Proceedings of the 12th International Conference of Control Systems, and Robotics (CDSR 2025)
July 13, 2025 - July 15, 2025 | Imperial College London Conference Center, London, United Kingdom
Paper No. 109
DOI: 10.11159/cdsr25.109

Controlling the Charging Of Electric Vehicles Using a Distributed Cooperative Solution Converging To the Wardrop Equilibrium

Vincenzo Suraci[1]
[1] Department of Theoretical and Applied Sciences, eCampus University
Via Isimbardi 10, 22060 Novedrate (CO), Italy,
vincenzo.suraci@uniecampus.it

Abstract **-** In this paper the mathematical model of an electric vehicle load area is provided, where a networked set of charging stations collaborate to converge in real time to a fair solution of the underlying problem of power load control, relying on a distributed algorithm which is proved to converge to a Wardrop equilibrium. Numerical simulations of a realistic network scenarios based on the Open Charge Point Protocol architecture are reported to show the effectiveness of the proposed approach.

Keywords**:** electric vehicles, Wardrop equilibrium, power load control, OCPP

1. Introduction

The ongoing climate crisis, driven primarily by anthropogenic greenhouse gas (GHG) emissions, has necessitated an urgent an*d* systemic transition toward sustainable energy and transportation systems. Among the primary sources of GHG emissions, the transport sector represents approximately 25% of total CO_2 emissions in the European Union (EU) [1]. In response to these challenges, the EU has established ambitious policies to mitigate emissions and promote the decarbonization of road transportation: one of the most pivotal measures introduced by the EU is the ban on the sale of new non-electric vehicles by 2035 [2]. This challenging objective requires the widespread deployment of Electric Vehicle Supply Equipment (EVSE) and the development of smart grid systems to accommodate the increasing demand for electric power. The use of standardized, international, technological solutions involving ICT is a mandatory step of this transition [3]. The Open Charge Point Protocol (OCPP) is an open-source communication standard widely adopted in the electric vehicle (EV) charging infrastructure. It facilitates interoperability between EVSE and Charging Station Management Systems (CSMS), promoting vendor-agnostic integration and scalability [4]. Developed and maintained by the Open Charge Alliance, the protocol is crucial for ensuring seamless communication in modern EV charging ecosystems. The latest versions of OCPP (v2.0.1 released in 2020 and v2.1 that will be released in Q1 2025) introduces significant advancements in security features, addressing critical vulnerabilities that have been identified in earlier versions [5]. Research highlights the necessity of implementing robust security measures within OCPP to protect against potential threats that could destabilize both the charging infrastructure and the electric grid [6]. In addition to its technical advantages, OCPP plays a vital role in the broader context of EV roaming, which allows users to access charging stations across different networks with minimal hassle [7]. The protocol's adaptability to various operational contexts, including off-grid charging solutions, further highlights its versatility and importance in the evolving landscape of electric mobility [8]. As a matter of facts, the OCPP ability to standardize communication, enhance security, and facilitate interoperability among various stakeholders makes it a foundational element in the development of a robust and efficient EV charging infrastructures.

In the last decade a solid literature has been produced dealing with the problem of EV Power Load Control focusing mainly on solutions applying for peak load shifting, demand response, vehicle-to-grid (V2G), energy storage and smart charging ([9],[13]), while optimizing grid operations and guaranteeing grid stability [10] and economic benefits to EV owners [11]. These approaches rely on a centralized problem formulation an provide solutions based on machine learning (Reinforcement Learning [12]) or on optimization (mixed-integer linear programming [14], [15], [16]). In this paper, a distributed, dynamic, non-cooperative EV load control algorithm is formulated and developed relying on mean-field game theory. Specifically, the presented algorithm exploits the architectural topology offered by the OCPP v2.0.1 with the introduction of a networked element: the Local Controller (LC) [17] that allows to control locally multiple EVSEs, each hosted in a Charging Station, belonging to the same load area. Indeed, while in OCPP v1.6 (and previous versions) each

Charge Point (CP) was supposed to be centrally controlled by a unique Central System (applying for a centralized power load control), with the new versions of the protocol (v2.0.1 and v2.1) the LC can be still controlled centrally by the same Charging Station Management System, but can also autonomously interoperate with other LCs to coordinate the Charging Stations and related EVSEs under their control within the same load area. Thus, each EVSE acts as an agent of a distributed control system aiming at fairly share the electric energy source of the load area (e.g. a mix of grid, batteries, photovoltaic systems, etc.).

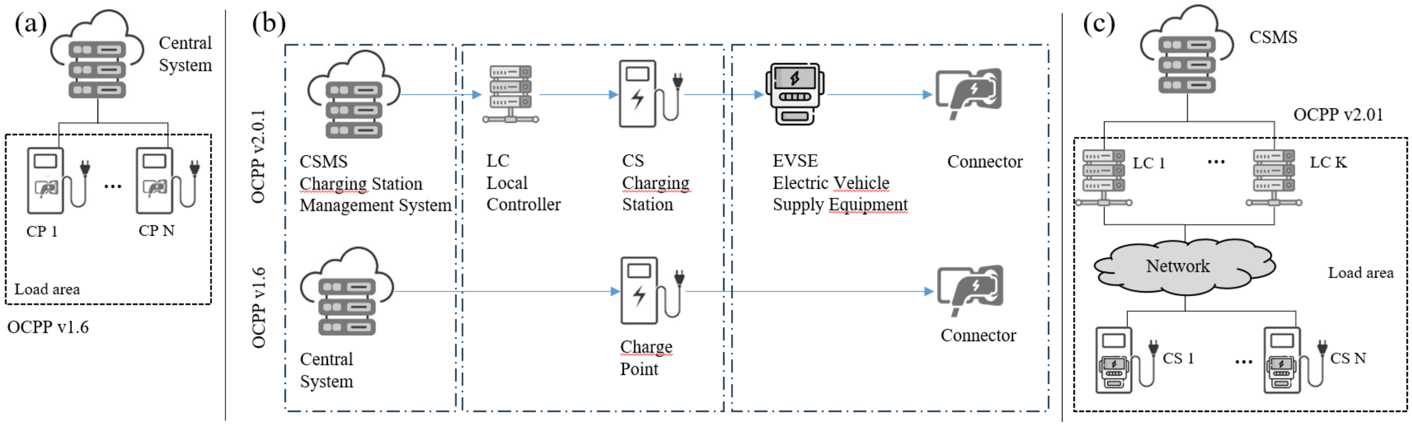

Fig. 1: (a) in OCPP v1.6, each Charge Point (CP) of a load area is directly connected to a Central System; (b) OCPP v.20.1 introduces new architectural elements: the Local Controller (LC) and the Electric Vehicle Supply Equipment (EVSE) extending the networking capabilities of load area; (c) in OCPP v2.0.1, the EVSEs are hosted in the Charging Stations of a load area and can be networked through the Local Controllers

Having in mind the architectural paradigm introduced and standardized by OCPP v2.0.1, it is possible to formulate the distributed EV power load control problem where each EVSE acts as an agent whose decision is to define, time by time, how much power to deliver to the connected charging EV while not overcoming the total power capacity offered by the load area. Considering that the total available power is a scarce and precious resource, the more power an EVSE requires the more it worths. So, the algorithm should be such that the agents' decisions must converge to an equilibrium value (known in mean-field game theory as Wardrop equilibrium [18],[22]), where the values of the cost functions of an EVSE are equalized.

The *paper* is organized as follows. Section 2 presents the distributed EV power load control problem formulation as a networked dynamical system, outlines the properties of the EVSEs' cost functions and defines the system dynamics. Section 3 demonstrates the system dynamics stability reporting the proof that the system converges to a Wardrop equilibrium. Section 4 presents an analysis of the numerical results, highlighting the performance of the proposed solution across several realistic scenarios and the convergence speed of the algorithm. Section 5 reports concluding remarks and future works.

2. Problem formulation

Consider a load area that serves a set E of networked EVSEs with a total maximum power of $\Pi \in \mathbb{R}^+$ kilowatts (kW). At a given time, $t \in \mathbb{R}_{\geq 0}$, each networked EVSE $e \in E$ requires a power load $p_e(t) \in \mathbb{R}_{\geq 0}$. The flow vector $\boldsymbol{p}(t) = [p_e(t)]_{e\in E}^T$ represents the power load required by each networked EVSE, at a given time $t \in \mathbb{R}_{\geq 0}$. $\boldsymbol{p_0} = \boldsymbol{p}(0)$ is the initial flow vector. From this moment on, we will always assume that the EVSE are requesting more power than the load area can provide, so that the role of each EVSE is to manage the requested power to not overcome the total maximum power Π offered by the load area. At a given time $t \in \mathbb{R}_{\geq 0}$, a flow vector is feasible if the sum of the power loads required by all the EVSEs is equal to the total available power, Π:

$$\sum_{e\in E} p_e(t) = \Pi, \forall t \geq 0. \qquad 1)$$

Therefore:

$$\sum_{e\in E} p_e(t) = \sum_{e\in E} p_e(0) = \Pi, \forall t \in \mathbb{R}_{\geq 0}. \quad 2)$$

Since each EVSE is using a scarce resource (the load area power) the requested power $p_e(t)$ is weighted with a non-negative cost function c_e. Hence, each EVSE $e \in E$ has a cost function $c_e(p): \mathbb{R}_{\geq 0} \to \mathbb{R}_{\geq 0}$ that maps the power load $p_e(t)$ to the cost that the EVSE incurs by requesting to the load area an amount of power load equal to $p_e(t)$.

*Assumption*Δ. Let assume a cost function $c_e(p)$ to be characterized by the following properties $\forall e \in E$:

1. $c_e(0) = 0$;
2. $c_e(p)$ is non-decreasing.

The above properties are intuitive and reasonable, since the first assumption states that a non-charging EVSE ($p_e(t) = 0$) does not have any cost. The second assumption states that the more an EVSE request for power, the more it should cost. In this paper, without loss of generality, a cost function exhibiting a twofold structure (*piecewise-linear* and *divergent-exponential*) has been chosen:

$$c_e(p) = \sum_{i=1}^{T} \lambda_{e,i}(p) + \varepsilon_e(p) \quad 3)$$

Where:

$$0 = \tau_{e,0} < \tau_{e,1} < \cdots < \tau_{e,T} = \tau_e^{Max} \quad 4)$$

$$\lambda_{e,i}(p) = \begin{cases} \gamma_{e,i} + s_{e,i}(p - \tau_{e,i-1}), if\ \tau_{e,i-1} < p \leq \tau_{e,i} \\ 0, \quad otherwise \end{cases} \quad 5)$$

$$\gamma_{e,i} = \begin{cases} 0, & if\ i = 0 \\ \gamma_{e,i-1} + (\tau_{e,i} - \tau_{e,i-1}) \cdot s_{e,i}, & if\ 0 < i \leq T \end{cases} \quad 6)$$

$$\varepsilon_e(p) = \begin{cases} 0, & if\ 0 \leq p \leq \tau_e^{Max} \\ \gamma_{e,T} + e^{(p-\tau_e^{Max})} - 1, & if\ p > \tau_e^{Max} \end{cases} \quad 7)$$

Each EVSE $e \in E$ is characterized by a maximum value of transferrable power to an EV (τ_e^{Max}) so, ranging from 0 to τ_e^{Max}, it is reasonable that the cost increases linearly ($\lambda_{e,i}(p)$) with a slope ($s_{e,i}$) that increases when power achieves a given threshold ($\tau_{e,i}$). If the power is higher than τ_e^{Max} the cost function increases exponentially ($\varepsilon_e(p)$) since the EVSE is overcoming its normal operating conditions. The slopes $s_{e,i}$ can be the energy prices (per kWh) and the power values of $\tau_{e,i}$ can be the thresholds to have a price that progressively increases (the more power you require, the more you pay the energy). It is worth to note that the cost functions in (3) satisfy *Assumption* Δ.

Since the EVSE are networked, they can exchange the required power with each other to jointly minimize their cost functions. As not all the EVSEs are neighbours, then, due to network constraints, there obviously could not exist a direct transmission link $\langle e, g \rangle$ between a couple of EVSEs $e, g \in E$. However, in our scenario, it is reasonable to assume that each couple of networked EVSEs $e, g \in E$ is connected: e.g., even though they are not neighbours, there exist $k \geq 1$ EVSEs $f_j \in E, j \in \{1,2,\dots,k\}$ such that the k+1 couples of EVSEs $\langle e, f_1 \rangle$, $\langle f_1, f_2 \rangle$, ..., $\langle f_k, g \rangle$ are all neighbours. The EVSEs sequence $\langle e, f_1, \dots, f_k, g \rangle$ is a path connecting the EVSE e to the EVSE g. We can thus introduce a graph adjacency matrix $A = \{\alpha_{e,f}\}_{e,f\in E}$ where the generic element $\alpha_{e,f}$ represents the maximum rate at which EVSE f can exchange a unitary amount of power with EVSE e. In the context of the mathematical framework introduced so far, the networked EVESs' primary objective is to cooperate with the aim of minimizing the cost associated with the EV charging. It implies that dynamically each EVSE $e \in E$ transfers an amount of power to another EVSE $f \in E$ in the load area if $c_e(p_e(t)) > c_f(p_f(t))$. As a result, the differential equation describing the evolution of the power required by an EVSE $e \in E$ is:

$$\dot{p}_e(t) = \sum_{f \in E} \left(\alpha_{f,e}\rho_{f,e}(t) - \alpha_{e,f}\rho_{e,f}(t) \right), \forall e \in E, \qquad 8)$$

where $\rho_{e,f}(t)$ is the *migration ratio* between two networked EVSEs $e, f \in E$ and is defined as:

$$\rho_{e,f}(t) = p_e(t) \cdot \mu_{e,f}(\boldsymbol{x}) = p_e(t) \cdot \mu\left(c_e(p_e), c_f(p_f) \right), \qquad 9)$$

being $\mu(c_e, c_f)$: $\mathbb{R}_{\geq 0} \times \mathbb{R}_{\geq 0} \rightarrow [0,1]$ the *migration policy function*, needed to determine the amount of power assigned to the EVSE e that is migrated to the EVSE f. A reasonable migration policy is the *linear migration policy*, where the amount of power to be exchanged is proportional to the difference of the costs of the given couple of EVSESs and weighted by the maximum difference in the load area:

$$\mu(c_e, c_f) = \max\left\{ 0, \frac{c_e - c_f}{\Delta c_{max}} \right\}, \qquad 10)$$

where $\Delta c_{max} = \max_{e \in V} c_e - \min_{f \in V} c_f$. The set of *migration policy functions*, denoted with M, contains all the migration policy functions associated to each couple of EVSEs $e, f \in E$. It is easy to demonstrate that if the system starts from a feasible flow vector $\boldsymbol{p_0}$, then it evolves always in feasible flow vectors. Indeed, the system dynamics defined in (8) has the following property:

$$\sum_{e \in E} \dot{p}_e(t) = \sum_{e \in E} \sum_{f \in E} \left(\alpha_{f,e}\rho_{f,e} - \alpha_{e,f}\rho_{e,f} \right) = \sum_{e \in E} \sum_{f \in E} \alpha_{f,e}\rho_{f,e} - \sum_{e \in E} \sum_{f \in E} \alpha_{e,f}\rho_{e,f} = 0, \qquad 11)$$

therefore,

$$\sum_{e \in E} p_e(t) = \sum_{e \in E} p_e(0) = \Pi, \forall t \geq 0 \qquad 12)$$

Assuming to starting from a feasible flow vector, it is important to demonstrate the stability of the system dynamics defined in (8), indeed if the system convergences towards a *stable* flow vector, it means that no fraction of the EVEs' power can decrease the overall cost by moving unilaterally from one EVSE to another. It is intuitive that being in a stable flow vector state implies that all EVSEs are in the minimal cost condition: this condition can be defined as *Wardrop equilibrium*.

Definition 1 (*Wardrop Equilibrium*). A feasible flow vector $\boldsymbol{p} = [p_e(t)]_{e \in E}^T$ is at a Wardrop equilibrium if, for every couple of networked EVSEs $e, f \in E$, with $p_e > 0$, $c_e(p_e) \leq c_f(p_f)$ holds.

From an engineering point of view, it is not necessary to mathematically achieve a Wardrop equilibrium to stop the system dynamics: the evolution of the system dynamics can terminate as soon as the maximum variation $\Delta c_{max}(t)$ between the costs associated with any couple of networked EVESs goes below an acceptable tolerance ΔC_{MAX}. In particular, the convergence time, denoted with t^*, is the first time instant when the following inequality is met:

$$\Delta c_{max}(t) = \max_{e \in E} c_e(p_e(t)) - \min_{f \in E} c_f\left(p_f(t) \right) \leq \Delta C_{MAX} \qquad 13)$$

Definition 2 (*Distributed Electric Vehicle Power Load Control*). Given a set E of networked EVSEs, a total power Π provided by the load area, a set C of cost functions associated to each EVE, an initial flow vector $\boldsymbol{p_0} = [p_e(0)]_{e \in E}^T$, a strongly connected adjacency matrix $A = \{\alpha_{e,f}\}_{e,f\in E}$, a set $\mathrm{M} = \{\mu(c_e, c_f)\}_{e,f\in E}$ of migration policy functions and a tolerance $\Delta C_{MAX} > 0$, the *distributed electric vehicle power load control problem* Π is the tuple $\mathrm{P} = \langle E, \Pi, C, \boldsymbol{p_0}, A, \mathrm{M}, \Delta C_{MAX}\rangle$ characterized by the system dynamics defined in (8).

3. Stability proof

Theorem 1. Given a distributed electric vehicle power load control problem $\mathrm{P} = \langle E, \Pi, C, \boldsymbol{p_0}, A, \mathrm{M}, \Delta C_{MAX}\rangle$ *controlled by the system dynamics defined in (8), where:*

a. E *is the set of EVSEs with* $|E| = n > 1$*;*
b. $\Pi \in \mathbb{R}^+$*;*
c. M *is the set of EVSEs cost functions defined in (3);*
d. $\boldsymbol{p_0}$ *is the initial feasible flow vector;*
e. A *is a strongly connected adjacency matrix;*
f. M *is a set of linear migration policy functions;*
g. $\Delta C_{MAX} \in \mathbb{R}^+$.

The system dynamics defined in (8) that controls the problem P *evolution admits a solution. More specifically, the electric vehicle power load control problem* P *converges towards a unique feasible flow vector* $\boldsymbol{p}^*$ *that is at a Wardrop equilibrium, and at the Wardrop equilibrium all the utilization factors are equal and minimal:* $c(p_e^*) := c_{wardrop} \in \mathbb{R}^+, \forall e \in E$ *and, consequently, the tolerance* $\Delta c_{max}(t^*) = 0$*. This means that there exists a time* $\bar{t} \in \mathbb{R}_{\geq 0}$ *such that* $\Delta c_{max}(\bar{t}) \leq \Delta C_{MAX}$.

Proof of Theorem 1. Given the system dynamics defined in (8) and the migration ratio defined in (9), by enumerating the EVSEs in E from 1 to n, given any $i \in \{1, \dots, n\}$, we have:

$$\dot{p}_i(t) = \sum_{j=1}^{n} \left(\alpha_{j,i} p_j(t) \mu_{j,i}(\boldsymbol{p}(t)) - a_{i,j} p_i(t) \mu_{i,j}(\boldsymbol{p}(t))\right). \tag{14)}$$

By defining:

$$\gamma_{i,j}(\boldsymbol{p}(t)) = \alpha_{i,j}\mu_{i,j}(\boldsymbol{p}(t)), \tag{15)}$$

it follows that:

$$\dot{p}_i(t) = \sum_{j=1}^{n} p_j(t)\gamma_{j,i}(\boldsymbol{p}(t)) - p_i(t)\sum_{j=1}^{n} \gamma_{i,j}(\boldsymbol{p}(t)). \tag{16)}$$

The system can be rewritten in compact form as:

$$\dot{\boldsymbol{p}}(t) = G(\boldsymbol{p}(t))\boldsymbol{p}(t) := F(\boldsymbol{p}(t)), \quad \boldsymbol{p}(0) = \boldsymbol{p}_0. \tag{17)}$$

Where the $G(\boldsymbol{p}(t))$ matrix is:

$$G(\boldsymbol{p}(t)) = \begin{bmatrix} -\sum_{j=2}^{n} \gamma_{1,j}(\boldsymbol{p}(t)) & \gamma_{1,2}(\boldsymbol{p}(t)) & \dots & \gamma_{1,n}(\boldsymbol{p}(t)) \\ \gamma_{2,1}(\boldsymbol{p}(t)) & \sum_{j=1,j\neq 2}^{n} \gamma_{2,j}(\boldsymbol{p}(t)) & \dots & \gamma_{2,n}(\boldsymbol{p}(t)) \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{n,1}(\boldsymbol{p}(t)) & \gamma_{n,2}(\boldsymbol{p}(t)) & \dots & -\sum_{j=1}^{n-1} \gamma_{n,j}(\boldsymbol{p}(t)) \end{bmatrix} \quad 18)$$

We therefore obtain a nonlinear dynamical system. As proven in [19], since $F(\boldsymbol{p}(t))$ is Lipschitz-continuous with respect to $\boldsymbol{p}(t)$ and t, it satisfies the standard conditions for the global existence and uniqueness of a solution. Moreover, from assumption c., the cost functions $c_e(p), \forall e \in E$ satisfy the *Assumption* Δ. The proof then follows immediately from the proof of Theorem 1 reported in [20], which demonstrates the convergence to Wardrop equilibria in the more general case of time-varying graphs. As in this paper the considered cost functions are strictly increasing, from [21] it follows that the Wardrop equilibrium is unique.

4. Numerical results

Thanks to the proof of Theorem 1, we know that the system dynamics defined in (8) makes the distributed electric vehicle power load control problem converge to a unique Wardrop equilibrium. Several simulations for different power load control problems $\mathrm{P} = \langle E, \Pi, C, \boldsymbol{p_0}, A, \mathrm{M}, \Delta C_{MAX} \rangle$ controlled by the system dynamics defined in (8) have been carried out to assess the performances of the proposed solution. Three typical load area topologies have been considered: Undirected Full-Mesh (UFM); Undirected Half-Mesh (UHM) and Undirected Balanced Binary Tree (UBT). The UFM topology accounts for a typical (ethernet or WiFi) local area network (LAN) where all the EVSEs can communicate directly with each other. The UHM topology accounts for a typical scenario of federated LANs connected thorough virtual private network (VPN). The UBT accounts for a typical hierarchical network, where EVSEs can communicate only by means of higher layer OCPP elements (e.g., CS, LC and CSMS). To account for the different networked EVSEs topologies, the adjacency matrix A has been chosen to be a binary matrix. The overall load area power Π counts $7.36 \cdot n$ kW to be distributed among the n EVSEs. The set M uses the linear migration policy function specified in equation (10). The initial feasible jobs vector $\boldsymbol{p_0}$ is randomly generated for each simulation. To have a set of comparable results Alternate Current (AC) EVES have been divided into three types: 1) mono phase, charging at max 7.36 kW, 2) two phases, charging at max 14.72 kW and 3) three phases charging at max 22.08 kW. To each EVSE's type, a piecewise-linear + divergent-exponential cost function specified in (3) has been associated characterized by the parameters reported in Table 1. To show how the proposed system dynamics converges to a stable state, we considered a UFM topology of $n = 25$ networked EVSEs, with a tolerance $\Delta C_{MAX} = 10^{-4}$. The set of cost functions C contains 25 piecewise-linear + divergent-exponential cost functions: 17 of type 1; 2 of type 2; and 6 of type 3. As expected, the simulations reported in Fig. 2 shows that (graph a) in Fig. 2) the EVSEs' cost functions converge all to the same value (indeed, achieving the Wardrop equilibrium), while the EVSEs' required charging powers converge to three different steady-state values (approximately 6.3 kW, 8 kW and 10 kW for type 1, 2 and 3, respectively; see graph b) in Fig. 2. To show how the topology impacts on the convergence time, another set of simulations have been carried out: for each topology an increasing number of AC EVSEs $|E| = n \in [5,10,15,20,25]$ and a tolerance value $\Delta C_{MAX} = 10^{-3}$ (one thousandth of the cost unit, e.g. 0,1€/cent) have been considered. The AC EVSEs have been grouped following this distribution: 20% of Type 1, 10% of Type 2 and 70% of Type 3. The simulation results show that the EVSEs' topology impacts on the convergence time. In a UFM topology, the number m of EVSEs interconnections (edges) is $n(n-1)/2$, while the diameter (D) is 1; in a UHM topology, $m = n(n-1)/4$, and $D = 2$; while in a UBT $m = 2(n-1)$ and $D = 2(log_2(n+1) - 1)$. As shown in Fig. 3, when the number of EVSEs' interconnectios n increases: a) in a UFM topology the convergence time decreases exponentually; b) in a UHM topology, the convergence time decreases in more-than-linear fashion, yet slower than in UFM topology; and c) in a UBT topology the convergence time increases in a linear fashion.

Table 1: Cost functions' parameters by EVSE type

Parameter	**EVSE Type 1**	**EVSE Type 2**	**EVSE Type 3**
Max power [kW]	7.36	14.72	22.08
Slopes	$s_{e,1} = 0.3, s_{e,2} = 0.4$	$s_{e,1} = 0.2, s_{e,2} = 0.3, s_{e,3} = 0.5$	$s_{e,1} = 0.1, s_{e,2} = 0.2,$ $s_{e,3} = 0.4, s_{e,4} = 0.6$
Thresholds [kW]	$\tau_{e,1} = 4.9, \tau_{e,2} = 7.36$	$\tau_{e,1} = 4.9, \tau_{e,2} = 7.36, \tau_{e,3} = 14.72$	$\tau_{e,1} = 4.9, \tau_{e,2} = 7.36,$ $\tau_{e,3} = 14.72, \tau_{e,4} = 22.08$

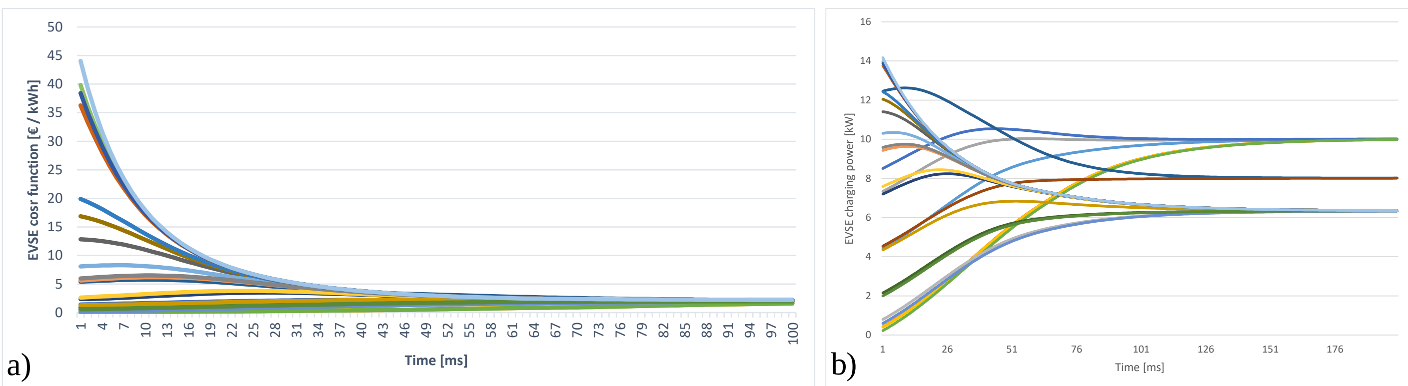

Fig. 2: a) EVSEs' cost function convergence to the Wardrop equilibrium; b) EVSEs' charging power convergence to a stable state

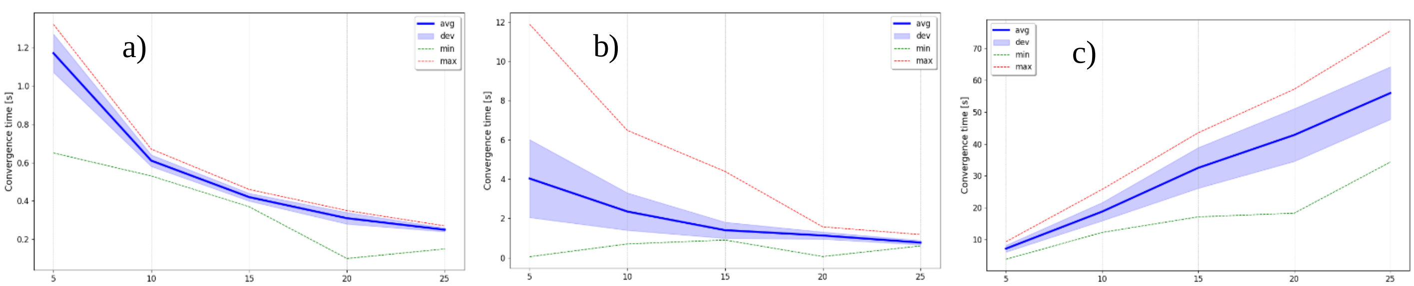

Fig. 3: a) UFM converge time decreases exponentially when the number of edges (n) increases; b) UHM converge time decreases when n increases; c) UBT converge time increases linearly when n increases.

5. Conclusion

The presented work defines a mathematical model of an electric vehicle load area where a networked set of EVSEs *interacting* using the OCPP protocol, collaborate to share the available load, acting has agents of an autonomous distributed system aiming at minimizing the overall energy costs experienced by each EVSE. The problem has been formulated adopting a game theory approach where the system dynamics evolves over time and, under proper assumptions, it has been demonstrated to converge exponentially to a Wardrop equilibrium. The main advantage of relying on a Wardrop equilibrium rather than on a supervised learning approach is to avoid the long training and exploration phases. The simulation results show that the convergence to the solution depends on the number of interactions between the EVESs and the maximum distance between them. The interesting results obtained in the experimentation phase pave the way for undertaking future works and further studies on the properties of the proposed solutions (e.g., conjecture a mathematical dependency between the convergence speed to the Wardrop equilibrium and the EVEs topology characteristics) as well as to develop an OCPP-compliant software implementation of the proposed solution (as an open-source) to be tested on field.

References

[1] European Environment Agency, “Environmental Statement 2022”. ISBN: 978-92-9480-593-5, doi: 10.2800/351036

[2] Regulation (EU) 2023/851 of the European Parliament and of the Council of 19 April 2023. Document 32023R0851.

[3] Neaimeh, M. and Andersen, P. (2020). Mind the gap- open communication protocols for vehicle grid integration. Energy Informatics, 3(1). https://doi.org/10.1186/s42162-020-0103-1.

[4] Kirchner, S. (2024). Ocpp interoperability: a unified future of charging. World Electric Vehicle Journal, 15(5), 191. https://doi.org/10.3390/wevj15050191.

[5] Girdhar, M., Hong, J., You, Y., Song, T., & Govindarasu, M. (2022). Cyber-attack event analysis for ev charging stations.. https://doi.org/10.48550/arxiv.2211.08530.

[6] Garofalaki, Z., Kosmanos, D., Moschoyiannis, S., Kallergis, D., & Douligeris, C. (2022). Electric vehicle charging: a survey on the security issues and challenges of the open charge point protocol (ocpp). Ieee Communications Surveys & Tutorials, 24(3), 1504-1533. https://doi.org/10.1109/comst.2022.3184448.

[7] Priyasta, D., Hadiyanto, H., & Septiawan, R. (2022). An overview of ev roaming protocols. E3s Web of Conferences, 359, 05006. https://doi.org/10.1051/e3sconf/202235905006.

[8] Hadi, M. (2024). Off-grid electric vehicle charging station with integrated local server ocpp protocol as a management system. Transport and Telecommunication Journal, 25(3), 321-334. https://doi.org/10.2478/ttj-2024-0024

[9] Yu, F. and Lao, P. (2022). Optimal scheduling of electric vehicle aggregators based on sac reinforcement learning. Journal of Physics Conference Series, 2216(1), 012021. https://doi.org/10.1088/1742-6596/2216/1/012021

[10] Golla, N., Dharavat, N., Sudabattula, S., Suresh, V., Kantipudi, M., Kotb, H., … & Alenezi, M. (2023). Techno-economic analysis of the distribution system with integration of distributed generators and electric vehicles. Frontiers in Energy Research, 11. https://doi.org/10.3389/fenrg.2023.1221901

[11] Ahsan, M. (2023). Integration of electric vehicles (evs) with electrical grid and impact on smart charging. International Journal of Multidisciplinary Sciences and Arts, 2(2), 225-234. https://doi.org/10.47709/ijmdsa.v2i2.3322

[12] F. Liberati, A. Mercurio, L. Zuccaro, A. Tortorelli and A. Di Giorgio, "Electric vehicles charging load reprofiling," *22nd Mediterranean Conference on Control and Automation*, 2014, pp. 728-733, doi: 10.1109/MED.2014.6961460.

[13] Tortorelli A, Sabina G, Marchetti B. A Cooperative Multi-Agent Q-Learning Control Framework for Real-Time Energy Management in Energy Communities. *Energies*. 2024; 17(20):5199. https://doi.org/10.3390/en17205199

[14] Huang, J., Wang, D., Wu, R., Lai, C., Xie, C., & Zhao, Z. (2020). Optimal operation of smart buildings with stochastic connection of electric vehicles., 1-7. https://doi.org/10.1109/isc251055.2020.9239064

[15] El-Sayed, M. (2024). Smart grid operation with hybrid renewable resources and electric vehicle. Renewable Energy and Power Quality Journal, 16(1). https://doi.org/10.24084/repqj16.222

[16] Sains, N. and Al-Anbagi, I. (2018). Optimal charging and discharging for evs in a v2g participation under critical peak conditions. Iet Electrical Systems in Transportation, 8(2), 136-143. https://doi.org/10.1049/iet-est.2017.0073

[17] Open Charge Point Protocol (OCPP) 2.0.1, March 31, 2020, Open Charge Alliance, Specification OCPP part1 Architecture Topology https://www.regulations.gov/document/FHWA-2022-0008-0404

[18] J.G. Wardrop, “Some Theoretical Aspects of Road Traffic Research,” ICE Proc., vol. 1, no. 3, pp. 325–362, Jan. 1952.

[19] H. K. Khalil, Nonlinear Systems, Third Edition, Pearson, 2001.

[20] A. Pietrabissa and V. Suraci, “Wardrop Equilibrium on Time-Varying Graphs,” Automatica (Elsevier, Great Britain), Vol. 84, 2017, pp. 159-165, DOI: 10.1016/j.automatica.2017.07.021

[21] S. Fischer, B. Vöcking, “Adaptive routing with stale information,” Theoretical Computer Science, 2009, pp. 3357-3371.

[22] V. Suraci, L.R. Celsi, A. Giuseppi, A. Di Giorgio, “A distributed wardrop control algorithm for load balancing in smart grids”, 25th Mediterranean Conference on Control and Automation, MED 2017, Pages 761 – 767, Article number 7984210. DOI: 10.1109/MED.2017.7984210