Received May 10, 2020, accepted May 26, 2020, date of publication June 1, 2020, date of current version June 11, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2998783

Dynamic Model for the EV's Charging Infrastructure Planning Through Finite Element Method

MORRIS BRENNA[1], (Member, IEEE), GEORGE CRISTIAN LAZAROIU[2], (Senior Member, IEEE), MARIACRISTINA ROSCIA[3], (Member, IEEE), AND SOHEIL SAADATMANDI[3]

[1]Politecnico di Milano, 20156 Milan, Italy
[2]Department of Power Systems, University POLITEHNICA of Bucharest, 060042 Bucharest, Romania
[3]Department of Engineering and Applied Sciences, University of Bergamo, 24044 Dalmine, Italy

Corresponding author: George Cristian Lazaroiu (clazaroiu@yahoo.com)

ABSTRACT The rapid increase in the number of electric vehicles around the world, the high demands on the charging stations, and the challenges for locating the charging stations made researchers around the globe to think for a proper solution. In this paper, a new method to locate EV's charging infrastructures, based on the parallelism between mobility needs and heat equation implemented with Finite Element Method analysis (FEM), is proposed. The method is applied for two cities with similar metropolitan area: Boston (USA) and Milan (Italy), with further results. Although FEM is a mathematical tool for solving physical problems, the behavior of different parameters in this paper is modeled as physical objects. In addition, the parameters are modeled according to the heat equation. Heat density maps are elaborated for the considered case studies. The two cities with extremely different characteristics are chosen to demonstrate the general application of the proposed method. Heat density maps show the likely demand points to establish charging infrastructures for EV's. The annual electricity consumption maps of the two considered cities are reported. The analysis of heat density and electricity consumption maps, together with the considerations of mains supply capacity can give a perspective for the location of charging stations in the future urban environments. The developed method contributes to deploy charging stations in an urban environment.

INDEX TERMS Charging infrastructures, EV's, finite element methodologies, planning analysis.

I. INTRODUCTION

Electric Vehicles (EVs) distribution has grown rapidly, exceeding 5.1 million units. In 2018, around 45% of the electric cars in circulation were in China, while Europe represented 24% of the world fleet, and the United States 22% [1]. The number of charging stations globally was estimated around 5.2 million at the end of 2018, with an increase of 44% over 2017 in which more than 90% was related to the private section. Energy demand of electric vehicles is expected to reach nearly 640 terawatt-hours (TWh) in 2030 (1110 TWh in the EV30@30 Scenario [1]). One can also mention that the concerns regarding the levels of greenhouse gases and other air pollutants, in addition to global warming which emanates from industries and consumption of fossil fuels by vehicles around the world has been increased in the recent years [2]. On the other side, the gradual reduction of fossil fuel resources has raised the idea of using alternative fuel sources. One of the most popular trends towards the reduction of pollutants is using electricity as the primary source of energy for vehicles. The growth in investigations and researches on development of electric vehicles over the past decade indicates the importance of this topic among scientists, researchers and car companies.

Despite the benefits of such vehicles, the expansion of EV's as daily driving cars has resulted in raising other concerns. "Range anxiety" is quite common among the electric car owners in these days. Not being able to charge a vehicle over night or lack of enough charging stations on the road may lead in arising of unreliability of electric cars at the first place among people. Establishing enough number of charging stations at the right spots on the roads with right

The associate editor coordinating the review of this manuscript and approving it for publication was Mouloud Denai.

charging equipment installed onboard on the cars not only overcomes ''range anxiety'', but also can turn electric vehicles to reliable daily driving vehicles among commuters. Due to the rapid spread of EVs, it is important to ensure that charging of electric vehicles does not impact on the effective energy management systems. EV's Slow chargers flexible service are estimated to account for more than 60% of the total electricity consumption globally in 2030. A review of charging infrastructures topologies (chargers and wireless) for electric vehicles, together with the analysis of powertrains configurations is conducted in [3].

II. LITERATURE REVIEW

In [4], Amini and Mohammadi conducted a holistic approach applied to power systems and electrified transportation network in smart cities for deployment of charging stations. Their fully distributed consensus-innovations approach provides an optimal decision making on charging strategies among plug-in electric vehicles which involves all the agents inside a smart network. In this way the external information of one agent can affect internal operation of other agents. A multi objective optimization problem for scheduling electric vehicles in smart grids to minimize costs and pollution in a power system from Portugal is formulated in [5]. In the paper, the authors used a multi criteria Cuckoo search to schedule green energy sources and electric vehicles for minimizing the operation and pollution costs. They evaluated and compared the efficiency of their proposed algorithm in two power systems (a 33-bus standard power system and a 94-bus Portugal network) with other algorithms such as Genetic Algorithm (GA). In [6], the analysis of the impact of traffic network topology on the charging characteristics of electric vehicles group for Guangzhou (China) is conducted. They found out, based on the simulations of JADE/Multi-Agent, that charging power probability of regional EV's follows a logarithmic normal distribution with a cyclical variation. Comparing the traffic network data from different cities, they presented how traffic topological features impact the charging characteristics of EV's. A classification method for predicting the location of charging spots using Geographic Information Systems and data on charging infrastructure is proposed in [7]. In the paper, using the $l1$-regularized logistic regression, gradient boosted decision trees and random forests, the popularity of charging pools was represented. According to their findings, charging pools located in frequently visited places were more likely to become popular. The charging spots located in areas periodically visited by small number of EV owners were associated with a lower popularity. A pricing methodology considering the charging facility service ratio, traffic flow and renewable energy generation, was proposed and tested in [8]. This method maximizes the use of charging stations and renewable energy sources applied to the Dublin (Ireland) traffic. Their methodology increased wind energy consumption and improved solar energy use for wind-rich and solar-rich charging stations, also reducing traffic jams in both on-peak and off-peak hours. The mathematical problem of locating charging stations for public electric vehicles in Beijing to increase the sharing charging level is formulated and analyzed in [9]. To tackle the problem three factors were considered: public electric vehicles (PUEVs) distribution, passenger distribution, and mileage. Then, an optimization of charging stations location was done using a multi agent algorithm based on the Non-deterministic Polynomial (NP) model.

Reference [10] discussed the uncontrolled charging of electric vehicles in one day, based on Monte Carlo method. The simulation results determined that charging electric vehicles in an uncontrolled way will increase the peak load curve. To address this challenge, the authors proposed a two-stage scheduling optimization model considering the thermal power units, electric vehicles and basic power load. Using K-means clustering algorithm, they divided vehicles into different groups to avoid the ''dimension disaster'' caused by the centralized dispatching of large numbers of electric vehicles. Finally, particle swarm optimization algorithm is used to provide scheduling for each specific group of EV's.

In [11], a charging optimization for delivery electric vehicle fleets based on dynamic programming methods is proposed. Each individual vehicle has been optimized separately within the fleet to provide globally optimal solution regarding the charging status. The battery models of each vehicle were realized using recorded data for an electrical vehicles fleet in Croatia. A novel electric vehicle (EV) classification scheme for a photovoltaic (PV)-powered EV charging station (CS), that reduces the effect of intermittency of electricity supply and the cost of energy trading of the CS is proposed in [12]. An analysis of electric vehicle charging impact on the electric power grid based on smart grid regional demonstration project in Los Angeles is done in [13]. This paper presents monitoring of actual EV charging behavior of 64 EV owners (5 brands, 8 models) and charging stations for more than one year. Plug-in electric vehicles (PEV) are becoming more commonplace on streets all around the globe. A typical summer-winter load profile for domestic customers in UK has been evaluated firstly in [14], for 100 customers. Three scenarios are considered in this research: 1) uncontrolled domestic charging 2) off peak domestic charging 3) charging scheduling. In the first scenario, it has been assumed that the uncontrolled domestic charging, has no control over modification of load scheduling. Thus, users will tend to plug their vehicles into the charging outlets, as soon as they get home from work – at approximately 6:00 p.m. Apart from the impact of electric vehicles on the whole network, the charging methodologies should not be disregarded, since they play a crucial role in decreasing the time and charging costs of electric vehicles. Despite of its environmental performance, large scale photo voltaic (PV) production is bounded by its limited predictability and high variability that enhances solicitations and raises needs for spinning reserves as highlighted in [15].

The introduction of large-scale storage unit into the grid is one of the investigated solutions to compensate for production variability [16], [17]. The impact of the electrochemical aging mechanism on the bulk storage of electricity relevance has been highlighted in [18].

Gong, Fu and Li proposed a hybrid optimization strategy for public fast charging stations (PFCSs) planning in [19]. The maximization of the probability of charging BEVs represents the main objective of this paper. This is done under the constraints of minimizing the infrastructure cost of PFCSs, mitigating their negative impacts on both the transportation system and the power system, and enhancing long-term social benefits They exploited an abstract-map-based multi-layer optimization strategy in which three layers are considered. The results from each layer are used as inputs for the next layer. Transportation system factors such as population and vehicle distribution, road network, traffic conditions, and householder travel behavior are considered in the first layer. For the second layer, the electric power system with respect to the impact of BEV charging load is taken into account. Third layer combines features of first and second layer to achieve an integrated panning of PFCS's. In [20], the researchers suggested an analysis of electric vehicle charging infrastructure allocation within a city and a region, based on open source GIS tools. According to their methodology, there are several high potential locations inside cities for placing the charging infrastructure. In rural regions, the charging stations should be placed in already build areas, like gas stations or rest areas to reduce investment costs. A genetic algorithm for predicting the locations of EV's charging infrastructures is proposed in [21]. Due to the scarcity of data regarding EV's, the origin-destination (OD) of conventional vehicles is used in this paper. This approach deploys a plan for locating the charging stations and is able to cover up to 80% of electric vehicles demands in Greece. In [22], the authors propose a mixed integer linear programming optimization model for allocating plug-in electrical vehicle charging stations based on trip success ratio. By setting this ratio above a threshold and using different charging station service ranges, the authors apply the optimization model for locating charging station in a city of 100 km^2 and on Ontario 401 highway. A two-level multicriteria method is proposed for locating charging stations on a country territory in [23]. The authors use a macroscopic (district) and microscopic level (small hexagons) approach to locate the charging stations in Hungary close to park and ride facilities, concentrated services or high-density area. A methodology based on geographic information system coupled with multi-criteria decision analysis (using fuzzy analytical hierarchy process) to locate electric vehicles charging station in the city of Ankara is proposed in [24]. The authors proposed and used 15 criteria from environmental-geographical, economic and urban domains for possible location of charging stations, the potential station sites being ranked using techniques for order preference by similarity to ideal solution.

The rapid increase in the number of electric vehicles around the world and high demands on the charging stations and the problems regarding projections of charging station locations made us to think of a proper solution. All the referred papers previously, are mainly based on proposing some new methods to reduce the impact of EV's on the whole electrical grid, not considering the fact that planning's regarding the location of charging stations is an important part of the development of electric vehicles in the future. To address this issue, in this paper, a planning method with respect to the location of charging infrastructures based on the parallelism between mobility needs and heat equation implemented with FEM analysis, is proposed.

This paper is organized as follows: the methodology and the explanation regarding the usage of FEM are presented in section III. FEM mathematical development needed to solve the heat equation is explained in section IV. The application of FEM on projection of EV's charging infrastructures is realized in section V and the electricity consumption data for the two considered cities are provided in section VI. The results are summarized in section VII. Finally, conclusive remarks are presented in section VIII.

III. METHODOLOGY

The finite element method (FEM) is a numerical method for solving problems of engineering and physics. Typical areas of application include structural analysis, heat transfer, fluid flow, mass transport, and electromagnetic potential [25]. The analytical solution of these problems generally requires solving partial differential equations, providing boundary and/or initial conditions. The method yields approximate values of the unknowns at discrete number of points over the domain [26]. The finite-element method thermal analysis is often applied in electrical engineering, e.g. machines in electrical vehicles [27], [28].

In this paper, a method based on the Finite Element Methodology (FEM) to forecast the location of charging infrastructures is proposed. For addressing this, the involved parameters like population, roads, and power transmission lines are modeled based on the heat equation. For establishing the charging infrastructures for EV's, the peak load in the electrical network should be considered. The following hypothesis is made: the concentration of population, routes, and grid somehow implies peak load spots in the near future. Hence, the demands for charging infrastructures in locations with a large number of people, routes and grid could be considered higher compare to those with lower concentration of mentioned parameters. The city populations are points that are scattered randomly on the map. All the data are converted to points with coordinates in ArcGIS for further processes in MATLAB.

ArcGIS is used for creating and using maps, compiling geographic data, analyzing mapped information, and managing geographic information in a database [29]–[31].

IV. MATHEMATICAL MODELS

The implementation of FEM to solve a two-dimensional heat equation, finding the points' temperature in a mesh, is presented. The steps to solve this heat equation are:

1) establishing strong formulation for 2D heat conduction;
2) establishing weak formulation for 2D heat conduction;
3) discretization over space;
4) weight and shape functions;
5) defining load vectors;
6) assembling.

The heat equation is given by:

$$q = -D \cdot \nabla T \tag{1}$$

where q is the heat flow, D is the thermal conductivity matrix, and T is temperature.

This expression can be written in matrix form as:

$$q = \begin{pmatrix} q_x \\ q_y \end{pmatrix} = -\begin{bmatrix} k_{xx} & 0 \\ 0 & k_{yy} \end{bmatrix} \begin{pmatrix} \frac{\partial T}{\partial x} \\ \frac{\partial T}{\partial y} \end{pmatrix} \tag{2}$$

According to the energy conservation law, the amount of heat supplied to the body per unit of time must be equal to the amount of heat leaving the body per unit time:

$$\int_A Q \cdot t \, dA = \oint_L q_n \cdot t \, dL \tag{3}$$

$$\oint_L q_n \cdot t \, dL = \oint_L q^T \cdot nt \, dL = \oint_L (t \cdot q)^T n \, dL = \oint_A div(t \cdot q) dA \tag{4}$$

where Q is the internal heat supply [J/m^{3}s] and t represents the thickness [m] of the solid. Expression (3) can be written in form of (4) based on the Gausses' divergent theorem with the divergent formula:

$$div(tq) = t\frac{\partial q_x}{\partial x} + t\frac{\partial q_y}{\partial y} \tag{5}$$

Rearranging (3) results in:

$$\int_A (Q \cdot t - div(t \cdot q)) \, dA = 0 \Leftrightarrow Q \cdot t - div(t \cdot q) = 0 \tag{6}$$

Substituting (1) in (6) leads to the:

$$div(t \cdot D \cdot \nabla T) + t \cdot Q = 0 \tag{7}$$

Expression (7) can be written as:

$$div(t \cdot D \cdot \nabla T) + t \cdot Q = \frac{\partial}{\partial x}(tk_{xx}\frac{\partial T}{\partial x}) + \frac{\partial}{\partial x}(tk_{yy}\frac{\partial T}{\partial y}) + tQ = 0 \tag{8}$$

By multiplying the strong formulation and the weight function $v(x, y)$, and integrating over the domain A it can be obtained:

$$\int_A v \cdot div\,(t \cdot D \cdot \nabla T) \, dA + \int_A v \cdot t \cdot Q \, dA = 0 \tag{9}$$

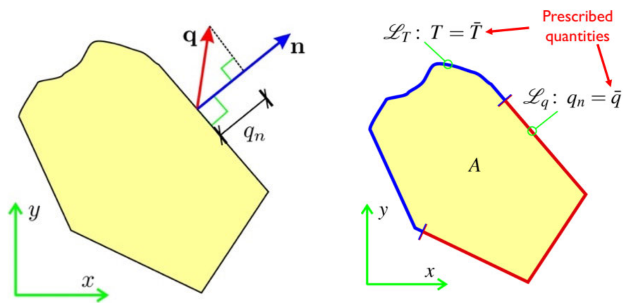

FIGURE 1. Triangular element in the population mesh.

Applying the Green-Gauss theorem, the first term of (9) can be expressed as:

$$\int_A v div\,(tD\nabla T) \, dA = \oint_L v(tD\nabla T)^T n \, dL \int_A (Dv)^T tD\nabla T \, dA \tag{10}$$

$$\oint_L vtq_n \, dL - \int_A (Dv)^T tD\nabla T \, dA + \int_A vtQ \, dA = 0 \tag{11}$$

The first term in (11) is the boundary integral which is splitted into two terms reflecting different types of boundary conditions:

$$\oint_L vtq_n \, dL = \oint_{L_q} vt\bar{q} \, dL + \oint_{L_T} vtq_n \, dL \tag{12}$$

The weak form of 2D heat flow can be written as:

$$\int_A (\nabla v)^T tD\nabla T \, dA = \oint_{L_q} vt\bar{q} \, dL + \oint_{L_T} vtq_n \, dL + \int_A vtQ \, dA \tag{13}$$

where the last term in (13) is the internal heat supply (heat load). Substituting $B = \nabla N$ in (13), the stiffness matrix regarding each specific triangular element in the population mesh (see Fig. 1) as [25]:

$$K = \int_A B^T tDB \, dA \tag{14}$$

with

$$\boldsymbol{B} = \begin{bmatrix} \frac{\partial N_1}{\partial x} & \frac{\partial N_2}{\partial x} & \frac{\partial N_3}{\partial x} \\ \frac{\partial N_1}{\partial y} & \frac{\partial N_2}{\partial y} & \frac{\partial N_3}{\partial y} \end{bmatrix} \text{ and } \quad \boldsymbol{D} = \begin{bmatrix} k_{xx} & 0 \\ 0 & k_{yy} \end{bmatrix} \tag{15}$$

where N_1, N_2, N_3 are the interpolation functions of a single triangular element. There are different forms of interpolation functions used in FEM. In this paper, the interpolation function of the Simplex elements is used.

The simple triangular plate element is considered and illustrated in Fig. 2. In a heat conduction problem, the primary unknown is temperature T with $\Phi(x,y) = T(x,y)$ and the corresponding nodal quantities are: $\Phi_1 = T_1$, $\Phi_2 = T_2$, and $\Phi_3 = T_3$.

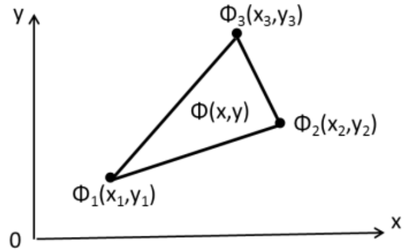

FIGURE 2. Simple triangular element for FEM.

Because there is only one nodal value, i.e., the temperature involved, it may be assumed the following linear interpolation function to link the element temperature $T(x,y)$ and the corresponding nodal values:

$$T\,(x,y) = \alpha_1 + \alpha_2 x + \alpha_3 y \tag{16}$$

Leading to the nodal values:

$$\begin{aligned} T_1\,(x,y) &= \alpha_1 + \alpha_2 x_1 + \alpha_3 y_1 \text{ node } 1 \\ T_2\,(x,y) &= \alpha_1 + \alpha_2 x_2 + \alpha_3 y_2 \text{ node } 2 \\ T_3\,(x,y) &= \alpha_1 + \alpha_2 x_3 + \alpha_3 y_3 \text{ node } 3 \end{aligned} \tag{17}$$

where α_1, α_2, and α_3 are constant coefficients. The interpolation function in FEM connects the element quantity $\Phi(x, y, z)$ and the corresponding Nodal quantities: Φ_1, Φ_2, and Φ_3. The $\Phi(x, y, z)$ is the primary unknown for a triangular plate element. The terms x_1, x_2, x_3 and y_1, y_2, y_3 are constant values. A "linear function" relating $\Phi(x, y)$ and $\emptyset(x, y)$ and Φ_1, Φ_2, and Φ_3 is assumed [25]:

$$\emptyset(x,y)=\alpha_1+\alpha_2 x_1+\alpha_3 y_1=[\,1 \quad x \quad y\,]\begin{bmatrix}\alpha_1\\ \alpha_2\\ \alpha_3\end{bmatrix}=R^T\alpha \tag{18}$$

Substituting all the coordinates in (18), the expressions for each specific node are obtained as:

$$\begin{aligned} \emptyset_1 &= \alpha_1 + \alpha_2 x_1 + \alpha_3 y_1 \text{ node } 1 \\ \emptyset_2 &= \alpha_1 + \alpha_2 x_2 + \alpha_3 y_2 \text{ node } 2 \\ \emptyset_3 &= \alpha_1 + \alpha_2 x_3 + \alpha_3 y_3 \text{ node } 3 \end{aligned} \tag{19}$$

or in a matrix form:

$$\{\emptyset\} = [A]\{\alpha\} \tag{20}$$

and

$$\{\alpha\} = [A]^{-1}\{\emptyset\} = [h]\{\emptyset\} \tag{21}$$

Matrix **A** in (20) and (21) contains the coordinates of the three nodes:

$$\boldsymbol{A} = \begin{bmatrix} 1 & x_1 & y_1 \\ 1 & x_2 & y_2 \\ 1 & x_3 & y_3 \end{bmatrix} \tag{22}$$

The matrix **h** could be performed as following:

$$\boldsymbol{h} = \frac{1}{|A|}\begin{bmatrix} x_2y_3 - x_3y_2 & x_3y_1 - x_1y_3 & x_1y_2 - x_2y_1 \\ y_2 - y_3 & y_3 - y_1 & y_1 - y_2 \\ x_3 - x_2 & x_1 - x_3 & x_2 - x_1 \end{bmatrix} \tag{23}$$

where $|\mathbf{A}|$ is the determinant of matrix **A**. Its equal to area of the triangular element [25]. The formation of an internal heat source is shown in (24) and (25).

$$f_b = -\oint_{L_q} N^T t\bar{q}\,dL - \oint_{L_T} N^T t q_n\,dL \tag{24}$$

In case of internal load vector, the internal heat supply must be converted to the nodal values as mentioned previously:

$$f_b = \int_A N^T tQ\,dA \tag{25}$$

V. APPLICATION OF FEM

For exemplification, the method is applied for charging station sitting in Boston (USA) and Milan (Italy). These two cities, geographically distant and with different characteristics, were considered to demonstrate how the method can be applied in a useful way in completely different contexts. The population points are scattered randomly in each quartier of the city as shown in Figs. 3 and 4.

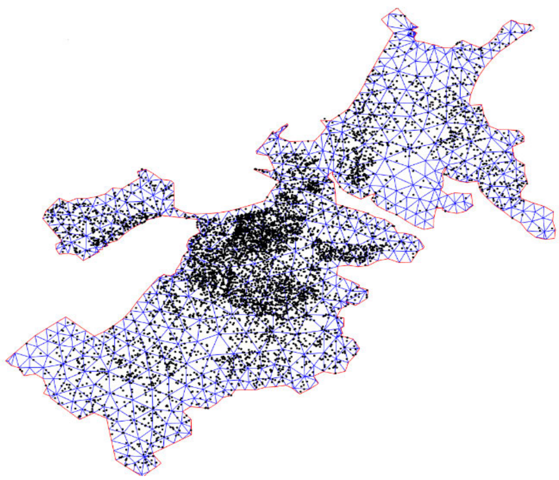

FIGURE 3. Boston population points.

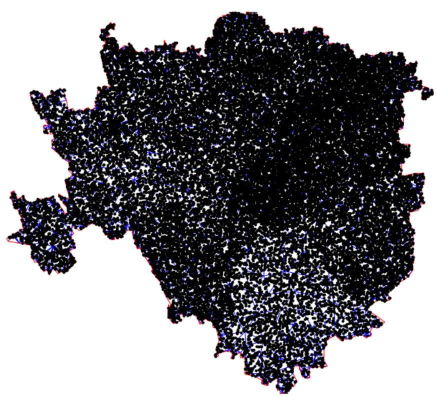

FIGURE 4. Milan population points.

A mesh generated throughout the whole map using techniques in MATLAB is generated for solving the equations

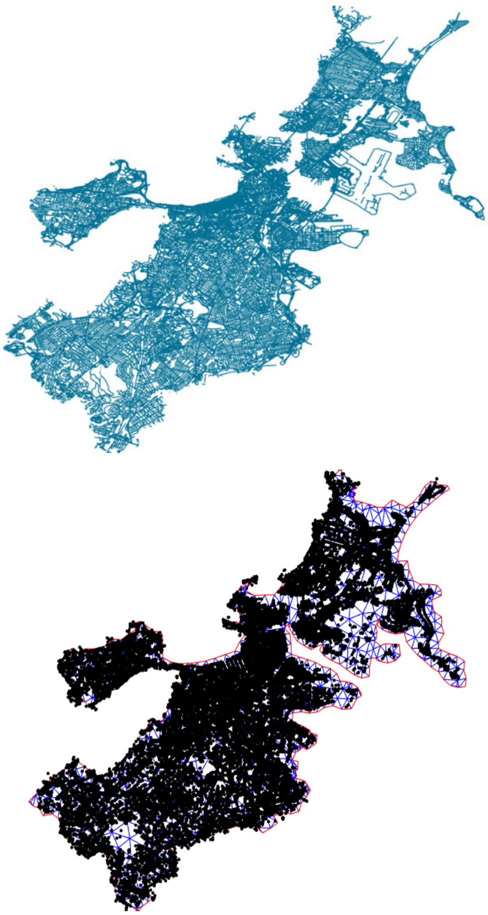

FIGURE 5. Boston routes and Boston route points.

FIGURE 6. Milan routes and Milan route points.

using FEM. The route maps are downloaded from the official government website of two cities. Figs. 5 and 6 show routes of Boston and Milan which are converted to coordinate points using ArcGIS, for further processes in MATLAB.

In the next step, the whole map is considered as a solid substance which is exposed to heat sources. The heat conducts on the surface of the solid material (map) with the heat sources based on the roads, population and power lines. Considering the heat conduction equation helps to find out the temperature at vertices of triangles inside the generated mesh. The higher the temperature is at a vertex, the demand for power would be higher. Therefore, such locations are not suitable to establish EV's charging infrastructures in the future.

Thermal conductivity is the property of the material to conduct heat. However, it does not play a role in this paper as there is not a physical problem in which the temperature is important. The important aspect is the heat density where the temperature in a spot is 1 degree or 1000 degrees. Thickness is another parameter that is considered for solving heat equation. Thicker material means less heat transfers on the surface and this fact is applied in the field of heat insulation materials. Thickness could be substituted with any random number because, like thermal conductivity, its impact is only on the temperature. In the other words, thickness and thermal conductivity are set for the sake of solving equations and obtaining heat density map. Simulations with different values of thickness and thermal conductivity were carried on making sure that, in each round, the heat density maps remain the same, while the temperatures change. Solving heat equation using FEM requires also the internal heat source.

In the proposed method, an internal heat source is dedicated to each triangular element of generated mesh. The summation of the number of population points, route points and grid points which are generated by ArcGIS inside of each triangular element in the mesh is defined as the internal heat source of the corresponding element. It was assumed that the elements with the higher number of points inside get heated with a bigger internal heat source, which will be resulted in a hotter spot in the heat density map. These hot spots show higher demands.

Figs. 7 and 8 illustrates the population random points, road points and the grid points of each city. Each population point represents 100 people.

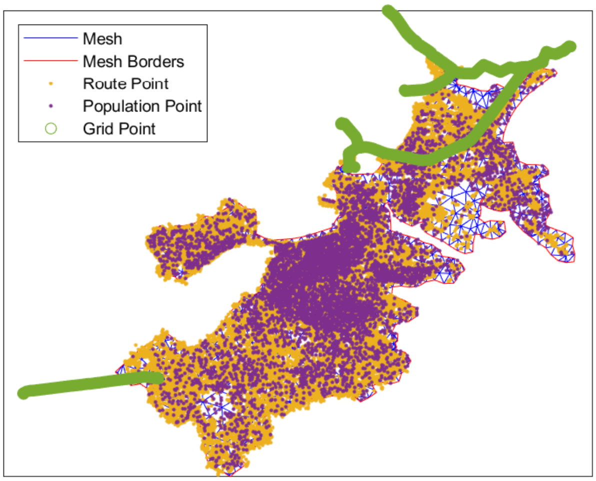

FIGURE 7. Population points, routes points, and grid points inside Boston mesh.

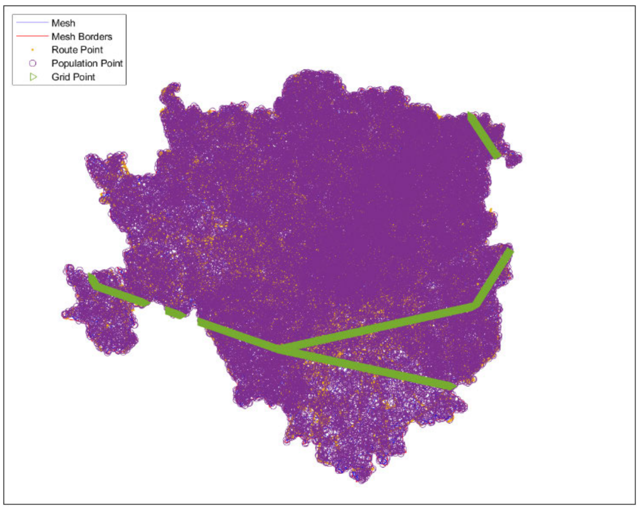

FIGURE 8. Population points, routes points, and grid points inside Milan mesh.

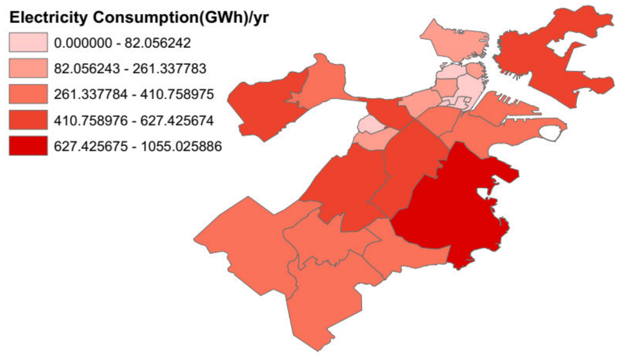

FIGURE 9. Boston electricity consumption map.

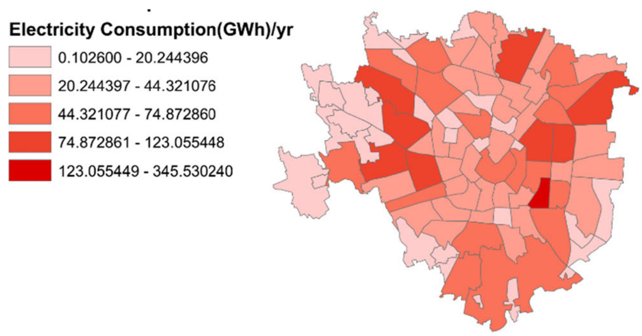

FIGURE 10. Milan electricity consumption map.

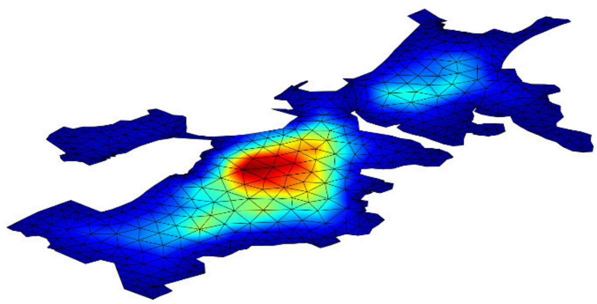

FIGURE 11. Boston heat density map.

VI. ELECTRICITY CONSUMPTION MAPS

The Italian Regulatory Authority for Energy, Networks and Environment (ARERA) stipulates that typical family's electricity consumption is 2700 kWh per year [32]. In the EU, the average annual consumption, per m^2, for all types of buildings is about ~200 kWh/m^2, from which 32% is related to the electricity consumption [33], [34]. The number of families living in each district of Milan and occupying the total building area given in [35] can give an estimation of the electricity consumption in different districts of this city. In [36], the most important measurement in the energy balance of United States is the annual total consumption of 3902 billion kWh. Per capita, this leads to an average of 11944 kWh. The population of Boston, per districts, is given in [37]. Knowing the per capita energy consumption in the USA and the Boston population, by district, the annual electricity consumption of Boston can be found.

The electricity consumption maps for the districts of Milan and Boston are illustrated in Fig. 9 and Fig. 10, respectively.

VII. RESULTS

The projection on the location of charging infrastructures for electric vehicles is based on the hypothesis that each population point represents 100 people. These points are spread randomly through the whole map. Solving the heat equation using FEM with the proposed internal heat sources, the obtained results are shown in Figs. 11-14. The simulations are repeated for different thermal conductivity and thickness values. As mentioned previously, the heat density map implies the severity of demands which may lead to grid overload in spots where there is high electricity consumptions. The results were also repeated with a refined mesh of both cities.

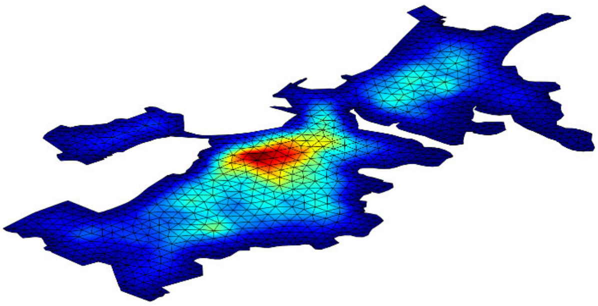

FIGURE 12. Boston heat density map with refined mesh.

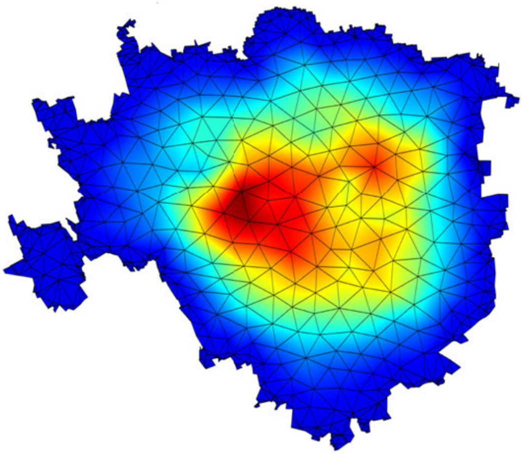

FIGURE 13. Milan heat density map.

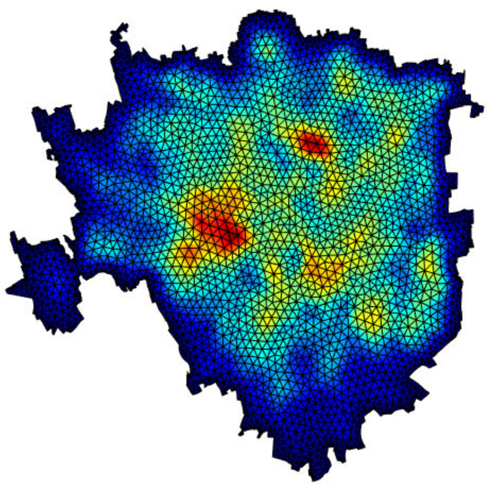

FIGURE 14. Milan heat density map with refined mesh.

Based on Figs. 11-14, the ideal locations for charging stations are those with high demand and low electricity consumption, since there would not be much concern regarding the congestion of the electrical network. Figs. 11-14 also indicate that some of hot spots which overlap locations with high electricity consumptions should be avoided for the establishment of EV's charging infrastructures in the future in case of lack of electrical grid capacity. Therefore, one should mention that installation of charging stations on these spots should not be considered without accurate analyzing on the capacity of electrical network. In this way, it is avoided the possible burden on the main grid, or the main grid could be supported by renewable energy sources, if there is a requirement to locate charging stations on high demand locations. In this way, not only the congestion of the grid will be reduced, but also the maximum grid capacity could be exploited without overloading it in areas with high demand and low electricity consumption.

The hot spots are illustrated in Figs. 11-14 with red color. These are locations where there is a concentration of population and route points, as the internal heat sources are higher according to the made definition. Obviously, the higher the concentrations of roads and population, the higher the demand would be in that corresponding spot. The grid points do not affect the results in these two cases, since grid points are in minority with respect to population and route points.

Thus, the concentration of heat is not at locations with the presence of all three parameters. Using FEM, the results could be expanded to each entire country for the projection of EV's charging infrastructure locations.

VIII. CONCLUSIONS

Finite Element analysis is a mathematical tool to solve numerical problems in different fields of science. In this paper, FEM is applied to project the critical spots for the location of charging stations for electric vehicles in the near future based on the population, routes and power system. Thermal conductivity and thickness are considered as low importance, since these parameters affect temperature in physical problems. However, in this paper, the temperature of each node or each element inside the mesh is not required. Like thickness and thermal conductivity, the size of parameters doesn't affect the results as they only impact on temperatures obtained by solving problems in the realm of mechanics. An internal heat source is defined inside of each triangular element.

The summation of population points, route points and grid points it was assumed to lead in the formation of internal heat sources. Thus, a greater internal heat source is expected when a high number of populations, routes and grids are inside an element at the same time. This will result in spots with higher temperature on heat density map. This would not represent a challenge if EV's charging stations are highly demanded in a location with low electricity consumption. Heat density maps demonstrate some locations where may be pruned to overload, as some of these spots have high electricity consumption. If the grid capacity is not sufficiently high, network overloading can occur. Therefore, the charging stations can be transferred to the vicinity of these places with lower electricity consumption. Photovoltaic power plants may also be considered to be located in such areas with higher temperature due to higher demands for further support to the grid. More accurate forecasts could be obtained using heat density maps with more refined meshes, as shown in Figs. 12 and 14.

The results clearly demonstrate the utilization capability of the proposed method in cities with different characteristics and geographical locations.

REFERENCES

[1] IEA, Paris, France. (2019). *Global EV Outlook 2019*. [Online]. Available: https://www.iea.org/reports/global-ev-outlook-2019

[2] G. C. Lazaroiu and M. Roscia, "Definition methodology for the smart cities model," *Energy*, vol. 47, no. 1, pp. 326–332, Nov. 2012, doi: 10.1016/j.energy.2012.09.028.

[3] A. Adib, M. B. Shadmand, P. Shamsi, K. K. Afridi, M. Amirabadi, F. Fateh, M. Ferdowsi, B. Lehman, L. H. Lewis, B. Mirafzal, and M. Saeedifard, "E-mobility—Advancements and challenges," *IEEE Access*, vol. 7, pp. 165226–165240, 2019, doi: 10.1109/ACCESS.2019.2953021.

[4] M. H. Amini, J. Mohammadi, and S. Kar, "Distributed holistic framework for smart city infrastructures: Tale of interdependent electrified transportation network and power grid," *IEEE Access*, vol. 7, pp. 157535–157554, 2019, doi: 10.1109/ACCESS.2019.2950372.

[5] O. Abedinia, M. Lu, and M. Bagheri, "An improved multicriteria optimization method for solving the electric vehicles planning issue in smart grids via green energy sources," *IEEE Access*, vol. 8, pp. 3465–3481, 2020, doi: 10.1109/ACCESS.2019.2960557.

[6] C. Chen, Z. Wu, and Y. Zhang, "The charging characteristics of large-scale electric vehicle group considering characteristics of traffic network," *IEEE Access*, vol. 8, pp. 32542–32550, 2020, doi: 10.1109/ACCESS.2020.2973801.

[7] M. Straka, P. De Falco, G. Ferruzzi, D. Proto, G. Van Der Poel, S. Khormali, and L. Buzna, "Predicting popularity of electric vehicle charging infrastructure in urban context," *IEEE Access*, vol. 8, pp. 11315–11327, 2020, doi: 10.1109/ACCESS.2020.2965621.

[8] S. Zhou, W. Gu, Y. Qiu, F. Zou, D. He, P. Yu, J. Du, X. Luo, C. Wang, and Z. Wu, "Dynamic EV charging pricing methodology for facilitating renewable energy with consideration of highway traffic flow," *IEEE Access*, vol. 8, pp. 13161–13178, 2020, doi: 10.1109/ACCESS.2019.2958403.

[9] D. Gong, M. Tang, B. Buchmeister, and H. Zhang, "Solving location problem for electric vehicle charging stations—A sharing charging model," *IEEE Access*, vol. 7, pp. 138391–138402, 2019, doi: 10.1109/ACCESS.2019.2943079.

[10] X. Wang, C. Sun, R. Wang, and T. Wei, "Two-stage optimal scheduling strategy for large-scale electric vehicles," *IEEE Access*, vol. 8, pp. 13821–13832, 2020, doi: 10.1109/ACCESS.2020.2966825.

[11] B. Skugor and J. Deur, "Dynamic programming-based optimization of electric vehicle fleet charging," in *Proc. IEEE Int. Electr. Vehicle Conf. (IEVC)*, Florence, Italy, Dec. 2014, pp. 1–8.

[12] W. Tushar, C. Yuen, S. Huang, D. B. Smith, and H. V. Poor, "Cost minimization of charging stations with photovoltaics: An approach with EV classification," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 1, pp. 156–169, Jan. 2016, doi: 10.1109/TITS.2015.2462824.

[13] Z. Jiang, H. Tian, M. J. Beshir, S. Vohra, and A. Mazloomzadeh, "Analysis of electric vehicle charging impact on the electric power grid: Based on smart grid regional demonstration project—Los Angeles," in *Proc. IEEE PES Transmiss. Distrib. Conf. Expo.-Latin Amer. (PES T&D-LA)*, Morelia, Mexico, Sep. 2016, pp. 1–5.

[14] G. A. Putrus, P. Suwanapingkarl, D. Johnston, E. C. Bentley, and M. Narayana, "Impact of electric vehicles on power distribution networks," in *Proc. IEEE Vehicle Power Propuls. Conf.*, Dearborn, MI, USA, Sep. 2009, pp. 827–831.

[15] A. Canova, L. Giaccone, F. Spertino, and M. Tartaglia, "Electrical impact of photovoltaic plant in distributed network," *IEEE Trans. Ind. Appl.*, vol. 45, no. 1, pp. 341–347, Jan./Feb. 2009, doi: 10.1109/TIA.2009.2009726.

[16] A. P. Manjunatha, P. Korba, and V. Stauch, "Integration of large battery storage system into distribution grid with renewable generation," in *Proc. IEEE Grenoble Conf.*, Grenoble, France, Jun. 2013, pp. 1–6.

[17] D. I. Doukas, P. Bakas, A. Marinopoulos, and H. Kim, "Energy storage integration into grid connected utility-scale photovoltaic (PV) systems," in *Proc. IEEE Grenoble Conf.*, Grenoble, France, Jun. 2013, pp. 1–6.

[18] M. Lippert, C. Jeuffrain, S. Lascaud, and P. Rioual, "Making the sun reliable with Li-ion energy storage: Solar PV energy management for large PV power plants on isolated islands," in *Proc. 5th World Conf. Photovoltaic Energy Convers.*, Valencia, Spain, Sep. 2010, pp. 3812–3820.

[19] L. Gong, Y. Fu, and Z. Li, "Integrated planning of BEV public fast-charging stations," *Electr. J.*, vol. 29, pp. 62–77, Dec. 2016, doi: 10.1016/j.tej.2016.11.010.

[20] D. Gkatzoflias, Y. Drossinos, A. Zubaryeva, P. Zambelli, P. Dilara, and C. Thiel, "Optimal allocation of electric vehicle charging infrastructure in cities and regions," Joint Res. Center, Ispra, Italy, Tech. Rep. EUR 27894 EN, 2016.

[21] D. Efthymiou, K. Chrysostomou, M. Morfoulaki, and G. Aifantopoulou, "Electric vehicles charging infrastructure location: A genetic algorithm approach," *Eur. Transp. Res. Rev.*, vol. 9, no. 2, pp. 1–9, Jun. 2017, doi: 10.1007/s12544-017-0239-7.

[22] Y. A. Alhazmi, H. A. Mostafa, and M. M. A. Salama, "Optimal allocation for electric vehicle charging stations using trip success ratio," *Int. J. Elect. Power Energy Syst.*, vol. 74, pp. 173–180, Jan. 2019, doi: 10.1016/j.ijepes.2017.03.009.

[23] C. Csiszár, B. Csonka, D. Földes, E. Wirth, and T. Lovas, "Urban public charging station locating method for electric vehicles based on land use approach," *J. Transp. Geogr.*, vol. 74, pp. 173–180, Jan. 2019, doi: 10.1016/j.jtrangeo.2018.11.016.

[24] M. Erbaş, M. Kabak, E. Özceylan, and C. Çetinkaya, "Optimal siting of electric vehicle charging stations: A GIS-based fuzzy multi-criteria decision analysis," *Energy*, vol. 163, pp. 1017–1031, Nov. 2018.

[25] L. J. Segerlind, *Applied Finite Element Analysis*. Weinheim, Germany: Wiley, 1979, pp. 1–422.

[26] D. L. Logan, *A First Course in the Finite Element Method*. Mason, OH, USA: Cengage Learning, 2011, pp. 1–992.

[27] A. Boglietti, A. Cavagnino, D. Staton, M. Shanel, M. Mueller, and C. Mejuto, "Evolution and modern approaches for thermal analysis of electrical machines," *IEEE Trans. Ind. Electron.*, vol. 56, no. 3, pp. 871–882, Mar. 2009, doi: 10.1109/TIE.2008.2011622.

[28] A. Soualmi, F. Zidat, P. Lombard, and N. Mokhtari, "Thermal study comparison of permanent magnets machines using finite element method (FEM) electric vehicles application," in *Proc. 21st Int. Conf. Electr. Mach. Syst. (ICEMS)*, Jeju, South Korea, Oct. 2018, pp. 59–64, doi: 10.23919/ICEMS.2018.8549302.

[29] *ArcGIS*. Accessed: Apr. 10, 2020. [Online]. Available: https://en.wikipedia.org/wiki/ArcGIS

[30] L. Yu, D. Kong, X. Shao, and X. Yan, "A path planning and navigation control system design for driverless electric bus," *IEEE Access*, vol. 6, pp. 53960–53975, 2018.

[31] M. Ma, Y. Wu, N. Guo, L. Chen, Q. Gong, and J. Li, "A parallel processing model for accelerating high-resolution geo-spatial accessibility analysis," *IEEE Access*, vol. 6, pp. 52936–52952, 2018.

[32] *Autorita di Regolazione per Energia Reti e Ambiente*. Accessed: Apr. 10, 2020. [Online]. Available: https://www.arera.it/

[33] ENERDATA. (2018). *Energy Efficiency Trends in Buildings Policy Brief*. Accessed: Apr. 10, 2020. [Online]. Available: https://www.odyssee-mure.eu/publications/policy-brief/buildings-energy-efficiency-trends.pdf

[34] *Energy Use in Buildings*. Accessed: Apr. 10, 2020. [Online]. Available: https://ec.europa.eu/

[35] *Nuclei di Identità Locale*. Accessed: Apr. 10, 2020. [Online]. Available: https://geoportale.comune.milano.it/

[36] *Energy Consumption in the United States*. Accessed: Apr. 10, 2020. [Online]. Available: https://www.worlddata.info/

[37] *Population by Neighborhood in Boston*. Accessed: Apr. 10, 2020. [Online]. Available: https://statisticalatlas.com/

MORRIS BRENNA (Member, IEEE) received the M.S. degree in electrical engineering from the Politecnico di Milano, Italy, in 1999, and the Ph.D. degree, in 2003. He is currently an Associate Professor with the Department of Energy, Politecnico di Milano. His current research interests include power electronics, distributed generation, electromagnetic compatibility, and electric traction systems. He is a member of the Italian Electrical Association (AEIT) and the CIFI (Italian Group of Engineering about Railways).

GEORGE CRISTIAN LAZAROIU (Senior Member, IEEE) received the B.Sc. and M.Sc. degrees from the Department of Electrical Engineering, University POLITEHNICA of Bucharest, Bucharest, Romania, in 2002 and 2003, respectively, and the Ph.D. degree in electrical engineering from the Politecnico di Milano, Italy, in 2006. He is currently an Associate Professor with the Department of Power Systems, University POLITEHNICA of Bucharest. His research interests include renewable energy sources, power quality, power electronics, and optimization. He was a co-editor of *Power Engineering: Advances and Challenges Part A: Thermal, Hydro and Nuclear Power* and *Power Engineering: Advances and Challenges Part B: Electrical Power* (CRC Press Taylor and Francis Group, Boca Raton, FL, USA, 2018). He is a member of the IEEE 1453 Flicker Task Force, the IEEE PES/IAS/IES, JWG C4.24/CIRED Power Quality, and EMC issues associated with future electricity networks. He was the General Co-Chair of the IEEE 16th International Conference on Harmonics and Quality of Power (ICHQP 2014) and the 2019 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe). He is the Editor-in-Chief of the *International Journal of Energy and Environmental Engineering* (IJEEE).

MARIACRISTINA ROSCIA (Member, IEEE) received the degree in electrical engineering and the Ph.D. degree from the University of Naples Federico II, in 1999 and 2004, respectively. Since 2019, she has been an Associate Professor for the courses of electrical systems and smart home into smart city at the University of Bergamo. She was an Adjunct Professor with the Politecnico di Milano, from 2004 to 2015, the Automation of Transport Systems Course, from 2003 to 2004, and the Electric Transport Systems I Course. Her main research interests include electrical systems for transport and smart grids in the presence of distributed generation, especially from renewable sources, for the control and management of energy flows between the grids, smart home, and building (smart appliances). Her research activity has also found development and implementation in practical applications both in the implementation of pilot projects related to the creation of a smart city and the drafting of the action plan for sustainable efficiency (SEAP) of the European Commission, for the municipality of Naples, both in participating in the CDP (formerly the Carbon Disclosure Project) of the European Commission, a global platform for cities to measure, manage and disseminate their environmental data, for risk management, promote dissemination, insights, and actions towards a sustainable economy.

SOHEIL SAADATMANDI received the B.Sc. degree in electrical and electronics engineering from the Shahid Bahonar University of Kerman, Kerman, Iran, in 2014, and the M.Sc. degree in electrical engineering from the Politecnico di Milano, Milan, Italy, in 2018. He is currently a Research Assistant with the University of Bergamo. His research interests include smart energy systems, smart grids, and transportation electrification.