Multi-Objective Optimal Allocation of Wireless Bus Charging Stations Considering Costs and the Environmental Impact

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ABSTRACT

In recent years, due to environmental concerns, there is an increasing need to develop alternative solutions to traditional energy sources (e.g., fossil fuels). Since transportation is a major fossil fuel consumer, development of electric vehicles (EVs), especially electrical buses, reduces fossil fuels uses, and, therefore, provide a better living environment. The aim of the work is the development of a system-wide wireless charging stations optimal allocation model. The main advantages of wireless charging are the need for a much smaller battery, and the contactless charging, both static and dynamic (in-motion). Unlike previous works that dealt with the allocation of wireless charging stations along a single route, or for a given network, the suggested model is a multi-objective model that selects the location for the charging stations while minimizing the costs (charging stations installation and batteries), maximize the number of routes that can be operated by wireless charging buses, and maximizes the environmental impact. The problem is formulated as a multi-objective non-linear optimization model. An efficient genetic algorithm is introduced for solving the problem. A test case is used to demonstrate the model, so the decision maker is provided with a solution set from which the best fit solution can be selected considering costs, the number of routes and environmental impact.

Key words: Electric Buses, Wireless Charging, Network Allocation, Multi-Objective

INTRODUCTION

In recent years, due to environmental problems, there is an increasing need to develop alternative solutions to traditional energy sources (e.g., fossil fuels). Since transportation is a major fossil fuel consumer, development of electric vehicles (EVs), especially electrical buses, reduces fossil fuels uses, and, therefore, provide a better living environment (Lebeau et al., 2013, Hui et al., 2012, Dyke et al., 2010, Wu et al., 2014, Rigas et al., 2014).

Electric vehicles use electric motors for propulsion and are powered through a collector system by electricity from, usually rechargeable lithium-ion batteries (Li-Ions or LIBs). Lithium-ion batteries have a higher energy density, longer life span, and higher power density than most other practical batteries. In the case of electric buses, standard battery charging is performed mainly at the bus depot during long brakes and overnight. For that reason, high capacity battery, which increases the weight of the vehicle, is needed for the entire day operation of the bus (Sinhuber et al., 2012).

Kowalenko (2011) and Ulrich (2012) reported that charging a 24 kWh battery using a Level 2 charger (240 VAC, delivering 3.3 kW) in a Nissan LEAF (a popular EV available in the US, Japan, and some EU countries) takes 7 hours. However, it can be reduced to 30 minutes using a Level 3 charger (480 VDC, 50 kW).

Korea Advanced Institute of Technology (KAIST) has developed a wireless charging electric vehicle system called the On-Line Electric Vehicle (OLEV), that can charge EV's batteries wirelessly from the power transmitters using the innovative noncontact charging mechanism, even when the EV is in motion. Accordingly, by providing sufficient charging times at certain locations, fast wireless charging on the track during bus operation can reduce the battery capacity and therefore reduce the weight of the system. The main advantages of wireless charging are the need for a much smaller battery, and the contactless charging, both static and dynamic (in-motion). For comparison, a popular electric bus BYD K9 has a 324kWh battery weighing 1500 kg with a range of 250km, and charging time of 6 hours (Wikipedia contributors, 2016) whereas the OLEV bus uses a 13kWh battery weighing only 130kg that can be charged in less than 5 minutes..

Modeling Concept and Motivation

The aim of the work is the development of a system-wide wireless charging stations optimal allocation model. However, unlike previous works that dealt with a single route (Jang et al., 2015a, Jang et al., 2015b), or a given network (Liu and Song, 2017) the suggested model is a multi-objective model that selects the location for the charging stations minimizing the costs (charging stations installation and batteries), maximize the number of routes that can be operated by wireless charging buses, and maximizes the environmental impact. Each charging station can be installed along the bus route and at bus stops. For the former, the charging is proportional to the charger size (length) and bus speed. Whereas for the latter, the charging is proportional to the dwell time. This approach provides the decision maker the opportunity to select which routes should be converted for a wireless bus system. Given that budget is limited, it is required to select which routes should be converted considering the associated benefits. Moreover, the model enables the decision maker to prioritize the order in which routes are converted, as a route must be fully converted before wireless buses can start operating. Figure 1 provides insights on the benefits of selecting multiple routes for conversion, as shared stops will use the same charging station. For demonstration purposes, a grid network with stops near each intersection is presented. A charging station is to be installed every second stop. The left side network illustrates the allocation of charging stations for each route separately. In that case, 9 stations are required for the solid line route, and 13 for the dotted route, with a total of 22 stations. However, as the right-side network presents, a joint allocation will lead to 16 stations, with 7 of them jointly used by the routes.

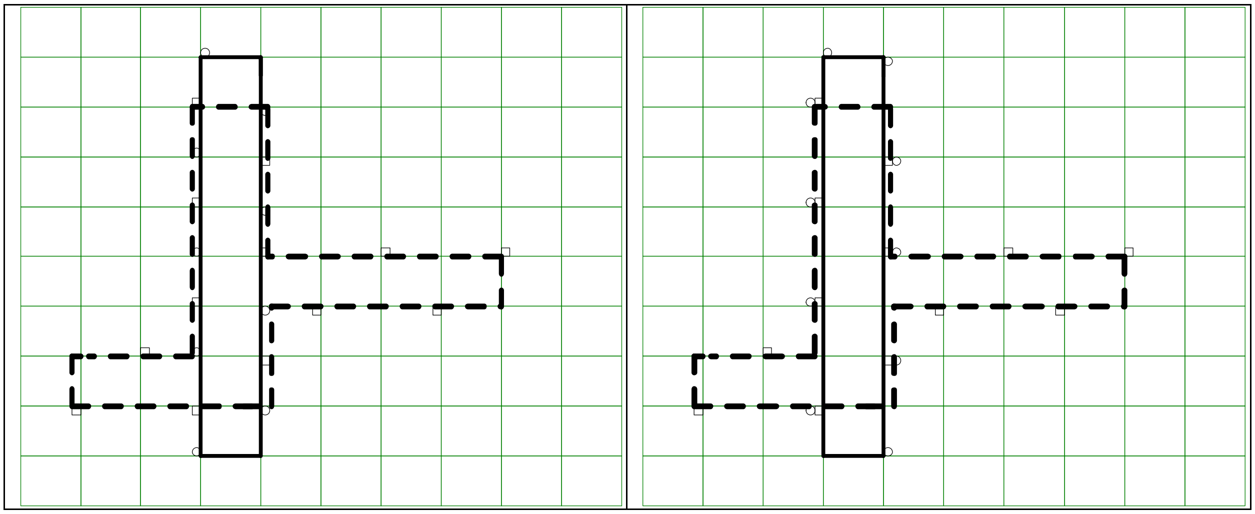

Figure 1 Separate Versus Joint Charging Stations Allocation

The remaining of the paper is structured as follows. 1) a literature review concerning wireless charging and optimization is introduced. 2) a mathematical multi-objective model is formulated for the optimal location of charging station considering costs, the number of charging stations, and environmental impact. 3) an efficient genetic algorithm capable of solving large problems is designed. 4) the model is demonstrated with a PT system consists of 10 routes. 5) conclusions are drawn.

LITERATURE REVIEW

Wireless Charging

Public bus system provides people with an economical and sustainable travel mode, and it helps to reduce traffic congestion and exhaust emissions (Song, 2013). Due to vehicle technology limitations, diesel-powered buses still dominate today's bus fleet (Liu and Song, 2017). Electrical buses reduce fossil fuels uses, and, therefore, provide a better living environment, however, range limitations associated with on-board batteries as well as the problem of battery size, cost, and life, have limited the popularity of electric buses (Liu and Song, 2017).

Wireless power transmission technology was first invented by Nikola Tesla in the late 19th century, and since numerous applications using it have been introduced, among them is wireless charging, including wireless charging of electric vehicles.

Wireless charging in EVs was first introduced by Bolger et al. (1978). According to Bolger et al. (1978), an inductive charger which is placed beneath the roadway generates a magnetic field. Then, the EV's power pickup device converts the magnetic field into electrical power.

The major issue for EVs wireless charging is efficiency caused by the large air gap between the charger and the EV's power pickup device. Therefore, much of the research has aimed to improve charging efficiency across the air gap. Esser (1995) achieved 92% charging efficiency with a 0.2 mm air gap. In more recent research, Ayano et al. (2002) achieved 91% charging efficiency with 10 mm air gap.

New inductive power transfer systems were presented by Wu et al. (2009) and by Budhia et al. (2011). On the other hand, Huang et al. (2009) proposed an improved design of the power regulator. Both power transfer systems and improved power regulator improve the efficiency of the vehicle using the wireless power transfer technology.

The On-Line Electric Vehicle (OLEV) system, developed by Korea Advanced Institute of Technology (KAIST), is the first successfully commercialized EV wireless charging system (Jang et al., 2015b, Lee et al., 2010, Shin et al., 2013). The OLEV consists of shuttles (similar to conventional EVs) and a charging infrastructure comprising a set of power transmitters, that can charge the shuttles battery wirelessly using an innovative non-contact charging mechanism while the shuttles are moving over the charging infrastructure.

Later research dealt with EVs infrastructure design for EVs. Ip et al. (2010) used hierarchical clustering performed on data from urban areas in which private charging stations in each garage cannot be sustained, as a mean for proposing locations for charging stations. Similarly, Ge et al. (2011) used a genetic algorithm combined with a grid partition-based approach for determining both the location and size of the charging stations. Economical aspects of electrical charging systems, such as electrical charging systems market price and its effect on the system's cost (Kristoffersen et al., 2011), cost minimization (Steinmauer and Del Re, 2001) and optimal energy control (Tate and Boyd, 2000), were also studied.

Liu and Song (2017) proposed both deterministic and robust models for simultaneously selecting the optimal location of the charging facilities and determining the optimal battery sizes. The results of the models, demonstrated with a real-world bus system, showed that it is possible to effectively determine the allocation of charging facilities and the battery sizes of electric buses for an electric bus system.

Riemann et al. (2015) also studied the problem of finding the optimal locations of charging facilities for electric buses. In their problem, the objective is to locate a given number of wireless charging facilities for EVs out of a set of candidate facility locations for capturing the maximum traffic flow on a network. Similarly, Liu and Wang (2017) developed a model in which the objective is to assist the government planners on optimally locating multiple types of charging facilities to satisfy the need of different EV types within a given budget such that the total cost is minimized.

Multi-Objective Optimization

A survey on multi-objective optimization methods (Marler and Arora, 2004) classifies the various methods into four groups: (1) Methods with a priori articulation of preferences (such as the weighted sum (Zadeh, 1963) and lexicographic (Stadler, 1988) methods), (2) Methods for a posteriori articulation of preference (such as the normal boundary intersection (NBI) (Das and Dennis, 1999, Das and Dennis, 1998) and Normal constraint (NC) (Messac et al., 2003) methods), (3) Methods with no articulation of preferences (such as the min-max method (Yu, 1973)) and (4) Genetic algorithms (such as the VEGA, MOGA, NPGA, and NSGA methods, which are non-elitism multi-objective genetic algorithms, in which the best solutions of the current population are not preserved when the next generation is created, and PAES, SPEA2, PDE, NSGA-II and MOPSO methods, which are example elitism multi-objective genetic algorithm, which preserve the best individuals from generation to generation. In this way, the system never loses the best individuals found during the optimization process (Coello et al., 2007)).

As can be seen from the above, genetic algorithms are suitable for solving multi-objective optimization problems; moreover, they can be used for stochastic optimization problems as well. Genetic Algorithms (GAs) usually assumes a stationary environment for solving an optimization problem. In the first stage, a typical GA usually generates a random set of individuals, known as population, each associated with a solution. Next, an iterative session starts. At each iteration, each individual from the current population is evaluated and assigned with a fitness value (using a fitness function), which states how “good” it is. Then, a new population of size is created. The new solutions are created by randomly choosing two parent solutions from the current population, based on their goodness, on whom crossover and mutation operations are performed to create two new solutions. By using this method, we assume that the new solutions of the new population are better than those of the current population. The current population is replaced with the new population, and the process continues until a stop condition is met, which could be a number of iterations, specific run time or any other condition (Yoshitomi et al., 2000).

For a stochastic optimization problem, the fitness function literally expresses the fitness of the individual; therefore the fitness function is fluctuated, according to the stochastic distribution-functions for the stochastic variables. In each generation, the fitness function is determined by a random number generated according to the stochastic distribution-functions. Eventually, the frequencies of individuals associated with solutions are investigated through all generations. With the roulette wheel selection strategy, for choosing parent solutions for creating new solutions, suitable individuals are selected in proportion to their fitness function value. Moreover, since roulette wheel selection allows sampling with replacement, the selection pressure is relatively high. Therefore, by using roulette wheel selection, it is expected that the higher the expected value is, the higher the individual frequency through all generations is (Yoshitomi et al., 2000).

MATHEMATICAL MODEL

Assumptions:

1. Each bus starts a trip fully charged and must remain within as a certain level of energy throughout the trip.

2. All routes are clustered to cycles, i.e., each cluster is composed of a set routes each one start from the terminus of the previous route and the last routes terminate at the first stop of the first route. This assumption is reasonable, as a bus can either operate on a single route (inbound and outbound), or on a set of routes, including dead-heading segments that connects routes. For example, a cycle is R1(s1, s2, s3)-R2(s4, s5, s6)-DH-R3(s7, s8, s1), in which the cycle start with route R1, continues with route R2, then traveling empty the operate on route R3, which terminates at the start of route R1. As the dead-heading path is known, it can be considered as an artificial route.
3. A bus is fully charged when starting a cycle. Due to the small battery, charging can last few minutes, hence even during a short layover between runs, the battery will be fully charged.
4. Vehicles costs are omitted. We assume that the authority is responsible to the charging station, and once a route can be operated by wireless electric buses, the operator will have the incentive to procure electric buses or to convert electric buses to wireless charging. Nonetheless, the model can be easily adjusted to include the costs of the vehicles.
5. Battery weight is omitted. As the battery weight is small (100-150 kg), the selection of a larger battery is neglect able and equivalent to the variation of one to two passengers.
6. A stop can be a physical stop or an artificial stop related to a road section. As defined, a charging station can be located anywhere along the route. The locations are pre-selected by a team of professionals, given other infrastructures, construction costs, traffic and urban constraints. A location can be at a bus stop, in which the size should fit the bay or curb (for a single bus or multiple buses) or along a road section. For both cases, the model requires the location, installation costs, and energy charge per unit of time.

Consider an electric public bus system with m bus routes in $\mathrm{R} = \{1, 2, \ldots, m\}$ and n bus stops in $S = \{s_1, s_2, \ldots, s_n\}$ along the bus routes. To simplify the presentation, let R_j denote the set of the bus stops on bus route j, e.g., $R_j \subseteq S$, and use s_{j_l} to denote the l-th bus stop on bus route j. Charging stations can be located at each stop.

Due to the different locations of the bus stops and the different number of bus routes passing through each bus stop, the cost of installing the charging station at different places should be different, i.e., bus stops may have different recharging requirement and thus lead to different installing costs. Suppose that c_i is the cost of installing a charging station at bus stop s_i, where $s_i \in S$. Suppose that $d_{js_{ji}}$ is the power consumed for bus on route j traveling from bus stop s_{i-1} to the next bus stop s_i. Using this notation, $d_{j_{s_{j0}}}$ is always equal to 0. To make sure the successful service of public bus, charging station placement should consider the worst scenario of energy consumption. Hence, besides depending on the distance between bus stop s_{i-1} and s_i, $d_{js_{ji}}$ is the worst-case energy requirements, obtained by historic information or prediction with the distance, vehicle acceleration characteristic, etc. Similarly, $e_{js_{ji}}$ denotes the power charged at stop s_i. for a bus on route j. Furthermore, let b be the battery size in kWh and p the battery cost per kWh. Let k_j be the number of buses serving route j and u_{umj} the environmental contribution for converting route j (the route length, air pollution reduction, fuel consumption, etc.).

Let x_i denote a decision variable, which is equal to 1 if a charging station is placed at s_i, and 0 otherwise. Let $E_{js_{ji}}$ denote the energy level of bus on route j arriving at bus stop s_{ji}. Let Y_j denote a decision variable, which is equal to 1 if route j can be fully operate on electric buses, and let $y_{js_{ji}}$ an auxiliary decision variable, which is equal to 1 if the remaining energy of bus on route j traveling to bus stop s_{ji} is sufficient, and 0 otherwise.

In the studied problem there are three objective functions.

$$\min Z_1 = \sum_{i \in S} x_i c_i + \sum_{i \in R} Y_i k_i bp \tag{1}$$

$$\max Z_2 = \sum_{j \in R} Y_j u_j \tag{2}$$

$$\min Z_3 = \sum_{i \in S} x_i \tag{3}$$

$$E_{js_{ji+1}} = \min\left(E_{js_{ji}} + x_{s_{ji}} e_{js_{ji}}, b\right) - d_{js_{ji+1}} \tag{4}$$

$$y_{js_{ji}} = \begin{cases} 1 & E_{js_{ji}} > 0 \\ 0 & otherwise \end{cases} \tag{5}$$

$$Y_i = \prod_{j \in \mathcal{L}_m} y_{js_{ji}} \tag{6}$$

$$x_i, Y_j, y_{js_{ji}} \in \{0,1\} \tag{7}$$

The first objective function, denoted by equation (1), is minimizing the total cost of the charging stations and the costs of the batteries. The second objective function, denoted by equation (2), is maximizing the environmental impact achieved by routes which can be operated using electric buses. The third objective function, denoted by equation (3), is minimizing the number of stations to be installed. Equation (4) calculates the energy level at stop s_{ji}. The level is the level energy at the arrival to the previous bus stop plus the energy charged (if a charging station is installed) minus the energy consumption to stop s_{ji}. The charging level is limited by the battery capacity. Moreover, the energy level can be negative, which implies that not sufficient energy is supplied to reach the bus stop. Equation (5) defines whether sufficient energy is available to reach stop s_{ji}. Finally, equation (6) defines if all stops along route *j* has sufficient energy, hence electric buses can operate along this route.

HEURISTIC APPROACH

The Vector Evaluated Genetic Algorithm (VEGA proposed by David Schaffer (Schaffer, 1985, Schaffer and Grefenstette, 1985), is normally considered the first implementation of a multi-objective evolutionary algorithm (MOEA). The vector is by definition the vector of *k* objective functions of the MOP. The VEGA approach is an example of a criterion or objective selection technique where a fraction of each succeeding population is selected based on separate objective performance. The specific objectives for each fraction are randomly selected at each generation. VEGA tends to converge to solutions close to local optima with regard to each individual objective.

In this paper, an improved version of the VEGA algorithm is used. Elitism guarantees that the best solutions found in each iteration are passed on to the next iteration and not lost. The original VEGA algorithm does not use elitism. Conventionally, elitism is achieved by simply copying the solutions directly into the new generation. In order to describe how the elitism, or the preservation of high-performance solutions, is done in the improved VEGA algorithm, the concepts of dominated and non-dominated solution have to be defined first. In single-objective optimization problems, the “best” solution is defined in terms of an “optimum solution” for which the objective function value is optimized when compared to any other alternative in the set of all feasible alternatives. In multi-objective optimization problems, however, the notion of an “optimum solution” does not usually exist, since the optimum of each criterion does not usually point to the same alternative. The optimal solution in a multi-objective optimization problem is usually equivalent to choosing the best compromise solution. In the absence of an optimal solution, the concepts of dominated and non-dominated solutions become relevant.

A feasible solution, x_1, dominates another feasible solution, x_2, if x_1 is at least as good as x_2 with respect to all objective functions and is better than x_2 with respect to at least one objective function. A *non-dominated solution* is a feasible solution that is not dominated by any other feasible solution. Hence the solution of a multi-objective problem is a set of non-dominated feasible solutions.

Using the definition above, the set of high-performance solutions can be defined as the set of non-dominated solutions obtained in all iterations of the algorithm. This set of non-dominated solutions, denoted as E, can be obtained if, in each iteration, any newly obtained solution is added to the set E if it is not dominated by any solution already in E. Moreover, if a newly obtained solution should be added to the set E, then any solution already in E that is dominated by the newly obtained solution is removed from E. After the last iteration, the result of the algorithm is the set E, which is the set of non-dominated solutions obtained in all of the algorithm’s iterations.

The process of the improved VEGA algorithm presented in Algorithm 1.

Algorithm 1 – Pseudocode of the improved VEGA algorithm

```
Algorithm: Improved VEGA
Input:   $P_C$ – Probability for crossover, $P_M$ – Probability for mutation, $P_{Size}$ – Population size,
         $N$ – Number of objective functions
Output:  Set of non-dominated solution

$P \leftarrow \emptyset$
$E \leftarrow \emptyset$
Add $P_{Size}$ randomly created feasible individuals to $P$
For each individual $p \in P$, evaluate $f_{pk}$, which is the fitness value of individual $p$ in regard
    to objective function $k$, for all $k \in N$
$E \leftarrow$ all non-dominated solution in $P$
While stop condition is not met do
    $M \leftarrow \emptyset$
    While the size of $M < P_{Size}$
        $k \leftarrow 1$
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            Select $P_{Size}/N$ individuals from $P$, based on the fitness value of each individual calculated for objective function $k$, $f_{pk}$, and add them to $M$
            $k \leftarrow k + 1$.
        $M \leftarrow M \cup E$
        Shuffle the $M$
        $P_{New} \leftarrow \emptyset$
        While the size of $P_{New}$ is less than $P_{Size}$
            Randomly select $p_1$ and $p_2$ from $M$
            Apply crossover operation, with probability $P_C$, on $p_1$ and $p_2$ to create $c_1$ and $c_2$
            Apply mutation operation, with probability $P_M$, on $c_1$
            Apply mutation operation, with probability $P_M$ on $c_2$
            $P_{New} \leftarrow P_{New} \cup c_1 \cup c_2$
        $P \leftarrow P_{New}$
        $\bar{E} \leftarrow \emptyset$
        $\bar{E} \leftarrow$ all non-dominated solution in $P \cup E$
        $E \leftarrow \bar{E}$
    Return $E$
```

For the problem studied in this paper, each candidate solution must specify a set of charging station and battery size. This information is coded by a binary array (i.e., a chromosome), with size equals to the number of bus stations plus the number of binary digits needed for the representation of an index corresponding to the different battery sizes. For each bus station represented in the chromosome, a value of "1" indicates the existence of a charging facility in that bus station, while a value of "0" indicates that such a station does not exist. As for the battery, assuming that there are a number of batteries available for use, it is possible to code an index for these batteries using binary representation. The resulting chromosomes are subjected to a set of genetic operations as follows: Two-parent chromosomes are selected using roulette wheel selection and subjected to a two-site crossover operator to produce two new chromosomes. These represent new combinations of charging stations. The resulting chromosomes are further mutated to increase the diversity of the solution population and to prevent trapping in local minima. In this study the mutation operation simply changes the value of a random bit in the chromosome, from "1" to "0" or "0" to "1", depending on its current value.

For each new generation, raw fitness values are calculated for each individual on the basis of the information encoded in its chromosome. The algorithm was coded in Phyton 3.7.

EXPERIMENTAL RESULTS

As large deployment of electric bus systems is not yet common, a synthetic network is used for demonstration. The network is composed of 10 routes, each with inbound and outbound directions. The road network is a 5km by 5km grid, as depicted in Figure 2 with 500m distance between each block. For simplicity, stops are evenly spaced at the near side of each intersection, as illustrated at the bottom of Figure 2.

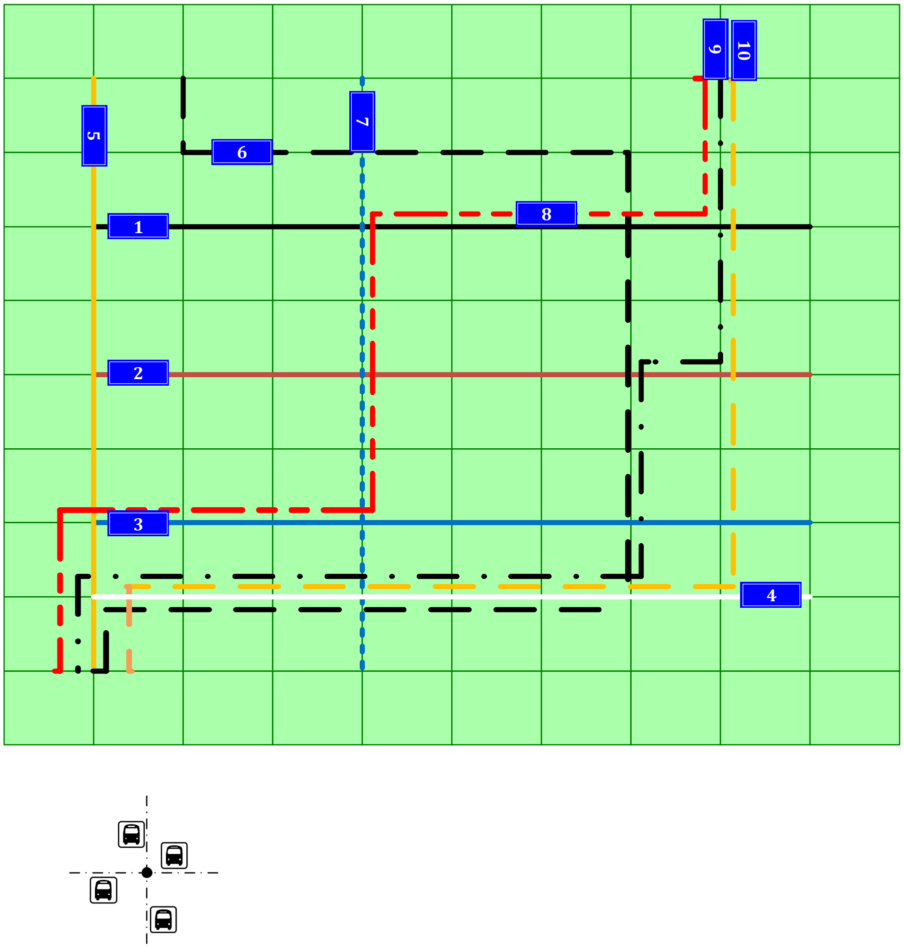

Figure 2 The PT network

In order to select the location for the charging stations which maximize the environmental impact of routes (in this case the routes length) that can be operated by wireless charging buses and at the same time minimize costs, the improved VEGA algorithm was used with the following assumptions:

1. Five types of batteries can be used with electric buses, 5kWh, 10kWh, 15kWh, 20kWh and 25kWh batteries. The costs of the batteries are 1000$, 1500$, 2000$, 2500$ and 3000$ respectively.
2. Batteries optimal operation condition is achieved when the battery charge is 90% to 20% of its maximum capacity. Therefore, in the analysis it is assumed that charging a battery cannot exceed the 90% limit. And on the other hand, if the charge of a battery decreases bellows the 20% limit, the battery is considered empty.
3. The cost of installing a charging station at a bus stop is 1000$. This cost is the same for all bus stops.
4. The charging time at each bus station is in the rage of 20-40 seconds. For each bus stop, the charging time was randomly selected. The charging time include dwell time as well as the time the bus is maneuvering to and from the bus stop.

5. For each bus route, both the length of the each route (8,8,8,8,15,19,15,8,8,15) in KM and the number of buses allocated (4,4,4,4,6,8,6,4,4,6) are given.

As the problem is solved as a multi-objective optimization problem, the result of the improved VEGA algorithm for the test network is a set of non-dominated solutions, which is summarized in TABLE 1, from which the decision-maker can select a single solution based on a set of preferences.

As can be seen from the results, the set of non-dominated solutions contains 21 different solutions. For each solution the following information is given: (1) Cost – which is the cost of the charging stations plus the cost of the batteries for the buses. (2) Total length – the total length of all bus routes that can be operated with electric buses. (3) Number of routes – the number of bus routes that can be operated with electric buses. (4) Battery size – the battery size used in the given solution. (5) Bus routes - the indexes of bus routes that can be operated with electric buses. (5) Number of charging stations – the number of bus stations containing charging facilities in the given solution.

The first solution is a trivial solution, in which there are no charging stations. In this case the cost, total length and number of routes of the solution are zero. Since a battery must be selected by the algorithm, the selected battery, in this case, is a 5kWh battery. As to the rest of the 20 solutions, they can be divided into four groups. In the first group, all solutions use a 10kWh battery, in the second group all solutions use a 15wKh battery, in the third group all solutions use a 20wKh battery and in the fourth group all solutions use a 25wKh battery. Moreover, it can be seen that the cost of each solution is dependent on the number of bus stop containing charging stations and the number of routes (which affect the cost of batteries).

TABLE 1 Non-dominated Solutions for the test network

Solution	Cost ($)	Total length (km)	Number of routes	Battery size (kWh)	Routes	Number of charging stations
1	0	0	0	5	-	0
2	74000	112	10	20	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	59
3	74000	112	10	20	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	59
4	74000	112	10	20	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	59
5	74000	112	10	25	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	56
6	74000	112	10	25	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	56
7	74000	112	10	25	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	56
8	20000	16	2	10	8, 9	14
9	20000	16	2	10	8, 9	14
10	28000	24	3	10	1, 2, 3	22
11	28000	24	3	10	3, 4, 8	22
12	34000	31	3	10	2, 6, 9	28
13	36000	32	4	10	3, 4, 8, 9	30
14	38000	39	4	15	1, 5, 8, 9	30
15	43000	47	5	15	1, 2, 5, 8, 9	35
16	49000	48	6	15	1, 2, 3, 4, 8, 9	41
17	51000	63	7	25	1, 2, 3, 4, 5, 8, 9	39
18	59000	70	7	15	1, 3, 4, 5, 8, 9, 10	47
19	12000	0	1	10	8	6
20	12000	112	1	10	9	6
21	64000	112	9	20	1, 2, 3, 4, 6, 7, 8, 9, 10	49

For example, in solution number 2, which uses a 20kWh battery, the total number of bus routes that can be operated with electric buses is 10. The total length of the electric buses routes is 112km, and the total cost is 74000$. The locations of the charging stations used in this solution are presented in Figure 3(left). Solution number 5, for which the total number of bus routes that can be operated with electric buses, the total length of the electric buses routes and the total cost is that same as in solution 2, uses a 25kWh battery. This is achieved by selecting a different set of charging stations, as illustrated in Figure 3(right). The decision-maker can then decide whether to use a 25kWh battery or add 3 more charging stations.

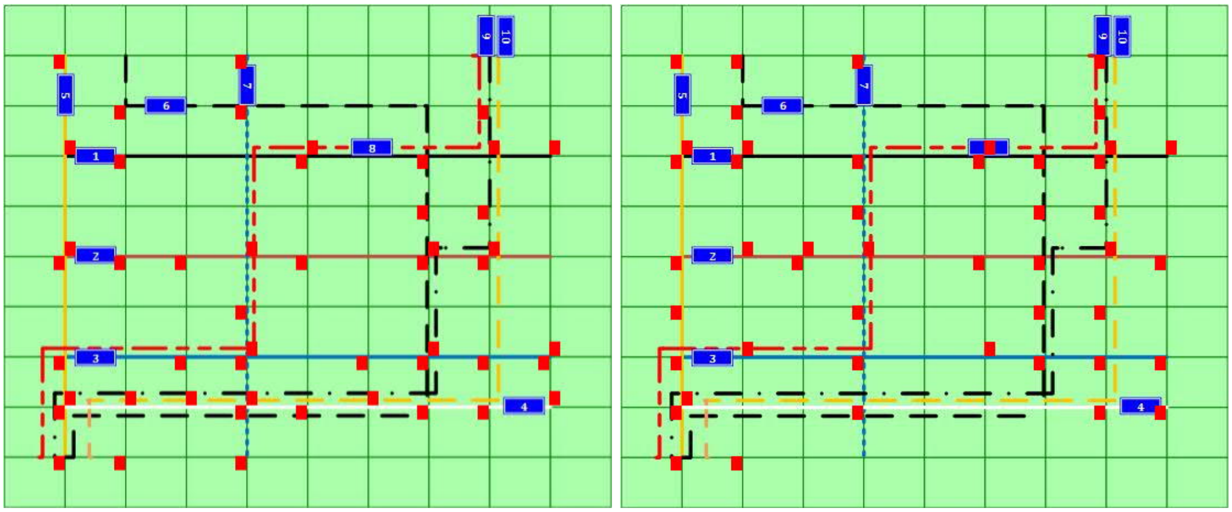

Figure 3 Locations of the Charging Stations for Solution 2 (left) and 5 (right)

On the other hand, both solutions 17 and 18 have the same number of bus routes that can be operated with electric buses. However, solution 17 uses a 25kWh battery, has a total length of the electric bus routes of 63km, and it's the total cost is 51000$, while solution 18 uses a 15kWh battery, has total length of the electric bus routes of 70km, and it's the total cost is 59000$. This is, again, achieved by selecting a different set of charging stations for each solution. The locations of the charging stations used in solutions 17 and 18 are presented in Figure 4 (solution 17 – left, solution 18 - right). Again, the decision-maker can further investigate the locations of the charging station and take into consideration other parameters which are difficult to integrate within the model (such as illegal parking at the bus stops).

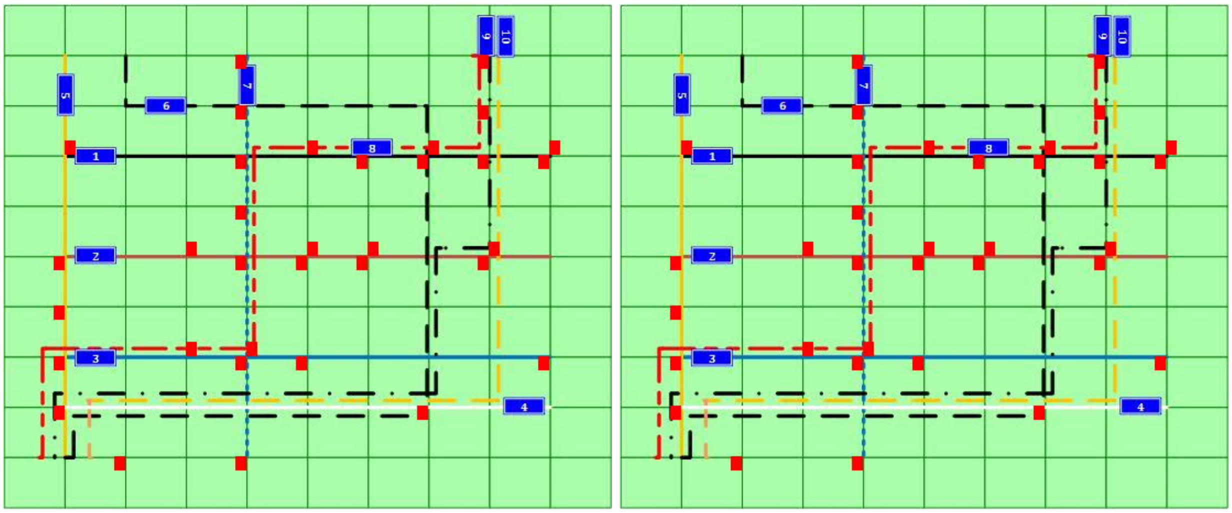

Figure 4 Location of the Charging Stations for Solution 17 (left) and 18 (right)

For simple sensitivity analysis, the cost of a charging station was increased to 4000$. TABLE 2 summarizes the results. The main difference is the higher costs. However, as the solution set provides solution for various costs, the general solution pattern has not been changed.

TABLE 2 Non-dominated Solutions for the test network (charging station cost – 4000$)

Solution	Cost ($)	Total length (km)	Number of routes	Battery size (kWh)	Routes	Number of charging stations
1	0	0	0	5	-	0
2	235000	104	9	20	1, 3, 4, 5, 6, 7, 8, 9, 10	55
3	242000	112	10	25	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	56
4	50000	16	2	10	2, 8	11
5	86000	24	3	10	3, 4, 8	20
6	116000	39	4	15	1, 3, 5, 8	27
7	146000	40	5	20	1, 2, 3, 8, 9	34
8	152000	47	5	15	1, 3, 5, 8, 9	36
9	160000	54	5	15	4, 7, 8, 9, 10	37
10	176000	55	6	15	1, 2, 3, 4, 5, 8	42
11	188000	62	6	15	1, 4, 7, 8, 9, 10	44
12	192000	63	7	25	1, 2, 3, 4, 5, 8, 9	45
13	214000	78	8	25	1, 2, 3, 4, 5, 8, 9, 10	49
14	34000	8	1	10	1	7
15	34000	8	1	10	3	7
16	34000	8	1	10	4	7
17	34000	8	1	10	8	7
18	34000	8	1	10	9	7
19	208000	81	7	15	1, 4, 6, 7, 8, 9, 10	49
20	232000	85	8	15	1, 3, 4, 5, 7, 8, 9, 10	55
21	234000	93	9	25	1, 2, 3, 4, 5, 7, 8, 9, 10	54

CONCLUSIONS

A multi-objective model for the allocation of wireless bus charging stations is proposed. The model is based on the increasing popularity of wireless charging in transportation. For example, the Israeli start-up company Electreon (Electreon, 2019) which developed a dynamic wireless electrification system for electric transportation, with an initial focus on public transport and heavy trucks, as they usually operate on fixed, known routes. The company has projects both in Israel and Sweden. The aim of the model is to provide the decision-maker with a tool to select where and when to install wireless charging station on a large-scale PT network, considering the costs and the environmental impact.

Further research is to consider the stochastic nature of the network (travel and dwell times, the number of passengers, etc.). For that, a stochastic modeling approach, based on chance constraints is to be investigated. Moreover, a more detailed analysis of the charging characteristics given online and offline bus stops, shared bus stops, priority lanes will be investigated. This can be done based on data collected from electric shuttles operation at Bar-Ilan campus and electric buses operating on Israel.

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