Model for optimal transition towards a fully electric public transportation system

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***Abstract*—In this paper, a comprehensive optimization model for decision support on public transportation system electrification is given. The basic assumption is that the transition is being governed centrally. This assumption together with a rather deterministic nature of the public transportation compared to a private enables a holistic approach in transition towards a fully electric system. The model comprises the following components: the electrification of the buses, the building of the charging stations and the electric grid reinforcement. These investment components are combined with the planned operating costs related to the cost of the energy used for charging and together yield a holistic model for transition planning.**

Nomenclature

Sets

Γ^B	Set of all electric buses
Γ^I	Set of all potential charging stations
Γ^L	Set of all distribution lines affected by the potential charging station connections
Γ^N	Set of all distribution nodes incident to the lines in Γ^L
Γ^{L_n}	Set of all lines connected to the node n, $n \in \Gamma^N$

Optimization variables

c^C	Components of the costs $C = \{bs, cs, gr, op\}$ (bs - battery storage, cs - charging station, gr - grid reinforcement, op - operating costs)
z_i	Binary variable denoting if the charging station i is built, $i \in \Gamma^I$
P_i^{cs}	Installed charging capacity of i-th charging station, $i \in \Gamma^I$
E_b^{max}	Maximal battery capacity of b-th E-Bus, $b \in \Gamma^B$
$S_{b,t,\xi}^{ch}$	Power bought for charging E-bus b at time t in scenario ξ
$SoC_{b,t,\xi}$	State-of-charge of the battery in E-bus b at time t in scenario ξ
w_l	Binary variable denoting if the distribution line l is overloaded, $l \in \Gamma^L$
P_l, Q_l	Active and reactive power flow on distribution line l, $l \in \Gamma^L$
$\Delta V_n, \delta_n$	Voltage magnitude change (from nominal) and angle n, $l \in \Gamma^N$

Input parameters

$c^{I.f.}, c^{I.v.}$	Fixed and variable costs associated with investment $I = \{bs, cs, gr\}$ (bs - battery storage, cs - charging station, gr - grid reinforcement)
$\lambda_{t,\xi}$	Electricity price, period t, scenario ξ
$S_{b,t,\xi}^{dr}$	E-bus storage power used for driving, bus b, period t, scenario ξ
g_l, b_l	Distribution line parameters (real and imaginary parts of nodal admittance matrix), $l \in \Gamma^L$
d_l	Distribution line length, $l \in \Gamma^L$
S_l^{max}	Distribution line loading limit, $l \in \Gamma^L$
P_n, Q_n	Active and reactive load connected to node n, $n \in \Gamma^N$

I. Introduction

Presence of electric vehicles (EV) has been steadily increasing in recent years and is expected to grow with even greater trends [1] following various policies which promote the use of EVs. It is well known that a large portion of human energy consumption and the consequent carbon emissions are related to the transportation. In order to reach any significant reductions in human impact on environment, this sector has to undergo a major transition towards an carbon neutral transportation. Furthermore, electrification of the transportation system has other benefits related to the grid support. Fluctuating nature of renewable sources requires storages which are available when the electric vehicles are not used for driving.

The trends are present in the public transportation as well and in this paper we are focused on improving the planning of public transportation transition towards a fully electric. Compared to the private transportation, the public transportation systems are managed centrally and hence it is reasonable to systematically plan and optimize the transition. The biggest difficulty in these models is to take into account all of the costs influencing the transition while maintaining the model complexity manageable. Two primary components of the transition are the bus fleet electrification and the building of the supporting charging infrastructure. These objectives conflict since the larger battery means less frequent charging requirements and vice versa. Secondary component of the transition is related to the necessary grid reinforcement following the newly added electric load. All of these components are further constrained by different technical limitations. In this paper, we propose a comprehensive optimization model that accounts for all of these factors and as such presents a novel contribution to the existing body of modeling approaches. Figure I depicts these three major components considered in the model.

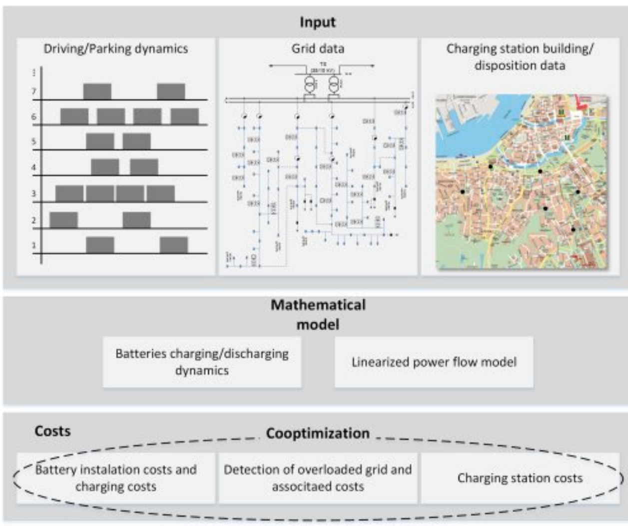

Fig. I. Principal depiction of the components of the model

In existing literature different components of this problem have been investigated. For example, in [2] and [3], a detailed description of the formulation, complexity and solution of the EV charging station placement and design is given. However, due to the major difference in the private and the public transportation system, these approaches are not suitable. Moreover, the impact on the electric grids has not been considered in [2]. On the other hand, in [4], [5] emphasis is given to the impact on the grid, but again, for the private vehicles. However, charging station placement based on the grid impact alone, without the costumer side of the problem, provides only a partial conclusion. A step further in terms of comprehensiveness is taken in [6] and [7]. In [6], a bi-level optimization is adopted in order to co-optimize EV parking lot participation on electricity market and vehicle accommodation versus their disposition. Even within the class of private vehicles, a single approach is inadequate since the different types of areas can require a completely different approaches as indicated in in [8]. Modeling techniques vary as well, while these papers mainly adopt a centralized optimization, a game-theoretic approach is adopted in [9].

Compared to all of the mentioned models, the major contribution we present here is the comprehensiveness of the model enabled by the characteristics of the public transportation and the fact that its electrification is governed centrally. We consider both the investment and the operational costs. Furthermore, within investment costs, the model accounts for the fleet electrification, the supporting infrastructure and the electric grid reinforcement as indicated in Fig. I. This kind of framework has not been introduced so far and presents a novel approach in the existing body of transportation planning frameworks. The model is validated on an existing public transportation system in Gothenburg, Sweden which is currently undergoing a transition towards a fully electric system.

II. Cost identification

Charging station disposition optimisation is guided by several distinct costs. This problem is further complicated by the fact that it comprises both the long-term costs of operating the charging stations as well as the immediate investment costs. Due to the size of the problem, it is necessary to neglect several costs/benefits since their impact is rather negligible. The investment costs considered in this problem are:

- costs of batteries,
- costs of building charging stations,
- costs of grid reinforcement.

The only operating cost considered in this problem is the costs of charging energy. Other operating costs like maintenance and running can be discounted and added to the investment costs.

Each of the investment costs identified above has a typical structure decomposable to fixed and variable costs. In the case of battery costs, the fixed cost (costs independent of the battery size) are constant and mandatory since the batteries must be installed and, as such, are not subject to the decision making. The battery size, on the other hand, is the variable component of the costs and subject to the decision making. In the case of charging station building, both the fixed costs related to the charging stations building and the variable costs related to the size of each station are subject to the decision making, i.e. the number, location and the size of charging stations are a result of the optimization problem. In the last component, the matter is less straightforward and requires necessary simplifications in order to make the problem manageable. If the charging stations (during the time of extreme conditions) cause a line overload, these lines would have to be reinforced. However, the problem of line overloading could be solved via alternative solutions (reconfiguration, grid-support devices, etc.) or through a construction of new lines which would alternate the existing grid configuration. Inclusion of these options into the decision making process is out of the scope. Instead, we establish a functional connection between the grid reinforcement costs and the distance of the overloaded grid. This means that if a grid line l is overloaded, an additional investment cost will appear consisting of the fixed costs and the costs dependent on the line length.

A. Mathematical formulation

The costs introduced above can be mathematically modelled in the following set of equations.

The costs for batteries installed in buses are captured with the following equation:

$$c^b = N^{bus} c^{b.f.} + c^{b.v.} \sum_b E_b^{max}. \tag{1a}$$

In (1a), fixed and size-dependant battery costs are multiplied with the number of buses. More details on the battery costs can be found in [10], and for the second-life batteries in [11].

The costs for charging station building are captured with the following equation:

$$c^{cs} = \sum_i \Big(z_i c_i^{cs.f.} + c_i^{cs.v.} P_i^{ch} \Big). \tag{1b}$$

In (1b), fixed and variable costs can be identified. In this case, fixed costs are dependent on whether the station is built or not. Variable costs are dependent on the size of the charging station determined with the charging capacity. This charging capacity is zero if the charging station is not built.

Finally, the last component in the investment costs is the necessary grid reinforcement. As it was explained above, we will assume that these costs can be determined as a function of the distance of the overloaded grid [12]. The following equation captures these costs:

$$c^{gr} = \sum_l w_l \Big(c^{gr.f.} + c^{gr.v.} d_l \Big). \tag{1c}$$

In (1c), both the fixed and variable costs are multiplied by the lines identified as overloaded.

Operational costs are the costs for the energy used for battery charging. These can be determined with following

$$c_y^{op} = \sum_\xi \pi_\xi \sum_t \lambda_{t,\xi} S_{t,\xi}^{ch}. \tag{1d}$$

The expression 1d is a sum of products of the energy spend in a single temporal instance and the corresponding price within representative days. These days should resemble typical days in terms of driving schedules (weekday, weekends, special events, ...) which will then form a set of representative daily energy usage patterns. Each of these days is then weighted with its probability in a year with a factor π_ξ. It should be noted that there are other opportunities for profit, for example, the storage renting to the power supplier as described in [13]. However, it is still not clear to which extent are these opportunities feasible, and a further research should be conducted in order to evaluate this opportunity.

Finally, the objective of this optimisation problem is to minimise the total investment and operational costs

$$\min \quad c^b + c^{cs} + c^{gr} + \gamma \sum_{y=1}^{N_y} c_y^{op} \tag{2}$$

where γ represents the discount factor, while the operating costs are calculated for the following N_y years. The formulation in 2 captures the net present costs of the transition.

III. Bus charging/driving pattern estimation

The basic assumption here is that the bus driving patterns are known based on the existing schedules made by the public transport operator. These schedules are determined with the set of times when the driving regime starts $\{t_{d_1}, t_{d_2}, ..., t_{d_N}\}$, the set of pairs of times when the parking regime starts and the locations where the parking regime takes place $\{\{t_{p_1}, i_1\}, \{t_{p_1}, i_2\}, \{t_{p_3}, i_1\}, ...\}$ with $i \in \Gamma^I$. It is important to clarify that these sets are related only to those parking locations where the building of charging station is considered. Parking times at other locations are included in the estimated power usage for driving. Figure II depicts these times and locations for an arbitrary bus line. The same figure depicts the dynamics of the battery storage usage in this bus.

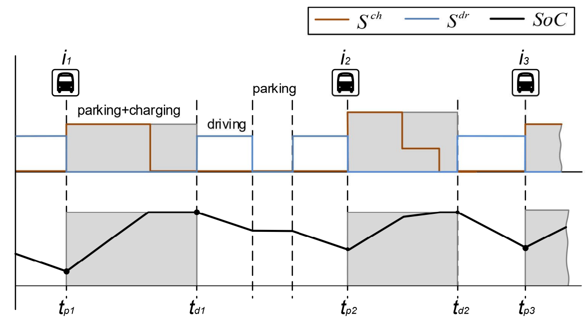

Fig. II. Graphical description of the bus schedules

Another clarification is necessary, while the times when the driving starts are quite deterministic, parking start times can vary depending on the traffic conditions. However, for the sake of simplicity, these parking start times will be considered as deterministic. Furthermore, the storage power used for driving will also be considered deterministic, although this power can vary depending mostly on the number of passengers in the bus.

These schedules are used for calculation of the matrix which establishes the temporal relation between each bus and each charging station. Elements of this matrix are defined in the following:

$$A_{b,i}(t) = \begin{cases} 1 & \text{if bus } b \text{ is on the location } i \text{ at time } t \\ 0 & \text{else} \end{cases} \tag{3}$$

Following set of constraints capture the dynamics of each bus storage.

$$SoC_{b,t,\xi} = SoC_{b,t-1,\xi} + \Delta t \big(S_{b,t,\xi}^{ch} - S_{b,t,\xi}^{dr} \big), \quad \forall b, \forall t, \forall \xi \tag{4a}$$

$$0 \leq A_{b,i}(t) S_{b,t,\xi}^{ch} \leq P_i^{cs}, \quad \forall b, \forall t, \forall \xi \tag{4b}$$

$$0 \leq S_{b,t,\xi}^{ch} \leq 6 E_b^{max}, \quad \forall b, \forall t, \forall \xi \tag{4c}$$

$$SoC^{min} \leq SoC_{b,t,\xi} \leq SoC^{max}, \quad \forall b, \forall t, \forall \xi \tag{4d}$$

$$SoC_{b,0,\xi} = SoC_{b,T,\xi}, \quad \forall b, \forall \xi \tag{4e}$$

In constraint (6), a battery charging dynamics are described, where S^{dr} denotes an estimate on the average E-bus energy usage for driving. According to [14], this parameter ranges from 0.8 kWh/h to 2.82 kWh/h, Constraints (4b) and (4c) describe the bounds on the charging power. The first bound is related to the charging station capacity stating that the sum of all charging powers related to the instantaneously connected buses has to be lower than the charging station capacity. The second bound is related to the maximal battery charging rate which equals 6 times the capacity [15]. Constraint (4d) bounds the energy content of a battery between the admissible bounds while the constraint (4e) imposes the continuity on the charging dynamics.

In the constraints above, no requirements on the order of charging are placed. This kind of formulation might end up in a feasible but unrealistic charging dynamics. For example, the buses might switch charging order each time instance. In order to avoid these kinds of results an additional objective can be added which minimizes the number of charging startups. Since this objective is not of the same nature as the primary economic objectives, they need to be combined carefully. In a different approach, limitations on the charging interchanges could be added through constraints.

Finally, the last constraint in this part of the model is related to the decision on whether the station is built and what is it's size. This is captured in the following:

$$z_i P_i^{ch,min} \leq P_i^{ch} \leq z_i P_i^{ch,max}, \quad \forall i \tag{5}$$

In (5), the size is bounded between the minimal and the maximal required size if the binary variable is active, otherwise, the station is not being built and the size is forced to zero.

IV. Electric grid conditions estimation

A. Mathematical formulation

Charging stations connect to the 10 kV distribution grid. In a similar manner to that of Bus-to-charging station, the relation between each charging station and the node in the distribution grid has to be established. The following matrix establishes this connection:

$$B_{n,i} = \begin{cases} 1 & \text{if charging station } i \text{ is connected to the node } n \\ 0 & \text{else} \end{cases} \tag{6}$$

Linearized power flows have been extensively used in large-scale problems. The nodal formulation of the power-flow equations is defined in the following two equations which essentially state that the net injections at each node have to equal zero for both the active and reactive power.

$$P_i + B_{n,i} P_i^{ch} - \sum_{l \in \Gamma^{L_i}} P_l = 0, \quad \forall i \in \Gamma^N \tag{7a}$$

$$Q_i - \sum_{l \in \Gamma^{L_i}} Q_l = 0, \quad \forall i \in \Gamma^N \tag{7b}$$

where $\cos\phi^{cs}$ is the load angle of a charging station and P_l and Q_l are the branch l active and reactive power flow defined in:

$$P_l = V_i^2 g_l - V_i V_j \left(g_l \cos\delta_{ij} + b_l \sin\delta_{ij} \right) \tag{7c}$$

$$Q_l = -V_i^2 b_l + V_i V_j \left(b_l \cos\delta_{ij} - g_l \sin\delta_{ij} \right) \tag{7d}$$

Here, we adopt linearisation proposed in [16]. Assuming that the voltages will not deviate significantly from the nominal conditions, the voltage at a node i can be reformulated as

$$V_n = 1 + \Delta V_n, \quad \forall n \in \Gamma^N \tag{7e}$$

The second simplification arising from the assumption on a near nominal operating conditions (small δ) is the following

$$\begin{aligned} \sin\delta_{ij} &\approx \delta_{ij} \\ \cos\delta_{ij} &\approx 1 \end{aligned} \tag{7f}$$

The equations (7c) and (7d) now reduce to

$$P_l = \Big(\Delta V_i - \Delta V_j \Big) g_l - b_l \delta_{ij} \tag{7g}$$

$$Q_l = -\Big(\Delta V_i - \Delta V_j \Big) b_l - g_l \delta_{ij} \tag{7h}$$

with additional assumption that the second-order terms can be neglected.

The above equations determine the approximate operating conditions in the distribution network which we want to use as an indicator of the necessary grid reinforcement costs. This can be achieved through the assumption that, if the the apparent power flow through the branch ij is higher than the maximal loading, the same branch requires replacement with a new one. In (1c), the requirement for the replacement is denoted with w_i, and based on the previous statement, it can be defined with the following

$$w_l = \begin{cases} 1 & \text{if} \quad S_l > S_l^{max} \\ 0 & \text{else} \end{cases} \tag{8a}$$

where

$$S_l^2 = P_l^2 + Q_l^2 \tag{8b}$$

In order to ensure the realization of the binary variable w_l according to 8a, the following constraint is used:

$$w_l \left(S_l^{max} \right)^2 \leq S_l^2 \leq (1 - w_l) \left(S_l^{max} \right)^2 + w_l M \tag{8c}$$

where M is a large number greater than S_l^{max}. Obviously, if the S_l^2 is lower than $(S_l^{max})^2$, w_l is forced to zero. Otherwise, w_l is forced to 1. The only difficulty here is that the model is no longer mixed-integer linear due to the quadratic term in in the constraint 8c. This difficulty is resolved through the linearization of the quadratic function depicted in Fig III.

The following constraints determine the approximated value of the active and reactive component of the power-line flow.

$$\begin{aligned} P_l^{2,approx} &= \sum_{s=1}^{N_s} k_s^P \Delta P_{l,s} \\ Q_l^{2,approx} &= \sum_{s=1}^{N_s} k_s^Q \Delta Q_{l,s} \end{aligned} \tag{8d}$$

$$\begin{aligned} \sum_{s=1}^{N_s} \Delta P_{l,s} &= P_l \\ \sum_{s=1}^{N_s} \Delta Q_{l,s} &= Q_l \end{aligned} \tag{8e}$$

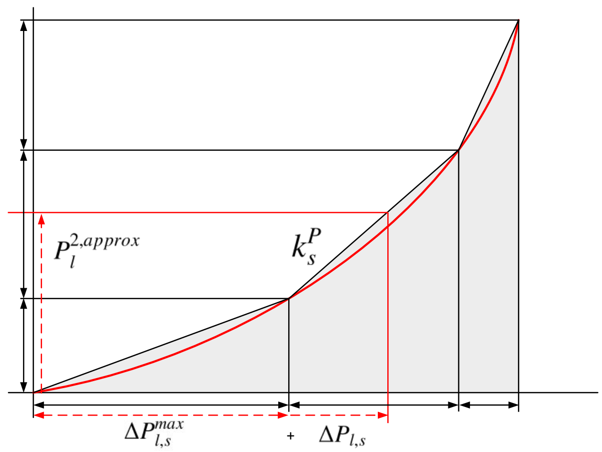

Fig. III. Graphical description of the quadratic function linearization applied on the power line loading approximation

$$0 \leq \Delta P_{l,s} \leq \Delta P_{l,s}^{max} \quad \forall s$$
$$0 \leq \Delta Q_{l,s} \leq \Delta Q_{l,s}^{max} \quad \forall s \tag{8f}$$

In (8d), the approximated value is calculated as the sum of linear segments. Constraint (8e) ensures that the sum of active and reactive power-line flows equals the actual power-line flows determined in (7c)-(7d). The last two constraints (8f) bound the segments between the linearized bounds. If the S_l^2 in (8c) is replaced with the linearized formulation, the following constraint can approximate the original quadratic expression:

$$w_l \left(S_l^{max}\right)^2 \leq \sum_{s=1}^{N_s} \left(k_s^P \Delta P_{ls} + k_s^Q \Delta Q_{ls}\right) \leq \left(1 - w_l\right) \left(S_l^{max}\right)^2 + w_l M \tag{8g}$$

The approximated apparent power flow in (8d) can be calculated with different combinations of segments while satisfying constraints (8e)and (8f). The correct choice is ensured with the optimization objective which "avoids" the line reinforcement. In order to avoid the line reinforcement, the segments will be chosen in a manner which favors smaller $k_s^{P,Q}$. However, if the apparent power flow is not on the borderline operation and the binary variable w_l is not affected, the correct choice is not ensured. This essentially means that the apparent power flow might be inaccurate in some situations but the line reinforcement requirements are correctly indicated in every situation. Since that is the main objective of this approximation, this formulation is appropriate.

If we assume that in some situation, all charging stations might be used at their maximal capacity, the same capacity can be superposed on the maximally loaded grid. Therefore, in equations (7a) and (7b) maximal nodal load is introduced via $P_i + B_{n,i} P_i^{cs}$ and $Q_i + B_{n,i} P_i^{cs} \cos\phi^{cs}$.

V. Case Study

A. Case study and solution technique

For a case study, the presented model is used as a decision support for the undergoing transition of Gothenburg public transportation system towards a fully electric system.

Due to the space limitations, we will focus on a district Vastra Frolunda in Gothenburg. The costs used in this analysis are depicted in Table V-A. Five potential locations for charging stations are considered together with an option of Depo charging. A bus scheduling system determines the timetable for each of 14 buses based on the trip frequency requirements including the charging time.

TABLE I
FIXED AND VARIABLE COSTS OF THE INVESTMENT COMPONENTS

	Fixed	Variable
Battery	5k €	0.4k €/kWh
Charging station	200k €	0.5k €/kW
Grid reinf.	5k €	0.1k €/km

Proposed optimization model is solved using GUROBI solver [17] within Python environment.

B. Results

In this section, the results of the proposed model applied on the case study described above are presented. It is important to point out that these results are related to this specific case study and should not be taken as general.

In this specific case study, optimal system structure includes a single charging station with a 32 kW charging power. This charging station is built at the location 6 which is related to Depo charging. It is important to point out that this result is related to the fact that the area under consideration is not large in terms of the number of buses. This kind of system can thus favor larger batteries with a single charging site.

The second important result of the proposed model is the battery size. The choice for the investor in this case is to order buses with the same battery size across the entire fleet. The required battery capacities for each bus are depicted in Fig. IV Since the optimal choice for charging stations is the Depo charging, batteries will be charged for the complete day in a single charging. Therefore, the battery capacity has to handle the required driving duty. Depending on the driving requirements, battery capacities vary. Smaller capacities in Fig IV are related to buses driving rush hours during couple of hours in a day. The maximal capacity required is related to the bus 3 and equals 21.23 kWh. This amount is hence, the necessary capacity for the entire fleet.

Finally, the cost decomposition depicted in Fig. V indicates the impact of each cost component in this case study. Obviously, the biggest component is the battery cost which equals approx. 370000€. The second largest component is the charging energy equaling approx. 330000€. The cost of charging stations is the third component equaling approx 200000€. Finally, the last component, which is negligible compared to the other components in this case study, is the grid reinforcement cost equaling approx. 10000€.

VI. Conclusion

The model presented in this paper comprises a comprehensive framework for the public transportation system

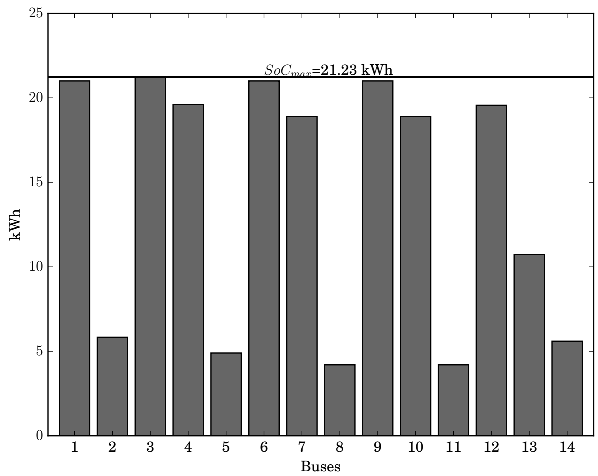

Fig. IV. Resulting battery capacity requirements for each bus

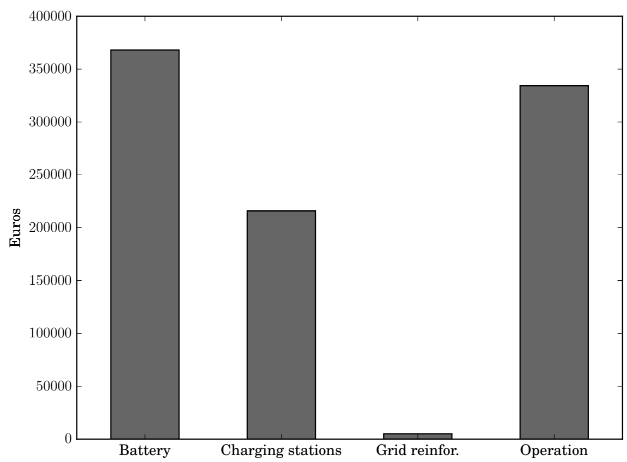

Fig. V. The cost structure

electrification. Compared to the existing models, a significant level of comprehensiveness has been achieved through the incorporation of several objectives which arise in the transportation electrification planning. These objectives span from the bus electrification design (battery sizing) to charging stations installation (disposition and sizing), from the grid reinforcement to charging energy consumption. This kind of framework is necessary due to the main difference between the public and the private transportation electrification. With the public transportation, the transition is managed centrally and performed in short intervals with high investments. Due to this specificity, decision support in terms of the presented optimization model is essential.

The proposed model is tested on a realistic case study. In Gothenburg district of Vastra Frolunda, a local public transportation service provider is conducting an electrification of the bus fleet. The results of the model provide information on the optimal system design per each component and the corresponding costs.

References

[1] E. A. Nanaki and C. J. Koroneos, "Climate change mitigation and deployment of electric vehicles in urban areas," *Renewable Energy*, vol. 99, pp. 1153 – 1160, 2016.

[2] A. Y. S. Lam, Y. Leung, and X. Chu, "Electric vehicle charging station placement: Formulation, complexity, and solutions," *IEEE Transactions on Smart Grid*, vol. 5, no. 6, pp. 2846–2856, Nov 2014.

[3] O. Hafez and K. Bhattacharya, "Optimal design of electric vehicle charging stations considering various energy resources," *Renewable Energy*, vol. 107, pp. 576 – 589, 2017.

[4] C.-L. Su, R.-C. Leou, J.-C. Yang, and C.-N. Lu, "Optimal electric vehicle charging stations placement in distribution systems," in *IECON 2013 - 39th Annual Conference of the IEEE Industrial Electronics Society*, Nov 2013, pp. 2121–2126.

[5] A. Ul-Haq, C. Cecati, and E. El-Saadany, "Probabilistic modeling of electric vehicle charging pattern in a residential distribution network," *Electric Power Systems Research*, vol. 157, pp. 126 – 133, 2018.

[6] N. Neyestani, M. Y. Damavandi, M. Shafie-Khah, J. Contreras, and J. P. S. Catalo, "Allocation of plug-in vehicles' parking lots in distribution systems considering network-constrained objectives," *IEEE Transactions on Power Systems*, vol. 30, no. 5, pp. 2643–2656, Sept 2015.

[7] P. Sadeghi-Barzani, A. Rajabi-Ghahnavieh, and H. Kazemi-Karegar, "Optimal fast charging station placing and sizing," *Applied Energy*, vol. 125, pp. 289 – 299, 2014.

[8] I. S. Bayram, A. Tajer, M. Abdallah, and K. Qaraqe, "Capacity planning frameworks for electric vehicle charging stations with multiclass customers," *IEEE Transactions on Smart Grid*, vol. 6, no. 4, pp. 1934–1943, July 2015.

[9] C. Luo, Y. Huang, and V. Gupta, "Placement of ev charging stationsbalancing benefits among multiple entities," *IEEE Transactions on Smart Grid*, vol. 8, no. 2, pp. 759–768, March 2017.

[10] B. Nykvist and M. Nilsson, "Rapidly falling costs of battery packs for electric vehicles," *Nature Climate Change*, vol. 5, pp. 329–332, 03 2015.

[11] U. K. Debnath, I. Ahmad, and D. Habibi, "Quantifying economic benefits of second life batteries of gridable vehicles in the smart grid," *International Journal of Electrical Power and Energy Systems*, vol. 63, pp. 577 – 587, 2014.

[12] S. de la Torre, A. J. Conejo, and J. Contreras, "Transmission expansion planning in electricity markets," *IEEE Transactions on Power Systems*, vol. 23, no. 1, pp. 238–248, Feb 2008.

[13] J. Vasilj, D. Jakus, and P. Sarajcev, "Virtual storage-based model for estimation of economic benefits of electric vehicles in renewable portfolios," *Energies*, vol. 13, no. 9, p. 2315, 2020.

[14] J. E., *Opportunity charged electric buses*, ser. Volvo buses Environmental blog.

[15] X. Luo, J. Wang, M. Dooner, and J. Clarke, "Overview of current development in electrical energy storage technologies and the application potential in power system operation," *Applied Energy*, vol. 137, pp. 511 – 536, 2015.

[16] H. Zhang, G. T. Heydt, V. Vittal, and J. Quintero, "An improved network model for transmission expansion planning considering reactive power and network losses," *IEEE Transactions on Power Systems*, vol. 28, no. 3, pp. 3471–3479, Aug 2013.

[17] I. Gurobi Optimization, "Gurobi optimizer reference manual," 2015. [Online]. Available: http://www.gurobi.com