

# Impact of electric-drive vehicles on power system reliability

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## Abstract

The paper assesses the impact of electric-drive vehicles (EDVs) on power system reliability. For this purpose, it introduces direct optimization of reliability indices LOLE and EENS. The analysis is performed by the proposed optimization model applied in different strategies of charging/discharging of EDV batteries. In general, it is observed that numerous EDVs increase the system loading resulting in weakening of the system reliability. However, the paper comes to the conclusion that EDVs could support the system to some extent, depending on the penetration level of EDVs, if an appropriate charging/discharging strategy is applied. Besides this technical question the paper also addresses the costs of the system reserve provision required for the system reliability support. A system operator could engage additional power plants in order to maintain the system reliability or, if this is more cost effective, the support could be provided by EDVs applying the appropriate charging/discharging strategy. The paper proposes a new approach for the techno-economic assessment of possible solutions that are ranked by its price-performance ratio.

## Keywords

Electric-drive vehicles, expected energy not supplied, linear programming, loss of load expectation, normalized marginal cost index, power system reliability.

## 1 Introduction

With increasing environmental awareness, technology advances and high liquid fuel prices, electric-drive vehicles (EDVs) are gaining ground as a promising alternative to internal combustion engine vehicles. The transition from fossil fuels to electrical energy in automotive sector will bring many obvious benefits to the society such as reduction of CO<sub>2</sub> emissions, cleaner environment, lower transport costs, etc.

However, EDVs impact also power systems. It is discussable whether EDVs bring some benefits to the power system operation, what are the impacts of EDVs on power systems in general. These questions have been investigated in numerous papers from different perspectives. Exploitation of EDVs in frequency regulation and ancillary service provision was addressed in [1-4], since the idea of using EDVs for energy storage is increasingly promising due to intensive development of energy storage technologies, [5]. It is also emphasized the importance of further development of vehicle to grid (V2G) concept [6, 7]. With current technology, EDV's batteries are not suited for providing base-load power, which is shown in [8], but represent a strong candidate for the provision of frequency regulation services and load peak-shavings [6]. Involvement of EDVs in unit

commitment was considered in [9-12], where new approaches for implementing the V2G in the short term unit commitment problem are presented. New approaches strive to achieve reduction of operational costs and an increase of profit, spinning reserve and system reliability. An interesting idea was presented in [13] that proposed the activation of EDVs in the concept of virtual power plants (VPPs). The findings show that with the inclusion of EDVs in VPP, economic gains can be achieved. The study also focuses on determination of optimal number of EDVs in VPP portfolio to minimize the total costs of the VPP. Recently, the exploitation of EDVs in electricity markets has been frequently examined [14-18]. The results showed that with proper charging and discharging of EDVs economic gains can be achieved. The use of EDVs for maximization of exploitation of renewable energy is addressed in [19, 20], where two optimization algorithms for charging and discharging of EDVs for maximization of use of renewable energy are presented. Reference [21] and [22] present the impact of EDVs on distribution networks from the perspective of investment planning, energy losses, harmonic distortion levels, thermal loading, unbalance, and voltage regulation. Reference [23] discusses how a large-scale implementation of plug-in hybrid electric vehicles (PHEVs) affects power system operation and investment planning. Results show that when charged/discharged intelligently, EVs can facilitate wind power investments already at low vehicle fleet shares and due to vehicle-to-grid capability; EVs can reduce the need for new coal/natural gas power capacities. Reference [24] evaluates the impact of PHEVs on generation capacity requirements, fuel types used, generation technologies and emissions.

Since this paper addresses the impact of EDVs on power system reliability, a special attention was paid to the papers addressing this subject. The impact of EDVs on load profiles is analysed in various studies [4, 25, 26], where an efficient peak-load reduction solutions is proposed that results in better system reliability. Reference [27] analyses the potential impacts of plug-in hybrid electric vehicles (PHEVs) on the Portuguese electric consumption profile. The results show that the dispatchable load offered by PHEVs could increase the minimum system load, increase the utilization of base-load units, and decrease plant cycling without increasing the need for new investments in generation. Reference [28] simulates the effects of Arrive & Plug charging scheme on power system reliability at various penetration levels of PHEVs in power network. The reliability of power system was evaluated using indices Loss of Load Expectation (LOLE), Loss of Load Probability (LOLP) and Expected Energy Not Served (EENS). The results show that with increasing penetration levels of EDVs system reliability deteriorates. Reference [29] discusses charging costs, charging generation source, total electricity load, load shape and emissions associated with penetration of PHEVs in power system. The authors state that a very large penetration of EDVs would place increased pressure on peaking units if charging is completely uncontrolled. The aforementioned issue is addressed in [30], where results show that the dispatchable load offered by PHEVs could increase the minimum system load, increase the utilization of base-load units, and decrease plant cycling all without increasing the need for new generation assets. In addition authors claim that EDV discharge ability could replace a substantial fraction of the capacity currently in place to meet system peak reserve margin.

Even though several studies discuss the effects of EDVs on power system reliability and valuable conclusions are drawn, there is a need to investigate these effects from additional technical and economic aspects. The paper is focused on the charging/discharging strategies, their influence on

the system reliability and the costs of its provision. The importance of selecting of a certain strategy is emphasized through several case studies (CSs) assessed by a stochastic approach. For example, system operators would prefer the strategy that supports the system reliability since in this case the costs for the system reserve provision required for the reliability provision are minimized. On the other hand, EDV users are not concerned with the reliability, they expect that the applied strategy would provide the cheapest transportation possible. For the purpose of performed investigation, the optimization model for EDV charging/discharging for each strategy is developed. In addition, the method for the techno-economic assessment and ranking of possible reserve provisions by their price-performance ratios is proposed.

What distinguishes the paper from the existing ones is (i) a clear mathematical presentation of proposed optimization models with straight optimization of reliability indices LOLE and EENS incorporated in the objective function and not in the optimization constraints, (ii) the stochastic approach to the problem, and (iii) the proposed method for techno-economic assessment of system reserve provision required for reliable operation of power system.

The rest of this paper is organized as follows: the optimization procedure of EDV charging/discharging is presented in Section 2, with Subsections 2.1 and 2.2 presenting the optimization models and the economic assessment of the system reserve provision, and Section 3 presents and discusses the obtained results. Conclusions drawn from the study are provided in Section 4.

## 2 Optimization Procedure of Charging/Discharging of Electric-Drive Vehicles

The optimization procedure proposed in the paper consists of several tasks presented in Figure 1. Due to uncertainties, a stochastic assessment of input data is performed in the initial step: (i) future energy requirements for transportation – driving patterns, (ii) future energy consumption, and (iii) prices of electric energy. The Monte Carlo (MC) simulation is applied in order to produce sets of input data resulting in numerous scenarios, [15, 20].

A random trajectory of the energy required for the transportation in hour  $h$ ,  $D_h$ , is provided by:

$$D_h = (\delta_h + RU_{h,k}) \cdot (1 + RND_{h,k}), \quad (1)$$

where  $\delta_h$  presents the most expected driving pattern of a certain EDV fleet in hour  $h$ , and  $RU_{h,k}$  and  $RND_{h,k}$  are the random components of the pattern in hour  $h$ , in scenario  $k$  with uniform and normal distribution. If this formulation is not appropriate, some other distribution function that is expected to better describe behaviour of EDVs can be applied in the MC simulation.

Similar to the driving patterns the expected energy consumption,  $P$ , is stochastically simulated with the MC method using the formulation:

$$P_{h,k} = p_h \cdot (1 + RNP_{h,k}), \quad (2)$$

where  $p_h$  represents the mean of forecasted energy consumption in hour  $h$ , and  $RNP_{h,k}$  is the random component with normal distribution in hour  $h$ , in scenario  $k$ . The same formulation is used for the expected hourly prices of electric energy on the wholesale market,  $C$ :

$$C_{h,k} = c_h \cdot (1 + RNC_{h,k}), \quad (3)$$

where  $c_h$  represents the mean of forecasted price of electric energy in hour  $h$ , and  $RNC_{h,k}$  is the random component with normal distribution in hour  $h$ , in scenario  $k$ .

These scenarios are created with the MC approach in order to simulate uncertainties of input data. To reduce the problem complexity, the scenarios are not individually studied in the optimization, but clustered into three scenarios applying the K-means clustering approach. In the literature, the GAMS/SCENRED tool is frequently used for this task, [15, 20, 31, 32].

Once the reduced number of scenarios is prepared, the optimization procedure can be performed for each scenario, thus the index  $k$  is omitted in all equations in the subsequent text. In this research, three CSs with different charging/discharging strategies are observed:

- **CS1**: non-optimal charging of EDVs, EDVs are charged immediately after transportation,
- **CS2**: optimal charging of EDVs resulting in a maximization of system reliability,
- **CS3**: optimal charging of EDVs resulting in a minimization of transportation costs of EDV users.

In CS1, the EDV charging is actually not optimized, a “dump” charging strategy is applied. This CS gives the reference for other two cases only. In CS2, the load profile is optimally reshaped by the appropriate charging/discharging strategy of EDVs in such a way that the system reliability is maximized. In CS3, the objective function is a minimization of the transportation costs. EDVs are charged in hours with lower prices of electric energy discharged in hours with peak prices. It is presumed that EDVs trade on the wholesale market, thus the simulated hourly prices are required for this CS. Discharging results in incomes of sold energy in the market and consequently compensates the charging costs. This CS is elaborated in detail in [15].

The final task of the proposed procedure is a technical and economic assessment of impacts of EDVs on the system reliability. From the technical perspective, it has to be answered if EDVs can improve the system reliability, even though it is generally known that EDVs increase the system loading resulting in weakening of the system reliability, what is the impact of each charging/discharging strategy on the system reliability. From the economic point of view, it is important to assess the costs for the system reserve provision required for the power system reliability support. The reserve can be provided by power plants, consumers or, as presented in this paper, by EDVs. This service is crucial for a system operator in order to maintain a reliable operation of power system. In this task, the possible solutions are assessed and ranked by their price-performance ratios.

In the subsequent Subsections, the proposed charging/discharging strategies and the techno-economic assessment are mathematically modelled and explained in detail.

## 2.1 Optimization model of charging/discharging of EDVs

Each charging/discharging strategy requires an appropriate objective function in the optimization model. In this research, the main focus is put on the assessment of EDVs’ impact on system reliability. System reliability is measured by well-known and frequently applied indices LOLE and EENS presented in [33]. To be more exact, these two indices serve as measures for resource adequacy which is a part of system reliability. LOLE is calculated as:

$$LOLE = \sum_{i=1}^g p_i t_i . \quad (4)$$

where  $p_i$  represents the probability of state  $i$  with a certain resource capacity configuration,  $t_i$  is obtained from the load duration curve and represents the duration that load demand exceeds the remaining capacity  $P_i$ , and  $g$  is the number of possible resource capacity states. If  $a$  generators are considered,  $2^a$  capacity states are possible since each generator can operate as scheduled with a probability defined by its availability  $A$ , thus its status is “1”, or can be out of operation with a probability defined by its unavailability  $U = 1 - A$ , thus its status is “0”. Figure 2 presents the load duration curve with defined  $t_i$ .

Index EENS is calculated as:

$$EENS = \sum_{i=1}^g p_i w_i, \quad (5)$$

where  $w_i$  represents the curtailed energy due to the capacity outage in state  $i$ , Figure 2.

Once the reliability indices are defined, the optimization model used in the charging/discharging strategy in CS2 can be addressed. The chosen indices should be minimized in order to maximize system reliability. When LOLE is considered, the optimization problem is formulated as a mixed-integer linear program (MILP) with the objective function  $J_{CS2}$ :

$$\text{Min} \left\{ J_{CS2, LOLE} = LOLE = \sum_{i=1}^g p_i t_i = \sum_{i=1}^g p_i \sum_{h=1}^H \alpha_{i,h} \right\}, \quad (6)$$

where  $\alpha_{i,h}$  represents the indicator variable in state  $i$  and hour  $h$  defined as:

$$\alpha_{i,h} = \begin{cases} 1 & \text{for } P_i - (P_h + x_h - b_h) \leq 0 \\ 0 & \text{for } P_i - (P_h + x_h - b_h) > 0 \end{cases} \quad \forall i = 1, \dots, g, \forall h = 1, \dots, H. \quad (7)$$

These indicator variables are integer, binary variables that take values  $\{0, 1\}$  depending on the condition (7). This condition is graphically presented for states  $i$  and  $i+1$  in Figure 3. Symbols  $P_h$  and  $P_i$  represent the electric power consumption in hour  $h$  as a part of the initial load profile, and the remaining capacity in state  $i$ , respectively. Only to mention, the load duration curve presented in Figure 2 is derived from the electric power consumption,  $P_h$ , presented with the bold line in Figure 3. Symbols  $x_h$  and  $b_h$  are the continuous optimization variables that represent the charged and discharged energy of EDVs in hour  $h$ , respectively. Consequently,  $P_h + x_h - b_h$  in condition (7) and in Figure 3 represent the optimal load profile in hour  $h$ , i.e. the load profile with maximal system reliability.

The objective function in (6) is limited by the following constraints:

$$E_1 = EIS, \quad (8)$$

$$E_{h-1} + \eta_c x_{h-1} - \frac{b_{h-1}}{\eta_d} - D_{h-1} = E_h \quad \forall h = 2, \dots, H, \quad (9)$$

$$E_h + \eta_c x_h - \frac{b_h}{\eta_d} - D_h \geq D_{h+1} \quad \forall h = 1, \dots, H, \quad (10)$$

$$0 \leq E_h + \eta_c x_h - \frac{b_h}{\eta_d} \leq K \quad \forall h = 1, \dots, H, \quad (11)$$

$$0 \leq \eta_c x_h \leq L_c C \quad \forall h = 1, \dots, H, \quad (12)$$

$$0 \leq \frac{b_h}{\eta_d} \leq L_d C \quad \forall h = 1, \dots, H, \quad (13)$$

$$E_h \geq D_h \quad \forall h = 1, \dots, H, \quad (14)$$

$$E_h \geq 0 \quad \forall h = 1, \dots, H, \quad (15)$$

$$x_h \geq 0 \quad \forall h = 1, \dots, H, \quad (16)$$

$$b_h \geq 0 \quad \forall h = 1, \dots, H, \quad (17)$$

where  $\eta_c$  and  $\eta_d$  represent the charging and discharging efficiencies, respectively.  $E_h$  represents the available energy in the battery at the beginning of hour  $h$ , and  $EIS$  represents the stored energy in the batteries in the initial state, i.e. the available energy in batteries at the beginning of simulation.  $D_h$  is the energy requirement of EDVs for transportation in hour  $h$ . The optimization model also considers the charging and discharging ramp-rate limits  $L_c$  and  $L_d$  that represent the speed of charging and discharging of the battery capacity  $K$ . Symbol  $H$  represents the number of hours of the observed period.

The equality constraint (7) ensures the energy for driving purposes in the first hour, if required, i.e. if  $D_1 > 0$ . The equality constraint (8) stands for the energy balance in hour  $h$ . The available energy in hour  $h$ ,  $E_h$ , depends on the amount of available energy in previous hour,  $E_{h-1}$ , the charged energy,  $x_{h-1}$ , if the charging is applied in previous hour, the discharged energy,  $b_{h-1}$ , if the energy supplier traded this energy on the market, and the energy required for transportation in previous hour,  $D_{h-1}$ . The inequality constraint (9) ensures the energy for transportation in hour  $h+1$ ,  $D_{h+1}$ . The battery capacity is considered in the inequality constraint (10), and the charging and discharging speeds are constrained by (11) and (12). The inequality constraint (13) prevents from the shortage of energy required for transportation in hour  $h$ ,  $D_h$ , and the rest constraints (15) and (16) define the optimization variables  $x$  and  $b$  as positive. Since EDV fleets that aggregate numerous EDVs are considered in the optimization and not each EDV individually, the optimization model does not include a frequently used constraint that prevents from simultaneous charging and driving of EDVs. It is presumed that in each moment some EDVs from a certain EDV fleet are parked and available for charging whether other EDVs are driving according to the driving pattern.

MILP is actually not applicable to the optimization problem in the current form (6)-(17) due to the condition (7), thus it has to be transformed into the following set of constraints applying the binary variables  $\alpha$ :

$$-x_h + b_h \leq -P_i + P_h + M_1(1 - \alpha_{i,h}) \quad \forall i = 1, \dots, J, \forall h = 1, \dots, H, \quad (18)$$

$$x_h - b_h \leq P_i - P_h + M_2\alpha_{i,h} \quad \forall i = 1, \dots, J, \forall h = 1, \dots, H, \quad (19)$$

where  $M_1$  and  $M_2$  are sufficiently large upper bounds of the constraints. In this modified form of the optimization model, MILP can be efficiently applied.

If EENS is considered instead of LOLE in the optimization, the objective function takes the following form:

$$\text{Min} \left\{ J_{CS2,EENS} = EENS = \sum_{i=1}^g p_i w_i = \sum_{i=1}^g p_i \sum_{h=1}^H P_h + x_h - b_h - P_i + \gamma_{i,h} \right\}, \quad (20)$$

s.t. (8)-(17) and:

$$P_h + x_h - b_h - P_i + \gamma_{i,h} \geq 0 \quad \forall i = 1, \dots, g, \forall h = 1, \dots, H, \quad (21)$$

$$\gamma_{i,h} \geq 0 \quad \forall i = 1, \dots, g, \forall h = 1, \dots, H, \quad (22)$$

where  $\gamma_{i,h}$  represents the additional continuous optimization variable. Since no indicator variables are present in this case, LP can be efficiently applied as presented in the results.

In CS3, the driving costs are minimized. The optimization problem is formulated as a linear program (LP) with the objective function  $J_{CS3}$ :

$$\text{Min} \left\{ J_{CS3} = \sum_{h=1}^H C_h x_h - C_h b_h \right\}, \quad (23)$$

where the first term presents the purchase costs of electric energy for EDVs and the second term presents the profits from energy trading of EDVs in the market. The optimization model in SC3 has the same constraints as (7)-(16).

It is presumed that electric energy suppliers purchase the energy for customers in their portfolios, i.e. the EDV users, on the wholesale market. As already mentioned, the energy suppliers are interested in providing the energy to the EDV users for driving purposes at the lowest prices possible, which is achieved by the appropriate charging strategy of EDV batteries. Moreover, EDVs present a business opportunity for electric energy suppliers, since available battery capacities of EDVs could be efficiently exploited in electricity markets, [15]. The main idea is to charge EDVs when energy prices are low and sell the energy back to the network when the prices are high, i.e. bidding of vehicle-to-grid (V2G) electric energy in the market is similar to the bidding of energy produced by pumped-storage hydro power plants. Energy providers are motivated to exploit EDV batteries in the markets for several reasons: (i) extra profits, (ii) affordable lower energy prices for EDV users for transportation due to possible compensation of charging costs with extra profits, (iii) a competitive position among energy providers due to lower prices for EDV users, (iv) a stable portfolio due to satisfied consumers, i.e. EDV users. EDV users are motivated for allowing the battery exploitation due to lower prices for the energy required for transportation.

## 2.2 *Techno-economic assessment of the system reserve provision*

With increasing number of EDVs in the system, the total consumption is expected to grow resulting in a decrease of the system reliability. As already mentioned, an important influence on the system reliability has the applied strategy of EDV charging/discharging. System operators would prefer exploitation of the strategy in CS2 since with this strategy the reliability is expected to be improved or at least its decline due to increasing number of EDVs can be reduced. However, EDV users would prefer utilization of the strategy in CS3 since by this strategy the transportation costs are minimized.

System operators have to obtain a sufficient system reserve in order to maintain the required level of system reliability. In this paper, two possibilities are considered. A conventional solution is to provide a reserve with the existing or new power plants. Another possibility is to exploit EDVs applying the strategy in CS2, but in this case some incentives have to be offered to the EDV users. System operators have to perform the techno-economic assessment of these two solutions.

In this paper, the normalized marginal cost indices (NMCI) are proposed as a measure applied in the techno-economic assessment of all possible solutions, in our case two solutions. NMCI are proposed since they are successfully applied in similar research, [34], but for another purposes. These indices are defined as a ratio between the total costs of a certain solution,  $\Delta TC$ , and the normalized improvement of indices LOLE and EENS,  $\Delta LOLE$  and  $\Delta EENS$ , respectively:

$$NMCI_{LOLE} = \frac{\Delta TC}{\Delta LOLE}, \quad (24)$$

$$NMCI_{EENS} = \frac{\Delta TC}{\Delta EENS}. \quad (25)$$

If the system reserve is provided by a new power plant, NMCI is defined as:

$$NMCI_{LOLE} = \frac{IC}{|LOLE_{PP} - LOLE_0|/LOLE_0}, \quad (26)$$

$$NMCI_{EENS} = \frac{IC}{|EENS_{PP} - EENS_0|/EENS_0}, \quad (27)$$

where  $IC$  is the annuity of the investment. Periodical operation and maintenance costs are neglected but can be easily considered in the calculation.  $IC$  is calculated as:

$$IC = Inv \frac{p(1+p)^N}{(1+p)^N - 1}, \quad (28)$$

where  $Inv$  is the total investment cost,  $N$  is the number of stream payments in the lifetime of the power plant, and  $p$  is the period interest rate. Indices  $LOLE_{PP}$  and  $EENS_{PP}$  are indices for the system with installed power plant, and  $LOLE_0$  and  $EENS_0$  are valid for the case with no power plant installed – the initial state. In our case,  $LOLE_0$  and  $EENS_0$  are equal to  $LOLE$  and  $EENS$  in CS3, since in this case EDVs are charged/discharged with the strategy that provides the lowest transportation costs.

If the system reserve is provided by EDVs, the strategy in CS3 is replaced with the strategy in CS2 resulting in higher transportation costs. These costs have to be compensated by the system operator, and this is a minimal incentive offered to the EDV users for performing the charging/discharging strategy in CS2. Indices  $NMCI$  are calculated as:

$$NMCI_{LOLE} = \frac{TC_{CS2} - TC_{CS3}}{|LOLE_{CS2} - LOLE_{CS3}|/LOLE_{CS3}}, \quad (29)$$

$$NMCI_{EENS} = \frac{TC_{CS2} - TC_{CS3}}{|EENS_{CS2} - EENS_{CS3}|/EENS_{CS3}}. \quad (30)$$

Once NMCI is calculated, the system operator would choose the solution with lower NMCI since this would mean that a chosen solution has a stronger impact on the system reliability with the same costs or the same impact with lower costs.

### 3 Case Studies

The impact of EDVs on power system reliability is assessed in three CSs presented in Section 2. In all cases, for the simulation purposes the expected daily driving pattern  $\delta$ , the expected energy consumption  $p$ , and the expected hourly electric energy prices  $c$  presented in Table 1 are considered as a basis for the scenario preparation, where 10,000 scenarios are created with the MC method in order to simulate uncertainties of EDV behavior and consumption and price forecasts. The interval of  $RU$  is set to  $[0, 0.9\text{km}]$ , the mean the standard deviation of all  $RND$ ,  $RNP$  and  $RNC$  are set to 0 and 0.1, respectively. In order to reduce the calculation complexity 10,000 scenarios are reduced to the final three scenarios applying the K-means clustering method. Table 2 presents the resulting daily driving patterns, load diagrams and energy prices for all three scenarios.

Each EDV battery has the capacity  $K$  of 25kWh and no stored energy in the initial state,  $EIS$ . Energy is charged and discharged with the 90% and 93% efficiencies,  $\eta_c$  and  $\eta_d$ . Charging and discharging speeds  $L_c$  and  $L_d$  are limited to 50% of the total capacity per hour, meaning that the batteries are fully charged or discharged in two hours. Finally, the charging and discharging efficiencies are set to 6km/kWh.

For all three CSs and scenarios, the reliability indices LOLE and EENS are assessed for different penetration levels of EDVs in the system, i.e. the number of EDVs in the system goes from zero up to 65,000 vehicles. Table 3 presents installed power and availability of generators in power system required for a calculation of LOLE and EENS.

Figures 4 and 5 present LOLE and EENS indices for all three CSs and scenarios for cases with different number of EDVs in the system. In CS1 and CS3, the system reliability is reducing with the increasing penetration level of EDVs in the system. In CS2, an interesting phenomenon is observed since U-shape curves are obtained as presented in Figures 6 and 7. If LOLE index is considered, the system reliability is improving to the certain penetration level of EDVs in the system, i.e. 28,750 vehicles for scenarios 1 and 3, respectively, and 28,125 vehicles for scenario 2, followed by the system reliability decrease as strongly noticed in CS1 and CS3. Similar observation stands for EENS indices, where the limit is 28,750 vehicles in each scenario. In general, in this simulation the system reliability is improved if the number of EDVs connected to the system does not exceed approximately 28,750 vehicles, where the minimal points of U-shaped curves are. This would be the optimal number of EDVs in the system from the perspective of system reliability.

The results lead to the conclusion that the system operator would prefer exploitation of the charging/discharging strategy in CS2 since the system reliability can be improved. EDVs can efficiently replace the required system reserve provided by some existing power plant if available or by a new power plant that leads to the certain investment costs. Evidently, the costs of the system reserve provision can be reduced by EDVs.

However, EDV users would prefer utilization of the charging/discharging strategy in CS3 since this strategy leads to the minimal transportation costs which is the most important concern of the drivers. Table 4 provides the comparison of the driving costs per kilometer for all three scenarios for all three strategies. The results are present for the case with 28,750 EDVs in the system. The average transportation costs in simulated CSs are: 1.88 cEUR/km, 0.86 cEUR/km, and 0.49 cEUR/km, respectively.

Tables 5 and 6 present reliability indices for the case with 28,750 EDVs in the system. It is confirmed again that the strategy applied in CS2 ensures the highest system reliability among all assessed strategies.

In the subsequent text, two possibilities of provision of the system reserve are compared. If the reserve is provided by the 100 MW power plant (PP) with its availability 0.95, data in Table 7 are considered. Since the observed period in the research is one day (24 hours), the daily annuity  $IC$  for all three scenarios is calculated by (28). The results are presented in Table 8. This power plant improves indices LOLE and EENS as presented in Table 8, as well, together with indices NMCI.

If the system reserve is provided by 28,750 EDVs, the results in Table 9 are obtained. As expected, indices LOLE and EENS are improved due to the replacement of charging/discharging strategy CS3 with CS2, but with some additional costs  $\Delta TC$ .

The results in Tables 8 and 9 show that the system operator would choose EDVs for the system reserve provision. In this case, indices NMCI take lower values meaning that the same impact on the system reliability is achieved by lower costs.

Table 10 presents the same results but from different perspective that enables more transparent comparison. If the system reserve is provided by EDVs, for the improvement of LOLE or EENS for 1%, the system operator should compensate in average 1.00cEUR per 100 kilometers per each EDV user if LOLE is observed or 1.85cEUR in case of EENS. If the system reserve is supported by the power plant, the costs for this service converted in comparable units would be in average 2.38cEUR or 2.04cEUR per 100 kilometers per each EDV user, depending if LOLE or EENS is considered. Finally, the cheaper solution for the system operator is to engage EDVs for the system reserve provision.

#### 4 Conclusions

The paper assesses the impact of EDVs on power system reliability. The main contribution of this paper is the proposed straight optimization of reliability indices LOLE and EENS and techno-economic assessment of the system reserve provision required for reliable operation of power system. The paper discusses the importance of choosing a proper charging/discharging strategy of EDVs and its strong influence on the system reliability, especially in cases with numerous EDVs. In general, it is observed that numerous EDVs increase the system loading resulting in weakening of the system reliability, but the results confirm that EDVs can even improve the system reliability to some extent if an appropriate charging/discharging strategy is applied. Another question addressed in the papers is the costs for system reserve provision. A system operator has to maintain a reliable operation of power system. Support could be provided by classical power plans or, as presented in this paper, by an appropriate charging/discharging strategy of EDVs. Which solution to choose depends on their price-performance as assessed in the paper, as well.

#### References

- [1] Soohyeong J, Sekyung H, Soo Hee H, Sezaki K. Optimal decision on contract size for V2G aggregator regarding frequency regulation. Conference Optimal decision on contract size for V2G aggregator regarding frequency regulation. p. 54-62.
- [2] Ota Y, Taniguchi H, Nakajima T, Liyanage KM, Shimizu K, Masuta T, et al. Effect of autonomous distributed vehicle-to-grid (V2G) on power system frequency control. Conference Effect of autonomous distributed vehicle-to-grid (V2G) on power system frequency control. p. 481-5.
- [3] Shimizu K, Masuta T, Ota Y, Yokoyama A. Load Frequency Control in power system using Vehicle-to-Grid system considering the customer convenience of Electric Vehicles. Conference Load Frequency Control in power system using Vehicle-to-Grid system considering the customer convenience of Electric Vehicles. p. 1-8.
- [4] White CD, Zhang KM. Using vehicle-to-grid technology for frequency regulation and peak-load reduction. *Journal of Power Sources*. 2011;196(8):3972-80.

- [5] Divya KC, Østergaard J. Battery energy storage technology for power systems—An overview. *Electric Power Systems Research*. 2009;79(4):511-20.
- [6] Guille C, Gross G. Design of a Conceptual Framework for the V2G Implementation. *Conference Design of a Conceptual Framework for the V2G Implementation*. p. 1-3.
- [7] Lund H, Kempton W. Integration of renewable energy into the transport and electricity sectors through V2G. *Energy Policy*. 2008;36(9):3578-87.
- [8] Kempton W, Tomić J. Vehicle-to-grid power fundamentals: Calculating capacity and net revenue. *Journal of Power Sources*. 2005;144(1):268-79.
- [9] Saber AY, Venayagamoorthy GK. Unit commitment with vehicle-to-Grid using particle swarm optimization. *Conference Unit commitment with vehicle-to-Grid using particle swarm optimization*. p. 1-8.
- [10] Ghanbarzadeh T, Goleijani S, Moghaddam MP. Reliability constrained unit commitment with electric vehicle to grid using Hybrid Particle Swarm Optimization and Ant Colony Optimization. *Conference Reliability constrained unit commitment with electric vehicle to grid using Hybrid Particle Swarm Optimization and Ant Colony Optimization*. p. 1-7.
- [11] Goleijani S, Ghanbarzadeh T, Sadeghi Nikoo F, Parsa Moghaddam M, Reliability constrained unit commitment in smart grid environment. *Electric power systems research*. 2013;97:100-108.
- [12] Lei J, Huan Y, Fangbin C, Yuying Z, Rongxiang Z. A novel approach for the unit commitment with vehicle-to-grid. *Conference A novel approach for the unit commitment with vehicle-to-grid*. p. 1-6.
- [13] Musio M, Lombardi P, Damiano A. Vehicles to grid (V2G) concept applied to a Virtual Power Plant structure. *Conference Vehicles to grid (V2G) concept applied to a Virtual Power Plant structure*. p. 1-6.
- [14] Kempton W, Tomić J. Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy. *Journal of Power Sources*. 2005;144(1):280-94.
- [15] Pantoš M. Exploitation of Electric-Drive Vehicles in Electricity Markets. *Power Systems, IEEE Transactions on*. 2012;27(2):682-94.
- [16] Kiviluoma J, Meibom P. Methodology for modelling plug-in electric vehicles in the power system and cost estimates for a system with either smart or dumb electric vehicles. *Energy*. 2011;36(3):1758-67.
- [17] Tomić J, Kempton W. Using fleets of electric-drive vehicles for grid support. *Journal of Power Sources*. 2007;168(2):459-68.
- [18] Balram P, Le Anh T, Bertling Tjernberg L. Effects of plug-in electric vehicle charge scheduling on the day-ahead electricity market price. *Conference Effects of plug-in electric vehicle charge scheduling on the day-ahead electricity market price*. p. 1-8.
- [19] Soares M.C. Borba B, Szklo A, Schaeffer R. Plug-in hybrid electric vehicles as a way to maximize the integration of variable renewable energy in power systems: The case of wind generation in northeastern Brazil. *Energy*. 2012;37(1):469-81.

- [20] Pantoš M. Stochastic optimal charging of electric-drive vehicles with renewable energy. *Energy*. 2011;36(11):6567-76.
- [21] Green Li RC, Wang L, Alam M. The impact of plug-in hybrid electric vehicles on distribution networks: A review and outlook. *Renewable and Sustainable Energy Reviews*. 2011;15(1):544-53.
- [22] Pieltain F, x, ndez L, Go, x, mez San R, et al. Assessment of the Impact of Plug-in Electric Vehicles on Distribution Networks. *Power Systems, IEEE Transactions on*. 2011;26(1):206-13.
- [23] Hedegaard K, Ravn H, Juul N, Meibom P. Effects of electric vehicles on power systems in Northern Europe. *Energy*. 2012;48(1):356-68.
- [24] Hadley SW. Evaluating the impact of Plug-in Hybrid Electric Vehicles on regional electricity supplies. *Conference Evaluating the impact of Plug-in Hybrid Electric Vehicles on regional electricity supplies*. p. 1-12.
- [25] Kempton W, Kubo T. Electric-drive vehicles for peak power in Japan. *Energy Policy*. 2000;28(1):9–18.
- [26] Kiviluoma J, Meibom P. Influence of wind power, plug-in electric vehicles, and heat storages on power system investments. *Energy*. 2010;35(3):1244-1255.
- [27] Camus C, Silva C M, Farias T L, Esteves J. Impact of Plug-in Hybrid Electric Vehicles in the Portuguese electric utility system. *International Conference on Power Engineering, Energy and Electrical Drives*. p. 285-290.
- [28] Falahati B, Yong F, Darabi Z, Lei W. Reliability assessment of power systems considering the large-scale PHEV integration. *IEEE Vehicle Power and Propulsion Conference (VPPC)*. p. 1-6.
- [29] Parks K, Denholm P, Markel T. Costs and Emissions Associated with Plug-In Hybrid Electric Vehicle Charging in the Xcel Energy Colorado Service Territory. *Technical Report NREL/TP-640-41410*, 2007.
- [30] Denholm P, Short W. An Evaluation of Utility System Impacts and Benefits of Optimally Dispatched Plug-In Hybrid Electric Vehicles. *Technical Report NREL/TP-620-40293*, 2006.
- [31] Dupačová J, Gröwe-Kuska N, Römisch W. Scenario Reduction in Stochastic Programming: An approach Using Probability Metrics. *Mathematical Programming*. 2003;95:493–511.
- [32] GAMS/SCENRED Documentation. Available from [www.gams.com/docs/document.htm](http://www.gams.com/docs/document.htm).
- [33] Billinton R, Allan R N. *Reliability Evaluation of Power Systems - Second edition*. Plenum Press. 1996.
- [34] Božič D, Pantoš M. Assessment of investment efficiency in a power system under performance-based regulation. *Energy*. 2013;51:330-338.

**Figure captions**

Figure 1: Optimization procedure

Figure 2: Load duration curve with  $t_i$

Figure 3: Indicator variables  $\alpha$

Figure 4: LOLE indices for different number of EDVs in the system

Figure 5: EENS indices for different number of EDVs in the system

Figure 6: LOLE indices for CS2

Figure 7: EENS indices for CS2

**Table captions**

Table 1: Expected daily driving pattern, energy consumption and hourly prices

Table 2: Daily driving patterns, energy consumption and hourly prices for three scenarios

Table 3: Parameters of generators in power system

Table 4: Transportation Costs

Table 5: LOLE index

Table 6: EENS index

Table 7: Investment in power plant

Table 8: System reserve provision by power plant

Table 9: System reserve provision by EDVs

Table 10: Additional transportation costs of system reserve provision

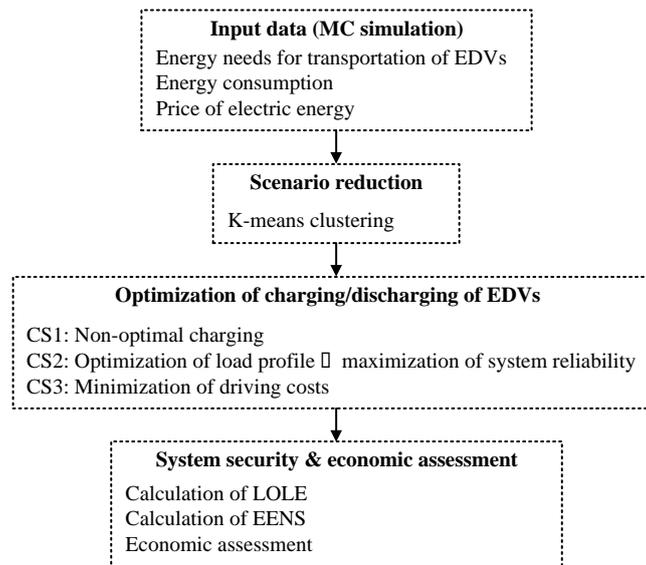


Figure 1: Optimization procedure

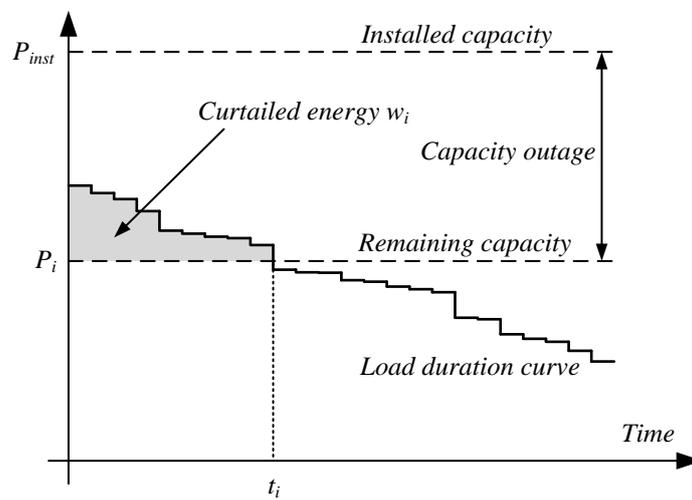


Figure 2: Load duration curve with  $t_i$

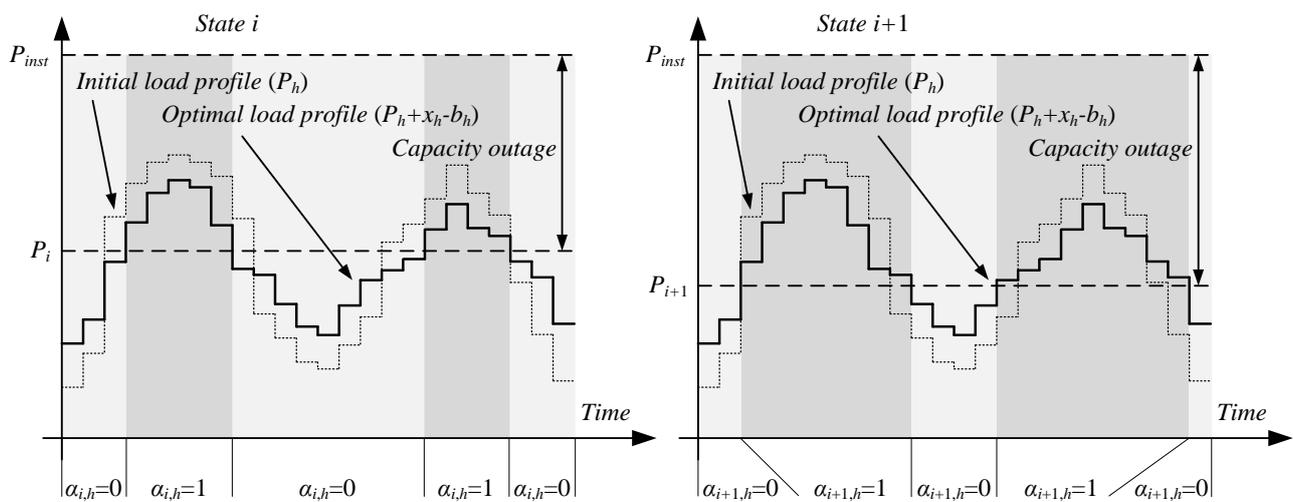


Figure 3: Indicator variables  $\alpha$

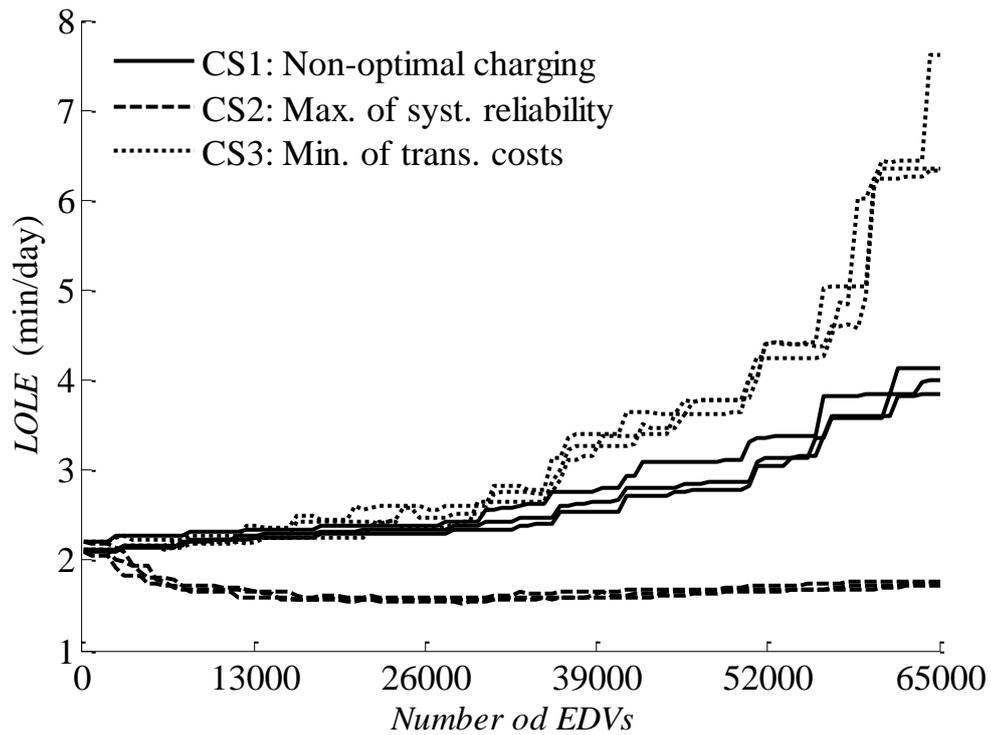


Figure 4: LOLE indices for different number of EDVs in the system

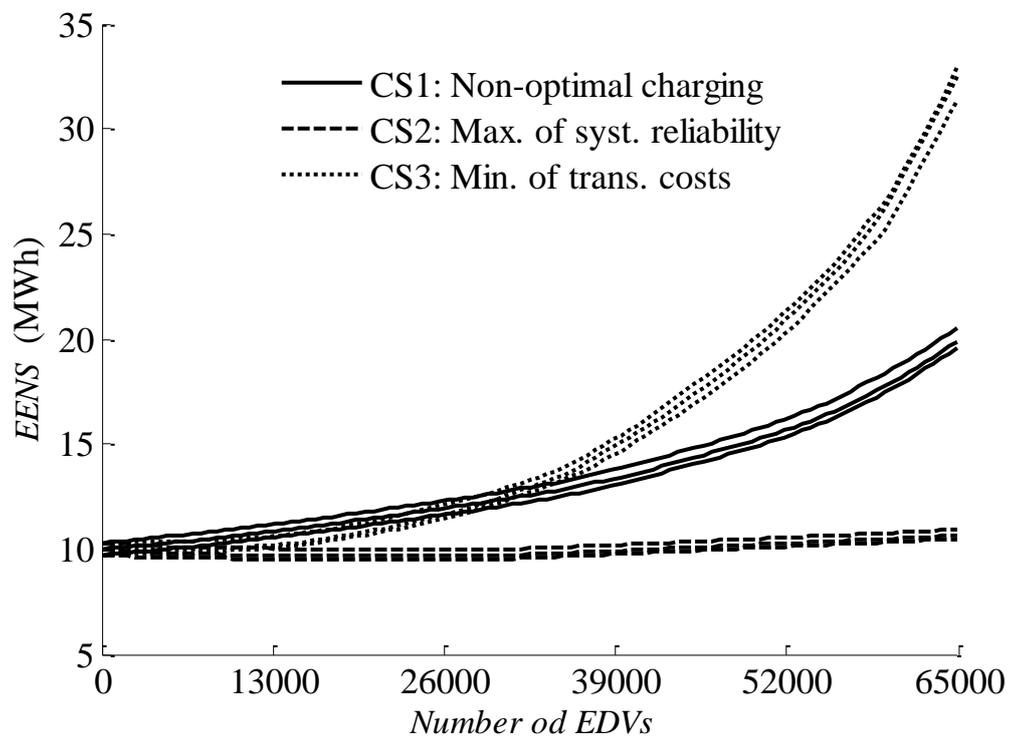


Figure 5: EENS indices for different number of EDVs in the system

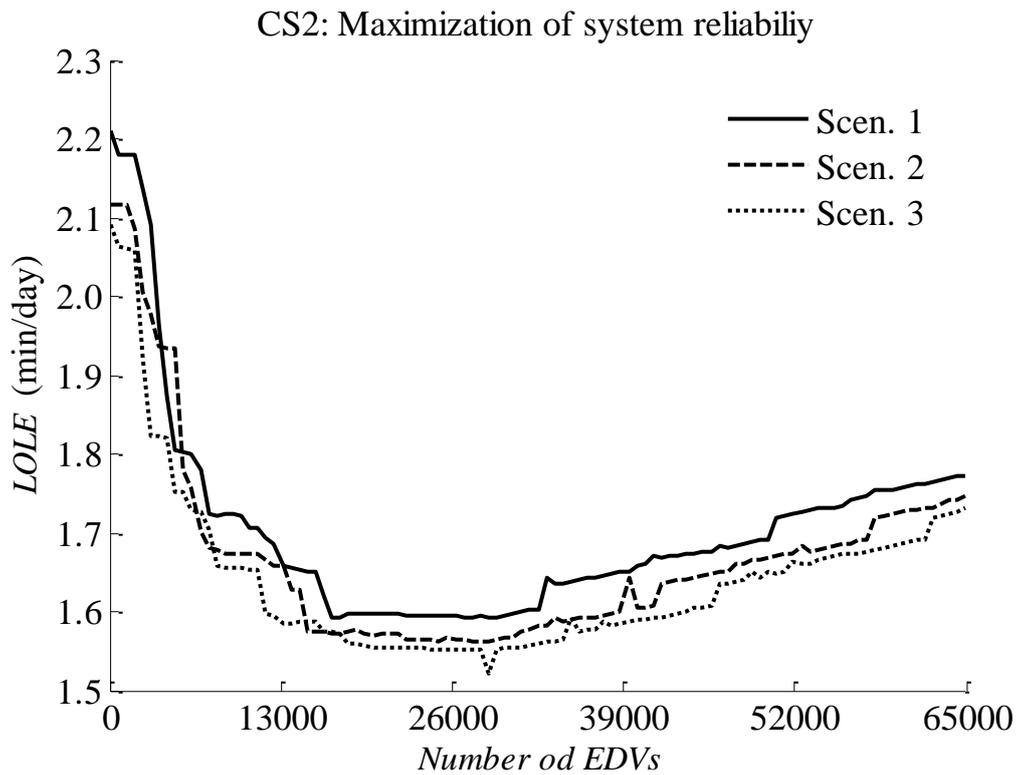


Figure 6: LOLE indices for CS2

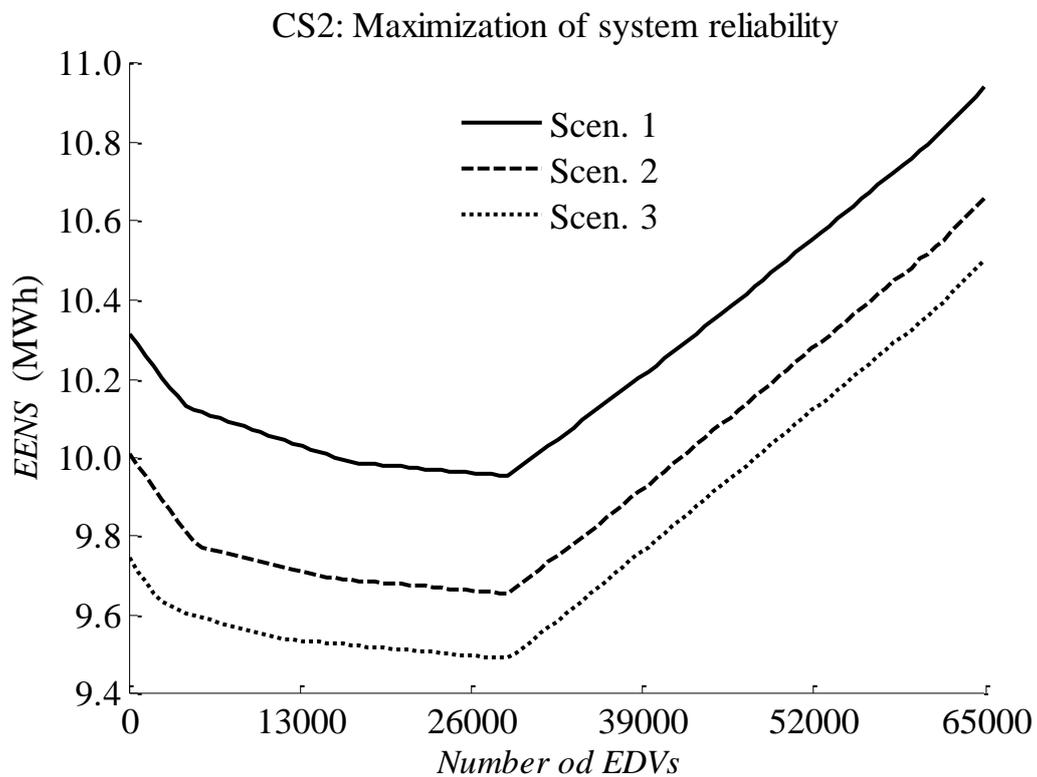


Figure 7: EENS indices for CS2

Table 1: Expected daily driving pattern, energy consumption and hourly prices

Hour $h$	$\delta_h$ (km)	$P_h$ (MWh)	$c_h$ (EUR/MWh)
1	1.00	1317.0	40
2	1.40	1247.5	42
3	2.00	1205.5	45
4	1.60	1184.2	40
5	2.20	1175.1	50
6	6.20	1188.5	50
7	9.20	1257.7	53
8	8.80	1384.8	55
9	6.60	1528.3	58
10	5.10	1642.5	63
11	3.30	1707.8	60
12	2.80	1751.2	55
13	2.70	1690.6	50
14	3.40	1595.4	40
15	5.90	1540.7	50
16	9.30	1500.6	50
17	10.40	1517.3	60
18	8.80	1585.9	60
19	6.60	1671.8	65
20	4.90	1743.2	63
21	5.00	1754.9	50
22	3.50	1682.0	40
23	1.60	1577.3	40
24	1.40	1431.3	40

Table 2: Daily driving patterns, energy consumption and hourly prices for three scenarios

Hour $h$	$\delta_h$ (km)			$P_h$ (MWh)			$c_h$ (EUR/MWh)		
	Scen. 1	Scen. 2	Scen. 3	Scen. 1	Scen. 2	Scen. 3	Scen. 1	Scen. 2	Scen. 3
1	1.27	1.27	1.27	1322.7	1312.7	1312.3	39.90	39.90	40.10
2	1.86	1.85	1.86	1243.5	1246.3	1249.2	42.00	42.10	42.10
3	2.58	2.58	2.59	1209.8	1208.6	1201.3	45.10	45.00	45.10
4	1.85	1.84	1.84	1183.7	1188.9	1179.7	40.00	40.00	40.00
5	2.61	2.61	2.61	1174.9	1173.7	1179.3	49.90	50.10	50.10
6	6.30	6.30	6.29	1190.9	1189.2	1184.5	50.10	49.90	50.00
7	9.67	9.68	9.66	1251.6	1259.3	1261.9	53.20	53.20	53.00
8	9.66	9.67	9.68	1389.7	1377.3	1385.7	54.90	54.90	55.00
9	6.77	6.77	6.76	1536.8	1518.5	1533.1	58.00	58.00	58.00
10	5.51	5.49	5.51	1653.5	1635.2	1645.1	62.90	62.80	63.10
11	3.95	3.95	3.94	1650.3	1737.6	1727.7	59.90	60.00	59.90
12	3.13	3.14	3.14	1657.0	1761.3	1837.9	55.00	54.90	55.10
13	2.98	2.97	2.96	1730.5	1653.7	1695.3	50.10	50.00	50.00
14	4.09	4.10	4.09	1591.4	1607.7	1594.3	40.00	39.90	40.00
15	6.70	6.70	6.69	1531.4	1550.9	1544.9	49.90	50.10	50.00
16	10.02	10.01	10.02	1496.9	1515.8	1483.3	49.90	49.90	49.90
17	11.16	11.14	11.15	1536.9	1510.4	1498.9	59.90	60.00	60.00
18	9.61	9.61	9.61	1567.4	1591.7	1595.2	60.00	60.00	60.00
19	7.42	7.40	7.42	1739.4	1629.7	1648.0	64.80	65.00	65.10
20	5.39	5.39	5.37	1773.1	1872.4	1583.5	63.00	62.90	63.00
21	5.87	5.88	5.85	1863.1	1651.8	1751.5	50.10	50.00	50.00
22	3.84	3.86	3.85	1725.6	1653.4	1660.6	40.00	39.90	40.10
23	1.95	1.95	1.95	1569.1	1586.8	1577.2	40.20	40.00	39.90
24	2.15	2.15	2.15	1433.6	1424.9	1438.2	40.10	40.00	40.00

Table 3: Parameters of generators in power system

Generator	Installed power (MW)	Availability
1	1273.0	0.9718
2	604.2	0.8954
3	319.2	0.8383
4	102.6	0.9923
5	129.2	0.9843
6	1065.9	0.9557
7	110.2	0.9886
8	85.5	0.9991
Total	3689.8	

Table 4: Transportation Costs

Trans. costs (cEUR/km)	Scen. 1	Scen. 2	Scen. 3	Average
CS1	1.88	1.88	1.88	1.88
CS2	0.89	0.84	0.87	0.86
CS3	0.49	0.49	0.49	0.49

Table 5: LOLE index

LOLE (min/day)	Scen. 1	Scen. 2	Scen. 3	Average
CS1	2.43	2.34	2.38	2.38
CS2	1.59	1.56	1.52	1.56
CS3	2.61	2.42	2.52	2.52

Table 6: EENS index

EENS (MWh)	Scen. 1	Scen. 2	Scen. 3	Average
CS1	12.56	12.20	11.89	12.22
CS2	9.95	9.66	9.49	9.70
CS3	12.56	12.14	11.93	12.21

Table 7: Investment in power plant

Parameter	Value
<i>Installed power (MW)</i>	100
<i>Lifetime (years)</i>	40
<i>Inv. cost (EUR/kW)</i>	1,500
<i>Interest rate (%/year)</i>	5

Table 8: System reserve provision by power plant

100 MW PP	Scen. 1	Scen. 2	Scen. 3	Average
<i>IC (kEUR)</i>	23.37	23.37	23.37	23.37
$\Delta LOLE$ (%)	27.15	26.37	27.55	27.02
$\Delta EENS$ (%)	29.13	31.94	33.84	31.64
<i>NMCI<sub>LOLE</sub> (EUR/%)</i>	860.87	886.27	848.32	865.15
<i>NMCI<sub>EENS</sub> (EUR/%)</i>	802.43	731.77	690.63	741.61

Table 9: System reserve provision by EDVs

28,750 EDVs	Scen. 1	Scen. 2	Scen. 3	Average
<i>TC<sub>CS2</sub> (kEUR)</i>	32.39	30.44	31.40	31.41
<i>TC<sub>CS3</sub> (kEUR)</i>	17.67	17.66	17.63	17.65
$\Delta TC$ (kEUR)	14.71	12.78	13.77	13.76
$\Delta LOLE$ (%)	39.00	35.41	39.65	38.02
$\Delta EENS$ (%)	20.72	20.42	20.43	20.52
<i>NMCI<sub>LOLE</sub> (EUR/%)</i>	377.26	360.93	347.24	361.81
<i>NMCI<sub>EENS</sub> (EUR/%)</i>	710.25	625.97	673.93	670.05

Table 10: Additional transportation costs of system reserve provision

Add. trans. costs (cEUR/100km/%)	Scen. 1	Scen. 2	Scen. 3	Average
LOLE 28,750 EDVs	1.04	0.99	0.96	1.00
LOLE 100 MW PP	2.37	2.44	2.34	2.38
EENS 28,750 EDVs	1.96	1.72	1.86	1.85
EENS 100 MW PP	2.21	2.02	1.90	2.04