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PREPRINT

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***Abstract*—This paper proposes a V2G charging scheduling scheme for energy invoice minimization of railway station parking lots hosting plug-in electric vehicles. Using a two layer optimization technique the daily load profile of the railway station is reduced in order to increase the load factor and minimizing the annual energy invoice (AEI) of the station. Binary linear programming is used as second layer for charging/discharging scheduling problem. The final results shows interests of using the proposed approach conducting its impact on minimizing annual optimum subscribed power, maximum demand power and annual energy invoice.**

***Index Terms*—Plug-in electric vehicle, vehicle-to-grid, binary linear programming, railway stations**

I. Introduction

The Growth of electrified vehicles in transportation sector in the near future increases the grid load demand, where the energy management systems can reduce the negative impacts. As the electric vehicles charging infrastructure are mainly connected to the distribution networks, downer side network infrastructure are mostly affected by negative impacts, e.g. harmonic increment, voltage drop, power losses and peak power augmentation [1]. These effects also could be variable in presence of bidirectional power flow due to the vehicle-to-Grid (V2G) functionality of grid integrated vehicles (GIV) [2]. Hence the impact of latter situation should be simulated and its impacts have to be estimated, where possible solutions should be proposed to reduce the negative effects.

Charging coordination to the off-peak hours and V2G technology are introduced as the possible solutions for impact reduction of massive electric vehicle charging demand on the distribution grid [3]. The main objectives for charging coordination problems include losses minimization, voltage regulation [4], frequency regulation [5], peak power shaving [6] and reactive power control [7] [8].

V2G technology is introduced as the possibility of power injection to the grid by plug-in electric vehicle using their unused battery stored energy [3]. It can provide more degree of freedom for energy management purposes compare to charging coordination strategies as the bi-directionality of the power is also controllable [9].

In the literature, different scheduling and coordination problems are proposed. The methods are mainly based on either optimization methods or artificial intelligence methods. Dynamic programming is proposed in [10] [11] for the maximization of load factor. A simulated annealing approach is introduced in [12] for energy resource scheduling of distribution grid containing distributed generation and V2G units. Convex optimization method in form of global scheduling problem is proposed by [13].

In this study V2G scheduling problem is analyzed in order to provide individual schedule to the electric vehicles and make the global management of a small EV fleet possible for the aggregator unit. Charging of the electric vehicles will be provided in different places such as home charging, office charging, commercial centers and transport stations. This work is representing the impact of non-controlled charging of electric vehicles inside the station parking lots on railway station energy consumption, while an energy management strategy is proposed to reduce the charging impacts on annual electricity bill of the station. Different charging rates are available in the station such as normal charging (3 kW), fast charging (23 kW) and rapid charging (43 kW), where different possible charging scenarios are simulated based on passengers commuting statistics in the morning and evening.

Non-controlled charging impacts have been estimated for 1 to 20 electric vehicles available in the parking lots. These impacts have two different aspects; economic and technical where both have been analyzed. The objective of the energy management is reducing the annual energy invoice (AEI) of the station. AEI of railway station has three components: Subscription, Consumed energy and Subscribed power exceeding component. Subscribed power is a fixed power which is asked by railway station (consumer) to have it at its disposal. This power is either constant over a year or variable for different tariff periods. In this case study, a constant one is chosen based on actual contract of railway station. Comparing to the annual

This work is a part of V2G project supported in part by *ADEME* (French Environment and Energy Management Agency), *SNCF* (French National Railway Network), *GEREDIS Deux-Sèvres* (Distribution System Operator of Deux-Sèvres/France) and *SEOLIS company* (Energy supplier Company).

consumption, choosing high value of subscribed power leads to extra payment on subscription component while, low value causes increment on subscribed power exceeding component. Hence an optimization framework is necessary to explore the optimum energy invoice while providing services to the costumer (electric vehicles).

A two layer optimization approach is proposed where in the first layer, optimum subscribed power and load profile will be calculated using nonlinear convex optimization. Afterwards, based on optimized load profile limited to the optimized subscribed power the charging/discharging scheduling will be calculated using binary linear programming for each single vehicle. These schedules will be transmitted to the vehicles in order to control their charging demand. Finally the advantages using proposed approach are presented in economic benefit over annual invoice.

The rest of the paper is organized as follow. In section II case study and charging scenarios are introduced. In section III, the problem formulation for two layer of optimization are conducted and finally the results are discussed in section IV.

II. Case Study and Assumptions

It is estimated to have numerous electric vehicles in the cities by near future. These vehicles need to be charged for their next trips. Considering the scenario of peoples who use the train for their daily commuting to works, the parking of railway stations will be a potential location to host future electric vehicles. Knowing that, the railway transportation organizations are thinking to propose innovative solutions concerning different steps of this new implementation in the railway stations. It starts from designing of charging stations inside the parking and the charging possibilities and offers to the customers.

The railway stations in France are one part of future smart grid projects with possible interactions between grid and the customers. Based on their contract they are connected to the distribution grid through a MV/LV substation (20 kv/0.4 kV). In this paper one of the railway stations in Paris has been considered as case study in order to propose charging solutions and analyze the impacts of different charging scenarios. The objective is to minimize the AEI using electric vehicles as controllable charge. In addition to that thanks to the Vehicle-to-grid technology the reversibility of energy flow from EVs to the grid would be also possible. The daily load profile (DLP) of the railway station is illustrated in Fig. 1. It shows a peak of consumption during morning and evening peak hours, the time when the passengers get train for work and home motives. This two peak intervals are considered also as the peak hours of PEV being in parking lots of the station (Fig. 2). Using a normal distribution, the arrival/departure time of the PEVs to/from the station are modelled with parameters in Table I.

The idea in this study is at first evaluate the uncontrolled charging impacts of PEVs with these mobility behavior on the railway station consumption for different charging scenarios and secondly evaluate the contribution of a V2G charging scheduling algorithm to the AEI minimization using a two layer optimization approach. Four charging scenarios are considered as base case in order to evaluate the algorithm performance.

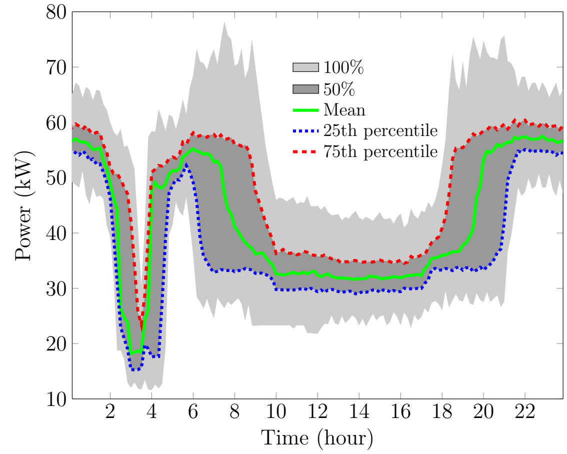

Fig. 1. Daily load profile of understudying railway station.

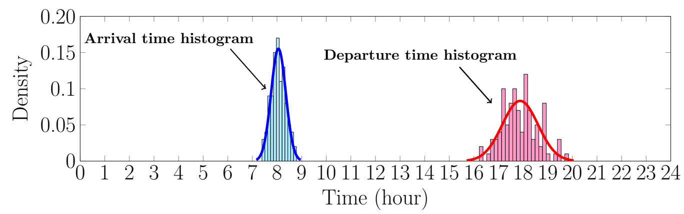

Fig. 2. Arrival/departure time histogram to/from the railway station.

TABLE I
Arrival/departure time normal distribution's parameters

Distribution	μ (hh:mm)	σ (minutes)
Arrival time	08:00	20
Departure time	18:00	40

A. *Normal charging (Scenario 1 (S1))*

It is supposed to have normal charging rate of 3 kW for all the vehicles demanding for the energy. This mode is the priority for vehicles having long station time.

B. *Mixed charging (Scenario 2 (S2))*

Mixed charging is considered by distribution of 40% normal charging, 40% rapid charging and 20% accelerated charging.

C. *Accelerated charging (Scenario 3 (S3))*

In this scenario, all PEVs in the stations will be charged by 23 kW charging rate. This takes approximately one hour for a completely empty battery of 20 kWh.

D. *Fast charging (Scenario 4 (S4))*

All the PEVs will be charged by rapid charging mode with the power of 43 kW in this scenario. The impact of this charging mode can be crucial to the internal grid installation.

III. PROFBLEM FORMULATION

An algorithm based on two layer optimization is discussed here. Annual energy invoice minimization (AEIM) algorithm at first minimizes the subscribed power of the station based on future energy consumption provision. Afterwards, using a convex optimization method the daily load profile of the station will be recalculated for the aim of minimizing the AEI. This DLP will be called as reference load profile and will be used as reference for second layer optimization. The second layer uses a Binary Linear Programming (BLP) algorithm in order to reschedule the charging procedure of PEVs in the station. The algorithm will take just zero sand ones as its possible values for the optimization variables which lead to calculation time reduction comparing to the continuous linear programming algorithms. The flowchart of the proposed algorithm is brought in Fig. 3, where it shows the flow of data and process simultaneously. The different parts of this algorithm will be explained thoroughly afterwards.

A. Optimizing subscribed power (P_{sub})

The subscribed power is contracted one time per year and should be carefully chosen. Comparing to the annual consumption, choosing high value of subscribed power leads to extra payment on subscription component while, low value causes increment on subscribed power exceeding component. Hence choosing appropriate subscribed power leading to optimum invoice needs to have *a priori* knowledge on amount and manner of consumption. Having a typical annual load profile, optimum subscribed power can be found via a convex optimization problem.
The yearly energy invoice is calculated using following formula [14].

$$Cost = \sum_{j=1}^{5}(d_j E_j) + \sum_{j=1}^{5}(K.T_j \sqrt{\sum(\Delta P_j)^2}) + \alpha.P_{sub} \quad (1)$$

$$E_j = \int_{t_j^a}^{t_j^b} LP(t)d(t) \quad (2)$$

Where the first component is for consumed energy E_j, with its price d_j, in €/kWh during 5 different periodical tariffs j. The second components is for penalty of subscribed power exceeding with T, the reduction coefficient for each tarif and K the price of subscribed power (P_{sub}) exceeding in €/kW. ΔP is the amplitude of P_{sub} exceeding averaged during 10 minutes intervals. Finally, the third components which is the subscription part with base rate value of α in €/kW/year. LP is representing the load profile of the station where its variation should be controlled in order to minimize the invoice. The optimum subscribed power of the under studying station is obtained using a convex optimization as 69 kW. Note that this subscription is considering the annual consumption without PEVs load demand.

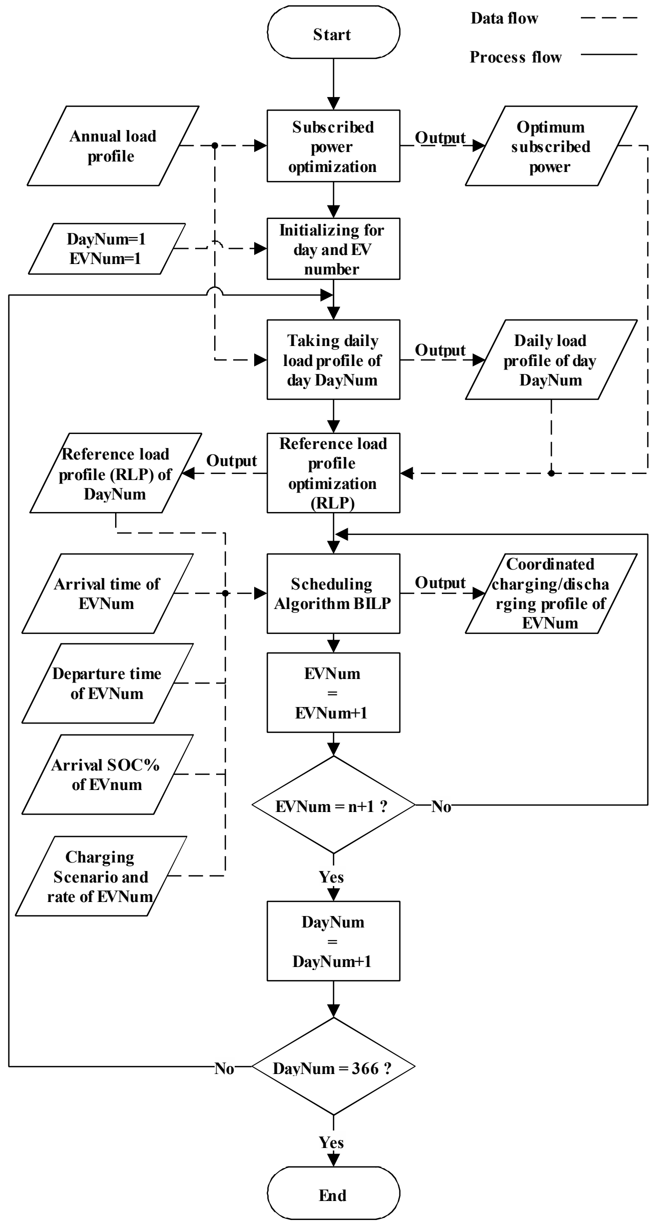

Fig. 3. Flowchart of AEIM algorithm

B. Energy invoice optimization

In this part optimizing the invoice using optimized subscribed power and actual load profile is addressed. In fact the load profile leading to minimum invoice will be found. This load profile will be considered as reference for charging/discharging scheduling problem in next section. This part is considered as the first layer of optimization.

$$\min_{RLP(t)} Cost \quad (3)$$

Subject to:

$$\int_{t_j^a}^{t_j^b} DLP(t)d(t) = \int_{t_j^a}^{t_j^b} LP(t)d(t) \quad (4)$$

Now $RLP(t)$ is the reference load profile which can minimize the invoice. This reference is considered in scheduling problem.

C. Formulation of PEV scheduling problem

Charging scheduling problem of N PEVs are formulated as a vector in time with elements equal to the 10 minutes time step over a day, which is equivalent to a row vector with size 1 by 144. This is called day sample times as k. The question to be answered is how coordinate the charging, no charging and discharging commands between plug-in time steps to achieve the objective of the coordination. For this reason $EV_{cp}^{i}(t)$ is defined as charging profile of PEVs with sample time coefficients of a_k as BLP variables and charging rate of CR^i. This charging rate is positive for charging and negative for discharging and the value is defined by the charging scenarios.

$$\begin{cases} EV_{cp}^{i}(k) = [a_1, a_2, ..., a_k] \times CR^i \\ i = [1, N] \in \mathbb{N}. \end{cases} \tag{5}$$

In equation (6), $Cap^i(k)$ represents the distance between RLP and actual LP. In fact, the purpose is to minimize this distance in order to minimize the energy invoice which is already minimized by RLP.

$$Cap^i(k) = LP(k) - RLP(k) \tag{6}$$

$$\gamma^i(k) = -\left|Cap^i(k)\right| \tag{7}$$

$$C^i(k) = \left(\gamma^i(k) + CR^i(k)\right) \times a_k \tag{8}$$

$$k = [1, 144] \in \mathbb{N} \tag{9}$$

$$a_k = [0, 1] \tag{10}$$

In order to prevent trivial answer of 0 for binary linear programming minimization problem, the coefficient $\gamma^i(k)$ is defined. Finally for optimization problem, $C^i(k)$ is defined as objective function.

$$\underset{a_1,..,a_k}{\text{Minimize}} \quad \sum_{k=1}^{T} C^i(k) \tag{11}$$

Subject to:

$$\sum_{k=1}^{T} A_{eq}(k).a_k = SOC_{need}^{i} \tag{12}$$

$$\sum_{k=1}^{T} A(k).a_k \leq SOC_{max}^{i} \tag{13}$$

$$\sum_{k=1}^{T} -A(k).a_k \leq -SOC_{min}^{i} \tag{14}$$

Constraint (12), ensure the energy need of each single PEV during its plug-in interval. Constraints (13) and (14) gaurantee the charging scheduling within possible range of SOC variation. Where SOC_{min}^{i} is considered as 20% to minimize the battery depth of discharge and SOC_{max}^{i} is equal to 100%, the constraint for departure of all PEVs.

$$A_{eq} = \frac{Cap^i(k)}{|Cap^i(k)|} \tag{15}$$

$$A_{eq} = [-1, 1] \in \mathbb{Z} \tag{16}$$

For principle formulation of linear programming the A_{eq} is the coefficient of linear equality constraints where for this problematic, its values are -1 for discharging, 0 for idle mode and 1 for charging mode. Finally, the matrix A for non-equality constraints is defined as follow:

$$A = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 1 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \cdots & 1 \end{bmatrix} \times \begin{bmatrix} A_{eq}(1) & 0 & \cdots & 0 \\ 0 & A_{eq}(2) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & A_{eq}(k) \end{bmatrix}$$

D. Optimum schedule for i^{th} PEV

After each iteration of the optimization algorithm in order to calculate the charging schedule of i^{th} PEV a factor of SOC progress as $SOC_{sign}^{i}(k)$ is defined.

$$SOC_{sign}^{i}(k) = [a_k] \times \begin{bmatrix} A_{eq}(1) & 0 & \cdots & 0 \\ 0 & A_{eq}(2) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & A_{eq}(k) \end{bmatrix}$$

Where the final optimized charging profile of concerned PEV considering its charging rate CR^i, will be as follow:

$$EV_{cp}^{i}(k) = \left[SOC_{sign}^{i}(1), \cdots, SOC_{sign}^{i}(k)\right] \times \left[CR^i\right] \tag{17}$$

E. Updated functions for next PEVs

In order to calculate the charging profile of next PEVs (based on their arrival time) the functions $LP(k)$ and $Cap^i(k)$ should be updated considering the optimized charging profile of previous PEVs.

$$LP^{i+1}(k) = LP^i(k) + EV_{cp}^{i}(k) \tag{18}$$

$$Cap^{i+1}(k) = LP^{i+1}(k) - RLP(k) \tag{19}$$

F. Constraints for PEV's Energy need

The PEVs which will arrive with low SOC rate have extra constraints that are introduced in form of two algorithms. If the number of admissible charging samples $Nb.^{+}$, is less than required charging sample time of a PEV (T_c^i), the A_{eq} will be updated until respecting the PEVs charging need constraint. This is considered in form of following algorithm.

$$\begin{cases} Nb.^{+} & A_{eq} > 0 \\ Nb.^{+} & A_{eq} < 0 \end{cases} \tag{20}$$

In addition, when a PEV arrives with SOC less than minimum SOC of the scheduling algorithm constraint, the constraint (13) will be updated by following algorithm in order to enforce the schdueling algorithm to start by charging the concerned PEV instead of discharging its battery.

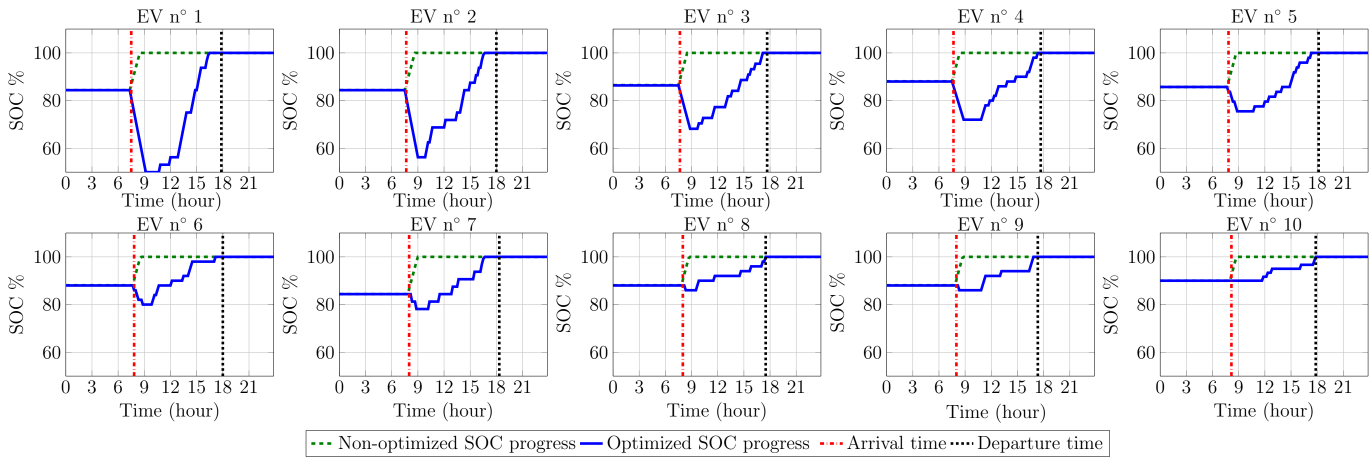

Fig. 4. SOC evolution comparison for a case of 10 PEVs.

Algorithm 1 Charging need check in A_{eq} vector

if $T_c^i > Nb.^+$ **then**
  Put 1 in vector A_{eq} where
  $A_{eq} \times Cap^i(k)$ has smallest value.
else
end if

Algorithm 2 Updating Minimum SOC constraint

if $SOC^i_{arrival} < SOC^i_{min}$ **then**
  $\sum_{k=1}^{T} -A(k).a_k \leq 0$
else
end if

IV. Results and Discussion

For a case study of 10 PEVs in Scenario 1, the variation of state of charging due to charging by the proposed approach is compared with non-controlled case in Fig. 4. The arrival time and departure time of each PEV is indicated to show the respecting of users satisfaction having fully-charged battery at departure time for all PEVs. Due to the peak of consumption during the morning the PEVs arriving sooner have been asked to provide V2G for peak power reduction of the station. For the other PEVs charging coordination is applied in order to minimize the impact of charging on peak to average ratio of the DLP and consequently reducing AEI.

The performance of proposed approach is evaluated using three indicators. Maximum power of yearly load profile is considered as the first indicator in order to represents the effectiveness of the scheduling scheme compare to non-controlled scenarios (Fig. 5). As it is illustrated, the maximum power is linearly increasing by PEV number increment for all non-controlled scenarios. S2 shows a stochastic variation as it has stochastic number of PEVs shared between 3 charging modes. S3 and S4 have reletively the same ΔP_{max} as the 10 minutes averaged power are considered in AEI calculation. However, for most of optimum scenarios the value of ΔP_{max} remained relatively constant and it shows the effective performance of AEIM algorithm for peak-to-average reduction of station's consumption.

$$\Delta P_{max} = P_{max}^{withPEV} - P_{max}^{withoutPEV} \tag{21}$$

Optimum subscribed power is the second indicator where

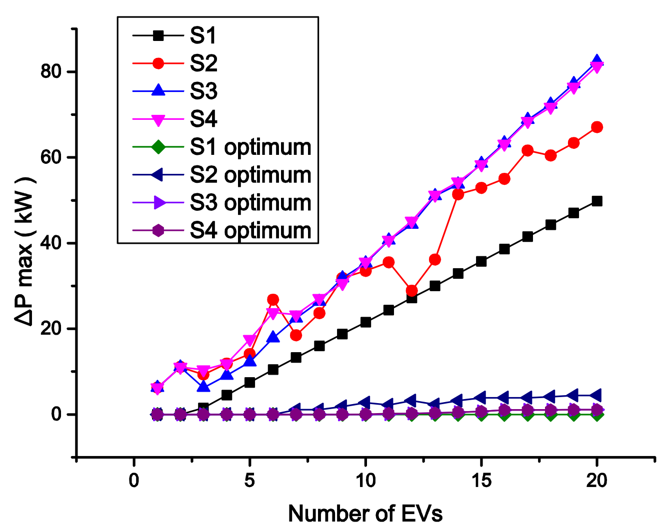

Fig. 5. Comparison of maximum power increment.

the impact of scheduling scheme leads to subscribed power reduction (Fig. 6). A sharp increment is occurred after 5 PEVs for most of non-controlled scenarios, while for optimum scenarios the optimum P_{sub} can remain as 69 or 70 kW upto hosting 20 PEVs (the actual horizon), the subscribed power of actual contract without PEVs.

Finally, the AEI of the station is presented for all the scenarios in Fig. 7. A slight increment of AEI for optimum scenarios is representing the energy part of the AEI, while the considerable differences betwwen non-controlled and optimum

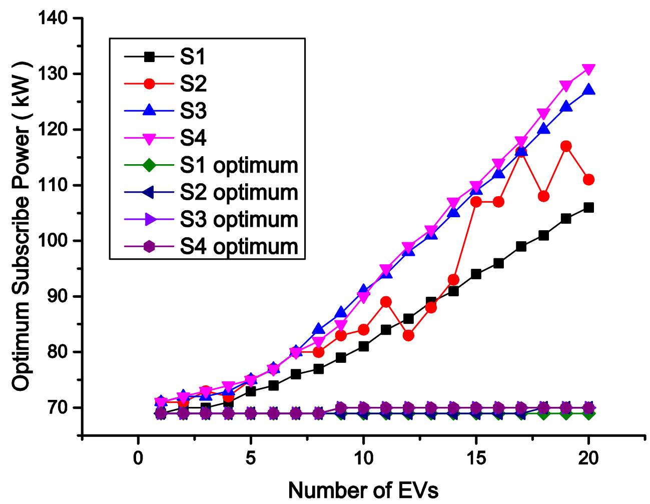

Fig. 6. Comparison of optimum P_{sub}.

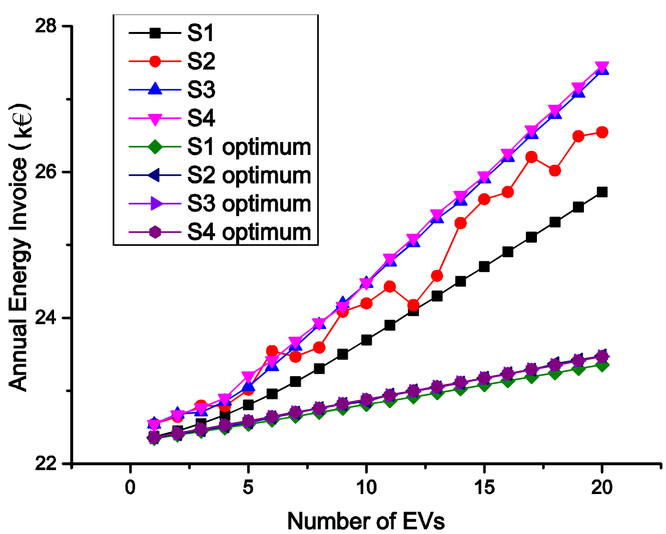

Fig. 7. Comparison of AEI for all scenarios.

scenarios is evident. This difference is comming from the impact of AEIM on peak power reduction and subscribed power optimization. Comparing the worst case, S4, the contribution of AIEM leads to approximately 20% reduction of AEI for 20 PEVs scenario.

V. Conclusion

In this study, contribution of AEIM algorithm to peak power reduction and AEI minimization of a railway station, hosting upto 20 PEVs, were presented. The proposed algorithm is able to minimize the peak power using V2G ability of PEVs parked during the day inside the railway station parking lots. In addition, charging scheduling is applied in order to minimize the annual energy invoice of the station. The minimization of the invoice is conducted using subscribed power minimization, subscribed power exceeding minimization, and PEVs charging during low cost hours. As in this case study the electricity price during the most of the plug-in intervals was constant, the impact of later factor was not evident. However, peak power reduction and exceeding minimization leads to minimizing upto 20% of AEI of the station. As the future works this algorithm would be updated for real-time applications and share of the same amount of V2G between all PEVs and priority based V2G service participation.

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References

[1] L. Pieltain Fernandez, T. Roman, R. Cossent, C. Domingo, and P. Frias, "Assessment of the impact of plug-in electric vehicles on distribution networks," *Power Systems, IEEE Transactions on*, vol. 26, no. 1, pp. 206–213, Feb 2011.

[2] W. Kempton and J. Tomić, "Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy," *Journal of Power Sources*, vol. 144, no. 1, pp. 280–294, 2005.

[3] J. Tomić and W. Kempton, "Using fleets of electric-drive vehicles for grid support," *Journal of Power Sources*, vol. 168, no. 2, pp. 459–468, 2007.

[4] S. Deilami, A. S. Masoum, P. S. Moses, and M. A. Masoum, "Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile," *Smart Grid, IEEE Transactions on*, vol. 2, no. 3, pp. 456–467, 2011.

[5] S. Han, S. Han, and K. Sezaki, "Optimal control of the plug-in electric vehicles for v2g frequency regulation using quadratic programming," in *Innovative Smart Grid Technologies (ISGT), 2011 IEEE PES*. IEEE, 2011, pp. 1–6.

[6] Z. Wang and S. Wang, "Grid power peak shaving and valley filling using vehicle-to-grid systems," *Power Delivery, IEEE Transactions on*, vol. 28, no. 3, pp. 1822–1829, 2013.

[7] M. Falahi, H.-M. Chou, M. Ehsani, L. Xie, and K. L. Butler-Purry, "Potential power quality benefits of electric vehicles," *Sustainable Energy, IEEE Transactions on*, vol. 4, no. 4, pp. 1016–1023, 2013.

[8] H. F. Farahani, H. Shayanfar, and M. Ghazizadeh, "Modeling of stochastic behavior of plug-in hybrid electric vehicle in a reactive power market," *Electrical Engineering*, vol. 96, no. 1, pp. 1–13, 2014.

[9] S. Sarabi, A. Bouallaga, A. Davigny, B. Robyns, V. Courtecuisse, Y. Riffonneau, and M. Regner, "The feasibility of the ancillary services for vehicle-to-grid technology," in *European Energy Market (EEM), 2014 11th International Conference on the*, May 2014, pp. 1–5.

[10] S. Sarabi, L. Kefsi, A. Merdassi, and B. Robyns, "Supervision of plug-in electric vehicles connected to the electric distribution grids," *Int J Electr Energ*, vol. 1, no. 4, pp. 256–263, 2013.

[11] S. Sarabi and L. Kefsi, "Electric vehicle charging strategy based on a dynamic programming algorithm," in *Intelligent Energy and Power Systems (IEPS), 2014 IEEE International Conference on*. IEEE, 2014, pp. 1–5.

[12] T. Sousa, H. Morais, Z. Vale, P. Faria, and J. Soares, "Intelligent energy resource management considering vehicle-to-grid: A simulated annealing approach," *Smart Grid, IEEE Transactions on*, vol. 3, no. 1, pp. 535–542, 2012.

[13] Y. He, B. Venkatesh, and L. Guan, "Optimal scheduling for charging and discharging of electric vehicles," *Smart Grid, IEEE Transactions on*, vol. 3, no. 3, pp. 1095–1105, 2012.

[14] S. Sarabi, A. Davigny, Y. Riffonneau, V. Courtecuisse, and B. Robyns, "Contribution and impacts of grid integrated electric vehicles to the distribution networks and railway station parking lots," in *Electricity Distribution (CIRED 2015), 23rd International Conference and Exhibition on*, June 2015, pp. 1–5.