Agent-based Modelling to Evaluate the Impact of Plug-in Electric Vehicles on Distribution Systems

Michele Falco, Francesco Arrigo, Andrea Mazza, Ettore Bompard, Gianfranco Chicco
Dipartimento Energia "Galileo Ferraris"
Politecnico di Torino
Torino, Italy
{francesco.arrigo, andrea.mazza, ettore.bompard, gianfranco.chicco}@polito.it

***Abstract*— Massive adoption of Electric Vehicles (EVs) could create issues in the electrical distribution system operation, in terms of currents and voltages. The analysis of the EV impact is a complex task, as the EVs loads are variable in space and time depending on people routines, traffic conditions and recharge strategies. In this paper, an agent-based tool is presented to study the evolution of a city system with different EV penetrations. The system representation is divided into a static part referring to the environment, and a dynamic part where EV agents interact with each other. This agent-based framework concurs in constructing a comprehensive bottom up approach to study the EV impacts.**

Keywords— electric vehicle, distribution network, agent-based system, driver, road traffic.

I. Introduction

A. Motivation

De-carbonization of the transport sector is a top priority of the European policy, to reduce the emission of greenhouse gases and improve air quality [1]. For this reason, the European Commission has launched an observatory for electrical mobility, denoted as EAFO (European Alternative Fuels Observatory) [2]. Among the various alternative technologies, Electric Vehicles (EVs) are considered one of the most prominent and efficient solutions as they tackle both local and global pollution. The EV diffusion is causing the installation of new power charging infrastructure, whose numbers are rising in the whole Europe, especially for chargers less than 22 kW. These chargers could have a great impact on electrical distribution networks, and need to be carefully evaluated considering the drivers' realistic behaviour, the road and electrical network real-time loading status, and the topological characteristics and constraints. Carrying out a realistic preliminary analysis on EV impact is fundamental to plan and optimize the use of chargers and incentivize the use of Vehicle-to-Grid (V2G) technology [3].

B. Literature review

Extensive research is dedicated to the impact of EVs on the distribution grid and the possibility of performing economic optimization and/or ancillary services like frequency regulation, load levelling, loss minimization, etc. Nevertheless, the approaches used to model drivers' behaviour are often insufficient. In fact, various approaches do not consider realistic driver behaviour and road/electric network presence and real time status. For example, in works like [4] and [5] simple rules in order to build the EV driving pattern and energy requirements are used. In [4] it is assumed that all vehicles are charged for 4 hours at 1.5 kW at specific hours and travel for a daily distance of 40 km. Small delays are randomly assigned to introduce some variability. In [5], while an agent-based approach is used to create new EV users as explained later, the rules to describe the EV use patterns are limited to the choice of 2 or 3 random actions with time range decided by an extraction from a normal distribution. Real data and probability distributions functions (for example, the Lognormal distribution) to decide the travel characteristics are also used in [6]-[10]. For example in [10], real EV data from a demonstrator were used to characterize the normal distributions used to set trip start time, duration and energy use, without considering any correlation between the three parameters. Multi-modal probability distributions are determined in [11] from real data. Generally speaking, the approaches presented in previous papers are essentially aimed to reproduce a single trip pattern, without creating consistent travel schedule structure for the drivers, neglecting the expected correlation between travel parameters (distance, start time, length, etc.). Moreover, they over-simplify spatial and temporal details [12].

In order to gain more realistic behavior, real data from surveys or from on-field measurement campaigns were exploited to generate archetypal driving patterns [13] or by using real car diaries coming from non-electric vehicles or already existing EV deployed in some countries [14][15]. While in this case more consistency can be obtained, these studies are based on an exogenous set of data to characterize trips, with the underlying assumption that the EV driving patterns will be similar even in the case of massive deployment, which cannot be the case. More importantly, the model variability is pretty much fixed and driving patterns will not change due to policy or other constraints. To obtain a better simulation framework, there is the need to step from a top-down approach, where single driving patterns depend on simple rules or real data, to a bottom-up approach in which EV driving requirements are computed explicitly starting from the single consistent (both spatially and temporally) activities the agent could perform. Moreover, it is also important to model the road network to explicitly compute the EV energy losses. In [5][16][17] some of these challenges are addressed. In [5] an attempt to use real EV agents is made, where eight traffic/electric nodes grids are integrated among each other, and agents drive in random ways towards random directions, but taking into account their need to recharge and their status as traffic-unaware or traffic-aware drivers. The road network and traffic models are accurate enough to capture the possible vehicle congestion and battery losses, and are based on graph theory and the Dijkstra's algorithm [18]. In [17], even if typical drivers' patterns and distribution were used, the EV fleet use is coordinated to decrease congestion in road network and at the same time minimize operating cost of the electric grid. Finally, in [16], Matsim (a tool for agent based activity-based transport models), and PMPSS (a power system tool) were integrated to study the impact of new price policy in EV drivers. The goal is to optimize the agent daily plan of activities considering different charging cost and traffic congestions. Agents have consistent behaviour and they can even respond to changes in pricing strategies trying to maximize their utility.

It is clear from these previous studies that a possibility to gain more realism and insights in simulating and studying the impact of EV could come from considering EV drivers as agents, whose interaction in predefined and common environments (for example road network or electric grid) influence the global results and the system response. The most suited theoretical framework to approach the problem is therefore the agent-based simulation [19], which provides a systematic framework to approach the study of complex systems. Under this framework, the system is divided into five fundamental components:

- *Agents*: a self-contained program capable of controlling the decision making of each individual, and able to influence or be influenced by the environment.
- *Environment*: It represents the space and dimensions where agents move and interact.
- *Object*: populates the environment along with agents.
- *Relationship*: links agents and objects.
- *Operations*: allows agents to perceive and transform objects.

C. Original contribution

This paper proposes the foundation to build a truly agent- and activity-based model to describe and study the interaction and impact that EV drivers have on the electric distribution grid. In the framework described, new agents' parameters and methods and new environment objects and characteristics could be easily integrated, as the framework expands considering also economical and technical optimizations such as the ones researched in the previously cited studies. For this purpose, a three-layer framework has been built (Figure 1) considering AGENTS, OBJECTS and ENVIRONMENTS. A time loop routine has been programmed to keep consistency of the time line.

D. Paper organization

In Section II the three layers are explained. In Section III the data and preliminary analysis are presented, and the simulation proposed is illustrated. In Section IV the main results are shown to validate the approach. Section V concludes the paper.

II. Models of the Layers

A. Environment Layer

The environment that the agents populate is composed of three networks, namely, the electrical network, the road network, and the city structure (Figure 2). The description is divided between the *static* part, which deals with the structural representation of the network, and the *dynamic* part, which gathers the methods to evaluate the time-dependent impact of the agents moving in the environment (Figure 3).

1) Static part

The distribution network is generally weakly meshed, usually operated radially. Each node is therefore connected with the HV/MV electric substation through a unique and re-constructible path. In this study, two power grids are combined and used as inputs to build the city layer. This is because, due to the difficulty to obtain real electricity distribution grid models, it is quite usual to use reference ideal network constructed to guarantee realistic results [21]. The generic electric node k is characterized by a certain

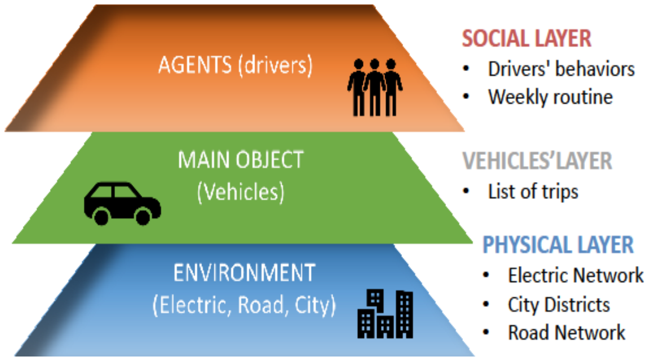

Figure 1: Layer structure of the work.

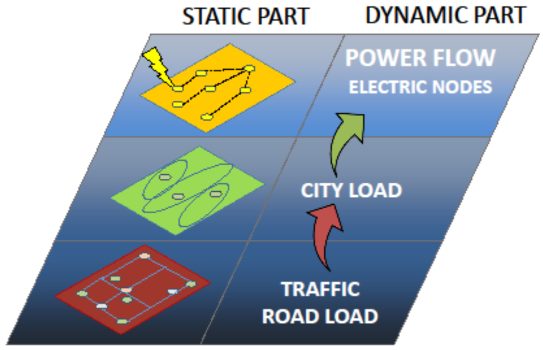

Figure 2. Environment Layer details

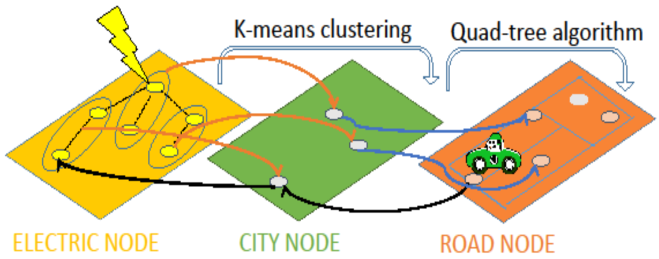

Figure 3: Main steps to create the System environment

nominal active power $P_{nom}^{(k)}$ and reactive power $Q_{nom}^{(k)}$ which are the sum of different nominal power components corresponding to different human activities. These components are related to residential, industrial, commercial, tertiary and agriculture areas. Starting from this description, the city layer is built by using k-means clustering to gather the electrical nodes into a certain number of groups, which represent the city districts and, like electrical nodes, can be described in terms of nominal power and geographical position. The nominal power characteristics of the nodes will be very important for defining the activity of the agents, as seen in the next section. In general, based on the characteristics of each city node, an agent has more or less probability of interaction. While the implementation of city nodes has apparently little significance in this study, from a conceptual point of view the presence of this mid-layer between road network and city layer is compulsory and opens the possibility of more precise sociological and urban descriptions. Note that if in the k-means clustering the number of groups is chosen equal to the number of electrical nodes, the electrical nodes will be equal to the city districts. Finally, the road network is obtained starting from the city districts. Since the starting point is a combination of two reference electric grids, a customized road network was built.

Taking inspiration from [22], a quadratic graph was built around city nodes. The algorithm, called "Quadratic-tree algorithm" inputs the city nodes and provides as output the branches and road nodes. The algorithm is implemented such that areas with more city nodes will be surrounded by a bigger number of roads, as expected in a typical city area. Every branch is then described by three parameters referring to the traffic (see the top diagram in Figure 4):

- u_f [km/h]: average travel speed of the vehicle without traffic (called *free mean velocity*);
- k_c [veh/km]: minimum vehicle density to make the vehicles starting to decrease velocity due to traffic;
- k_j [veh/km]: road vehicle density that creates road congestion and stops the traffic.

The nodes represent the entry/exit points for the vehicles driven by the agents, and the branches represent the roads of the network.

2) Dynamic part

Entire days are simulated with a fine temporal distribution (1 minute). For every time step a power flow is calculated, by means of the Backward-Forward Sweep method. The voltages at every node and currents in every branch are computed starting from the voltage at the MV side of the HV/MV substation (slack node), the loads connected to the networks (among which there are also the EVs), and the network impedances. Voltages, currents and losses can be computed as outputs. In general, for every branch a maximum temperature can be tolerated by the conductor insulation. The maximum temperature imposes a limit on the maximum current a conductor can withstand, taking into account the ambient temperature, the joule losses, and the heat transfer processes.

The city layer does not possess (in the present version) an independent dynamic. It basically serves to construct a consistent road network. The road network is indeed important, being where the interactions of agents (making use of the vehicles objects) work towards the creation of the traffic. The traffic dynamics are modelled following a microscopic traffic pattern method [23] able to trace the vehicle position at every time step. The goal is to compute the instantaneous vehicle density q in every road and subsequently the vector $\boldsymbol{u}_i$ for every vehicle i containing all the average speeds of cars (Figure 4). With these parameters it is possible to compute the energy consumption of the EV based on an aerodynamic model of the vehicle itself taken from [5]. The traffic method starts from a list of vehicles that enter the road network graph and update the vehicles position and velocity in every road based on the lines defined in Figure 4. The possibility of vehicles finishing their journey entering a new road before the one-minute time step is also taken into account.

B. Agent and Objects Layer

The agents of our simulation are the *drivers*. Each driver is distinguished in a proper and independent way, and is described by a unique set of parameters with which the weekly routine of the driver itself is built, as a collection of journeys detailed in time and space that the driver aims to fulfill in order to perform some activities. The following six activities have been defined:

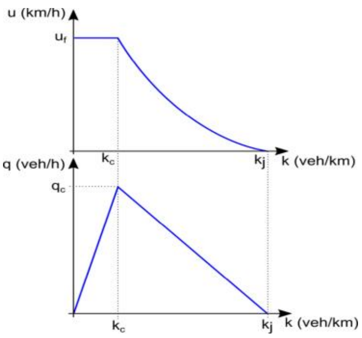

Figure 4. Parameters referring to the traffic model

1. HOME: the agent is at home
2. WORK: the agent is at work.
3. LEISURE: the agent is outside home to perform some social or spare time activity.
4. ERRAND: the agent is not home for mandatory activity (buying food, pharmacy, bureaucracy, doctor, etc.)
5. OUT: the agent is outside the city/simulated environment (for work, holidays, etc.).
6. ILL: the agent is ill at home (while in normal conditions should be outside home).

Manifold characteristics define a unique agent:

1. NODE HOME: it is the city node/district where the agent lives. The assignment of this node is not random, but is obtained by an extraction from the Cumulative Distribution Function (CDF) of residential power P_{res}. So nodes with higher P_{res} installed have bigger probability to be chosen as HOME of the agent.
2. NODE WORK: this is composed of a principal node, which is the primary working environment, extracted in the same way as NODE HOME considering the sum of industrial, commercial, tertiary and agricultural powers of city nodes (through a sum on electrical nodes). A second node is extracted to represent a secondary working place which could be used by some agents in some special days.
3. WORK TYPE: depending on the node where the driver works, the work sector is extracted from the cumulative work power installed. Then, by using real or reasonable statistics, the type of employment is chosen between full time worker, part time worker, and freelance.
4. SEDENTARINESS: the nodes where agents go to perform non-working actions are actually not fixed, and are extracted trip by trip according to a CDF influenced by three parameters: (a) the distance of the agent from the surrounding nodes; (b) the level of installed commercial power (for ERRANDS), and the tertiary installed power (for LEISURE activities); (c) the sedentary level of the agent, which is the tendency of performing LEISURE and ERRANDS activities far outside home. A high level of sedentariness means that the agent tends to use the car even to reach near places (from 500 meter to 1.5 km, for shorter paths the agent always goes on foot: for longer paths the agent always uses the car) and it will anyway try to perform activities near home. The sedentary parameter introduces an exponential condition on the previously computed CDF.
5. FAMILY: this binary flag [0, 1] indicates if a person has a family or is single, since this greatly influences agent activities like ERRAND and LEISURE. The activities at

this level, using the first 5 parameters, are divided on an hourly basis. To obtain sub-hourly and minute division the parameter ACCURACY and DELAY are used.

6. EV USER: Every agent is assigned a vehicle object to perform its activities inside the city. The possibilities are two: private non-electric car, or car-sharing EV. In the latter case, this means that the driver does not own an EV, but makes use of whatever electric vehicle is available. The EV car makes uses of an aerodynamic model to convert the average speed velocity of the power into energy consumed by the EV.
7. ACCURACY&DELAY: Normally the agent will start its journey considering the hour at which it should arrive at destination, subtracting the ideal time of travel (computed without considering the traffic). The true starting time is computed considering other two time steps: (a) a first extraction (ACCURACY) from a normal distribution with expected value of zero and variance 30 minutes to take into account the possible delay/advance of the agent due to the activity starting time differing from an hourly schedule, (b) a second component (DELAY) which add a stochastic delay (positive or negative) due to driver faults.
8. EVENTS: override all the other activities and could last a DAY or a WEEK. In particular ILL or OUT could be extracted and last one day or one week or a weekend (in case of OUT for short holidays).

In order to create an agent's routine, the actions are divided in three categories: *fixed actions*, *semi-aleatory actions* and *aleatory actions*. Depending mainly on the type of WORK and FAMILY status, every driver has a certain type of fixed actions (for example WORK) in predetermined days and hours of the week. Semi-aleatory actions are instead usually LEISURE or ERRAND activities, for which there is a fixed number of hours for the agents to fulfil, but the choice of the specific days and time when it is fulfilled depends on random extractions. A typical example could be the agent with family which two or more times a week will take the children to school before going to work. Finally, aleatory actions have to respect some basic constraints (as maximum number of times and hours) and depend on agent characteristics, but are quite random in nature and give the agent a more realistic routine. An example to explain the semi-aleatory activities is shown in **Error! Not a valid bookmark self-reference.** These activities provide a list of vehicle trips to perform with starting times and trip details (see Figure 5a). Finally the system dynamics are simulated. Figure 5b shows the main steps of the tool. In "load variable" the databases and the parameters to define the simulations are loaded. "Scenario initialization" deals with initialization" with the creation of the vehicle trip lists. "Minimal planning" is a particular initialization procedure to choose the number and initial position of EV such that the number is neither too small nor too big with respect to EV users, and positions are consistent with the request of the EV users. Finally in "Temporal loop" the dynamics of the networks are solved.

III. CASE STUDY

The electric grid used is the reference network developed by JRC [24], with semi-urban and rural grids to represent a rural city environment with more than 300 nodes.

TABLE I. ACRONYMS AND ACTIONS FOR THE AGENTS

Acronym	Meaning	Start hour	End hour	Prob.	Action
NFWD	No Family Working Days	18	20	0.5	ERRANDS
NFWE	No Family Week End	20	23	0.6	LEISURE
WFWD	With Family Working Days	18	19	0.4	ERRANDS
WFWE	With Family Week End	10	13	0.45	LEISURE

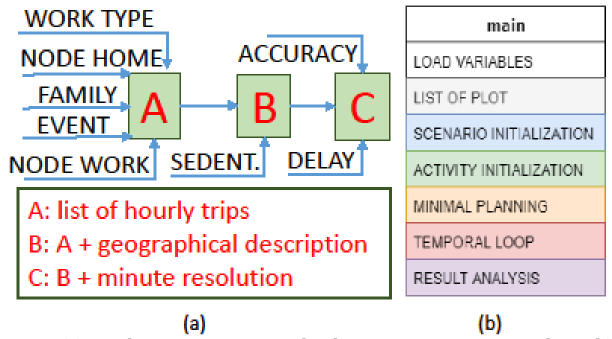

Figure 5: (a) A scheme summarizing the driver trip creation procedure. (b) Main Temporal loop steps of the simulation

The nominal installed power in every node is divided between the relevant city sectors (industrial, residential etc.). Typical power profiles time series are also provided to run the power flow. The road network was created following the procedure explained in Section II.A, while the road parameters were extracted from a normal distribution with an average value and standard deviation shown in Table II.

Four types of roads were considered:

1. *Backbone:* bigger roads that cross the city in length customized and chosen by the software user.
2. *Urban*: shortest branches in the center of the city, characterized by medium values of free-mean velocities.
3. *Semi urban:* extra-urban roads, characterized by longer lengths and higher speed limits.
4. *Rural:* most outlying streets, with limited width and difficult to travel in the presence of traffic.
5. *Bad road:* a fifth type of road used to create a different road graph and compare results between two different road conditions.

The three networks (electrical, city and road) are shown in Figure 6. To define the Type of work of the agents and their family conditions, and make other reasonable assumptions, data from the Italian institute of statistics and city municipalities were used [25][26].

A. Parametric Analysis proposed

A considerable number of simulations were performed by changing the most meaningful parameters. In these scenarios, the EVs recharge with a dumb strategy, which means that they are recharged at a fixed power as soon as they connect to the grid. The parametric analysis is summarized in Table III. GOOD road makes use of the first four road types presented in Table II, while BAD roads create the road graph with only the fifth road type. EV users% represent the percentage of drivers making use of the EV car sharing.

TABLE II. ROAD CHARACTERISTICS

Road Type	u_f	k_c	k_J	3σ
Backbone	25	8	20	1
Urban	10	4	10	2
Semi-urban	20	6	12	2
Rural	15	3	15	15
Bad road	10	3	9	1

TABLE III. PARAMETERS USED IN PARAMETRIC ANALYSIS

Num. drivers	EV users%	Road type	Power [kW]
1000	10	GOOD	3
5000	30	BAD	6
10000	60		11
20000			

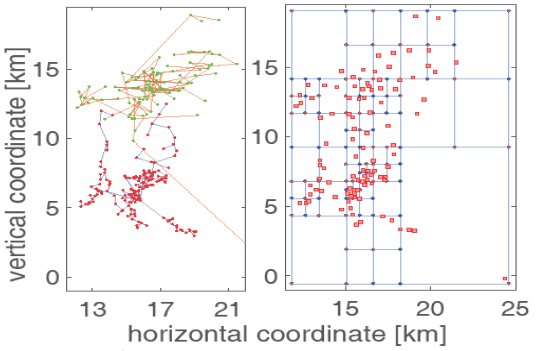

Figure 6: on the left the original electrical networks, on the right the quadratic road network (in blue) with city districts (in red).

Power refers to the power rate at which EVs are recharged once they reach the EV car parking (by hypothesis there is always the possibility to park). All the possible combinations of the parameters were simulated, for a total of 72 simulations (every simulations consists of 7 simulated days). All the simulations were performed in Matlab® in commercial available Desktop computers.

IV. RESULTS

A sample of the results that can be obtained from the proposed framework is shown below. In general, the agents tend to live in the city, while particular rural nodes with very high industrial power attract many workers. Figure 7 shows the nodes where people live and work for the case of 15000 people. Figure 8 shows the cumulative presence of vehicles in the case of 20000 drivers. The model is able to grasp the morning and night peak of working days, while the travels along the day are rather variable, less smooth than expected from typical traffic curves [27]. This suggest that new kind of work types could populate the model, such as retired or unemployed people, people who uses the car to work and perform multiple trips a day in not standard hours, and so forth. Moreover a better use of ACCURACY and DELAY parameters can help smoothing the traffic curve. The road characteristics influence the time spent by drivers in the grid and the energy spent by EVs. Figure 9 shows the energy discharged by all the EVs in the whole week. The energy discharged is higher when BAD road characteristics are used due to bigger traffic problems and more time spent by the drivers on the road.

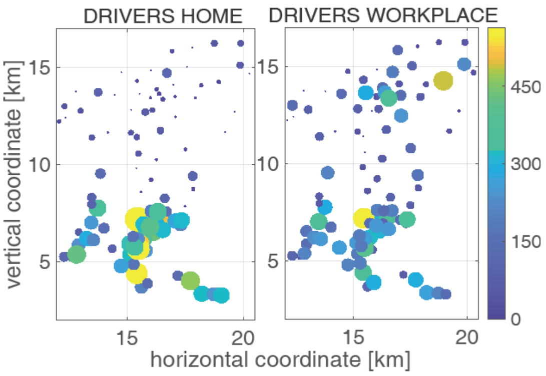

Figure 7: Nodes where drivers live/work. The size of the bubble is proportional to the number of driver agents.

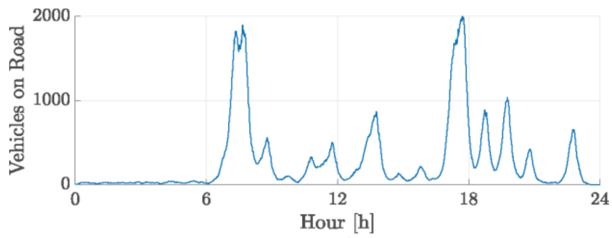

Figure 8: Vehicles presence for one working day

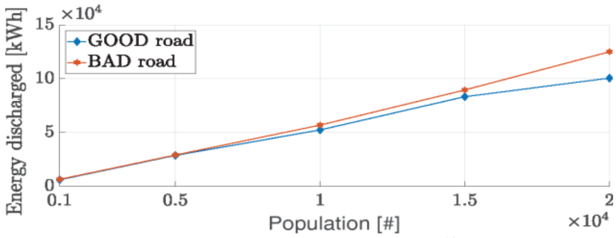

Figure 9: total Energy spent by EV considering different populations considering good and bad road characteristics

For what concerns the electric network, Figure 11 shows the time-spatial distribution of voltages (computed as $\Delta V_{i,t} = V_{i,t} - V_{nom}$ for every node i and time step t) for the rural network for one of the days in the case of 20000 people with a recharge power for EVs of 11 kW. The ΔV is caused both by the loads and the EVs recharging. By analyzing all the time-spatial series coming from the simulations, it is possible to evaluate that:

- the rural network, due to the resistive nature of the line impedances and less nominal power, tends to be more affected by EV introduction, both in terms of voltages and currents even if the presence of EVs is smaller. The semi-urban network is already characterized by a bigger installed load capacity, which makes more difficult for EVs to affect the grid. Figure 11 shows the maximum ΔV caused by EVs. With 20000 people and 11 kW used for recharging, the voltage changes more than 3.5% in the rural network and slightly less than 1% in the semi-urban network.
- The current in the branches almost reaches the thermal limits in the case with 20000 drivers, 60% EV adoption in the rural network (Figure 12) due to the EV recharging in the morning. In general, EVs could increase the $\frac{I_{BRANCH}}{I_{LIM}}$ ratio more than 20% in both grids.

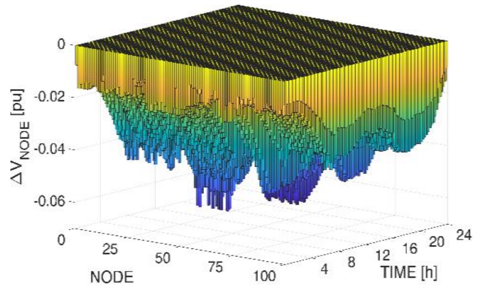

Figure 10: spatio-temporal distribution of Voltages in the rural network

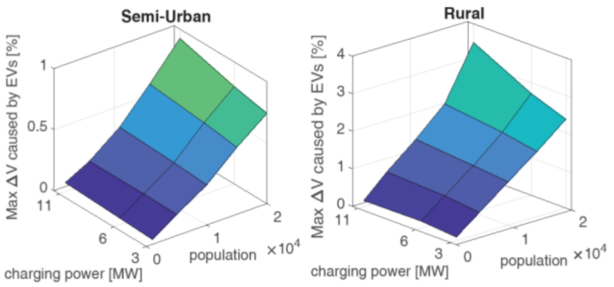

Figure 11: $\Delta V_{\max}$ caused by EVs in the grid

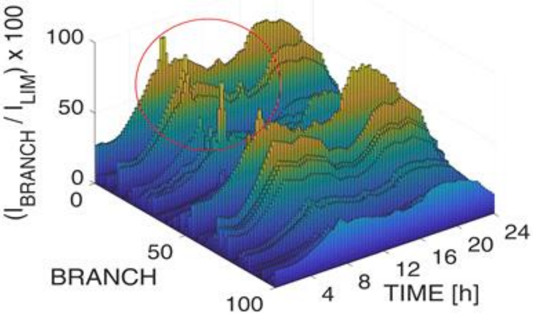

Figure 12: branch loading spatio-temporal distribution in rural network

V. CONCLUSION

This paper presented a new agent-based model to evaluate the impact of EVs on the electric grid and road network. The characteristics of each agent (driver) make the agent unique, with its own trip list to fulfill. The drivers interact in the road network and electric grid, by creating traffic and influencing grid voltages and currents. The framework is able to reconstruct sound road network and city districts and moreover handle the time loop analysis and provide realistic impact results. Possible expansions can be built, in particular to improve the agent layer, by adding new work type and parameters (such as INCOME) and flexibility to different policies, to construct load curves starting from the agent behavior in a similar fashion to what done with their trip behavior, and to construct an aggregator for car sharing, with technical-economic optimization able to minimize the cost for acquiring energy and deploy smart charging techniques.

VI. REFERENCES

[1] European Commission, EU climate action, Policy, 2018, https://ec.europa.eu/clima/citizens/eu.

[2] The European Commission initiative to provide alternative fuels statistics and information (electricity, hydrogen, natural gas, LPG), 2018, http://www.eafo.eu/.

[3] B.K. Sovacool, R.F. Hirsh, Beyond batteries: An examination of the benefits and barriers to plug-in hybrid electric vehicles (PHEVs) and a vehicle-to-grid (V2G) transition. *Energy Policy* 37(3), 1095-1103, 2009.

[4] J. Mullan, D. Harries, T. Bräunl, S. Whitely, Modelling the impacts of electric vehicle recharging on the Western Australian electricity supply system, *Energy policy*, 39(7), 4349-4359, 2011.

[5] C. Marmaras, E. Xydas, L. Cipcigan, Simulation of electric vehicle driver behaviour in road transport and electric power networks, *Transportation Research Part C: Emerging Technologies*, 80, 239-256, 2017.

[6] N. Neyestani, M.Yazdani Damavandi, M. Shafie-Khah, J. Contreras, J.P.S. Catalão, Allocation of plug-in vehicles' parking lots in distribution systems considering network-constrained objectives, *IEEE Transactions on Power Systems*, 30(5), 2643-2656, 2015.

[7] A. Zakariazadeh, S. Jadid, P. Siano, Integrated operation of electric vehicles and renewable generation in a smart distribution system, *Energy Conversion and Management* 89, 99-110, 2015.

[8] H. Zhang, Z. Hu, Z. Xu, Y. Song, Evaluation of achievable vehicle-to-grid capacity using aggregate PEV model, *IEEE Transactions on Power Systems*, 32(1), 784-794, 2017.

[9] D. Dallinger, D. Krampe, M. Wietschel, Vehicle-to-grid regulation reserves based on a dynamic simulation of mobility behavior, *IEEE Transactions on Smart Grid*, 2(2), 302-313, 2011.

[10] N. DeForest, J.S. MacDonald, D.R. Black, Day ahead optimization of an electric vehicle fleet providing ancillary services in the Los Angeles Air Force Base vehicle-to-grid demonstration, *Applied energy*, 210, 987-1001, 2018.

[11] M.G. Flammini, G. Prettico, A. Julea, G. Fulli, A. Mazza, G. Chicco, Statistical Characterisation of the Real Transaction Data Gathered from Electric Vehicle Charging Stations, *Electric Power Systems Research*, 166, 136-150, 2019.

[12] N. Daina, A. Sivakumar, J.W. Polak, Modelling electric vehicles use: a survey on the methods, *Renewable and Sustainable Energy Reviews*, 68, 447-460, 2017.

[13] A. Zakariazadeh, S. Jadid, P. Siano, Multi-objective scheduling of electric vehicles in smart distribution system, *Energy Conversion and Management*, 79, 43-53, 2014.

[14] J. Axsen, K.S. Kurani, Who can recharge a plug-in electric vehicle at home?, *Transportation Research Part D: Transport and Environment*, 17(5), 349-353, 2012.

[15] J.C. Kelly, J.S. MacDonald, G.A. Keoleian, Time-dependent plug-in hybrid electric vehicle charging based on national driving patterns and demographics, *Applied Energy*, 94, 395-405, 2012.

[16] R.A. Waraich, M.D. Galus, C. Dobler, M. Balmer, G. Andersson, K.W. Axhausen, Plug-in hybrid electric vehicles and smart grids: Investigations based on a microsimulation, *Transportation Research Part C: Emerging Technologies*, 28, 74-86, 2013.

[17] Y. Sun, Z. Chen, Z. Li, W. Tian, M. Shahidehpour, EV charging schedule in coupled constrained networks of transportation and power system, *IEEE Transactions on Smart Grid*, 2018.

[18] R. Rodríguez-Puente, M.S. Lazo-Cortés, Algorithm for shortest path search in Geographic Information Systems by using reduced graphs, *SpringerPlus*, 2(1), 291, 2013.

[19] C.M. Macal, M.J. North, Agent-based modeling and simulation, *Proc. 2009 IEEE Winter Simul. Conf. (WSC)*, December 2009, pp. 86-98.

[20] J. Ferber, O. Gutknecht, A meta-model for the analysis and design of organizations in multi-agent systems, *Proc. IEEE International Conference on Multi Agent Systems*, July 1998, pp. 128-135.

[21] M.G. Flammini, G. Fulli, G. Prettico, E. Bompard, G. Chicco, Interaction of Consumers, Photovoltaic Systems and Electric Vehicle Energy Demand in a Reference Network Model, *Proc. International Conference of Electrical and Electronic Technologies for Automotive*, Torino, Italy, 15-16 June 2017.

[22] D. Basu, S. Sengupta, A novel quad tree based data clustering technique. *Proc. IEEE International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN)*, November 2015, pp. 157-162.

[23] S. Maerivoet, B. De Moor, Cellular automata models of road traffic. *Physics reports*, 419(1), 1-64, 2005.

[24] G. Prettico, F. Gangale, A.M. Mengolini, A. Lucas, G. Fulli, *Distribution System Operators Observatory: From European Electricity Distribution Systems to Representative Distribution Networks*, Publications Office of the European Union, 2016.

[25] Italian Institute of Statistics, *Lavoro e retribuzioni*, *Occupazioni dipendenti e retribuzione* (in Italian), 2017, http: //dati.istat.it/.

[26] Statistiche veicoli (in Italian), http://www.comuni-italiani.it

[27] Open Mobility data of Turin, http://www.5t.torino.it/open-data/