An Electric Vehicles Smart Charging Based on Distributed Multi-Agent System

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Abstract
Due to the predictable increase in the fossil fuels price, proper to their rarefaction, electric mobility is one of mobility alternatives that actually attracting a huge interest. This innovative technology requires an intelligent control of electric charging stations since the vital issue in this technology is the recharging of EVs (Electric Vehicles) batteries. On the other hand, growth of EVs will have a significant impact on the power grid due to the increase in electric energy consumption. Therefore, it is crucial to operate smart and optimized EVs charging. This latter should be optimized for grid load while guaranteeing that trips requirements and vehicle owners' schedules are met. In this paper we propose a multi-agent based system which aims to provide an optimal set of available charging station for each vehicle in reply to the drivers' request. First, we propose a mathematical formulation of the problem before solving it using improved A* algorithm which forms a backbone of vehicle navigation systems. The Multi-agent-based system is built around a hierarchical and distributed architecture of subsystems represented by agents. These agents interact between them for performing a mission according to a distributed-coordination approach.

Key words:
Electric vehicle, smart grid, multi-agent system, heuristic, distributed-coordination approach, charging station.

1. Introduction

The development of Electric Vehicles (EVs) is part of the switching from fossil fuels to alternative energies in the sense of reducing dependency on fossil energy as well as CO2 emissions; therefore, they are a major approach to solving environmental problems as we move toward greener future [1]. This trend is sustained by the latest advances in battery and converter technology. Also sustained by government policies of energy independence and resilience promoted by the introduction of electric vehicles (EVs) and their close relatives Plug-in Hybrid Electric Vehicles (PHEVs) by major car manufacturers [2] [3]. Although there are diverging forecasts about the growth rate of the EV population [4], there is agreement that it is going to represent a substantial portion of the car fleet by 2025 - 2030. Manifestly, penetration rates could be significantly higher than these estimates depending on battery costs, petrol prices, government policies, and the availability of charging infrastructure. However, electric mobility brings with it new challenges, such as EVs charging problems due to three reasons: i) simultaneous charging of several EVs located in the same area will lead to a considerable additional load that can overload the grid, ii) EVs should preferably be charged during off-peak hours when the power delivery cost is at its lowest [5], and iii) The need to integrate various renewable energy sources in order to reduce the energetic bill among others. Therefore, EVs are considered as one of the major consumers of electricity in smart grid [6]. These numbers are expected to grow considerably over the next few years. As a natural consequence, analyzing the effect of EV charging on smart grid and designing an optimal charging strategy for EVs are crucial [6][7]. The most clear-cut strategy for charging EVs is to charge EVs when the price of electricity is low, e.g., at night time. In [6], the fluctuation of the power level of the grid was controlled by managing the charging of EVs. Furthermore, EV charging was analyzed and optimized by using state-of-the-art mathematical techniques. In [8], the comportment of EVs which try to be charged at minimum cost was analyzed using a mean-field game. Particle swarm optimization was applied in [9] to find the optimal EV charging schedule. In [10], a distributed congestion control for Internet traffic was modified to control EV charging in a distributed approach. Moreover, consumer preferences for EV charging were investigated in [7].

2. Method

The EVs are equipped with rechargeable batteries which can be charged by connecting it to an electric power source called charging station. Batteries differ in terms of charging capability as defined in the SAE J1772 standard for EV and PHEV Conductive Charge Coupler [11]:

- Level 1 (slow charging) using AC energy connected to the on-board charger of the vehicle, providing $120V/16A$ for $1.92kW$ through *charging time tc* $\approx$ *10 h.*
- Level 2 (standard charging) using AC energy connected to the onboard charger of the vehicle, providing 208-240V AC, single phase, 12A-80A for 2.5-19.2kW through *charging time tc* $\approx$ *6-8 h.*
- Level 3 (fast charging) using DC energy from an off-board charger; there is no minimum energy requirement but the maximum current specified is

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400*A* and 240*kW* continuous power supplied, through *charging time tc* $\approx$ *30 min.*

Thus, Level 1 charging is ideal for charging the vehicle at home (e.g., at night) at low prices. Level 2 charging is suitable for charging while the user resides at a place for a long time (e.g., at work), whereas Level 3 is appropriate solution for fast charging at higher prices to avoid running out of battery, when the user does not stop for long and the battery is getting empty.

Further, due to the normally long parking times of individual mobility vehicles, the degrees of freedom in EV charging are comparably high [12].

Recently, various works were published in the research domain related to this work. Particularly the optimization of EV charging subject to network constraints is addressed with several models seeking to determine grid-friendly charging strategies [13][14] or simulating the grid effects of different charging strategies [15][16]. Other works focus on methods to influence consumer behavior to achieve grid-optimal EV charging [17][18]. Several studies of smart charge scheduling algorithms were published [19] [20]. Some Multi-Agent Systems (MAS) have also been proposed [22][23] to achieve a decentralized optimal behavior.

In the environment of smart EVs charging systems, the central controller requires basic information to make appropriate decisions and perform basic tasks such as identifying and tracking users, resource allocation, the queue charge, monitoring of energy consumption, payment operations, etc.

Multi-agent system platform is a software infrastructure used as an environment for deployment and execution of agent's set. The developer can then create a platform for agents and used on all systems that support this platform without changing the code. Furthermore, the platform should hide the implementation details of communication protocols for developers. Since the choice of platform agents has a great influence on the design and implementation of agents, FIPA [30] produced the standards related to the agent platforms named ACL (Agent Communication Language). Several multi-agent platforms exist: simulation platforms, development and execution platforms. The most known is JADE [24].

3. JADE Platform:

JADE **J**ava **A**gent **DE**vlopment framework is a multi-agent platform created by TILAB laboratory and described by Belliffemine et al in [24]. JADE allows the development of multi-agent systems and applications conforming to FIPA standards [25].

The framework architecture is based on the coexistence of several Java Virtual Machines (JVM) and their inter-communications through the RMI (Remote Method Invocation) method. Each VM (Virtual Machine) is an agent container that provides a complete runtime environment for agent execution and allows multiple agents to run simultaneously on the same host. JADE consists of several agent containers. Each agent container is a runtime multi-agent environment made up of execution thread with more threads created at runtime by the RMI system to send messages.

4. Optimization approach:

The main function of the central controller is attributing to each EV appropriate charging stations. From there, charge managing of each EV can be customized according to customer requirements, charging device associated to the EV, the electric constraints of local installation or those of the distribution network. Furthermore, charge scheduling can be influenced by the user's preferences, the cost of electricity and the grid constraints in terms of energy consumption and availability of renewable energy sources. Moreover, coordination of EV's charging can also be advantageous for grids with a large share of renewable energy sources by concentrating the charging interval in periods of high renewable generation and therefore improving grid reliability, efficiency and economics and reducing the Greenhouse Gas emissions [27].

Coordinated charging approaches are currently being investigated by using devices with bi-directional communication capabilities [28]. This type of coordination is proposed to minimize the negative impacts on the grid due to a large number of vehicles charging at the same time by distributing this charge throughout a large period of time, smoothing the load peak.

Smart control over the introduction of new loads into the grid provides economic benefits given that peak demands involve the grid investments and operational costs [29] [30]. The algorithm is constrained by available resources. The charge optimization algorithm will aim to optimize EVs charging to achieve several goals, such as grid stability, meeting users' demands or the use of renewable energy sources such as solar or wind energy. The optimization will be able to consider any relevant information collectible. We can classify this information into two categories: Information related to user requests and information related to the distribution of electrical energy. The user requests Information match the customer perspective such as the Battery State of Charge (SOC), the amount of charge required, the charging urgency, cost and preference for renewable energy with reduced cost. Grid information are related to the availability of energy on the grid and her stability, the cost of energy in the market, the energy limits of local facilities and availability of renewable energy sources. As well, EV charging optimization can help to avoid recharges during peak of consumption.

5. Optimization Algorithm:

The optimization algorithm is an improved algorithm, built around an A* algorithm widely used in pathfinding and graph traversal. Such algorithm solves problems by searching among all possible paths to the target for the one with smallest cost (least distance travelled, shortest time, etc.). Pathfinding problem is formulated in terms of weighted graphs: starting from a specific node of a graph, it constructs a tree of paths starting from that node, expanding paths one step at a time, until one of its paths ends at the predetermined target node. Specifically, A* algorithm selects the path that minimizes:

$$f(x) = g(x) + h(x)$$

Where *x* is the last node on the path, *g*(*x*) is the cost of the path from the start node to *x*, and *h*(*x*) is a problem-specific heuristic that estimates the cost of the lowest-cost path to the target. In our case, *h*(*x*) heuristic estimates the *x* node cost as function of several attributes of *x* node *(*Average of service time, average of waiting time, Maximum Power delivered, EV Battery's SoC, etc.). Therefore, the *h(x)* heuristic is hybridisation of two pondered heuristics namely $h_1(x)$ and $h_2(x)$, *like:*

$$h(x) = \alpha . h_1(x) + \beta . h_2(x)$$

where:

- $h_1(x)$ is the distance to destination based heuristic.
- $h_2(x)$ is the average service time and waiting time based heuristic.
- $\alpha + \beta = 1$

Thus, $h_2(x)$ heuristic is described by the following expression:

$$h_2(x) = \sum_{j=1}^{NB\_CS} \left[\left(\bar{T}_{waiting_j} + \bar{T}_{service_j} \right) \times NB\_EV\_Waiting_j \right]$$

Where:

- $\bar{T}_{waiting_j}$ is the average waiting time at charge station j.
- $\bar{T}_{service_j}$ is the average service time at charge station j.
- NB_CS is total number of charge stations at LCA location.
- $NB\_EV\_Waiting_j$ is number of waiting EV at charge station j.

On the other hand, the instantaneous power provided in LCA location associated to x node is:

$$P_{L_T}(t) = \sum_{i=1}^{n} P_{s_i}(t) \leq P_{L_{Max}}$$

The power available in LCA location is giving by :

$$P_{L_a}(t) = P_{L_{Max}} - \sum_{i=1}^{n} P_{s_i}(t)$$

Where $P_{s_i}(t)$ is instantaneous power delivered by charge station ***i*** and ***n*** number of charge stations at LCA location. $P_{L_{Max}}$ represent the maximum power value delivered at LCA location.

Also, the instantaneous power delivered by each charge station ***i*** is constrained as below:

$$P_{S_i}(t) \leq P_{S_{Max}}$$

The battery state of charge of each EV is constrained by:

$$SoC_{Min} \leq SoC_{EV}(t) \leq SoC_{Max}$$

S	Start node
T	Set of terminal nodes
h(x)	Node cost heuristic
k(x,y)	Cost of edge (*x*,*y*) of the graph
C(Closed)	Set of developed nodes (successor generated)
O(Opned)	Set of generated nodes not developed yet
g(x)	Cost of path from s to x
f(x)	Total cost estimated of path from s to T passing through x

A* Algorithm

```
O ← {S}  ;  C ← ∅  ;  g(S)← 0  ;  f(S)← h(S)
while O <> ∅  do
    Extract from O element x such that f(x) is minimal
    Insert x in C
    if  x ∈ T
    then  Exit   // solution finded
    else
            for y successor of x
            do
                    if y ∉ (C ∪ O)  or  g(y)> g(x) + k(x,y)
                    then
                            g(y) ← g(x) + k(x,y)
                            f(y) ← g(y) + h(y)
                            Parent(y) ← x
                            Insert y in O
                    endif
            endfor
    endif
endwhile
```

6. Problem modeling

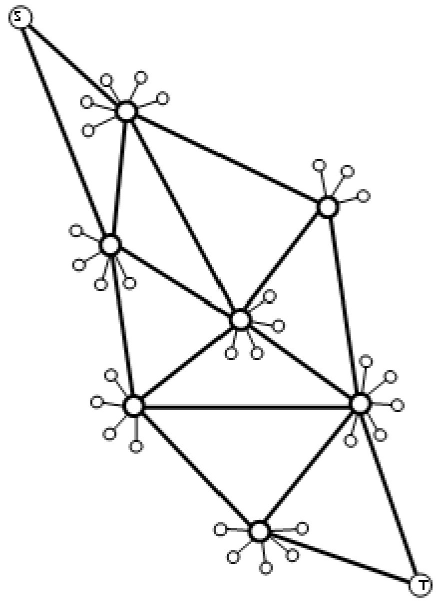

Fig. 1 Graph problem Modeling

Figure1 illustrates the graph modeling the network of charging stations. In that graph, each node represents a local controller handling a set of charging stations. Each local controller is characterized by a set of attributes (Maximal Power provided, number of charging stations handled, mode of EV battery's charging, Geographical coordinates, etc.). Likewise, the charging station it characterized by (Power provided value, Maximum charging current, Maximum output voltage, etc.)

7. Multi-agent system design:

The design of the proposed multi-agent systems is illustrated in *Figure2*, wherein the central controller is represented by an agent, Central Controller Agent (CCA). The network of charging stations being structured in domains. Domain may be a residence, commercial or workplace areas. However, a domain may also correspond to an isolated charging station on the highway. Each domain is under the control of a local controller represented by an agent, Local Controller Agent (LCA), providing communication between charging stations of the domain which it is associated and the central controller.
On the other hand, each charging station is also represented by an agent, Charge Station Agent (CSA). The set of CSA agents in a given domain is directly connected to the LCA of the same domain.

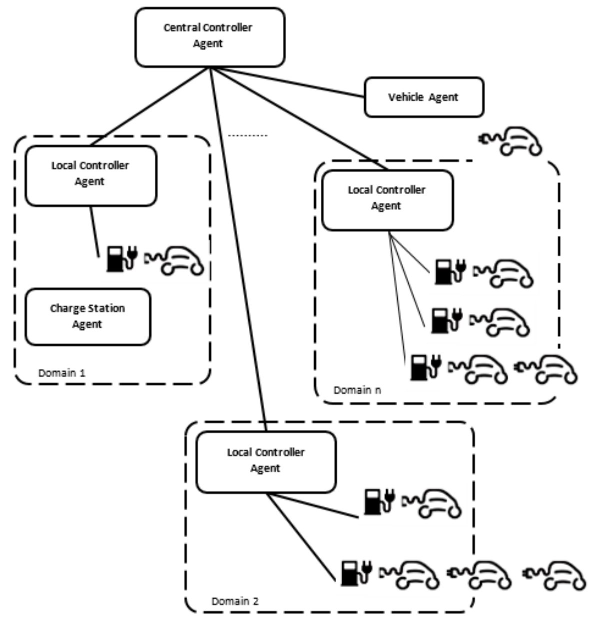

Fig. 2 Architecture of Multi-agent system

In the figure3, we depict the implementation platform of Multi-agent system proposed. This agent platform is splited on several hosts. Only one application agent, and then only one Java Virtual Machine (JVM), is executed on each host. Each JVM is a basic container of agents that provides a complete run time environment for agent. The main-container is the container where the AMS and DF lives. The other containers connect to the main container and provide a complete run-time environment for the execution of set of JADE agents.

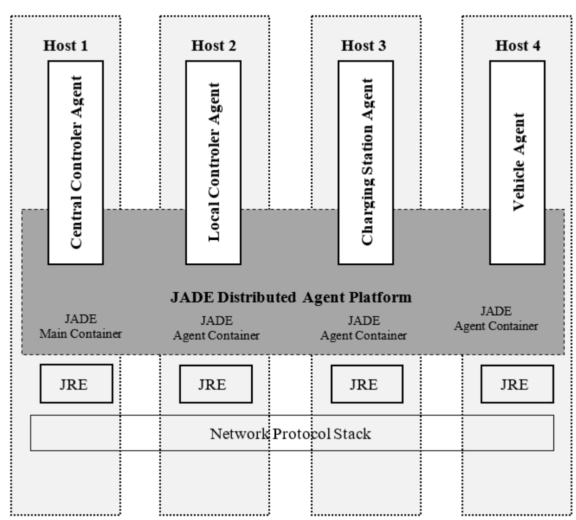

Fig. 3 JADE Agent Platform of Multi-agent system

8. Agent UML Interaction Protocol Diagrams

Agent Interaction Protocol (AIP) describes, with admissible sequences and constraints on the content of messages between agents having different roles, a communication pattern. Moreover, AIP diagram illustrate a semantics that is consistent with the communicative acts (CAs) within this communication pattern [26].

As claimed in FIPA [25], Agent Communication Language (ACL), messages must satisfy standardized communicative acts which define the type and the content of the messages. Protocols constrain the parameters of message exchange, their order or types, according to relationships between the agents or the intention of the communication.

This depiction of cooperation between software agents, combining sequence diagrams with the notation of state diagrams, characterize the exact behavior of a group of cooperating agents. In *fig.4*, we illustrate the Protocol Diagrams related to our Multi-agent system.

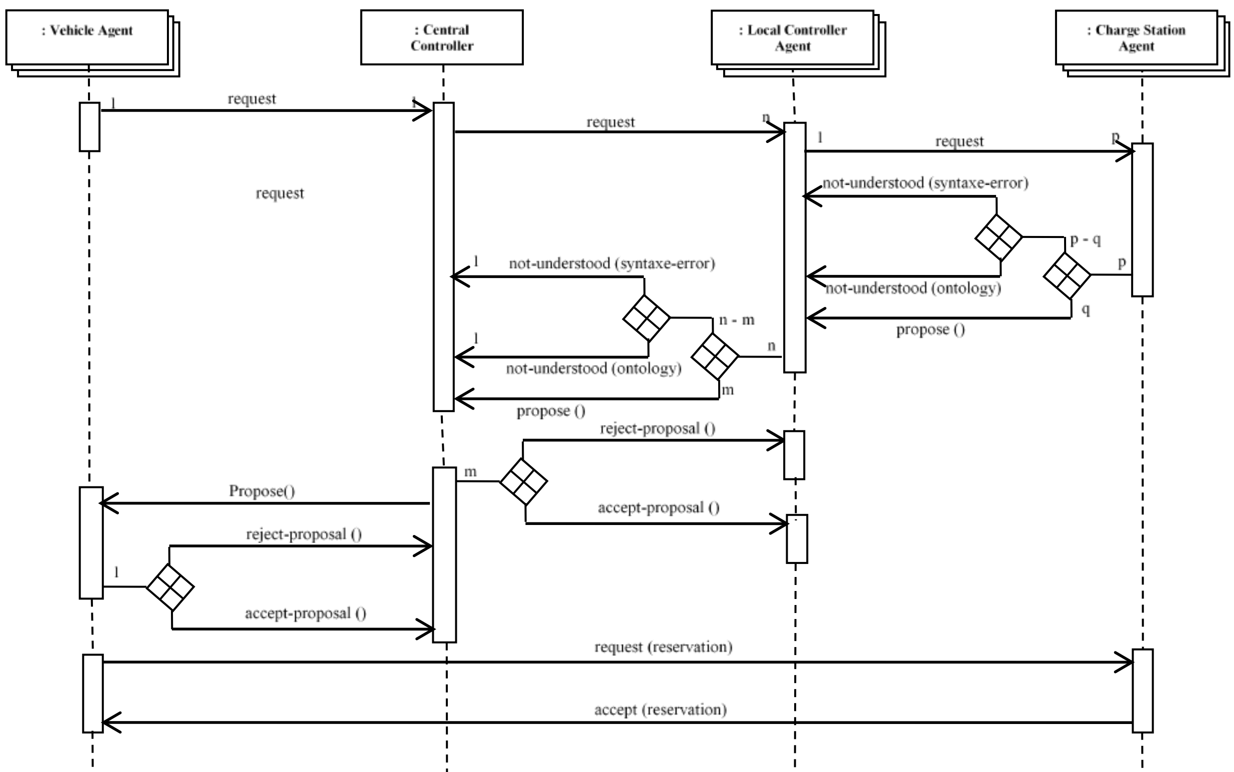

Fig. 4 Interaction Protocol Diagrams of Multi-agent system

Whenever charging is needed, Vehicle Agent associated to the vehicle try to establish communication with Central Controller Agent seeking to locate available and especially closest in distance charge station to avoid running out of battery on the way to the charging station, queuing if necessary, and recharging the battery until an *upper threshold* T_u is reached. This behavior is triggered whenever the State of Charge (SOC) is less than or equal to a *lower threshold* designated by T_L. Therefore, Central Controller Agent sends an information request to all Local Controller Agents LCAs that, in turn, will send similar information requests to Charging Station Agents under their control in their respective domain. These CSAs propose their availability in reply to the Local Controller Agent of their domain. All the Multi-agent system LCA's transmit to the Central Controller Agent a list of available charging stations under their control. The Central Controller Agent gather available charging stations through the network. Then, it proposes an ordered charging stations list to the vehicle agent apt to meet customer demand and through which the Vehicle Agent will have to choose the suitable charging station. Then, it will send a booking request to the Charging Station Agent concerned. Once the request is received by the Charging Station Agent, it sends a message of acceptance of the reservation request in regard addressed to the vehicle agent.

9. Results & Discussion

On *fig.6* and *fig.7* we exhibit a simulations graph result performed by our developed software application based on our Multi-agent distributed system. That weighted graph was obtained with a value set of nodes and edges attributes. Resulted weights used by the optimization algorithm are also displayed over each node and edge of that graph. The Tab. 1 and Tab. 2 boards illustrate the ordered node list proposed to EV driver. This node list represents all charging facilities that EV driver can uses to feed his vehicle in order to reach his destination. Each entry of the tables Tab. 1 and Tab. 2 informs in addition to the name of the node, the longitude and latitude coordinates of the node. These coordinates will allow the driver to easily locate the node on the map. Both simulations were performed with different α and β weighting coefficients in order to illustrate the effect of the $h_1(x)$ and $h_2(x)$ heuristics.

In comparison with energy management for a large-scale PHEV/PEV enabled municipal parking deck proposed by W. Su and al. in [20] and also that proposed by P. Kulshrestha, and al. in [19], our proposed smart charging system based on Multi-agent system is easily adaptable due to it distributed structure. Furthermore, our distributed system allows to reduce a bandwidth use and computing power needs thanks to Multi-agent system proactivity. Indeed, agents are proactive in seeking to meet their needs or objectives based on their roles and constraints. A charge station will therefore seek to flat local load power, as well as a central controller will seek to flat a global load power. In case of need, agents can also get the information they need to make decisions and plan actions. Therefore, we note that the characteristics of Multi-Agent Systems match with those required by our proposed smart charging system insofar as it is flexible, thanks to it distributed hierarchical architecture, and can therefore adapt to changes of the network, whether it is faults, adding or removing some of its components (Charge station out of service state), whether or not these events have been foreseen in the system configuration. Our system is therefore fault-tolerant and allow degraded operation and plug & play.

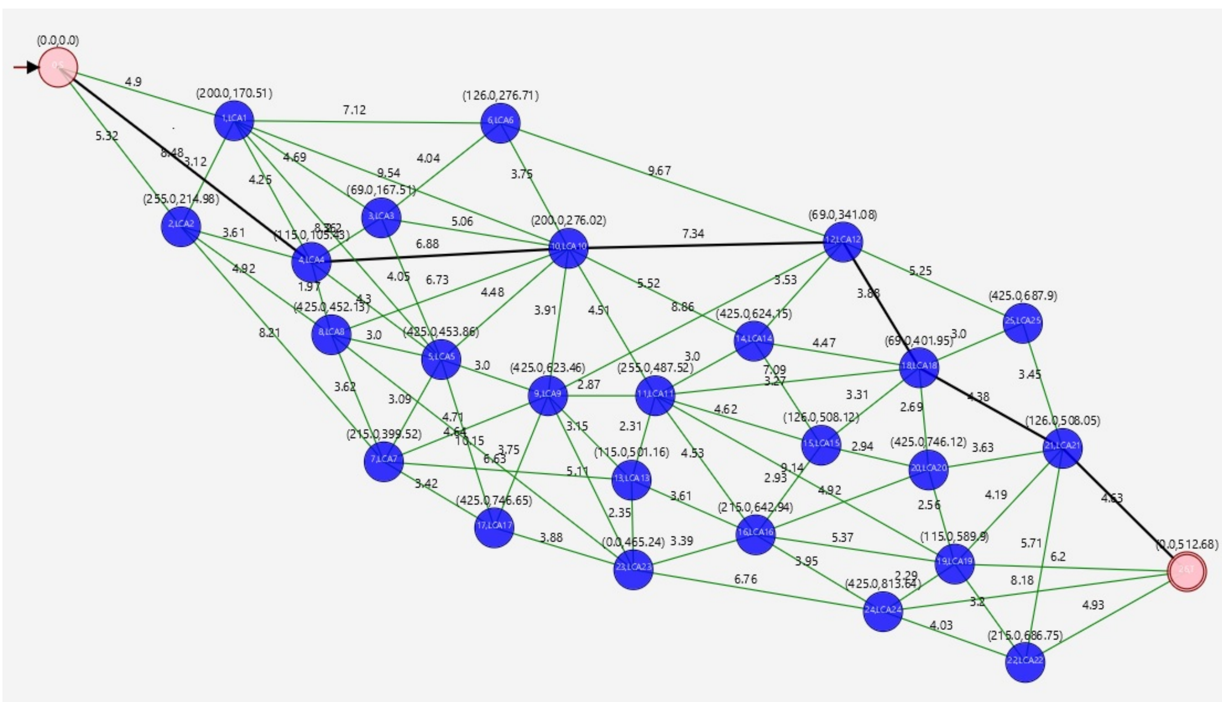

Fig. 6 Simulation result graph with α=0,2 and β=0,8

Table 1: List of proposed nodes with α=0,2 and β=0,8

N°_Node	Node_Name	Node_Longitude	Node_Latitude	Node_Cost	Cumul_Node_Cost
0	S	185	96	0	0
4	LCA4	221	211	115	51,28158467
10	LCA10	633	189	200	113,0159114
12	LCA12	1073	179	69	144,2484785
18	LCA18	1195	377	69	169,072483
21	LCA21	1425	504	126	202,3580224
26	T	1624	698	0	206,9880224

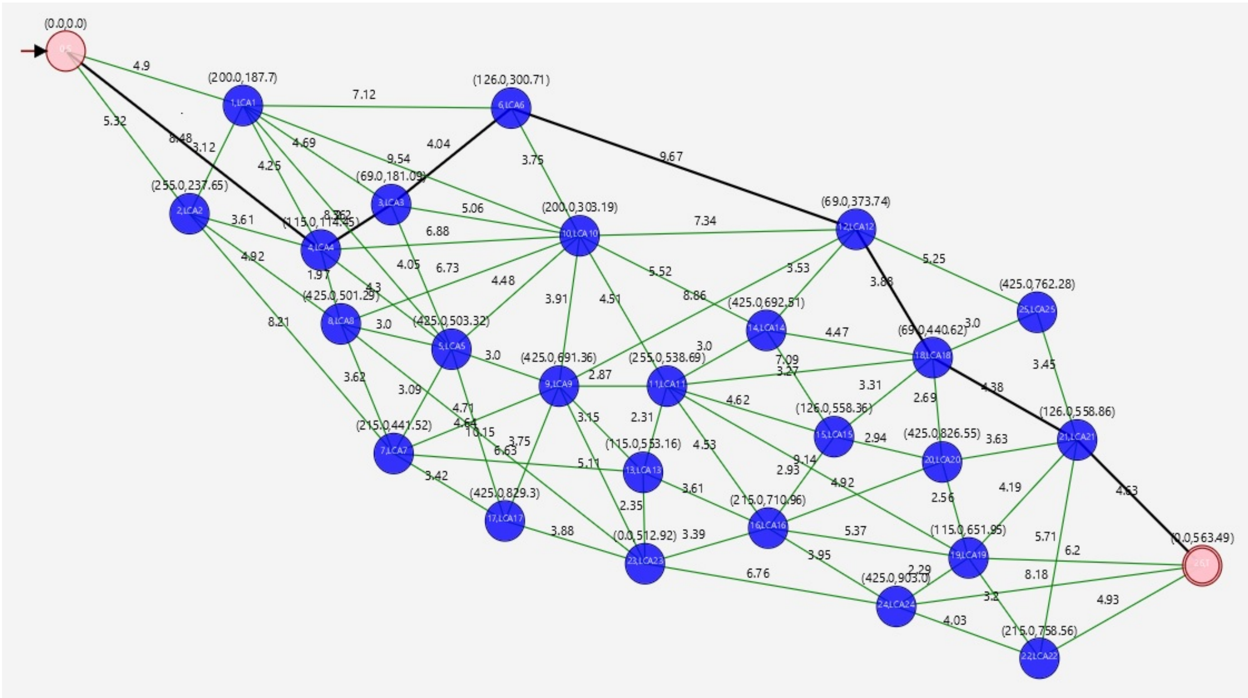

Fig. 7 Simulation result graph with α=0,8 and β=0,2

Table 2: List of proposed nodes with α=0,8 and β=0,2

N°_Node	Node_Name	Node_Longitude	Node_Latitude	Node_Cost	Cumul_Node_Cost
0	S	185	96	0	0
4	LCA4	221	211	115	114,4551981
3	LCA3	333	141	69	181,0985871
6	LCA6	524	8	126	300,7170397
12	LCA12	1073	179	69	373,7486106
18	LCA18	1195	377	69	440,6216111
21	LCA21	1425	504	126	558,8648036
26	T	1624	698	0	563,4948036

10. Conclusion

In the present work, the distributed Multi-agent systems theory was investigated and applied to the design of intelligent EV charging system. The Multi-agent system developed consisted of hierarchical community of agents which cooperated and communicated with each other playing up distributed intelligence in order to propose an optimal set of available charging stations to each Electric Vehicle further to vehicle owners' request. That Multi-agent system has the capability to optimally schedule EVs charging in order to safely maximize the use of available grid resources for charging EVs and by this means increase the number of EVs that can be connected to the grid while enhancing grid stability. The EVs charging system consists of a controller agent connected through the Internet. The proposed control system is network neutral and can connect to other devices and systems through Internet for data gathering and information exchange. Our Perspectives for future works related can be the improvement of optimization algorithm by means of queuing theory in order to introduce the concept of average arrival rate, average service rate, service efficiency, as nodes heuristic.

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