Challenges of Trustable AI and Added-Value on Health
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Can Artificial Intelligence Enable the Transition to Electric Ambulances?

Emmanouil S. RIGAS[1], Antonis BILLIS and Panagiotis D. BAMIDIS
Medical Physics and Digital Innovation Lab, School of Medicine, Aristotle University of Thessaloniki, Greece

Abstract. The electrification of the transportation sector is seen as a main pathway to reduce CO_2 emissions and mitigate the earth's climate change. Currently, Electric Vehicles (EVs) are entering the market fast. Although EVs have not been used as ambulances yet, the transition to the new type of vehicle is a matter of time. Thus, in this paper we discuss a number of research questions related to the efficient deployment of electric ambulances, focusing on the Artificial Intelligence (AI) point of view and we propose a framework for developing online algorithms that schedule the charging of electric ambulances and their assignment to patients.

Keywords. electric vehicle, electric ambulance, artificial intelligence

1. Introduction

The ever-increasing CO_2 emissions and the consequent greenhouse effect are causing the earth's climate to change. This change creates a major threat for human societies worldwide due to the frequent extreme weather phenomena. Given that the transportation sector is accountable for a substantial portion of greenhouse gas emissions, its electrification, through the use of Electric Vehicles (EVs), is seen as a major pathway to mitigate the climate change. Currently, several EV models have already been introduced to the market and many car manufacturers have set ambitious plans to terminate the production of non-electric vehicles by the end of the current decade.

Despite their many advantages, EVs have certain drawbacks related to their relatively low range and long charging times. To soften these disadvantages, intense research on battery technology is taking place aiming to increase the capacity of the EVs' batteries and, consequently, the autonomy they give to the vehicles. Additionally, charging infrastructure is evolving by the addition of new charging stations, many of them equipped with fast chargers. Now, in order for the EVs to be truly environmentally friendly, they need to charge their batteries using energy produced from renewable energy sources (RES), such as wind or solar [1]. However, these sources are characterized by intermittent production, as they are affected by the weather conditions and time of the day. Thus, the charging of the EVs, as part of the so-called Grid-to-Vehicle (G2V) schemes needs to be scheduled taking into consideration not only the drivers' needs, the available chargers and the network constraints, but it must also

[1] Corresponding Author, Emmanouil Rigas, Medical Physics and Digital Innovation Laboratory, School of Medicine, Faculty of Health Sciences, Aristotle University of Thessaloniki (AUTH), 541 24 Thessaloniki, Greece; E-mail: erigas@auth.gr.

maximize the utilization of the available renewable energy. Otherwise, the need to use EVs at first place would come into question. In this vein, EVs can assist by acting as temporal storage devices when not in use as part of the so-called Vehicle-to-Grid (V2G) schemes [2].

It becomes evident that the management of EVs involves several heterogeneous entities (e.g., EV owners, charging stations), each one having different needs and objectives (e.g., charging the vehicle within a certain deadline, maximizing the profit) which operate in a highly dynamic environment (e.g., charging demand, energy production from RES). Artificial Intelligence algorithms and techniques have already been proven highly efficient in such a domain [3]. For example, Franco et al. [4] propose mathematical programming techniques to schedule EV charging also considering the balance of the electricity network. Additionally, Kadri et al. [5] focus on the placement of the EV charging stations, which is highly important for the efficient charging of the EVs, and they propose both an exact solution using mathematical programming as well as an approximate one using a genetic algorithm. Moreover, Gerding et al. [6] propose mechanism design techniques for the scheduling and pricing of EVs' charging where the vehicles and the stations are considered as intelligent agents. At the same time, Shahriar et al. [7] propose data-driven tools, as well as machine learning (ML) algorithms to learn EVs' charging behavior and improve charging scheduling algorithms. Finally, Quddus et al. [8] propose a solution that is based on Sample Average Approximation with an enhanced Progressive Hedging algorithm in order to expand charging stations by integrating RES and V2G.

Given the progress of the EVs' sector, a crucial question that raises is whether such vehicles can be used as emergency response vehicles, and in particular as ambulances, without compromising their ability to serve people in need. To the best of our knowledge, to date electric ambulances do not operate. However, given the gradual electrification of the transportation sector, eventually ambulances will have to become electric as well. Indeed, UK's NHS is planning to introduce electric ambulances in the near future.[2] Thus, it is important to outline the path that needs to be taken, so as electric ambulances to become a reality and to efficiently replace the conventional ones. In what follows we describe a set of research questions related to the wide deployment of electric ambulances and we explain how AI can assist and, to some extent, enable this deployment.

2. Methods

RQ1: Given the plethora of AI-based algorithms that manage EV activities existing in the literature, which modifications and extensions are needed in order to make these algorithms applicable to electric ambulances? The management of fleets of electric ambulances has two significant differentiations compared to the management of EVs for other domains: 1) The algorithms need to operate in an online fashion and calculate high quality solutions fast as the requests arrive dynamically and 2) the vehicles need to have the highest possible efficiency in terms of the time needed for an ambulance to reach each patient. The existing algorithms schedule EV charging based on the availability of chargers and the spatial and temporal constraints imposed by the users. They operate either offline [9], where the requests are collected in advance and an (optimal) charging schedule is calculated, or online [10] where the requests are collected in a dynamic

[2] https://www.electrive.com/2021/08/09/nhs-procures-fleet-of-electric-ambulances

manner as these are communicated by the drivers. In contrast, when EVs act as ambulances knowing the demand in advance is impossible. Thus, the effort needs to focus in developing online algorithms which will be able to calculate solutions (i.e., assignment of ambulances to each patient request) fast, while utilizing the ambulances' fleet efficiently to minimize delays. In this vein, greedy algorithms with heuristic search can be used, while meta-heuristic approaches can further improve the calculated solutions. Such algorithms can step upon the state of the art algorithms in the EVs' domain. Additionally, previous work on conventional ambulance scheduling such as the work by Erdogan et al. [11] which uses a tabu search algorithm, or the work by Zhen et al. [12] which uses decision rules can be utilized. Moreover, the available charging infrastructure needs to be optimally utilized. In this vein, emphasis should be given on machine learning algorithms and techniques that can predict future demand, in terms of patients' requests, based on historical data, as well as, healthcare service demands as a result of term of the year periodicity or acute events or anomalies (catastrophes and/or pandemics etc).

RQ2: To what extend can electric ambulances utilize renewable sources without sacrificing their ability to transport patients? As discussed before, the utilization of energy from RES is of utmost importance in order the EVs to achieve their purpose and mitigate the greenhouse effect. However, when these vehicles act as ambulances, RES cannot be a priority. It is crucial to have as many ambulances as possible with high battery charge, in order to be able to respond to emergency situations where many ambulances will be needed simultaneously. Thus, the charging scheduling algorithms should consider the use of RES to the extent this does not have a negative effect in the availability of the vehicles. In this context, the use of machine learning techniques that have the ability to predict [13] future production from RES is important.

RQ3: What types and volume of data are available for the algorithms' design and evaluation? Moreover, are these data openly available? In the previous two research questions we outlined the importance of machine learning algorithms and techniques to predict demand for ambulance service and RES production. These algorithms demand data in order to be evaluated and fine-tuned. Thus, the question of the existence and the availability of real-world or realistic synthetic data arises, along with the question of the potential construction of synthetic datasets in order to alleviate potential data scarcity. Last but not least, demands related to open (linked) data availability become apparent.

RQ4: What takes for communities to trust electric ambulances? Public opinion on complex scientific topics can have a big impact on sectors such as the EVs one and to realize the benefits that autonomous systems can provide, they need to be trustworthy by design [14]. Electric ambulances might face a lack of trust from stakeholders and the community in general when it comes to replacing conventional ambulances. This lack of trust might be related both to the technical part of these vehicles, which is out of the scope of this work, and to the AI algorithms that would be used to manage and schedule the electric ambulances. Regarding the latter, the notion of explainable AI [15] comes into place. By using explainable AI techniques, the decisions taken, or the predictions made by the algorithms are explained to the stakeholders in a structured and convincing manner increasing in this way the acceptance of the new technology. To this end, contemporary approaches related to co-creation of solutions with their users and (urban) Living Lab processes [16] involving the whole value of stakeholders may be pivotal.

3. Results

Based on the RQs presented previously, we outline a proposed framework for the scheduling of the charging of electric ambulances and their assignment to patients' requests. This framework is depicted in Figure 1. In detail, initially the problem is mathematically formulated, potentially taking as input experts' opinion collected through participatory design sessions conducted through living labs. Then, the available historical data need to be collected and analyzed using ML algorithms in order to calculate predictions regarding both the future energy production from the available RES and the future patients' demand. Once these predictions are calculated, the focus needs to move to the design of the scheduling algorithm. In this vein and as has been discussed earlier, the developed algorithm needs to have very low execution time in order to calculate both the charging schedule and the assignment of the electric ambulances to the patients fast. The predictions calculated by the ML algorithms should be utilized in order to enhance the performance of the online scheduling algorithm. Regarding the ML and scheduling algorithms, explainability needs to be incorporated in order to assist their acceptance by the stakeholders. Finally, the algorithms need to be evaluated and their performance verified. In this case, an equivalent offline exact solution can be developed, to operate as a theoretical benchmark for the online algorithm. The offline algorithm will collect all the data for a time period (e.g., a day) and calculate the optimal schedule (i.e., the optimal schedule in case we could know all the demand and supply in advance). If the results of the evaluation are considered satisfactory, the procedure terminates, otherwise the algorithms need to be reworked and re-evaluated.

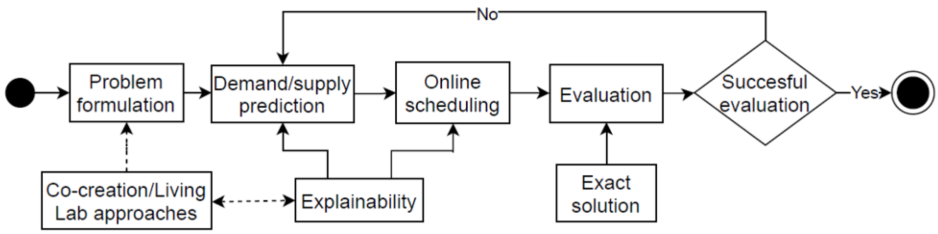

Figure 1. Overview of the proposed framework

4. Discussion and Conclusions

Electric vehicles are entering our lives fast and despite some disadvantages, they will probably dominate the personal transportation market in the next few years. Although electric vehicles have not been widely used as ambulances yet, it is crucial to investigate what are the necessary steps towards making electric ambulances a reality in the years to come. In this paper, once we introduced the concept of EVs and we described the state of the art, we outlined a set of research questions related to the deployment of electric ambulances, from the perspective of AI, and we proposed a general framework for the development of algorithms that can calculate the charging schedule and the assignment of electric ambulances to patients. Although we have not included an exhaustive list of requirements and solutions, we argue that this framework can act as a pathway for future research in this field.

Concluding, for the electric ambulances to become a reality, apart from the advancements in the engineering domain, the development of fast and efficient online scheduling algorithms accompanied with machine learning algorithms able to accurately predict future demand and supply is a key point to achieve a gradual transition from conventional ambulances to electric ones. In this context, AI can have a central role.

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