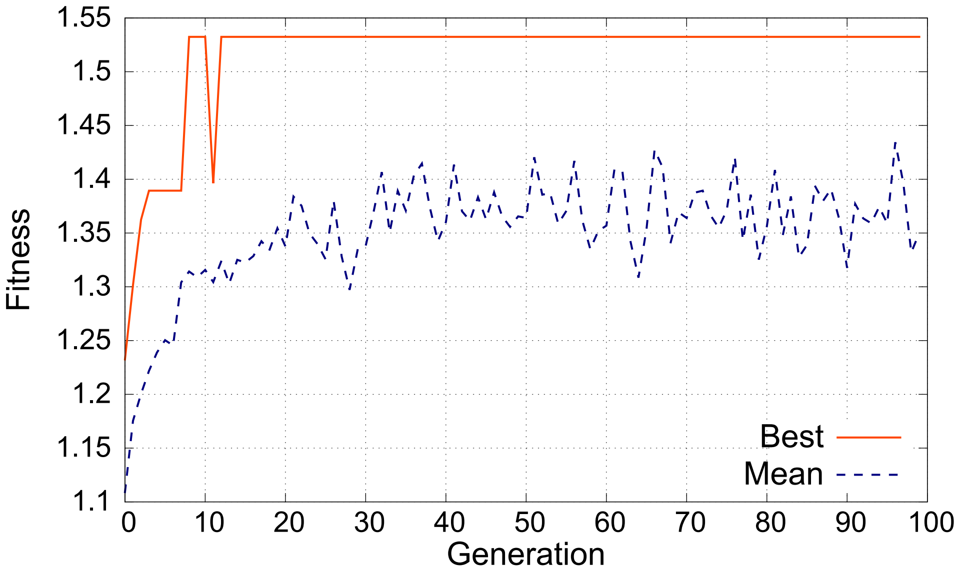

Figure 11: Fitness in each generation (20000 EVs)

of GA. Individuals with low fitness values are eliminated, and individuals with high fitness values are selected.

Tables 15, 16 show three parameter sets: the worst fitness value, the mean fitness value, and the best fitness value in all parameter sets searched by the proposed method. The parameter set with the best fitness value means the approximate solution derived by the proposed method. Pre-analysis in Section 6.2 reveals that the

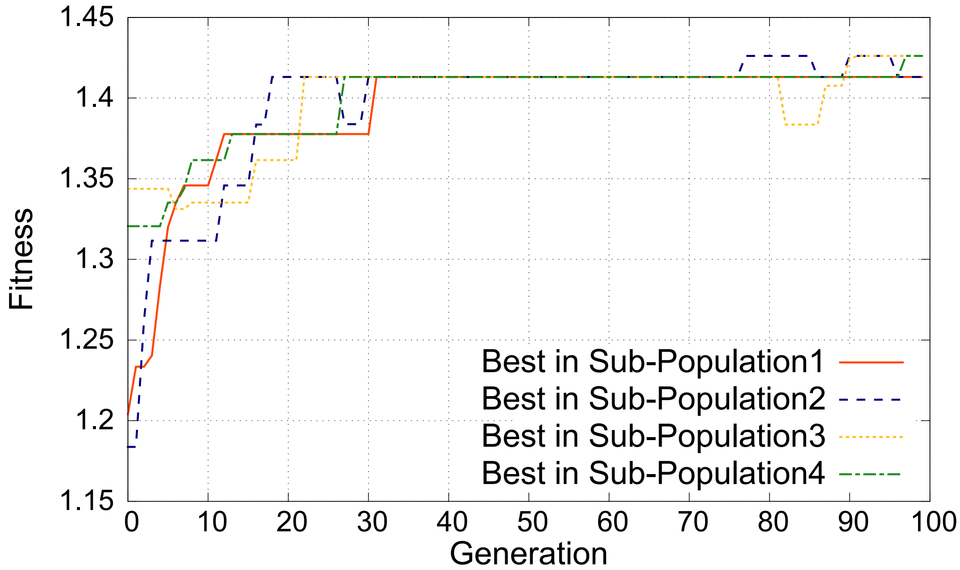

Figure 12: Best fitness in each island (9000 EVs)

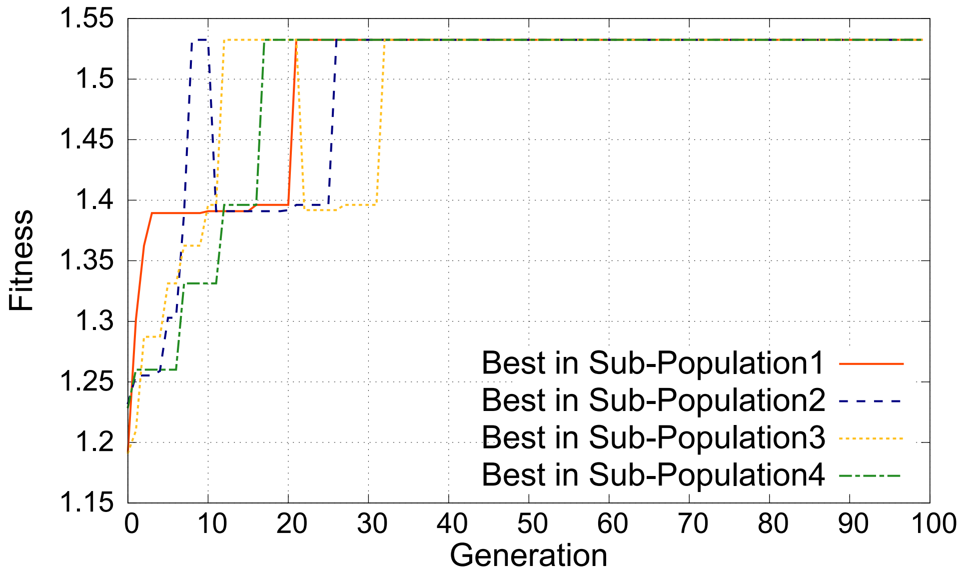

Figure 13: Best fitness in each island (20000 EVs)

derived approximate solution has the second best fitness value in all solutions in the experiment with 9000 EVs. In the experiment with 20000 EVs, the derived approximate solution shows the same tendency as that in the experiment with 9000 EVs, expect the number of stations.

Table 17 shows each power data in parameter sets in Table 15. Table 18 also shows each power data in parameter sets in Table 16. The solution, where the ratio

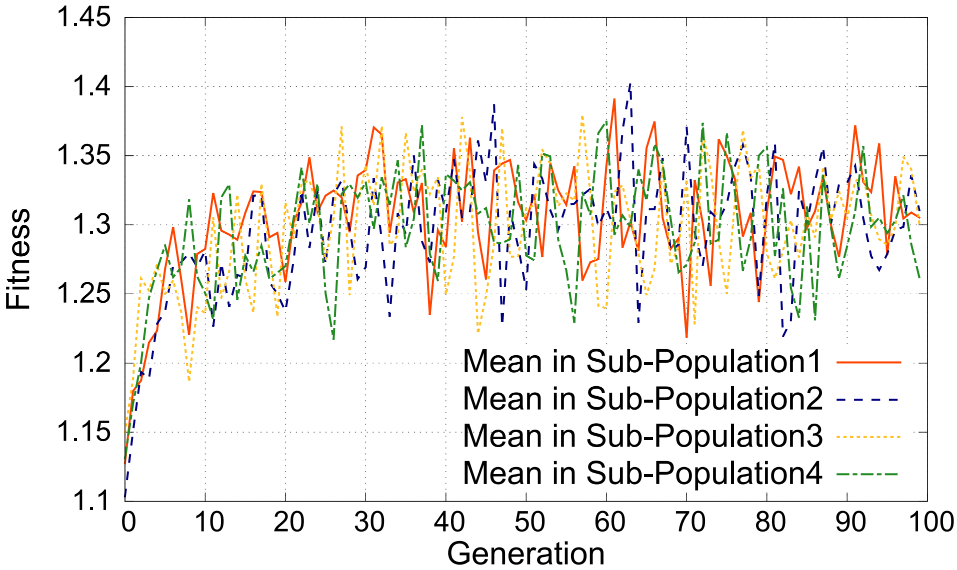

Figure 14: Mean fitness in each island (9000 EVs)

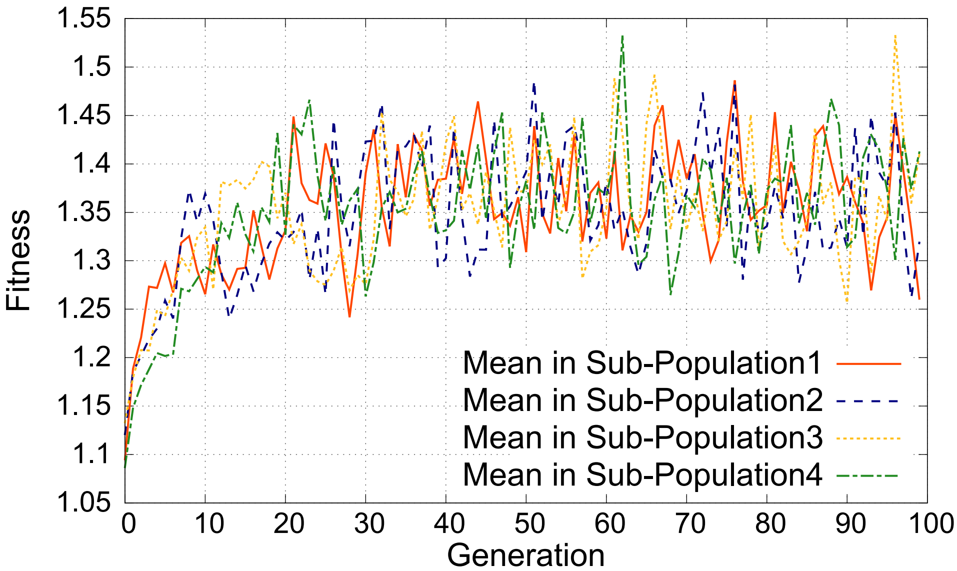

Figure 15: Mean fitness in each island (20000 EVs)

of (the amount of power provided by EVs in power exchange stations:the amount of power charged by EVs in power exchange stations) is close to 1:1, is derived on the basis of the evaluation function.

The total amount of power leaded from electrical grid is sum of that in homes and that in power exchange stations. In the experiment with 9000 EVs, the total amounts in worst, mean, and best fitness values are calculated as follows: $6.15+84.23 = 97.68$

Table 15: Comparison of parameters in worst, mean, and best fitness (9000 EVs)

	Parameters	Worst	Mean	Best
(3)	Participation rate of new system (%)	20	70	90
(4)	Acceptable range of the distance to station (m)	50	100	50
(5)	Number of stations	30	70	80
(6)	Station placement pattern	(3:2:1)	(1:4:1)	(1:4:1)
	Fitness	1.016	1.221	1.426

Table 16: Comparison of parameters in worst, mean, and best fitness (20000 EVs)

	Parameters	Worst	Mean	Best
(3)	Participation rate of new system (%)	20	80	90
(4)	Acceptable range of the distance to station (m)	50	100	50
(5)	Number of stations	50	90	50
(6)	Station placement pattern	(4:1:1)	(4:1:1)	(1:2:1)
	Fitness	1.026	1.279	1.532

MWh in the worst, 6.15 + 93.89 = 100.04 MWh in mean, and 2.66 + 94.29 = 96.95 MWh in the best. The solution with the best fitness values achieves 0.7% power saving as compared to the solution with the worst fitness value. The solution with the best fitness values also achieves 3.0% power saving as compared to the solution with the mean fitness value. Similarly, in the experiment with 20000 EVs, the total amounts in worst, mean, and best fitness values are calculated as follows: 11.82+206.95 = 218.77 MWh in the worst, 8.44+210.06 = 218.5 MWh in the mean, and 2.12+209.82 = 211.94 MWh in the best. The solution with the best fitness values achieves 3.1% power saving as compared to the solution with the worst fitness value.

Table 17: Comparison of power data in worst, mean, and best fitness (9000 EVs)

Total power consumption (MWh)	Worst	Mean	Best
EVs provide for stations	0.08	2.26	1.97
EVs charge from stations	4.70	12.49	6.62
Stations lead from grid	4.38	6.15	2.66
EVs consume	3.64	3.66	3.64
Homes lead from grid	93.30	93.89	94.29
Homes reverse power	85.44	84.23	84.65

Table 18: Comparison of power data in worst, mean, and best fitness (20000 EVs)

Total power consumption (MWh)	Worst	Mean	Best
EVs provide for stations	0.31	5.98	4.45
EVs charge from stations	12.60	27.66	12.80
Stations lead from grid	11.82	8.44	2.12
EVs consume	8.20	8.25	8.21
Homes lead from grid	206.95	210.06	209.82
Homes reverse power	187.48	184.34	185.73

The solution with the best fitness values also achieve 3.0% power saving as compared to the solution with the mean fitness value.

The derived solutions in both experiments are described as follows. In the experiments with 9000 EVs and 20000 EVs, the total amounts of power provided by EVs in power exchange stations are 1970 kWh and 4450 kWh, respectively. Generally, the amount of power consumption at home in a day is approximately 10 kWh[4)]. Therefore, the amount of power consumption for 200 homes and the amount of power consumption for 450 homes are aggregated in power exchange stations, respectively. The fitness values are high not because the amount of power provided by EVs is large, but because the amount of power charged by EVs is small.

[4)] The Federation of Electric Power Companines of Japan: Graphical Flip-chart of Nuclear & Energy Related Topics (2014).

6.4 Discussion

Pre-analysis in Section 6.2 reveals that the derived approximate solution has the second best fitness value in all solutions in the experiment with 9000 EVs. The derived solution is in the top 0.02% of all solutions since the number of all solutions is $2^{14} = 16384$. That is, the proposed method obtained not the optimal solution, but a good approximate solution. Therefore, in the experiment with 9000 EVs, the proposed method performed well.

The author compares the derived solution in Table 17 and the optimal solution in Table 6.2. The total amounts of power leaded from electrical grid in the derived approximate solution and the optimal solution are 96.95 MWh and 97.03 MWh, respectively. Both solutions achieve approximately 3% power saving as compared to the solution with the mean fitness value. That is, there is little difference in power saving between the derived approximate solution and the optimal solution. However, power transfer in power exchange stations in the optimal solution is more active than that in the derived approximate solution. Therefore, the optimal solution is better than the derived approximate solution, but the derived approximate solution obtains a result similar to that of the optimal solution in power saving.

It is unlikely that the nature of the problem with 9000 EVs is dramatically different from one with 20000 EVs. Therefore, the proposed method is expected to find a good solution in the experiment with 20000 EVs although this research doesn't conduct the full search for the solution space in the experiment with 20000 EVs. The proposed method derived the approximate solution with the high fitness value in the experiment with 20000 EVs as well as the experiment with 9000 EVs. Moreover, the solution achieves approximately 3.0% power saving as compared to the others. However, in comparing parameter sets of derived approximate solutions, there is a difference in the number of stations. The other parameters are similar. It seems that in the case of the small number of EV agents, the opportunity of power transfer decreases and power cannot be transferred well if the number of stations is not large. However, it seems that in the case of large number of EV agents, the opportunity of power transfer increases and power can be transferred well even if the number of stations is not large. After searching coarsely in the small-scale simulation environment and in the small number of agents , the method for searching finely in the large-scale simulation environment and in the large number of agents is considered to be useful in order to improve search efficiency. However, it is necessary to be careful about using the method because the nature of problems changes possibly.

Results of the experiments showed two trends. One is that the fitness value is high if the participation rate of PV power distribution system is high. The other is that the fitness value is high if acceptable range of the distance to station is short. Therefore, the proposed method can be expected to obtain better solutions by fixing two parameters mentioned above and searching the other parameters in detail. It is necessary to search the parameter representing station placement pattern in more detail, since the parameter were set roughly in this research.

Next, discussion about computational complexity of the proposed method is described as follow. There are the following environment variables in the proposed method.

g Limit number of generation (termination condition) .

t Time required to run one simulation.

p Number of processes to run simulations at one time.

s Population size.

i Number of sub populations.

Since t is very large in massively MASim, time for genetic operations is less than t. Thus, time for genetic operations is excluded here. By using the variables, execution time for the proposed method T is described as follows, however, $ceiling(x)$ represents the ceiling function, which returns the smallest integer not less than x.

$$T = g \cdot t \cdot \frac{s/i}{ceiling(p/i)}.$$

s/i represents sub population size. $ceiling(p/i)$ represents the number of processes capable to be allocated to each sub population. That means each sub population can run $ceiling(p/i)$ simulations at one time. The author defines a cycle as operations to run $ceiling(p/i)$ simulations at one time. Therefore, operations in one generation is finished in $\frac{s/i}{ceiling(p/i)}$ cycles. Thus, time for one generation is $t \cdot \frac{s/i}{ceiling(p/i)}$, and T is described above. In the experiments with 20000 EVs, $T \approx 5.2$ (days) holds, where $t = 25$ (minutes), $p = 12$, $g = 100$, $s = 32$, and $i = 4$.

$T = g \cdot t \cdot \frac{s}{p}$ holds as p/i is assumed to be the integer for simplicity. That is, T is proportionate to g, t, and s. On the other hand, T is inversely proportionate to p. Since time required to run one simulation t isn't improved by the proposed method, the author needs to consider the other parameters: g, s, and p.

First, g is the parameter representing a termination condition in GA. Besides, there is the termination condition that process is finished if the best fitness value isn't improved for a while. In that termination condition, execution time T can be shortened if the fitness values isn't improved as Table 11. However, process of finding can not always obtain a good approximate solution by using the condition.

Second, s is the parameter representing how far the proposed method search solutions. If the parameter is too large, it would take a lot of time to converge. In contrast, if the parameter is too small, the proposed method becomes easy to converge to a local solution. [17] also claims that how to set the parameter differs depending on the nature of target problems. Therefore, it is difficult to set the parameter if the nature of target problems is unknown as designing new social systems.

Finally, p is the parameter depending on the machine specification. The parameter becomes very large using super computers and grid computers. Since GA has high parallel efficiency, the proposed method enables parallel computers to fulfill their potentials.

In summary, the proposed method is superior in terms of high parallel efficiency that enables parallel computers, such as super computers, to fulfill their potentials. However, the proposed method has problems in setting the parameter how far the proposed method search solutions.

Chapter 7 Conclusion

In this research, the objective was to obtain a semi-optimal design in designing new social systems by using massively MASim, even if proper parameter sets are not clear, and exhaustive search is difficult within a realistic time because of large search space. For achieving this objective, this research has used GA that is one of EC and has proposed a GA-driven approach to reach a semi-optimal design. This research has treated a integrated system composed of traffic system and power system as a target for designing social systems. In the social system, EVs transport surplus power generated by PV generation, and people share surplus power through power exchange stations located in various places. Then, this research has applied the proposed approach to the social system, and has designed the new social system composed of various existing systems. This research has verified the proposed approach by analyzing search time, convergent trend and simulation results of obtained candidate designs.

This research has performed two types of experiments. One was in 9000 EVs, and the other was in 20000 EVs. In the experiment with 9000 EVs, this research has conducted the full search for the solution space in advance. Then, this research has verified how close the derived approximate solution is to the optimal solution. As a result, the research found that the derived approximate solution had the second best fitness value in all solutions. The derived solution was in the top 0.02% of all solutions since the number of all solutions is $2^{14} = 16384$. Therefore, the proposed method was found to be able to search a semi-optimal solution. Moreover, in the derived approximate solution, the amount of power consumption for approximately 200 homes in a day was aggregated and shared in power exchange stations. That is, surplus PV power equal to energy for approximately 2% of all homes was used efficiently without reversed. As a result, the derived approximate solution achieved approximately 3% power saving as compared to the other average solution. In the experiment with 20000 EVs, this research didn't conduct the full search for the solution space. However, the proposed method has obtained similar solutions to the experiment with 9000 EVs. In the derived approximate solution, the amount of power consumption for approximately 450 homes in a day was aggregated and shared in power exchange stations. That is, surplus PV power equal to energy for approximately 2% of all homes was used efficiently without reversed. As a result, the derived approximate solution also achieved approximately 3% power saving as compared to the other average solution. Moreover, this research has compared parameter sets of derived approximate solutions in the experiments with 9000 EVs and 20000 EVs. As a result, it was found that there is a difference in the number of stations, and that other parameters show similar trends. Sometimes the nature of problems changes, and sometimes doesn't change. Therefore, only searching coarsely in the small-scale simulation environment and in the small number of agents is insufficient to improve search efficiency.

This research makes a contribution as follows.

Proposal and analysis of the method for designing social systems This study has targeted complex social systems where it is difficult to see the effect on society by observing only individual actions, but seeing the effect on society becomes possible by observing the sum of many humans' actions. This study has proposed a method for getting a semi-optimal design by using GA-driven search algorithm, even if computational complexity necessary to search fully is high because of large search space since the social system is complex as described above. It was found that the proposed approach can search a semi-optimal solution in the target social system in this study.

As future work of this research, the following points may be mentioned. The first one is improvements in process of finding solutions. In this study, fitness values was not improved late in the search. Therefore, there would be the termination condition that search process is finished if fitness values aren't improved for a while. Furthermore, execution time for MASim depends on the scale of simulation environment. Thus, after deducing important parameters in the small-scale simulation environment, the method for searching in the large-scale simulation environment is considered to be useful. However, the method needs to investigate whether the nature of problems changes or not.

The other is elaboration and analysis of target problems. In this research, The initial amount of EV battery was the amount of full capacity at the beginning of the simulation. However, EV battery wasn't filled up at the end of the simulation. Therefore, EV battery must be filled up at the end of simulation before analyzing simulation results. Although this research assigned OD for each EVs considering not both going and returning but only going. This research should consider both going and returning. This research should also improve the model of power consumed of EVs. Furthermore, this research used discrete-valued parameters. However, this research must use real-valued parameters that can be expressed as real numbers. Moreover, this research should search general solutions by unfixing the random seed though this research fixed the random seed in simulations for ease in search. This research also used one evaluation function. However, it is necessary to use the multi-objective function because designing social systems has various objective. Moreover, this research focused on deriving the semi-optimal solution, and couldn't conduct structure analysis of the target social system. Thus, it is necessary to analyze the solution obtained in searching and structure of social systems.

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