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The electric vehicle routing problem with nonlinear charging function

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ABSTRACT

Electric vehicle routing problems (E-VRPs) extend classical routing problems to consider the limited driving range of electric vehicles. In general, this limitation is overcome by introducing planned detours to battery charging stations. Most existing E-VRP models assume that the battery-charge level is a linear function of the charging time, but in reality the function is nonlinear. In this paper we extend current E-VRP models to consider nonlinear charging functions. We propose a hybrid metaheuristic that combines simple components from the literature and components specifically designed for this problem. To assess the importance of nonlinear charging functions, we present a computational study comparing our assumptions with those commonly made in the literature. Our results suggest that neglecting nonlinear charging may lead to infeasible or overly expensive solutions. Furthermore, to test our hybrid metaheuristic we propose a new 120-instance testbed. The results show that our method performs well on these instances.

1. Introduction

In the last few years several companies have started to use electric vehicles (EVs) in their operations. For example, La Poste operates at least 250 EVs and has signed orders for an additional 10,000 (Kleindorfer et al., 2012); and the French electricity distribution company ENEDIS runs 2000 EVs, accounting for 10% of their fleet in 2016.[1] Despite these developments, the large-scale adoption of EVs for service and distribution operations is still hampered by technical constraints such as battery charging times and limited battery capacity. For the most common EVs used in service operations, the minimum charging time is 0.5 h and the battery capacity is around 22 kWh. The latter leads to a nominal driving range of 142 km (Pelletier et al., 2014). In reality, the driving range could be significantly lower because the energy consumption increases with the slope of the road, the speed, and the use of peripherals (De Cauwer et al., 2015). For instance, Restrepo et al. (2014) documented that the heating and air conditioning respectively reduce the driving range of an EV by about 30% and 8% per hour of use.

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[1] http://www.avere-france.org/Site/Article/?article_id=5644. Last accessed 11/16/2016.

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Automakers and battery manufacturers are investing significant amounts of capital and effort into the development of new technology to improve EV autonomy and charging time. For instance, General Motors (GM) reinvested USD 20 million into the GM Global Battery Systems Lab to help the company developing new battery technology for their vehicles (Marcacci, 2013). The results of these efforts, however, are transferred only slowly to commercially available EVs. In the meantime, companies using EVs in their daily operations need fleet management tools that can take into account limited driving ranges and slow charging times (Felipe et al., 2014). To respond to this challenge, around 2012 the operations research community started to study a new family of vehicle routing problems (VRPs): the so-called electric VRPs (E-VRPs) (Afroditi et al., 2014; Pelletier et al., 2016). These problems consider the technical limitations of EVs. Because of the short driving range, E-VRP solutions frequently include routes with planned detours to charging stations (CSs). The need to detour usually arises in rural and semi-urban operations, where the distance covered by the routes on a single day is often higher than the driving range.

As has been the case for other optimization problems inspired by practical applications, research in E-VRPs started with primarily theoretical variants and is slowly moving toward problems that better capture reality. In general, E-VRP models make assumptions about the EV energy consumption, the charging infrastructure ownership, the capacity of the CSs, and the battery charging process. Most E-VRPs assume that energy consumption is directly and exclusively related to the traveled distance. However, as mentioned before, the consumption depends on a number of additional factors. To the best of our knowledge only Goeke and Schneider (2015) and Lin et al. (2016) use consumptions computed over actual road networks taking into account the EV parameters and their loads.

Similarly, most E-VRP models implicitly assume that the charging infrastructure is private. In this context, the decision-maker controls access to the CSs, so they are always available. However, in reality, mid-route charging is often performed at public stations and so the availability is uncertain. To our knowledge only Sweda et al. (2015) and Kullman et al. (2016) deal with public infrastructure and consider uncertainty in CS availability.

CS capacity is another area in which current E-VRP models are still a step behind reality. All existing E-VRP research that we are aware of assumes that the CSs can simultaneously handle an unlimited number of EVs. In practice, each CS is usually equipped with only a few chargers. In some settings this assumption may be mild (e.g., a few geographically distant routes and private CSs). However, in most practical applications CS capacity plays a restrictive role.

Finally, in terms of the battery charging process, E-VRP models make assumptions about the charging policy and the charging function approximation. The former defines how much of the battery capacity can (or must) be restored when an EV visits a CS, and the latter models the relationship between battery charging time and battery level. In this paper, we focus on these assumptions.

In terms of the charging policies, the E-VRP literature can be classified into two groups: studies assuming *full* and *partial* charging policies. As the name suggests, in full charging policies, the battery capacity is fully restored every time an EV reaches a CS. Some studies in this group assume that the charging time is constant (Conrad and Figliozzi, 2011; Erdoğan and Miller-Hooks, 2012; Adler and Mirchandani, 2014; Montoya et al., 2015; Hof et al., 2017). This is a plausible assumption in applications where the CSs replace a (partially) depleted battery with a fully charged one. Other researchers, including Schneider et al. (2014), Goeke and Schneider (2015), Schneider et al. (2015), Desaulniers et al. (2016), Hiermann et al. (2016), Lin et al. (2016), and Szeto and Cheng (2016), consider full charging policies with a linear charging function approximation (i.e., the battery level is assumed to be a linear function of the charging time). In their models, the time spent at each CS depends on the battery level when the EV arrives and on the (constant) charging rate of the CS. In partial charging policies, the level of charge (and thus the time spent at each CS) is a decision variable. To the best of our knowledge, all existing E-VRP models with partial charging consider linear function approximations (Felipe et al., 2014; Sassi et al., 2015; Bruglieri et al., 2015; Schiffer and Walther, 2017; Desaulniers et al., 2016; Keskin and Cătay, 2016).

In general, the charging functions are nonlinear, because the terminal voltage and current change during the charging process. This process is divided into two phases. In the first phase, the charging current is held constant, and thus the battery level increases linearly with time. The first charging phase continues until the battery's terminal voltage increases to a specific maximum value (see Fig. 1). In the second phase, the current decreases exponentially and the terminal voltage is held constant to avoid battery damage. The battery level then increases concavely with time (Pelletier et al., 2017).

Although the shape of the charging functions is known, devising analytical expressions to model them is complex because they depend on factors such as current, voltage, self-recovery, and temperature (Wang et al., 2013). The battery level is then described by differential equations. Since such equations are difficult to incorporate into E-VRP models, researchers rely on approximations of the actual charging functions. Bruglieri et al. (2014) use a linear approximation that considers only the linear segment of the charging function, i.e., between 0 and (around) $0.8Q$, where Q represents the battery capacity. This approximation avoids dealing with the nonlinear segment of the charging function (i.e., from (around) $0.8Q$ to Q). Henceforth we refer to this approximation as first segment (FS). Felipe et al. (2014); Sassi et al. (2014); Bruglieri et al. (2015); Desaulniers et al. (2016); Schiffer and Walther (2017), and Keskin and Cătay (2016) approximate the whole charging function using a linear expression. They do not explain how the approximation is calculated, but two options can be considered. In the first (L1) the charging rate of the function corresponds to the slope of its linear segment (see Fig. 2b). This approximation is optimistic: it assumes that batteries charge to the level Q faster than they do in reality. In the second approximation (L2) the charging rate is the slope of the line connecting the first and last observations (see Fig. 2c) of the charging curve. This approximation tends to be pessimistic: over a large portion of the curve, the charging rate is slower than in reality.