Hybrid approach for optimizing energy of smart electric vehicle and finding the optimal charging station

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ABSTRACT

In the near future, the electric vehicle (EV) will be the most used in the word. Thus, the energy management of its battery and finding the optimal charging station when the battery will be in low-level are the most attractive subject specialty in the last decade. Thus, if a driver uses an electric vehicle, he wants to find an optimal method that can optimize the energy battery of its electric vehicle. Also, he wants to know where can find the optimal charging station according to it is location on the road, charging time and the energy amount demanded, when the energy level of the battery will be very low. In this paper, we propose a new concept of the smart electric vehicle (SEV) that can manage, control and optimize the energy of its battery, in condition to satisfy the drivers' and passengers' comfort and then, it can rapidly find the charging station when the energy level of the battery will be very low according to the distance, the amount of energy demanded and the charging time. Thus, we use hybrid approach that based on the multi-agent system and the genetic algorithm (MAS-GA).

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1. INTRODUCTION

Now, the European cities as Lyon encourage the electrification of urban transport because urban transport is one of the main consumers of energy and contributors to air pollution reduce. Thus, the policy maker should introduce the electric vehicle (SEV) in the modern city to replace traditional vehicles to reduce air pollution, improve energy efficiency and avoid the congestion in road traffic. In this paper, we introduce new concept that is SEV which based on a smart model. The SEV means that the electric vehicle can manage, reduce and control the energy consumption of its battery and also can find the optimal charging station when the energy level of its battery will be very low. Thus, we will treat in this paper, two main questions. The one is what is the smart model which permits to manage, reduce and control the energy consumption of the battery in SEV? The second is what is the optimal strategy which permits finding the charging station for the SEV?

After a deep study of this subject which conducted to prepare this paper, we have found that there are four factors which can affect the energy consumption of the battery in electric vehicle, as the peak time of the system (as congestion in road), energy costs, peak energy demand and the mount of energy per hours. Also, we find two mainly energy equipment such as heating, ventilation and air condition system (HVAC system) and lighting systems, we can use HVAC-L systems to designate these two systems.

In this paper, we propose to use a multi-agent system which allows to distribute the different tasks between the agents when each agent can perform genetic algorithms to optimize energy consumption of electric vehicle battery in real-time, thus adapting rapidly to battery consumption. Thus, all agents can cooperate and negotiate to find the best solution which can regulate the energy consumption battery in SEV. Then, we develop a geographic information system (GIS) which allows knowing the position of SEV and the position of charging station. This data can help the station agent to find rapidly the optimal charging station.

This paper is organized as the following. Firstly, we will present a state of the art review for optimization of energy consumption of battery in electric vehicle and a state of the art review for the location of the optimal charging station for electric vehicle. Then, we describe our proposed approach that is based on two approaches, the multi agent system and genetic agent (MAS-GA). Finally, we add a conclusion.

2. STATE OF THE ART FOR ENERGY MANAGEMENT OF ELECTRIC VEHICLES' BATTERY

The electric vehicles are quickly merged into the city, but many problems have appeared as the high consumption cost, the limited capacities, and the long recharge time of their batteries. To increase battery life's and reduces consumption costs, multi-battery systems that combine a standard battery with super-capacitors are currently one of the most promising ways [1]. However, their performance essentially depends on how they are designed. In this paper, we focus on a complementary aspect of the problem that is optimizing the energy consumption of batteries in electric vehicles.

Several works are introduced to address the different aspects of this problem. In particular, there are many studies that aim to improve the navigation systems with novel routing algorithms by taking into account the capacity of electric vehicles' battery, and the real-time data of traffic lights in all the road conditions. Piccolo *et al.* [2] used optimization methods which run in offline to solve the energy distribution problem in a given vehicle. These works present a good methodology for the tuning of the characteristic parameters. The proposed methodology identifies, using the genetic algorithm, the value of the energy flow management parameters that minimize the cost function in terms of fuel consumption and emissions, but cannot be employed in real-time applications.

Banvait *et al.* [3] propose a rule-based energy management strategy for a plug-in hybrid electric vehicle (PHEV) is presented. Since large amount of electric energy is stored in the battery from the electric power grid, the fuel consumption is reduced significantly as compared with HEV counterpart. The proposed strategy does not require future knowledge of the vehicle's path, and it works based on a set of the rules that have been set up before the current operation. Masjosthusmann *et al.* [4] take into account of the advantage of the heating vehicle system's power control to develop a vehicle energy management for a single source battery electric vehicle. Roscher *et al.* [5] also used the cooling system's power control to reduce the overall energy consumption and increase the battery health of battery through an adaptive control of the heating, ventilation and air conditioning of the vehicle (HVAC system), depending on the driving situation.

Kachroudi *et al.* [6] propose to use online particle swarm optimization (PSO) method to optimally control the energy flow between the power train and the other vehicle's auxiliaries for a given battery. Thus, using a PSO algorithm to search for a global optimum relative to specific objective functions, which take into account battery autonomy, driving comfort indexes, and travel time. According them decrease the vehicle's energy consumption, and at the same time maintain the comfort of the passengers, by providing some suggestions to the driver.

3. STATE OF THE ART FOR LOCATION OF CHARGING STATION

As we said previously, a driver of electric vehicle wants to find an optimal method which allows it to know where he finds the optimal charging station according to its position on the road, energy amount of the battery and the needed charging time. On the other hand, we know that battery charging depends on the vehicle characteristics and charging system type. Or, we have different charging systems: i) fast charge which can take between 20 to 30 minutes; ii) normal charge, it takes between 1 to 4 hours; and iii) or slow charge, it can take between 6 to 8 hours.

In this paper, we propose a smart model that permits us finding the optimal charging station. The driver can choose the fast, normal or slow charge according to its profile. Thus, to find the available charging station for electric vehicle, many works have been proposed. Wang *et al.* [7] created a numerical method for the layout of charging stations using a multi-objective planning model taking into account factors including electric vehicles, sustainable development, characters of the charging station, and characters of charging consumers, distribution of the charging demand, the power grid and factors of municipal planning. Then, a solution algorithm is designed based on demand priority and the usage of the existing gas station. Then, propose to use a genetic algorithm to find the optimal charging station location [8]. Thus, this signifies that the genetic algorithm can identify the candidate charging station locations. Their method is based on conservation theory of regional traffic flows, taking electric vehicles within each district as fixed load points for charging stations. The number and distribution of electric vehicle are forecasted, and the cost-minimizing charging station problem is heuristically solved using genetic algorithms.

Sweda and Klabjan [9] propose to use an agent-based decision support system to identify patterns of residential electric vehicle ownership and driving activities to determine strategic locations for new charging infrastructure. Driver agents consider their own driving activities within the simulated environment, in addition to the presence of charging stations and the vehicle ownership of others in their social network, when purchasing a new vehicle. Kameda and Mukai [10] developed an optimization model for locating charging stations, in the service area by using taxi probe data at Tokyo, Japan. They are focusing on stations for Japan's recently introduced on-demand bus system. The taxi probe data is a history of taxi such as the position and speed.

Worley *et al*. [11] formulate the problem of locating charging stations and also designing electric vehicle routes as a discrete integer programming optimization problem, based on the classic vehicle routing problem (VRP). The objective of this model consists to minimize the cost of locating a charging station and traveling. Baouche *et al*. [12] develop an integer linear programming algorithm mixed with a dynamic consumption demand model, for the City of Lyon. The model minimizes the fixed charge of charging station and the vehicle travel cost. Thus, they focus on the facility location models which consist of defining the best candidate site, the type and the size (number of terminals) of the CS to be assigned to the network in order to satisfy a given mobility demand. Dong *et al.* [13] proposed a genetic algorithmic framework to minimize range anxiety, defined as the total number of missed trips in the network, employing GPS data from conventional vehicles and a household travel choice survey.

4. THE PROPOSED APPROACH

The main problem of previous proposed approaches that are not guaranteed to find the optimum energy distributions between the different system of electric vehicles in different conditions, to satisfy the drivers' and passengers' comfort level and reduce the energy consumption. Then, when the energy level of battery will be very low, the previous proposed approaches cannot find the optimal charging station. Also, these models cannot be regulated by the driver to choose different operating modes, such as the comfort or fuel economy. In this paper, we will propose smart electric vehicle which based on hybrid approach that use MAS-GA to optimize the energy of electric vehicle and find the optimal charging station, when the energy of its battery will be very low.

4.1. Multi agent system

An agent is a software system that is situated in some environment, and that is capable of autonomous action in order to meet its design objectives [14]. In this work, we use the multi-agent system because it provides numerous advantages in the domain of energy consumption, passengers' and drivers' comfort level and the allocation of electric vehicle into different charging stations. The proprieties of multi-agent systems that offer autonomy, sociability and intelligence to solve complex problems. Thus, it provides a suitable framework for these systems. Also, they provide a number of important characteristics as the cooperation, negotiation, adaptation and the mobility. That is, on the one hand, this autonomous agent perceives its environment and on the other hand the agent modifies its environment by its actions. Hence, an agent can dynamically adapt to a changing of environment in real-time.

4.2. Genetic algorithms

Genetic algorithms (AG) are developed in [15] to imitate the phenomena adaptation of living beings. They are an optimization technique based on the concepts of natural selection and genetics. It searches an optimal solution among a large number of candidate solutions within a reasonable time (the process of evolution takes place in parallel). Each of these solutions contains a set of parameters that completely describe the solution. This set of parameters can then be considered the "genome" of the individual, with each parameter is composed of one or more "chromosomes". They allow a population of solutions to converge step-by-step toward the optimal solution. To do this, they will use a selection mechanism of the population of individuals (potential solutions). The selected individuals will be crossed with each other (crossover), and some will be mutating by avoiding, whenever possible, local optima. The genetic algorithms are used primarily to treat both problems [16] are the search space is large or the problem has a lot of parameters to be optimized simultaneously and the problem cannot be easily described by a precise mathematical model.

In this work, we will combine MAS-GA, for permitting the agent to choose the optimal actions. Therefore, our proposal model is based on the three following points.

– Vehicle agent is a software agent which can manage, control the local optimization process and exchange relevant information with neighbouring agents.
– Genetic patrimony which transformed between agents, are used as inputs to the genetic algorithm. This genetic patrimony represents the values of energy consumption of HVAC-L systems that are collected by sensor. Also, it represents the value of distance, the amount of demanded energy and the charging time in the charging station.
– Genetic algorithms are used to find the optimal solution for the current configuration; this is composed of the two objective functions, the energy consumption and the drivers' and passengers' comfort level. Also, it can find the optimal charging station according to the current parameters of electric vehicle in the road.

5. SYSTEM ARCHITECTURE

The objective of our proposed approach consists on one hand optimizing the energy consumption of the battery and increase the battery lives through an optimal distribution of energy on the different systems of electric vehicles as the heating, ventilation and air conditioning (HVAC) system and lighting system. And, in the other hand, find the available charging station when the energy level of the battery is very low. The proposed system determines the optimal energy distribution into the different components of the electric vehicle to achieve the driver's comfort level, as the reference speed, the values of temperature, illumination, air conditioning and ventilation system. Thus, our system considers two mainly parameters, the driver's satisfaction and vehicle's environment data. The result of a system can be suggested to the driver or can be applied automatically as a part of a control system. When the energy level of the battery will be very low, the system use the road data as input, GPS data, traffic road and radar to find the optimal charging station. The driver can get in its comfortable parameters to the system into graphic interface; this data is received by the profile agent.

In Figure 1, we present the architecture of our system. In this system, we are principally three agents, profile agent, vehicle agent and station agent. Vehicle agent can perform a genetic algorithm to find the optimal energy consumption in the electric vehicle in condition to satisfy the driver's constraint. The vehicle agent uses different data as input, road data and sensors data. The station agent can find the optimal charging station according to vehicle location, energy cost and charging time.

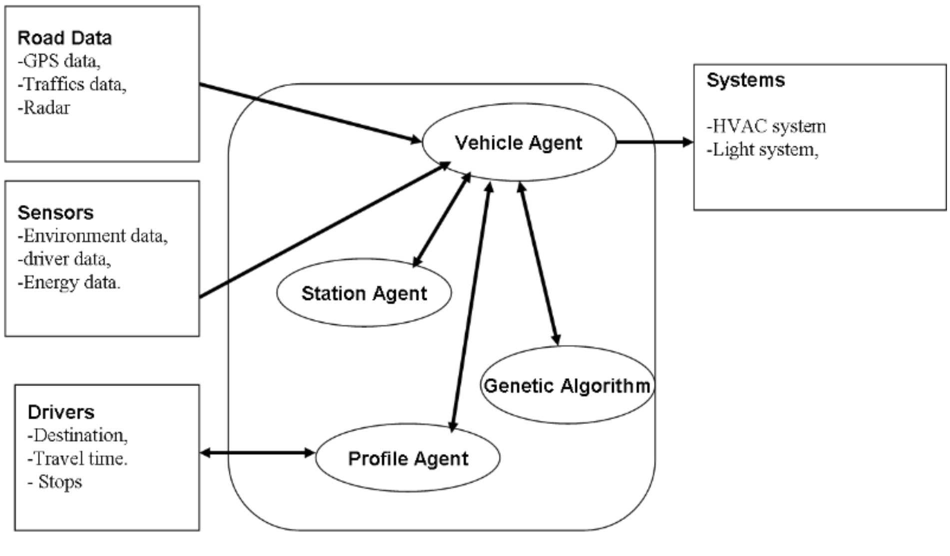


Figure 1. Architecture of our system

6. VEHICLE AGENT

As we tell previously, a vehicle agent is able to manage, control and regulate its cabin environment of electric vehicle to optimize energy consumption, satisfy the occupant's comfort, saving battery life's and increase the efficiency and productivity of systems. Therefore, the main objective of a vehicle agent is to solve the conflicts which can be occurred during energy consumption and satisfaction of passenger's and driver's comfort. Passenger's and driver's comfort satisfaction is related to the conditions of the environment and passenger's or driver's preferences over the environment. In order to evaluate the passenger's comfort level in the electric vehicle, environmental parameters can be used as indices to form the function of passenger's comfort by using the current values of the environmental parameters and passengers' preferences of these parameters. Therefore, the vehicle agent has been designed with three components for controlling and regulates its cabin environment that can optimize energy consumption. These components are an optimizer, simulator and comfort model.

6.1. An optimiser

The optimizer runs a genetic algorithm. Since heuristic algorithms have no guarantee to find the globally optimal solution within the limited iterations, in this research, the GA runs 100 iterations in each time, it tries to increase the possibility of achieving the global optimization, finding the optimal consumption of energy, saving battery life's and meet passenger's preferences. In principle, more runs of the optimization algorithm will lead to higher probability of achieving better results, but it will inevitably take more computation time. After many trials that we performed, we found that 100 iteration is a reasonable number of runs for finding the satisfactory balancing the solution quality and computational time cost.

6.2. Simulator

Each vehicle agent has a simulator and optimizer that are used together to discover the passengers' comfort level and optimized energy consumption in the prevailing conditions. The results of simulator could be optimized to achieve a satisfactory balance between discovery time and system performance. The optimizer repeatedly runs the energy flow simulations for every time and calculates the satisfaction of passengers' comfort level. The best passengers' comfort level is then used to generate the subsequent generation of general passengers' comfort level, and over a number of generations, the best candidates' comfort level is identified.

6.3. Comfort model

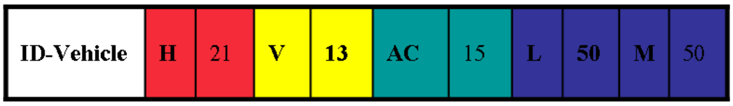
The passengers' comfort model permits to control the cabin environment in electric vehicle via computer techniques to optimize energy consumption and satisfy the drivers' and the passengers' comfort, saving battery and increase the efficiency and productivity of the system. In order to meet the compromise between the drivers' and passengers' comfort level and the energy efficiency, the vehicle agent needs to evaluate the energy consumption and passengers' comfort level in electric vehicle corresponding to the changes of the cabin environment. However, the driver's and passengers' comfort level and the energy consumption usually affect each other in an opposite way. Therefore, the main goal of a vehicle agent is to solve the conflicts between reducing energy consumption and increasing the driver's and passengers' comfort level. In order to evaluate the driver's and passengers' comfort in cabin environment of the electric vehicle, environmental parameters can be used as indices to form the function of passengers' comfort by using the current values of the environmental parameters and passengers' preferences corresponding to these parameters. Generally, the cabin temperature, the illumination level, the air conditioning and ventilation inside the electric vehicle are used as parameters to evaluate the drivers' and passengers' comfort level.

7. OPTIMIZATION PROCESS OF ELECTRIC VEHICLE

As we say previously, the vehicle agent has an optimizer and simulator that are used together to discover the values of HVAC-L systems that can optimize the energy consumption in the prevailing conditions and also satisfy the comfort level of driver and passengers. The use of genetic algorithm has a major advantage over systems that rely on predefined values, as each vehicle agent enables a genetic algorithm to discover the values of HVAC-L systems that may not resemble any predefined values, but they may be optimal values for the current cabin conditions of electric vehicle. The optimizer should achieve a satisfactory balance between discovery time of solutions and the optimal solution of energy consumption of electric vehicle. Thus, each vehicle agent executes a genetic algorithm to find the optimal values of HVAC-L systems that can be attributed to each system for finding the optimal energy consumption, in condition to increasing the passengers' and drivers' comfort level.

7.1. Chromosomes' structure

To apply the genetic algorithm, we should define the genes. As we said previously, our system considers two mainly parameters, the driver satisfaction data and energy consumption data. Thus, the gene can be characterized by it is identifier, and a set of values of HVAC-L systems that can be applied to perform the optimal energy consumption and satisfy the passengers' or drivers' comfort level. We use multiple forms to coding the genes. Firstly, we use the strings to coding the identifiers, and then we use real number for encoding the values of temperatures, the ventilation, the air conditioning and lighting system. Figure 2 presents the structure of the gene.



ID-Vehicle : electric vehicle identify,

H: heating system,

V : ventilation system,

AC: Air Conditioning system,

L: light System.

M: Motor consumption.

Figure 2. Gene structures

To identify the best chromosome from the populations, the optimizer runs a genetic algorithm with its different classic steps, as selection, crossover and mutation. The vehicle agent has a simulator, which permits it to identify the best available solution from the populations; the optimizer repeatedly runs the energy consumption simulator for each HVAC-L system in a given generation. After a number of generations, the best candidate values of HVAC-L system are identified.

7.2. Initialisation, crossover, and mutation

Firstly, the initialization operator determines how each chromosome is initialized for participating in the population of genetic algorithm. Here, the chromosome is filled with the genetic material from which all new solutions will evolve. In this work, we will use the steady state to initialize the generation process and select the population of genetic algorithm for the next generation. First, steady state creates a population of individuals by cloning the initial chromosomes. Then, at each generation during evolution, it creates a temporary population of individuals, adds these to the previous population and then removes the worst individuals in order that the current population is returned to its original size. This strategy means that the newly generated offspring may or may not remain within the new population, dependent upon how they measure up against the existing members of the population.

Then, the crossover operator defines the procedure for generating a child from two parent chromosomes. The crossover operator produces new individuals as offspring, which share some features taken from each parent. The probability of crossover determines how often crossover will occur in each generation. In this approach, we will use the single point crossover strategy was adopted for all experiments. In this paper, the results for all experiments presented were generated using a crossover percentage of 50%, which is to say that at each generation, 50% of the new population were generated by splicing two parts of each chromosome's parents together to make another chromosome. Figure 3 presents the crossover operator.

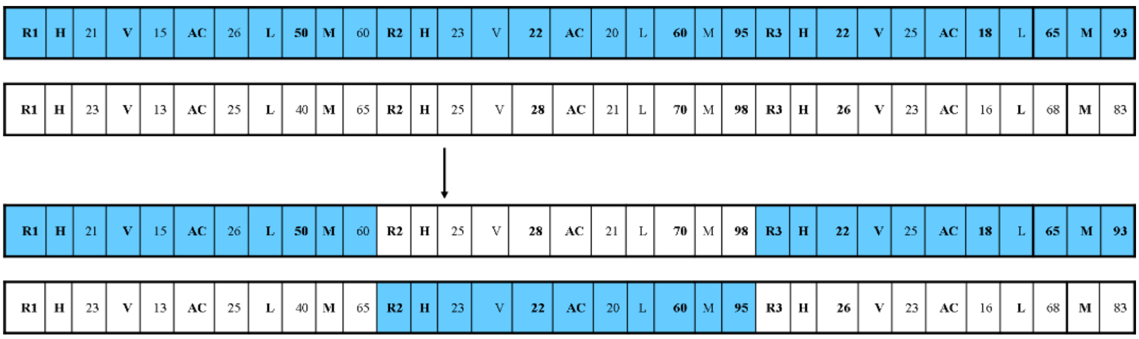


Figure 3. The crossover operator

Finally, the mutation operator will be applied. It defines the procedure for mutating the chromosome. Mutation, when applied to a child, randomly alters a gene with a small probability. It provides a small amount of random search that facilitates convergence at the global optimum. The probability of mutation determines how much of each genome's genetic material is altered, or mutated. If mutation is performed, part of a chromosome is changed. The mutation should not occur too often as this would be detrimental to the search exercise. In this work, the results presented here were generated using a 1% mutation probability, which was determined experimentally, using a single case of vector HVAC-L system of electric vehicle. Figure 4 presents the operator of mutation.

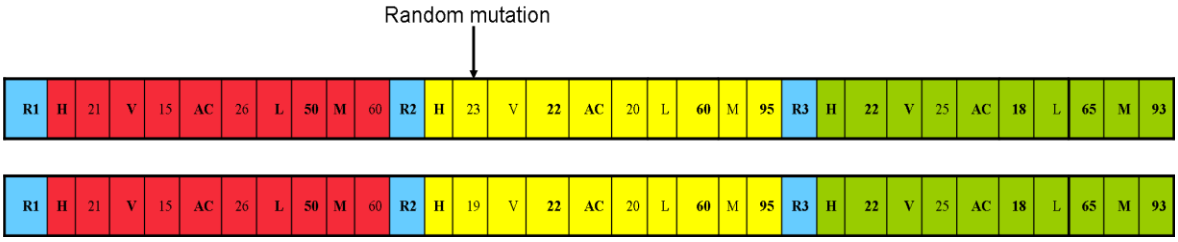


Figure 4. The operator of mutation

7.3. Evaluation of solutions

The purpose of evaluation system is to provide a measure for any given solution that represents its relative quality. In our resolution method of energy consumption problem in electric vehicle, the objective function used here works by calculating and summing the penalties associated with the temperature, the illumination, the air quality and ventilation in electric vehicle. Thus, we will use the objective functions to evaluate solutions of the energy consumption problem in electric vehicle and examines the weighted relationship between the current measured values of the temperature, the ventilation, the cabin air quality, illumination level and values of drivers' and passengers' comfort level according to these four parameters. The objective functions used to evaluate solutions require a number of definitions that model the problem underlying structure, specifically.

- $EV = \{EV_1, EV_2, EV_3, \ldots\ldots\ldots EV_n\}$ is the set of all electric vehicles in the road.
- $H = \{H_1, H_2, H_3, \ldots\ldots\ldots H_n\}$ is the set of all heating systems in the electric vehicles.
- $L = \{L_1, L_2, L_3, \ldots\ldots\ldots L_n\}$is the set of all illumination systems in the electric vehicles.
- $A = \{A_1, A_2, A_3, \ldots\ldots\ldots A_n\}$ is the set of all air conditions in the electric vehicles.
- $V = \{V_1, V_2, V_3, \ldots\ldots\ldots V_n\}$ is the set of all ventilation system in the electric vehicles.
- $CS = \{CS_1, CS_2, CS_3, \ldots\ldots\ldots CS_n\}$ is the set of all charging stations in city.
- $N1, N2$ is a number of all charging station in the city and all electric vehicle, respectively.
- $Hm, Lm, Am\ , Vm$ are the measured values of the temperature, the illumination, and the cabin air quality and ventilation, respectively.
- $Hc, Lc, Ac\ , Vc$ are the comfort values of the temperature, the illumination, and the cabin air quality, respectively.
- [C_{min}, C_{max}] represents the comfort range. This range can be defined by customers.
- [E_{min}, E_{max}] represents the consumption energy range.

Two important parameters are in our MAS-GA, the assigned energy to the HVAC systems is EH and the assigned energy to the lighting system is EL. In this context, we have mainly two important functions *f(C)* and *f(E)* which permits evaluating the performance and efficiency of the proposed approach. These two functions are calculated by vehicle agent. The objective of this optimization mechanism is maximization of passengers' and drivers' comfort f*(C)* and minimization of the energy consumption of the battery *f(E)*. For evaluating the performance and the efficiency of our system. Firstly, we have.

$$f(C) = C_1 * {}^{H_c}/_{H_m} + C_2 * {}^{Lc}/_{L_m} + C_3 * {}^{A_c}/_{A_m} + C_4 * {}^{V_c}/_{V_m} \tag{1}$$

C_1, C_2, C_3 and C_4 are the user-defined weighting factors, which indicate the importance of three comfort factors and resolve the possible equipment conflicts. These factors take values in the range of [0, 1]. The passengers or drivers can set their own preferred values in different situations according to the season or the travel period. As we said previously, since the travel period has a profound influence on energy savings, it should be taken into account in the control strategy design. Generally speaking, in the occupied hours, the vehicle agent activates the optimizer to tune the set point in order to obtain the acceptable cabin visual comfort with minimized energy. Otherwise, the vehicle agent turns off all the resource lights and keeps the blind position to save energy if there are no passengers in the electric vehicle. The objective function is defined in (1), and the optimization goal is to maximize these objective functions. Since the ratio between the measured value and comfort value determined by passengers which introduced via graphic interface, it has an important role in achieving the control goal. Thus, it permits increasing the passengers' comfort level and optimize the energy consumption.

The second objective function permits controlling the energy consumption of the battery in the electric vehicle. The objective of this function consists to minimize the total energy consumption of HVAC-L system. Thus, we can define this objective function as the following.

$$f(E) = E_{HVAC} + E_L + E_M \tag{2}$$

E_{HVAC}, E_L and E_M represent the energy consumption of HVAC systems, the lighting system and the motor, respectively.

8. STATION AGENT

When the electric vehicle needs to use charging station, vehicles agents change their behaviour and try to find a charging station. This behaviour of vehicle agent is triggered by a lower threshold E_1. If the electric vehicle wants to find the optimal charging station; three parameters have to take into account, the distance between the electric vehicle and charging station, availability of unused plug-in in the charging station and the charging time. The proposed smart model should find the closest distance and minimized the charging time.

Firstly, if the energy of electric vehicle will be less than E_1, the vehicle agent sends a request of charging to the closest charging station. Then, the station agent treats this request, if this charging station have unused plug-in, the station agent sends the response 'Ok' to vehicle agent that sent the request. If the concerned charging station hasn't a place, the station agent cooperates and negotiates with others station agents to find the optimal charging station. Figure 5 presents the communication between vehicle agent and station agent.

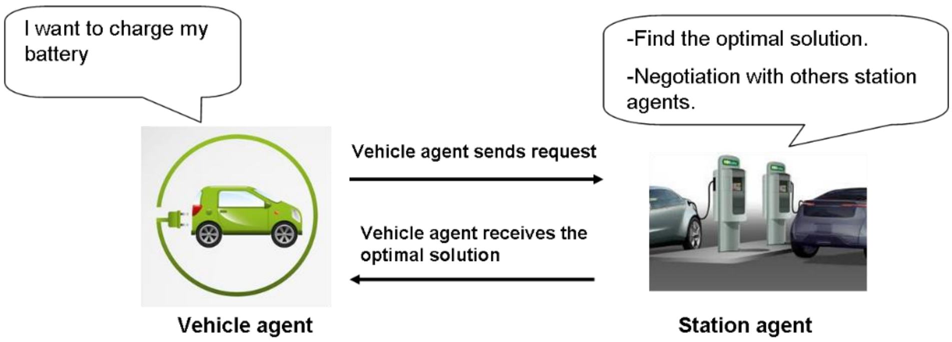


Figure 5. Communication between electric vehicle agent and charging station agent

9. NEGOTIATION AND COOPERATION

In this paper, we propose an efficient mechanism of negotiation, cooperation and coordination between different agents to model an optimal energy consumption system using the MAS-GA. We know that a single agent is unable to achieve some complex tasks, as the energy problems because its capability is individually limited or although can complete, but its performance and efficiency are far lower than the performance and the efficiency with the cooperation and the coordination of many agents [17]. In order to solve charging station location conflicts, the station agents negotiate with each other and coordinate with the vehicle agents to find the available charging station. Therefore, when conflicts occur between two or many electric vehicles, it is important to limit their effects. In such case, negotiation techniques enable the involved station agents to resolve different conflicts by reaching compromises between three principal parameters as the distance between the current location of electric vehicle on the road and the charging station, the time of charging and the availability of plug-in in the charging station. The main characteristics of negotiation concern the language, the protocol, and the decision-making process used by each station agent. This negotiation allows the station agents to solve various conflicts at once, and prevents new conflicts to appear. The station agents negotiate with each other in order to decide whether the optimal plan which can be applied to satisfy the need of electric vehicles' battery in energy and in the same time, reduce the waiting time of electric vehicle. Thus, in our proposed approach, the station agents negotiate with each other in order to determine the best possible arrangement. Thus, in order to reach a given agreement concerning a negotiation multiple messages must be exchanged between station agents. In Figure 6, we present an example of negotiation between two station agents; stations Agent 1 and Agent 2. Thus, these two agents negotiate by proposing a plan of actions which can arrange the two agents. The proposal plan can be found when each agent performs the genetic algorithm. In each cycle, one station agent makes a proposal plan to the other station agents, which they can accept or reject the proposal. If they accept, negotiation starts, otherwise, the other station agent makes a proposal at the next cycle. Figure 7 shows an example of negotiation plan. Here, the electric vehicle is represented by a letter and a number; the charging time is represented by a number.

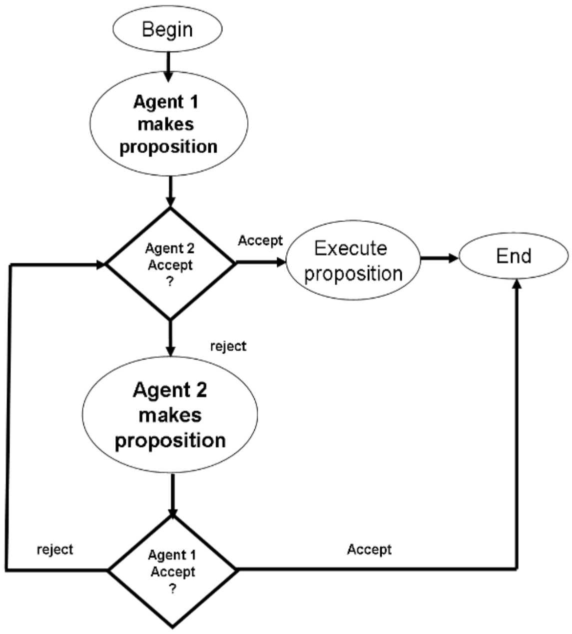


Figure 6. Negotiation between two agents

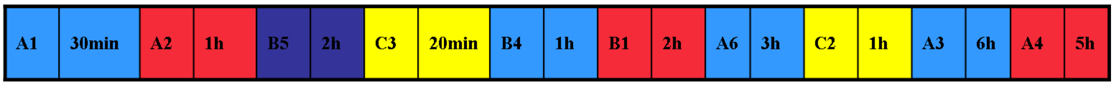


Figure 7. Example of negotiation plan

Also, the cooperation is defined as the collaboration between vehicle agents to find the optimal action to solve bottlenecks in charging stations. In this paper, we use cooperation in order to solve bottlenecks which can occur between the different electric vehicles. Each vehicle agent cooperates with the other vehicle agents in order to find the optimal solution which permits reducing the waiting time. Each vehicle agent sends some requests to the vehicle agents that include some data as the waiting time, the amount of energy needed and charging time. Next, each vehicle agent checks its list of requests to treat and analyze its data. Then, each vehicle agent tries to find the final best solution that can solve the conflict and avoid other conflicts to occur. Thus, vehicle agent sends the found solution to its neighbours and it waits to receive the responses to them. Then, it analyzes these responses and determines whether the solution is possible or not. If a solution is feasible, it sends a confirmation to those of its neighbours that accepted this solution. The vehicle agents can accept or refuse the request of other agents according to their current situations. Figure 8 presents a simple configuration of cooperation between four agents. The messages exchanged between agents during conflict resolution between electric vehicles to find the optimal charging stations. These messages are summarized in the Table 1.

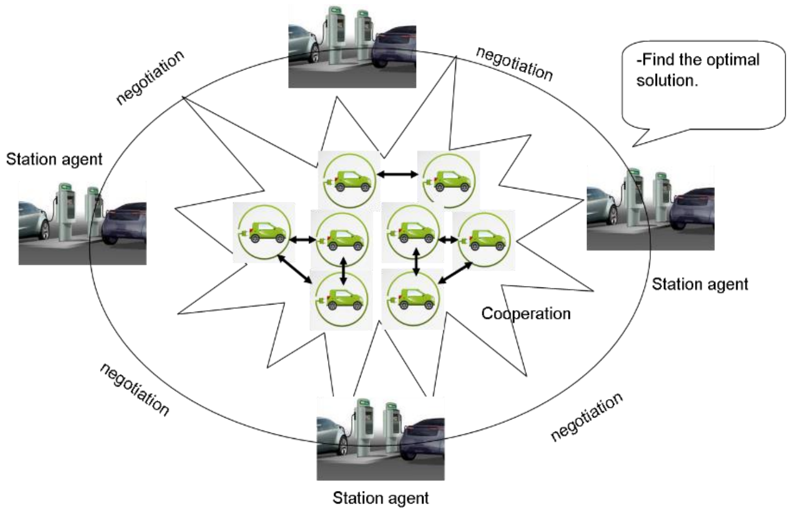


Figure 8. Cooperation between agents

Table 1. Messages exchanged between agents

Message	Comments
Inform (distance, energy, time)	Message sent by the vehicle agent to station agents. It contains the distance between the electric vehicle and charging station, the amount of energy demanded and the charging time.
Inform (conflict_resolution)	Message sent by agent to one of its neighbors with which it is in conflict. The message contains the result obtained by the agent after applying its conflict resolution procedure.
Notify (conflict)	Message sent by vehicle agent to one of its neighbors in order to notify it that a new conflict was created.
Notify (satisfaction)	Message sent by a vehicle agent to station agent in order to notify them about the end of its processing.
Help (demand)	Message sent by a vehicle agent to station agent asking it if it is possible to find free place in the charging station.
Help (response)	Message sent by a station agent to vehicle station agent in order to tell it whether it is possible to find free place for it.
Negotiate (demand)	Message sent by a station agent to station agent asking it if it is possible to make negotiation.
Negotiate (response)	Message sent by a station agent to vehicle station agent in order to tell it whether it is possible to make negotiation with it.
Inform (confirmation)	Message send by agent If a solution is feasible, it sends a confirmation to those of its neighbours that accepted this solution

10. CASES STUDY

In this section, we present a five case studies that illustrate how to design the different agents of our system and show collaboration between them. We use Jade to implement the different agents, vehicle agent, profile agent and station agent. Also, we use Java to implement the different steps of genetic algorithm as crossover operator, mutation operator and the evaluation function. The data used for these experiments are based on observations of electric vehicle in the city between 7:00 am and 5:00 pm in Lyon, France. In this experiment we use many personal computers. The characteristics of each one is, RAM capacity is 8 GB, processor speed is 3.8 GHz and hard drive capacity is 215 GB.

10.1. Management of battery energy

To compare the results of our proposed approach with other one. The following experiments were set up:

– Approach without MAS-GA: in this situation, we used the observed data of electric vehicles in the city of Lyon between 7:00am and 5:00pm
– Approach with MAS-GA: in this approach, we use collaborative agents and Genetic algorithm to find the optimal solution performed by the electric vehicle that can increase the driver's and passengers' comfort and decrease the energy consumption

Firstly, the vehicle agent uses the sensor to learn the HVAC-L data and motor energy consumption, which can use as input in the genetic algorithms. The passengers and drivers can introduce their preferences in the profile agent via a graphic interface which implemented using Java. The vehicle agent runs a genetic algorithm that can find the optimal values of HVAC-L system and motor energy consumption, which permit optimizing the energy consumption and increase the passengers' or drivers' comfort level. In the Table 2, we introduce the different intervals of drivers' and passengers' satisfaction and the energy consumption.

Table 2. Intervals of passengers' satisfaction

Evaluation Parameters	Unacceptable	Low satisfaction	High satisfaction
passengers' satisfaction	[0,2]	[2.25,3.5]	[3.75, 5]
Battery Energy Consumption (v)	[2.5,4.0]	[2.0,2.5]	[1.5,2.0]

To control the different systems, vehicle agent uses a data of the HVAC-L systems and motor energy consumption. As we know, to maintain higher drivers' and passengers' comfort level, we must increase the energy consumption of electric vehicle. Whereas, the vehicle agent tries to find a compromise between the energy consumption and the higher drivers' and passengers' comfort level. Thus, it should find the best values to determine energy consumption dispatched to both the HVAC-L systems and motor energy consumption.

The objectives of this optimization mechanism are to maximize drivers' and passengers' comfort level and to minimize the total of energy consumption of the electric vehicle. In Figure 9, we state that there is a difference in passengers' comfort level in the two approaches, with MAS-GA and without MAS-GA. With MAS-GA, the system achieves a higher passengers' comfort level compared to the second approach, without MAS-GA. Thus, the passengers' comfort level in the MAS-GA has been improved rapidly compared to the second approach.

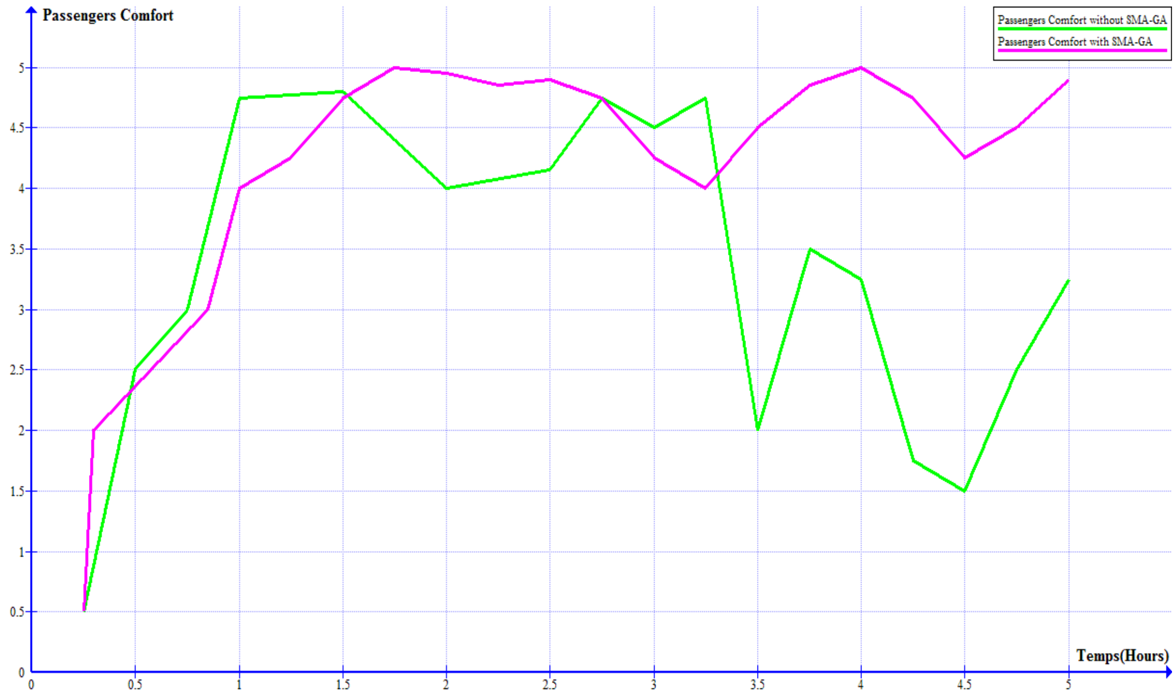


Figure 9. Passengers' comfort level with and without MAS-GA

Figure 10 shows that when we use our proposed approach, the energy consumption has been improved compared to the classic approach which use the observed data in Lyon city. Thus, when we use MAS-GA approach, we can minimize the energy consumption of electric vehicle. Thus, the MAS-GA approach permits optimizing the energy consumption compared to the classic approach, without MAS-GA.

The MAS–GA is designed to enable the interactions between the drivers and passengers and the environment by learning the drivers' and passengers behaviours. According to the case studies and simulation results, the proposed MAS-GA is capable of managing, regulate and controlling the electric vehicle effectively to satisfy drivers' and passengers' comfort level and minimize the energy consumption of electric vehicle.

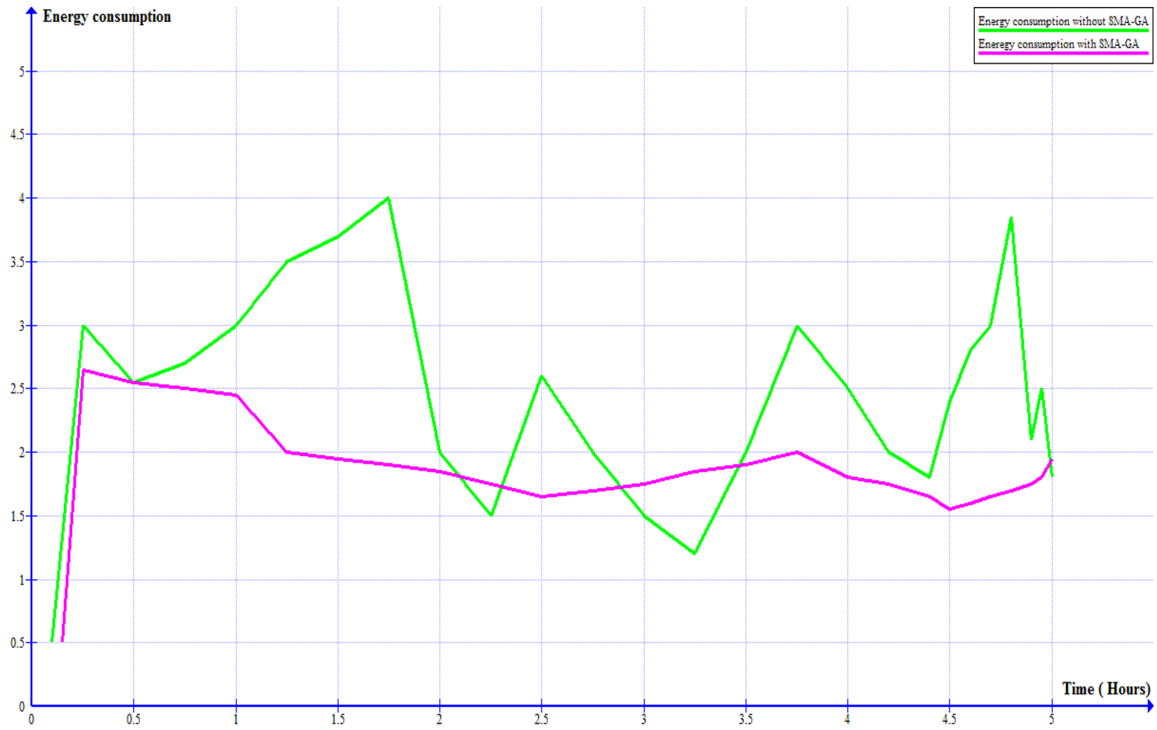


Figure 10. Energy consumption with MAS-GA and without MAS-GA

10.2. Management of charging station location

During each simulation process, the station agent can run a genetic algorithm. The optimizer computes the corresponding fitness value of each proposed charging station according to account the energy capacity of a battery, the distance and time charging. In this experiment, the total number of charging station is 10 and the plugs-in of each charging station that can be served is set to 10.

When the electric vehicle needs charging its battery. The vehicle agent sends a request to all station agents which neighbours with it. Each station agent can interact and negotiate with the other station agents to define the optimal response, according to the parameters of electric vehicle as the distance, the amount of energy demanded and the charging time. This data is sent by vehicle agent. It had the possible charging station configurations distributed in the city, which planted in map of Lyon using GIS. In this work, we use the Euclidean distance to measure the distance between the current position of electric vehicle and the demanded charging station.

In Figure 11, we present the waiting time of vehicles when we use the MAS-GA approach and when we do not use this approach. Thus, when we do not use the proposed approach, we observe that the waiting time increases according to the number of vehicles which demand the charging stations. But, when we use the approach with MAS-GA, each station agent can interact with the other station agents and it can perform the genetic algorithm to discover the optimal solution. We observe that the waiting time of vehicle decreases according to the electric vehicle numbers.

What is clear from Figure 11 is that by using multi-agents system and genetic algorithm, the waiting time of vehicles is decreased in a few generations, and in significantly low time than the approach without MAS-GA. For the MAS–GA approach, when the numbers of vehicle exceed 600 vehicles, the maximum waiting time achieved by Experiment 02 is less than 100 seconds, whereas the maximum waiting time achieved by Experiment 01 was rapidly augmented. Thus, the MAS-GA approach used in Experiment 2 converges to their optimal solution at a significantly faster than the other solution presented Experiment 01. Thus, we conclude that our approach find the optimal charging station in a short time compared with the other approaches.

In the Figure 12, we present the results of experimentation that values the ratio of the occupations' charging station according to the time, with MAS-GA and without MAS-GA. We observe that our proposed approach is the best one because it can rapidly find the best schema of distribution of electric vehicles between the different charging stations. Also, it can keep the best ratio through the time, when it converges to their optimal solution.

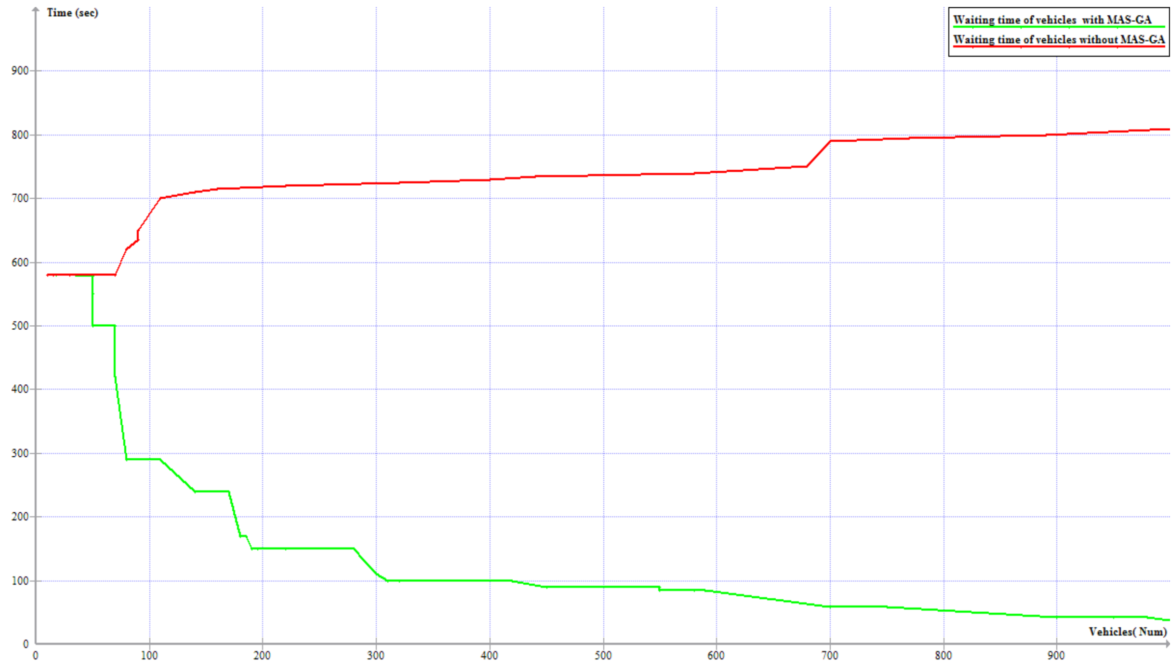


Figure 11. The waiting time of vehicle with MAS-GA and without MAS-GA

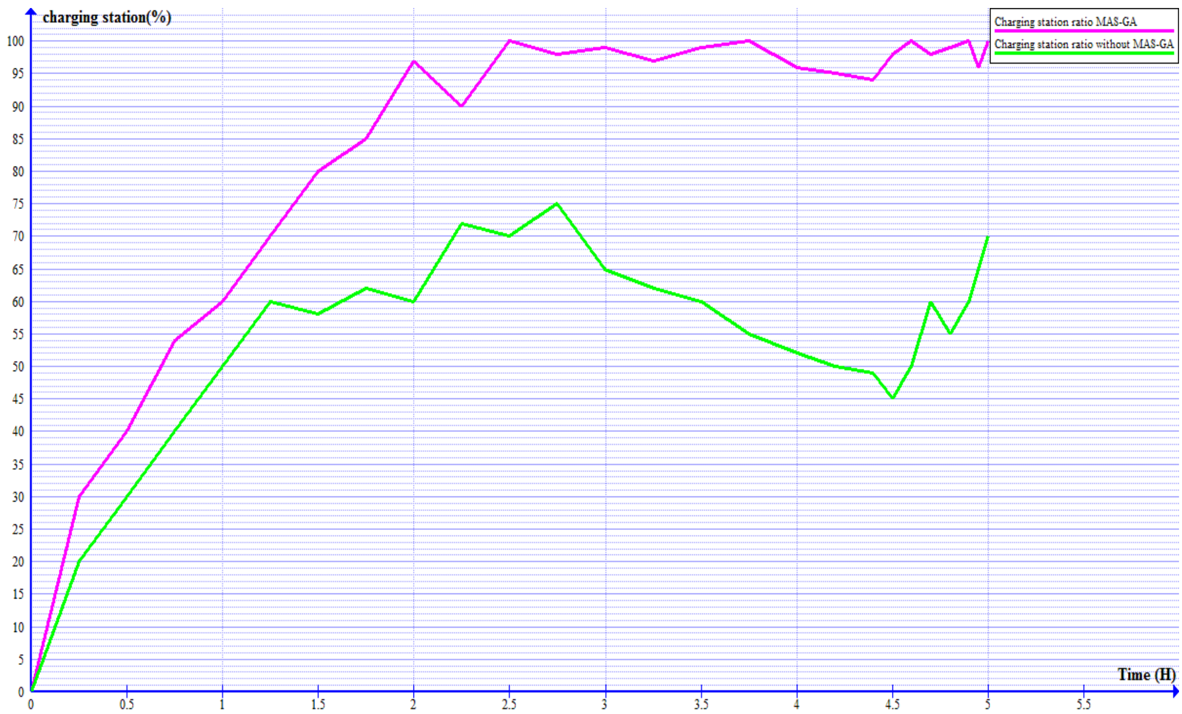


Figure 12. The occupation ratio of charging station with MAS-GA and without MAS-GA

In Figure 13, we use other experiments. These experiments are:

- Experiment 01: In this experiment, one agent was used to control and optimize the different the charging stations. This experiment was used to identify a benchmark solution.
- Experiment 02: In this experiment, ten agents which assigned to the ten charging stations were used to control and manage the ten charging stations. These experiments permit us to evaluate the performance of our proposed approach MAS-GA. For this experiment, each agent was run on a separate personal computer (PC).

Figure 13. The waiting time over the generations

It is clear from the Figures 13 is that by using multiple collaborative agents, the using of charging station is optimized in fewer generations, and in significantly less time than the centralized approach. After 1,000 generations, the waiting time achieved by Experiment 01 is 115 seconds, whereas the waiting time achieved by Experiment 02 was 58 seconds. Thus, from these results, we can conclude that the charging station Agents used in Experiment 02 converge to their optimal solutions at a significantly faster than the central agent solution that used in Experiment 01.

11. CONCLUSION

In this paper, we present a hybrid approach to control, manage and regulate the energy consumption in the electric vehicle in a way that a reduction of energy losses within the HVAC-L systems in condition to satisfy the passengers and drivers' comfort level. To save the energy in the electric vehicle, we have to regulate the maximum energy consumption of the HVAC systems, depending on the energy demand of the driver and passengers. Also, when the battery energy of electric vehicle will be very low, we should find the available and adaptable charging station according to the distance, the energy amount in the battery and charging time in charging station. The different agents can interact, cooperate and negotiate with each other to define the optimal charging station for electric vehicles. The vehicle agent can use GIS for detecting the position of all charging stations. The results of this work are very interesting that encourage us to continue in this domain. This work can open various future works, such as; In other work, we intend to expand on these initial experiments to optimize the battery energy of electric vehicle through larger cities, when there are huge numbers of electric vehicles and charging stations. Also, we can improve the performance of the optimizer of electric vehicle to optimize the energy consumption and find rapidly the optimal charging station. And finally, the foundations of a robust model with newly presented concepts of SEV, smart charging station can be more useful to help solve real problems in energy consumption, satisfaction of drivers' comfort level and charging station. Indeed, we need to design a theory which must be robust against conflicts and bottlenecks in charging stations.

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