Stochastic Petri Nets modelling, performances evaluation and simulation of one way electric cars- sharing systems

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Abstract. In recent years, Electric Car sharing (ECs) systems represent a green and innovative solution, positioning themselves as a real economic alternative to the private car. They are now present in many cities around the world (Paris, Berlin, Geneva, Rome, etc.). One-way ECs removes the constraint of returning the car to the origin station, and extending the use of the system. However this behavior usually leads to a situation for which some stations are full and other empty. Furthermore, cars are electric and a minimum charging time is required, which makes the system more constraint. In this paper, we address the issue of redistribution of electric cars to balance the network. We proposed a modelling, analysis and assessment of the system by using stochastic Petri Nets (PN) with variable arcs weight; dependent on the marking of network and discrete event simulation. Moreover, in this work we can determine and evaluate the performances of the system (determine the number of unserved users, estimate the relocation service launch moment…etc.) to respond to the largest number of requests. Our approach might helping to develop decision-making tool for analysis and performances optimization of ECs services.

Keywords: stochastic Petri Nets, Discrete event system, Electric Car-Sharing, Discrete event Simulation, Decision making.

1 Introduction

Environmental and sustainable transportation issues are today at the heart of scientific and sociological debates concerning the automobile. The electric mobility will significantly increase and become the unavoidable way for cities, particularly when combined with shared mobility. Many cities around the world are enthusiastic about Electric Car sharing. ECs-network is a set of stations, located at different places of the city, for example, residential areas, industrial zones, areas near to the stations, etc. A station includes a limited number of parking spaces. This system encourages consumers to return the EC as quickly as possible. In other words, this system is suitable for short duration's tours. There are two types of electric car sharing system today "one way" and "round trip", which can coexist together in the same urban context. We focus in this work on the model called "one-way". One-way systems permit users to rent Electric Car (EC) without having to return it at the departure station, unlike round-trip model. However, there are many challenges of electric cars sharing operators that may have a direct impact on the quality of service, the operational and economic viability of such systems. The crucial challenge is to ensure that Electric Cars are available for pick up and empty spots available for cars drop off at most stations. In a general way, the unbalance of the system can be ordered in two types: (a) temporary unbalance: In this case, we can have at a given moment in the day a set of unbalanced stations; but which can naturally return to a balance situation after certain time. (b) Persistent imbalance: In this case, the unbalance of the stations is not temporary and can extremely decrease the quality of service of the system if the rebalancing of the stations is not carried out by the operator. In order to minimize these two uncomfortable situation, the operators need to implement rebalancing service repositioning EC and parking spots among stations according the frequentation of stations.

In this paper, stochastic Petri nets and discrete event simulation are introduced as tools for modelling and structural analysis performances evaluation of ECs. The remainder of the paper is organized as follows. We present an overview on related work in the next section. Section 3 applies and discusses the proposed models based on the stochastic PN. Section 4 presents system behavior simulations under different scenarios and discusses the results. Finally, in Section 5 conclusions are presented.

2 Related works

Most of the studies related to ECs focus on methodologies extracting design guidelines or structural configurations that may help ECs operators to design their services. Two main approaches stand out in reading the recent publications:

Mathematical Optimization Techniques: ECs systems raise several decision-making and optimization issues such as the rebalancing of stations, the routing agent or truck problem for the redistribution of EC, as well as the problem of location of stations in city. From a certain point of view, these problems can be perceived as problems of the type operational research. In this category, linear programming techniques or more generally, mathematical models are used for the modelling and the resolution of these problems. Carlier (2016) address the optimal dimension of a one-way ECs system in a city using mathematical and time expanded graphs techniques with randomly generated demand data. Ait-Ouahmeda, Josselina, and Zhoua (2017) have suggested a linear programming model based on heuristic algorithms to obtain the optimal relocation team for one way ECs system, where the authors assume the balancing carried out by agents, while agents can take only fully charged cars. Clemente et al. (2013), have modelled ECs networks with incentive relocation strategies by using Petri nets and discrete event simulation on the UML formalism. Efthymiou et al. (2017) have presented a complete approach for the electric vehicle charging infrastructure location problem by using linear programming, multi-objective optimization and genetic algorithms. The decision concerning the truck fleet size for balancing, their location and capacity, are addressed by some authors, e.g. Hafez (1999), and Chauvet, Haouba, and Proth (2006), by using dynamic programming and metaheuristics. Other research studied the system in operation level, where they focuses on the relocation problem of EC systems as crucial problem. Many authors have considered this issue from different angles. Bruglieri, Alberto, and Luè (2014) proposed an approach to relocate vehicles by staffs taking into account the location and the capacity of station using linear programming. However, they do not specified which ECs should be relocated: charged at max or at medium of charging capacity. The challenge to design optimal fleet size of ECs rental is approached by various studies. Fanti, Mangini, and Pedroncelli (2016) propose a closed Petri nets model for solving the fleet-sizing problem applied to a network of three stations, without taking into consideration the relocation system.

Data collection and analysis techniques: The collection and predictive analysis of data on user mobility and / or the operation of ECs systems can play a key role in better design and effective management of this mode of urban transport. Indeed, this data can be useful before and after the system deployment. A strategic estimate of the number of ECs, stations and others is then possible before the deployment of the network. Operationally, use of the analysis of the history of the system's previous operation can allow, for example, prediction and thus system planning. Balac, Ciari, and Axhausen (2015, 2017) address the impact of parking spaces on the quality of service of car sharing by using the discrete event simulation-MATSim and a model developed by authors for round-trip car-sharing with real data for car sharing in Zurich. While, Kaspi et al. (2015) have addressed the management of car sharing service through parking reservation policies using mathematical models and discrete event simulation. Artificial neural network and big data receive attention in recent years to analyse, predict the demand of shared mobility systems (bike sharing, car sharing and ECs system). In this context, Zhu, Li, and Liu (2015) and Chen et al. (2017), have proposed method to estimate car-sharing/bike sharing demand based on deep learning and neural network approach and datasets. On other hand, there are some similarities between self-driving car and Automated Guided vehicle (AGV) used for transporting material in logistic areas, with respect to design, deadlock and optimization (Zhang et al. 2017). Karlqvist J., and L. A. Sundbeck (2016) have tried to combine some existing technologies of AGV to autonomous car transportation, in this context we aim to adapt some existing for decision-making solutions of AGV to electric self-driving car sharing in term of design, choice of alignment and of the battery charging level.

3 Stochastic Petri Nets Modelling of ECs

The stochastic Petri nets model developed take into account many decision parameters of system as station size, capacity, number of truck and influence the battery charging level on the behavior and dynamic of system. Due to the number of car to add or remove during the control of the station by truck, are according to the current number of available electric cars (EC) in the station. We introduced in the model new technique based on arcs variable weights according to the current marking of the places Pci (see relocation module).

The proposed model (see figure 2) based on periodical redistribution strategy of cars among stations, by trucks that are in charge of rebalancing. They move periodically according to a predetermined program (Δt) with stochastic duration of path according the traffic jam. These trucks move through the different stations of the system, and according to the needs of station, load or unload cars. In our model, we have based on the empty parking spaces Np and we set a re-balancing threshold Tsh, when the truck arrives in a station, it is in one of the following situations: the station is (or will be soon) empty (number of empty parking spaces is high Nep> Tsh); in this case the truck unloads cars in the station. The second situation is where the station is in congestion (number Nep is too low Nep < Tsh); in this case, the surplus cars are loaded into the truck. Finally, if the station contains an acceptable number of cars (Np = Tsh), it does not need to load or unload cars, and it can continue its journey. For clarity we developed stochastic PN model of 2 stations. Four modules are connected to build the model: (a) station subnet represents the charging processes, capacity of station and users request, (b) flux interstation represents dynamic of EC in city, (c) balancing module whose objective is to maintain the number of cars in each station at predetermined level, and (d) maintenance module represents the breakdown EC event and composed by two possibilities to charged car at max or just at threshold availability and transport it to stations by truck.

3.1 Description of station subnet:

This module takes into account important decision parameters of ECs, in particularly the charging battery level s and LC which represent the charging processes of station (see figure 3). As well the capacity of station Ci, is sum of number of empty parking spot (chargers) Nep, number of charged cars Ncd, number of current charging cars as well as number of available cars Nav as illustrated in equation followed.

$$C_{si} = \begin{cases} Number\ of\ empty\ parking\ spaces\ Nep + \\ Number\ of\ current\ charging\ cars\ Ncc + \\ Number\ of\ available\ cars\ in\ station\ Nav + \\ Number\ of\ charged\ cars\ in\ station\ Ncd \end{cases}$$

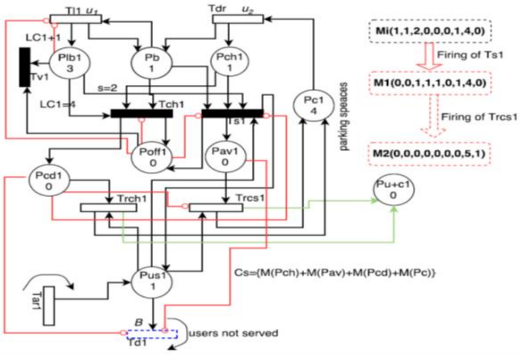

Fig. 1. Station subnet

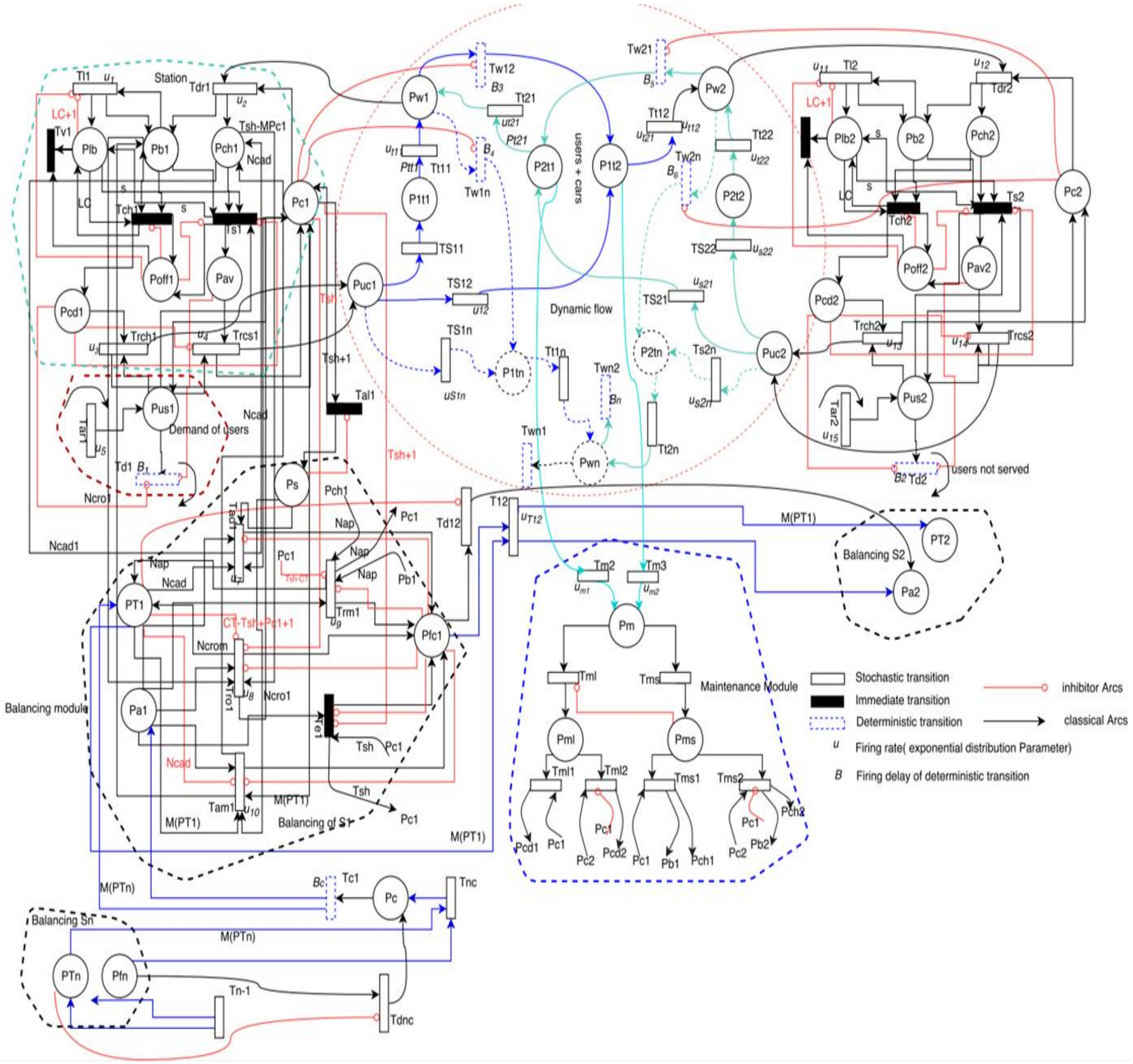

Fig. 2. Periodical balancing stochastic PN model

3.2 Description of dynamic and flux inter-station subnet

This subnet models the trip of users with electric cars between origin and destination stations. The ECs mobility is composed of diver events (see figure2 dynamic flow subnet). First, user rents a car from station Si (in the place Puci each token represents car+ users, it represents the number of rented cars from stations Si). When user rents a car from station Si, the following events can occur: user decides to make a round trip (return to original departed station) modelled by the transition Tsii and the place Piti; or take a one way trip (go to other station) modelled by the transition Tsij, $i \neq j$, with firing probability (Random switch Rsij) and the place Pitj. A token (EC+user) is marked at place Puci, which is a common resource for transitions Tsii and Tsij (j=1, 2… N). The firing of transition Tsii or Tsij represents the user decision to choose his destination. The firing of transition Titi or Titj (represent the trip delay), whose firing delay is stochastic. Thereafter, when user arrives with EC at destination Sj, this modelled by place Pwi, and if there is at least one available spot, the EC is returned to the station, as modelled by firing of transition Tdri. On the contrary, if station Sj is full (M(Pci)=0), the user decides to go to another station Sj $i \neq j$, to return the EC, or wait in station Si, i=j, until a spot becomes available (M (Pci)>0).

3.3 Description of relocation module

This module makes it possible to carry out five main events (see in figure 2 balancing of station subnet) described as follows:

- Removal event of electric car from station to truck, in term PN this event represented by firing of transition Tcroi (enabled if Ncadi<Navpi). That is mean that it is enabled if only there is sufficient cars in charging and there is sufficient available spots in truck.
- Removal event of minimum EC if there is not enough empty spots in truck, represented by firing of transition Trmin (enabled if M(Pc)>Nap and M(Pch)>Navp and M(Pbi)>Navp and M(Pc)<Tshi-Navpi).
- Addition event of EC to station is represented by firing of transition Tcadi (enabled if M(Pci)>Ncad and M(PT i)>Ncad.
- Min addition event of EC is interpreted by firing of transition Tadmi (enabled if number of car to add Ncad> number of car available in Truck M(PTi),
- No action to do is translated by firing of transition Tei then the truck continues to next station for balancing.

Where: Ncroi is number of EC to be removed from station Ncroi=Tshi –M(Pci), Ncadi is number of EC to be added to stations Ncadi=M(Pci)–Tshi , Tshi threshold of empty parking spaces, CTi capacity of truck, and Navpi is number of available empty places in truck Navpi=CTi-M(PTi). For further details and clarification. The table 2 interprets more the model.

4 Simulation and discussion

In this section we present an application of the proposed stochastic PN models to a ECs of N= 10 stations with various capacities and fleet of EC k=35. Order to lead a performance analysis and evaluation study, Petri nets is suitable for discrete event simulation when the modelled system is too complex (large, infinite number of statements stochastic complex process to characterize and / or resolve; ...) to perform an analytical study. We tested behavior of model in different scenarios (a) without relocation and with 95% charging level, (b) without relocation and with 50% charging level, (c) with relocation.

The performance evaluation through discrete event simulation is done through the dynamic evolution of the markings of the various places of the model according to the firing of transitions occurs in time (Cintra and Ruggiero 1992). An illustration, useful to interpret some measures of performances later, is shown in figure 8. The simulation generates set of events listing, saved during the simulation.

4.1 Simulation of scenario (a) and (b)

Using our simulation algorithm, we can noticed on the trajectories represented by Figure 9 that the number of EC (Ncc) in the scenario (a) "oscillates" around 4, unlike on the scenario (b) the number of EC oscillates around 9 (congestion). It can be seen that the limit Ci set here at 10 is also respected. These simulations effectively confirm that the behaviour of the model is consistent with our formal analysis performed.

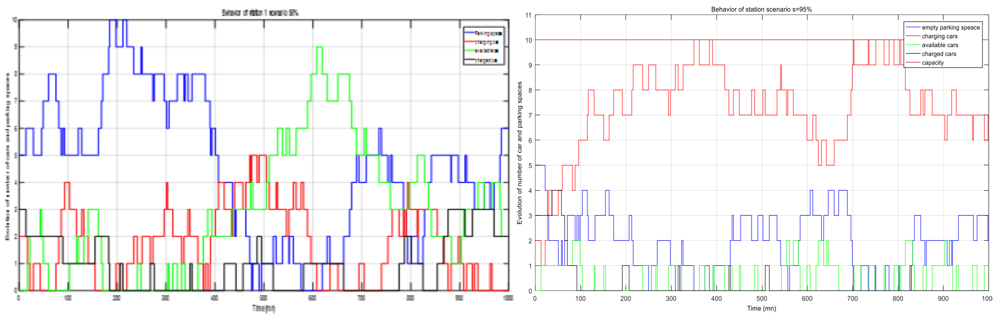

Fig. 3. Behaviour of station S1 and S2: scenario (a) and (b) s= 50% and s=95%

It is possible to evaluate several performances of the system as example:

- The average frequency of Trcs1 means that there are on average 0.0156 available electric cars rented per mn (time unit) for scenario 1. In other hand, on average one car available rented each 64.10 mn comparing with scenario 2 is 121. 80 mn.

$$F(t_{rcs1})_{avr} = \sum \mu_i \times \pi_i = \lim_{tsim \to \infty} (NF(T_{rcs1})/t_{sim})$$

Where *tsim* is total simulation time, *NF*(T_{rcs1}) firing number of transition T_{rcs} during simulation and π is the probability that this system is in this state .

- Sojourn time of available car in station corresponds to the average sojourn time of token in the places Pav, This means that there are on average the available car sojourn 53.16 mn in station before utilization.

$$S(P_i)_{avr} = M(P_{av})_{avr}/\mu_i = \lim_{tsim \to \infty} \sum_{0}^{tsim} (M(P_{av}) \times \tau \Big/ Nt)$$

Where, τ is Duration of each cycle and Nt is number of tokens crossing Place Pav at the end of each cycle.

4.2 Simulation of scenario (c)

In this scenario we simulate the system with relocation service and with 50% of charging availability threshold. In viewpoint of truck relocation strategy. It is possible to observe in the analysis of the influence of the suggested solution on the average unserved users and on the quality of service. We focus our attention on the behavior of the time evolution of the number of available electric cars in the stations which can be observed in Figures 11. According to the control function integrated in the model, it can be observed that the number of EC (marking the places Pci) in all stations "oscillates" around the threshold.
Graphs representing (see figure 10) the dynamic behaviour of a given system, such as those presented in our illustrative example, provide a valuable benefit to the operator. They allow a visual, fast and intuitive way to observe the good or the bad functioning of its system according to the management policies used or the parameters applied. The riches of our models also permit to evaluate, significant performances index as corporation gain for each scenario. The dynamic model developed is a valuable assistance for the implementation, operation and control of car sharing systems. It is pertinent to both the analysis for the simulation.

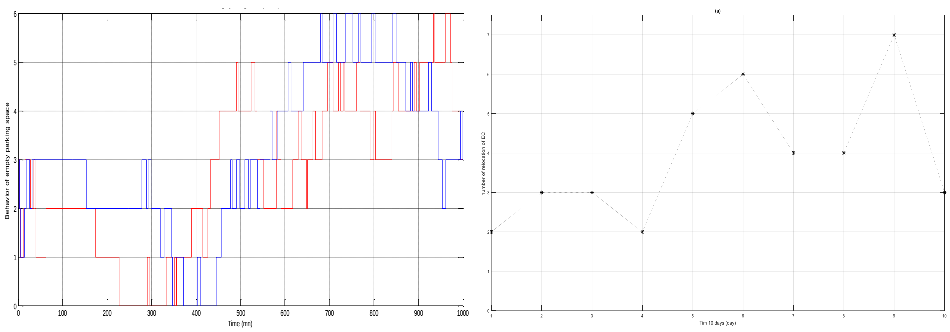

Fig. 4. Evolution of empty parking spaces with relocation and Evolution of number of relocation

We can also analyse more closely the rebalancing policy of the network: how many interventions? Which stations are visited? ... The measurements and the analysis to be carried out on the evolution of the markings of places and/ or the firing of the transitions of the PN model make it possible to express several performances of the system. The figures below are some illustrations in this frame.

5 Conclusion and perspectives

ECs system have been encounter many challenges crucial of them is to ensure users EC and empty parking spots in each station. Consequently, the optimal redistribution of ECs is unavoidable for the vivacity of system and avoid his failure. In this framework, we proposed relocation technique for optimal dynamic and balancing of this urban transportation mode; by using stochastic Petri nets and discrete event simulation. The relocation is periodical consists to visit stations periodically (each determinate time). The obtained results underline of 10 stations with one truck for online relocation strategy increase mostly the served users and decrease importantly the two extreme cases (empty and full). In this context, we will address in next to estimate and predict the optimal size of the relocation team (workers, trucks) and optimal charging level of EC for enormous ECs network by optimization techniques (neural network) and Petri nets through simulation; it will be tested on a realistic case study. Otherwise, the presented models permit evaluating some important decision keys to design or manage the system: sojourn time of EC in station, average unserved users, and % time full/or empty of stations. The numerical results of simulation show that strategy with 50% of charging level reduced the number of users not served (viewpoint demand) and create dynamic in system. However this politic drives system to the running out situation of EC. At the present time and although the introduction of computer equipment and new information technologies in the new generations of ECs, relocation or rebalancing of stations is often done on the basis of common sense, knowledge of the network and the instantaneous state of the stations at the time of the tour. Without performance evaluation and / or prediction tools, this does not necessarily lead to a good level of service, especially in the case of large networks whose organization and management are often complex. On other hand, in near future self-driving electric car will replace classical car and ECs will be automated and more flexible in city. In this context, we aim to re-drive our approach and for modelling of self-driving ECs system in urban area.

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