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# Profit Optimization of Energy Supply of Electric Drive Vehicles

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**Abstract.** An increased electric drive vehicle (EDV) use is expected in the future due to the rapid development of new EDV technologies, increased environmental concerns, increasing petroleum-based fuel prices and the possibility of EDV participation on electricity markets. In this paper, an optimization algorithm for EDV charging and discharging for electricity-spot market participation is presented. The use of the presented algorithm would bring lower EDV driving costs for its users and a competitive advantage for the EDV electricity provider that would use the EDV batteries as a storage system in order to purchase and sell additionally stored energy on the electricity market. To simplify the optimization algorithm, individual EDVs are grouped into larger EDV fleets. The use of EDV fleets introduces a constant number of optimization variables in the optimization process. K-means the clustering algorithm is used to group individual EDVs into larger fleets. The optimization problem was approached deterministically and in future work, a probabilistic approach to the problem will be presented.

**Keywords:** k-means clustering method, electricity-spot market, linear optimization

## 1 INTRODUCTION

An increased electric drive vehicle (EDV) use is expected in the future due to the rapid development of new EDV technologies, increased environmental concerns, increasing petroleum-based fuel prices and the possibility of EDV participation on electricity markets.

With an ever increasing number of EDVs, electric power systems (EPS) will be subjected to large technological changes, demands for new investments, such as the construction of new EDV charging stations and power system enhancements in transfer capabilities and voltage support.

Also, additionally, EDV batteries are expected to be used on the electricity spot markets, where the EDV batteries could be used as an energy storage system [1].

In this paper, an optimization algorithm for EDV charging and discharging is presented with the goal of optimal electricity spot market participation. The presented algorithm enables the electricity providers to maximize the revenue from using additionally stored energy in EDV batteries on the electricity spot market. The EDV electricity providers are expected to be the already functioning distribution companies and electricity providers. This would allow lower driving costs for EDV users, which would attract more EDV users to allow their vehicles to be used in the electricity markets.

To simplify the optimization algorithm, EDVs were merged into larger EDV fleets with similar driving needs. This enables the number of optimization variables to remain constant, even with the number of individual EDV changing. The change in the number of EDVs only affects the optimization algorithm as a change in the required power-demand curve for driving schedules. Therefore, a k-means clustering method is presented in this paper to group the various EDVs into fleets. This enables the presented algorithm to give optimal charging and discharging times for individual fleets with electricity spot market participation in mind. This enables the EDV electricity provider to purchase the required energy for EDV at times of lower electricity costs and sell the additionally stored energy at times of higher electricity costs.

In the literature, various studies in the EDV charging impact on EPS have appeared [1-3]. The increased interest in EDV participation on electricity markets has been noted [4, 5].

In this paper, the basis for further EDV participation on electricity markets is presented, where probabilistic approach can be included as well as taking into account other electricity markets and various other economic, environmental and technical impacts of EDV.

The paper is organized as follows. A short description of EDV and EDV electricity providers is given in Section 2. In Section 3, the developed optimization algorithm for EDV charging and discharging are presented and the k-means clustering method. In Section 4, results of the optimization algorithm for a test case are shown. Finally, in Section 5, the main findings of this paper are summarized.

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## 2 ELECTRIC VEHICLE AND ELECTRIC VEHICLE ELECTRICITY PROVIDER DESCRIPTION

During the last few decades the development of new EDV technologies has led to a renewed interest in the electric transportation infrastructure. According to the Slovenian Green Paper for the National Energy Policy, EDV will amount to all the newly sold vehicles in 2030. The EDV advantages are their energy conversion efficiency from batteries (90 % efficiency as opposed to the 30 % efficiency of internal combustion vehicles from the stored fuel), locally lower emissions (CO2 emissions are expected to lower thrice [6]), and decreased foreign oil dependency. The disadvantages are currently numerous and are most commonly linked to the current batteries and EDV prices. The range of the current EDVs is approximately 150 km per charging, which is approximately three times less than internal combustion vehicles. The charging time of the current EDV batteries also has its disadvantages, as charging can take from 4 to 8 hours [7]. Additional environmental issues must be taken into account, as large amount of EDV batteries will have to be properly recycled. Increased investments in the EPS will also be required, new smart grid technologies will be mandatory and new regulatory rules for EDV electricity providers created.

With the implementation of new smart grid technologies, EDV will be able to participate in electricity markets, aid in EPS frequency regulation and congestion management, participation in balancing markets, etc.. The basic idea is the use of EDV batteries as a storage system, and charging or discharging activated at optimal times during the day. This would enable the electricity provider to lower charging costs for EDV users, as the profits from participating on electricity markets would cover a certain amount of purchased electricity costs. This would bring competitive advantages to electricity providers participating in the above services.

## 3 OPTIMAL CHARGING AND DISCHARGING ALGORITHM FOR ELECTRICITY SPOT-MARKET PARTICIPATION

The electricity provider will require an optimization algorithm to determine optimal charging and discharging times for EDV to optimally participate on the electricity spot market. This will allow the provider to reduce the costs of energy purchases required for EDV driving needs and lower the electricity prices for EDV users. This would result in a competitive advantage over other electricity providers not using such tool. To simplify the optimization problem, the EDV driving schedules were grouped into larger EDV fleets thus limiting the amount of optimization variables to a smaller constant value not changing with the change in the number of EDVs under contract with the electricity provider.

As the driving schedules are mostly dependent on the EDV-user work habits, we used the k-means clustering method to group various EDVs into fleets with similar driving schedules (e.g. the EDV users driving to work at a specific time – early mornings, late evenings, during peak-traffic hours, etc.). In Subsection 3.1 we present various EDV driving schedules, reasons for grouping EDVs into fleets and the k-means clustering method. In Subsection 3.2, we describe on optimization algorithm for optimal charging and discharging times enabling electricity spot market participation.

### *3.1 Clustering of EDV driving schedules into EDV fleets*

EDV driving schedules of various users present a large uncertainty problem, as different users can drive at different times and require different amounts of energy for their driving needs. Moreover, optimizing charging and discharging times for individual EDVs is not recommended, as the large amount of EDVs in the optimization problem represented as optimization variables would cause serious problems to even the most capable optimization solvers. In this paper, we group individual EDVs into larger EDV fleets to limit the number of variables to a constant number, i.e. the number of fleets. The used k-means clustering algorithm creates representative clustered driving schedules for individual fleets to group individual EDV driving schedules into a fleet. As the number of EDVs changes, only the total battery capability in the fleet changes; the number of optimization variables remains unchanged.

In this paper, the k-means clustering method [8] is used to group individual EDV driving schedules into fleets with representative driving patterns.

The k-means clustering method uses an iterative refinement technique with the clustering algorithm aiming at minimizing the criterion (1) in order to group the individual EDV driving schedules into fleets. The method is a very popular clustering technique due to its simplicity.

$$J = \min \sum_{\mathrm{g}=1}^{\mathrm{k}} \sum_{\mathbf{d}_\mathrm{j} \in \mathrm{g}} \left\| \mathbf{d}_\mathrm{j} - \boldsymbol{\mu}_\mathrm{g} \right\|^2 , \tag{1}$$

$$\boldsymbol{\mu}_\mathrm{g} = \frac{1}{m_\mathrm{g}} \sum_{\mathbf{d}_\mathrm{j} \in \mathrm{g}} \mathbf{d}_\mathrm{j}, \tag{2}$$

where $J$ is the criterion function, k is the number of EDV fleets, $\mathbf{d}_\mathrm{j} = [d_{\mathrm{j},1}, d_{\mathrm{j},2},\ldots, d_{\mathrm{j,t}}]$ is the driving schedule of the j-th EDV, (t = 24 hours). $\boldsymbol{\mu}_\mathrm{g} = [\mu_{\mathrm{g},1}, \mu_{\mathrm{g},2},\ldots, \mu_{\mathrm{g,t}}]$ is the arithmetic mean of all the driving schedules in the g-th EDV fleet, $m_\mathrm{g}$ represents the number of EDVs in the g-th EDV fleet. The arithmetic mean represents the representative clustered driving schedule of the g-th EDV fleet, which is the goal of the k-means clustering method in this paper.

The k-mean clustering method consists of four steps. The aim of the method is to iteratively define the arithmetic mean of the driving schedules of the k EDV fleets in order to reach the minimum of the criterion function (1).

1. In the first iteration, the number of EDV fleets is selected, i.e. k, where k<m and the arithmetic mean of the k EDV fleets is calculated $\boldsymbol{\mu}_g(1)$.
2. In the q-th iteration, the driving schedules of individual EDV vehicles are assigned into the EDV fleets. The individual driving schedules are placed into the g-th EDV fleet if:

$$\left\|\mathbf{d}_j - \boldsymbol{\mu}_g(q)\right\| < \left\|\mathbf{d}_j - \boldsymbol{\mu}_{ng}(q)\right\|, \quad \forall\, 1, 2, ..., k \vee g \neq ng, \tag{3}$$

   where ng are all the other EDV fleets, except the g-th EDV fleet..
3. New arithmetic means of the k EDV fleets are calculated $\boldsymbol{\mu}_g(q+1)$.
4. If $\boldsymbol{\mu}_g(q+1) = \boldsymbol{\mu}_g(q)$ for all the k EDV fleets, the iterative process is completed.

To use the k-means clustering method, the user should experiment and observe the behavior of the clustering analysis in regard with the number of pre-defined EDV fleets and starting arithmetic means.
The results of the described clustering analysis are the combined representative driving schedules for each EDV fleet. The process is shown in Figure 1.

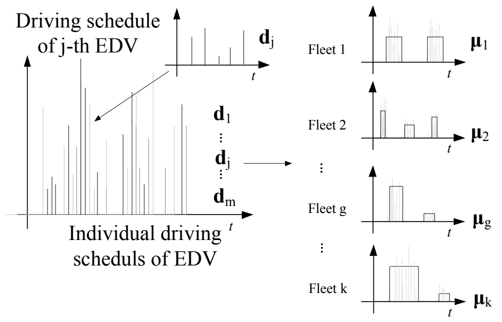


Figure 1. Clustering of EDV driving patterns into fleets

### 3.2 *Optimization algorithm description*

The proposed optimization algorithm enables optimal EDV charging and discharging with the goal of optimal participation on the electricity spot market. The goal of the optimization is to increase profits of the electricity provider by using EDV batteries as a storage system to participate on the electricity market [2-4].

Figure 2 presents the charging/discharging optimization algorithm with the aim of profit maximization for the electricity provider. The algorithm requires the k-means clustering method to define the representative combined driving schedules for the EDV fleets, as presented in Subsection 3.1. This requires either the EDV users or the electricity provider to provide driving schedules for individual cars for the day-ahead. Using the forecasted driving schedules, the optimization algorithm defines optimal EDV charging and discharging for electricity spot market participation.

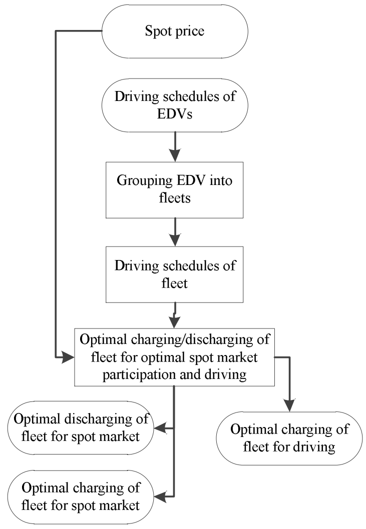


Figure 2. EDV optimization algorithm

Equations (4) to (10) describe the optimization algorithm for EDV charging and discharging. The criterion function describing the optimal EDV fleet market participation of the g-th fleet is as follows:

$$J_g = \sum_{i=1}^{t} c_i \cdot y_{g,i} \cdot \eta_{pra} - \sum_{i=1}^{t} c_i \cdot x_{g,i} \cdot \frac{1}{\eta_{pol}} \Rightarrow \max \tag{4}$$

where t is the number of the hours taken into account in the optimization algorithm, $c_i$ is the spot market price at the i-th hour, $y_{g,i}$ is the optimization variable representing the amount of energy that can be sold on the electricity spot market for the g-th EDV fleet at the i-th hour, $\eta_{pol}$ is the average efficiency of EDV battery charging of the g-th fleet, $x_{g,i}$ is the optimization variable that represents the amount of energy that must be purchased for EDV driving needs and for electricity spot-market participation for the g-th fleet at the i-th hour, $\eta_{pra}$ is the average efficiency of EDV battery discharging of EDV in the g-th EDV fleet.

The criterion function and the optimization algorithm do not take into account the increased battery-life degradation resulting from intensified use of EDV batteries. Also, the cost of the decreased battery life is neglected. The used optimization limitations are given in the next paragraphs.

The EDV battery charging rate is defined by the current limitation of charging stations, where EDV of the g-th fleet are charged:

$$0 \le x_{g,i} \cdot \frac{1}{\eta_{pol}} \le P_{pol}\,, \tag{5}$$

where $P_{pol}$ is the maximum charging power and is constant for all hours in the optimization process.

The battery discharging rate for market participation (i.e. the rate for discharging the stored energy into EPS) is also limited by the current limitation of the charging station where EDVs of the g-th fleet are discharged:

$$0 \le y_{g,i} \cdot \eta_{pra} \le P_{pra} \,, \tag{6}$$

where $P_{pra}$ is the maximum discharging power and is constant for all hours in the optimization process.

The amount of energy stored in EDVs of the g-th fleet cannot exceed its total capacity $K_{g,i}$ at the i-th hour:

$$0 \le \sum_{i=1}^{j} x_{g,i} \cdot \frac{1}{\eta_{pol}} - \sum_{i=1}^{j} y_{g,i} \cdot \eta_{pra} - \sum_{i=1}^{j} V_{g,i} \le K_{g,i} \,, \quad \forall\ j=2,...,t \,, \tag{7}$$

where $V_{g,i}$ is the energy needed for EDV driving needs of the g-th fleet.

When EDVs of the g-th fleet are not connected to EPS, they cannot participate as a storage unit:

$$x_{g,i} = y_{g,i} = 0 \,. \tag{8}$$

The EDV batteries must be charged so as to cover all driving needs and market participation up to the hour of the EDV use or EDV energy discharge into EPS:

$$\sum_{i=1}^{j} x_{g,i} \cdot \frac{1}{\eta_{pol}} - \sum_{i=1}^{j} y_{g,i} \cdot \eta_{pra} - \sum_{i=1}^{j} V_{g,i} \ge 0, \quad \forall\ j=2,...,t \,, \tag{9}$$

The optimization variables must take into account the following limitations:

$$x_{g,i} \ge 0, y_{g,i} \ge 0, \quad \forall\ i=1,...,t \tag{10}$$

In Section 4, results of the k-means clustering and optimization algorithm are shown for the presented test case.

## 4 RESULTS

In order to test the proposed optimization algorithm, we analyzed a test case of 17162 EDV with various driving schedules. The EDV number represents 6 % [6] of the total EDV consumption at the distribution level for the year 2030. The driving schedules ware defined by using the current driving habits of various Slovenian driver groups (industry workers, public service workers, students, professional drivers, etc.) and the following assumptions:

- The current traffic peak hours on the main Slovenian roads and random hours during the days representing the random impulsive drives during the day (e.g. short trips, shopping, etc.).
- The EDV energy use equals to 0.1 to 0.2 kWh/km [1, 2].
- The average driving range equals to 30 km for most of EDV users in urban areas and 60 km EDV users in rural areas.

The optimization algorithm was tested for one day on an hourly basis. The input data and assumptions used are:

- The EDV charging and discharging rate is defined by the current limitation of a charging station. This equals to 16 A, which represents the charging/discharging rate of 3,7 kWh/h.
- The EDV battery capacity is 16 kWh, which equals to a 80 – 160 km driving range [1, 2].
- The EDV battery efficiency for charging and discharging equals to 90 %.
- The total EDV battery capacity is not decreased over time and the cost of the reduced battery-life was not taken into account.

The EDV driving costs ware assumed to be:

- The EDV driving cost equals to 0.175 EUR/kWh, which is the average price for one tariff household counter [9]. The electricity provider margin is included in the price.
- All the revenue gained by the electricity provider by using EDV as a storage system for electricity spot-market participation is used to reduce the EDV driving costs in order to gain a competitive advantage.
- The electricity purchase and selling prices are equal.
- There is always enough demand and supply on the electricity market.
- The EDV batteries are either empty or have enough energy for the first hour in the day for EDV to be driven at the first hour.

Figure 3 shows the EDV plug-in times into charging stations and the amount of the energy used in the previous drive. Each column represents the plug-in time and the amount of energy used for the previous drive. The figure shows that most EDV users drive between 6 a.m. and 10 a.m. hours and from 1 p.m. to 6 p.m., as larger concentrations of columns. The average consumption EDV per drive equals to 1.6 kWh/h, which is the average driving distance of 16 km per drive with a 160 km maximum driving range.

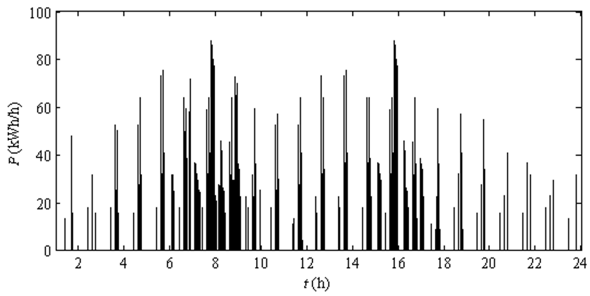


Figure 3. Connection of EDVs on charging stations and EDV energy consumption

To simplify the optimization problem, EDVs are clustered into different fleets. In this paper, five fleets were used in order to encompass all the possible driving needs of various EDV users.

Using the k-means clustering method, clustered representative driving schedules of the EDV fleets were obtained and the fleet is considered as a large energy storage system with a combined total storage capacity of all EDVs in the fleet.

Figure 4 shows the combined representative driving schedules of all the five fleets and the energy consumed by the fleets for their driving needs.

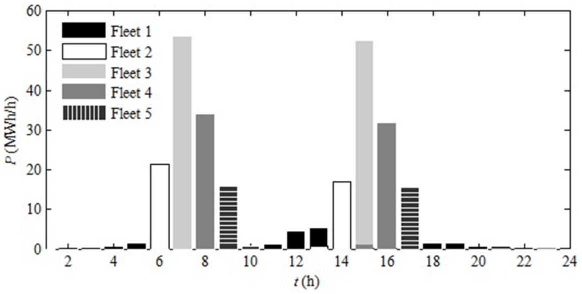


Figure 4. Fleet patterns

Figures 5 and 6 show results of the our optimization algorithm for the second fleet representing the driving schedules at 6 a.m. and 2 p.m. and the third fleet representing the driving schedules at 7 a.m. and 3 p.m.

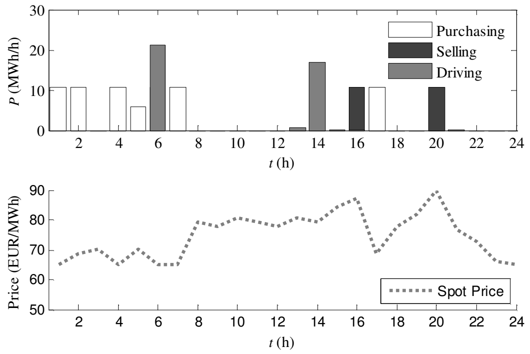


Figure 5. Optimal market participation of the second fleet

The optimization algorithm for the presented case almost always purchases the energy needed for EDV driving needs were the electricity price reaches its lowest value. The larger amount of EDVs in the second fleet drives at 6 a.m. and 2 p.m. and a lesser amount of EDV drives at 1 p.m. and 3 p.m. At 4 p.m. and 8 p.m. approximately 10 MWh of energy was sold on the market (this was limited by the current limitations of the charging stations). The purchase of energy at 5 p.m. was performed for market participation at 8 p.m. By participating on the market, a certain profit is made. It is used to reduce the EDV driving costs.

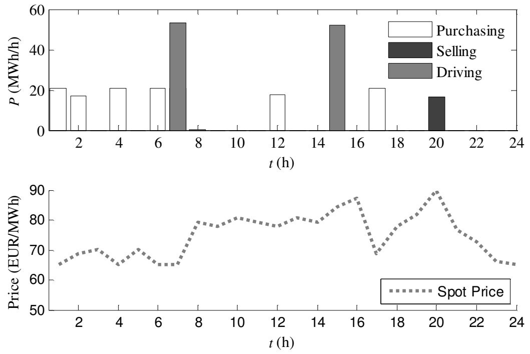


Figure 6. Optimal market participation of third fleet

The third fleet is larger than the second fleet considering the total number of EDVs inside each fleet. It thus requires more energy for its driving schedule. The purchase of energy for the driving needs at 7 a.m. and 3 p.m. is performed at 1 a.m., 2 a.m., 4 a.m. and 6 a.m. In like in this case in the second fleet, there is no additionally stored energy at 4 p.m., which could be sold on the electricity-spot market and so this fleet can only participate on the electricity-spot market at 20 p.m., as shown in Figure 6.

The EDV driving costs are shown in Table 1 and the electricity provider profits by using EDV as a storage system and using the additionally stored energy on the electricity-spot market. Reduction in the EDV driving costs due to market participation is shown too.

The first fleet has the smallest reduction in the EDV driving costs as EDVs in this fleet drive throughout the day and the batteries cannot be additionally charged to such a degree to effectively participate on the market. The second, fourth and fifth fleets have the largest EDV driving cost reduction for being available for market participation during the energy-price peak hours. As the third fleet uses most of its energy for driving needs, the resulting EDV driving costs are not reduced to the degree of the second, fourth and fifth fleet. The fourth and the fifth fleet diverge at 5 p.m., as the vehicles of fifth fleet are not available for additional charging in order to participate on the market at 8 p.m.

Table I. EDV driving costs and cost reductions

| **Fleet EDV** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| Number of EDV | 1529 | 2889 | 5607 | 4928 | 2209 |
| Average consumed energy for driving needs per day (kWh) | 3.54 | 7.24 | 5.01 | 5.24 | 4.74 |
| EDV driving cost (EUR/day) | 0.63 | 1.27 | 0.88 | 0.92 | 0.83 |
| Profit of one EDV due to market participation (EUR/day) | 0.02 | 0.06 | 0.028 | 0.046 | 0.04 |
| One EDV driving cost reduction due to market participation (%) | 3.17 | 4.73 | 3.2 | 5.02 | 4.82 |

By participating on the electricity-spot market, a certain profit can be made using the presented optimization algorithm thus reducing the EDV user driving costs. This enables the electricity provider to gain a competitive advantage over other electricity providers not participating on the electricity market.

## 5 CONCLUSION

An increased EDV use is expected in the future as a result of the rapid development of new EDV technologies, increased environmental concerns, increasing petroleum-based fuel prices and the possibility of EDV participation on electricity markets. Electricity providers will be able to use EDVs as an energy storage system and purchase and sell energy on

the electricity market in order to gain profits, which would in turn reduce EDV driving costs.
In this paper, an optimization algorithm for charging and discharging enabling electricity-spot market participation is presented. To simplify the optimization procedure, individual EDVs are combined into EDV fleets representing combined driving schedules of individual EDVs. This in turn gives us a constant number of optimization variables in the optimization algorithm despite of changes in the number of individual EDVs. To group EDVs into fleets, a k-means clustering method was developed and is presented in this paper.

By combining the EDV driving schedules into fleets, the optimization algorithm determines optimal charging and discharging as needed to participate on the electricity-spot market. The result is the reduction in the EDV driving costs due to additional profits assured by using EDV batteries as a storage system for the electricity market purposes. The reductions in the EDV driving costs vary depending on the driving schedules of EDV users. For the given test case, the profits due to EDV market participations range from 0.02 EUR/day to 0.06 EUR/day, which represents from 3 % to 5 % EDV driving cost reduction.

In this paper, a deterministic solution to the presented optimization problem is proposed. It can be expanded to include probabilities and inherent uncertainties in the EDV driving schedules. Other electricity markets and EPS services can be included as well as other technical and economical limitations, such as battery-life reduction costs and battery recycling costs, too.

## REFERENCES


[1] Shortt, A.; O'Malley, M., Impact of optimal charging of electric vehicles on future generation portfolios, Sustainable Alternative Energy, 2009 IEEE PES/IAS Conference on, 2009

[2] Tomic J., Kempton W., Using fleets of electric-drive vehicles for grid support, Journal of Power Sources, Volume 168, Issue 2, 2007

[3] Acha, Salvador; Green, Tim C.; Shah, Nilay, Effects of optimised plug-in hybrid vehicle charging strategies on electric distribution network losses, Transmission and Distribution Conference and Exposition, 2010 IEEE PES, 2010

[4] K. Capion, Optimized charging of electric drive vehicles in a market environment, magistersko delo, Technical University of Denmark, Danska, 2009.

[5] Mets, K.; Verschueren, T.; Haerick, W.; Develder, C.; De Turck, F.; Optimizing smart energy control strategies for plug-in hybrid electric vehicle charging, Network Operations and Management Symposium Workshops, 2010 IEEE/IFIP 2010

[6] Zelena knjiga za NEP Slovenije, Posvetovalni dokument za javno obravnavo, 2009

[7] Bradley T.H., Quinn C. W., Analysis of plug-in hybrid electric vehicle utility factors, Journal of Power Sources, Vol. 195, Issue 16, 2010

[8] Anders, G. J., Probability Concepts in Electric Power Systems, 1990

[9] Javna agencija RS za energijo http://www.agen-rs.si/sl/



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