Exploitation of Electric-Drive Vehicles in Electricity Markets

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***Abstract*—The paper presents the optimization algorithm which may eventually be used by electric energy suppliers to coordinate charging and discharging of electric-drive vehicles (EDVs) exploited in electricity markets. The research is focused on a day-ahead market and a provision of system regulation in an ancillary-service market. The proposed optimization minimizes the charging costs that can be partly compensated with profits obtained from participation in the energy markets. Due to the stochastic nature of transportation patterns, the Monte Carlo simulation is applied to model uncertainties presented by numerous scenarios. To reduce the problem complexity, the simulated driving patterns are not individually considered in the optimization but clustered into fleets using the GAMS/SCENRED tool. Uncertainties of energy requirements in the market and energy prices are presented by statistical central moments that are further considered in Hong's 2-point + 1 estimation method in order to define points considered in the optimization. Finally, each energy supplier has to offer competitive energy prices to EDV users for transportation. Due to uncertainties, the final prices cannot be deterministically calculated, thus the paper proposes the risk-based approach applying Value at Risk. Case studies illustrate the application of the proposed optimization in achieving competitive prices for EDV users.**

***Index Terms*—Electric-drive vehicles, linear programming, optimization, risk management.**

I. Nomenclature

Indices:

b	Subscript index for purchase energy price
c	Subscript index for charging efficiency
d	Subscript index for V2G efficiency
e	Subscript index for regulating energy price
g	Subscript index for concentration
k	Subscript index for scenario
m	Subscript index for output variables Y_m
n	Subscript index for input variable X_n
p, h, i, j	Subscript indices for hour
r	Subscript index for capacity payment price
s	Subscript index for selling energy price
v	Subscript index for EDV
x	Subscript index for input variable
y	Subscript index for output variable
0	Subscript index for scenario 0
$*$	Superscript index for determined value

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Variables and functions:

$b_{(\cdot),(\cdot)}$	Energy used from the battery
$w_{(\cdot),(\cdot)}$	Charged energy for system regulation
$X_{(\cdot)}$	Input data variable
$x_{(\cdot),(\cdot)}$	Charged energy for transportation
$Y_{(\cdot)}$	Output data variable
$y_{(\cdot),(\cdot)}$	Charged energy for electric energy market
$z_{(\cdot),(\cdot)}$	Charged energy of the first charging of reserved capacity for system regulation

Parameters and Constants:

a	Number of input data variables
b	Number of input data states
c	Energy price for transportation of EDVs
$C_{(\cdot)}$	Battery capacity
$D_{(\cdot)}$	Energy requirement of fleet for transportation
$d_{(\cdot),(\cdot),(\cdot)}$	Energy requirement of EDV for transportation
E	Stored energy in batteries in initial stage
$E(\cdot)$	Expectation operator
F	Number of output data variables
f	Number of EDVs in a fleet
G	Number of concentrations
H	Number of hours
J	Objective function
$l_{(\cdot)}$	Driving distance
$L_{(\cdot),(\cdot)}$	Charging ramp-rate limit
$M_{(\cdot)}$	Energy requirement in electric energy market
MP	Profit in electric energy market
o	Parameter in central moment calculation
$P_{(\cdot)}$	Reserved capacity for system regulation
$P_{(\cdot),(\cdot)}$	Concentration location
PC	Energy purchase cost
$pdf(\cdot)$	Probability distribution function
r	Risk level
$R_{(\cdot)}$	Energy requirement for system regulation
$RN_{(\cdot),(\cdot),(\cdot)}$	Random component with normal distribution
$RU_{(\cdot),(\cdot),(\cdot)}$	Random component with uniform distribution
RP	Profit in system regulation
T	Time of activation of system regulation service
t	One hour
$W_{(\cdot),(\cdot)}$	Concentration weight
$\delta_{(\cdot),(\cdot)}$	Expected energy requirement for transportation
$\xi_{(\cdot),(\cdot)}$	Standard location of concentration
$\lambda_{(\cdot),(\cdot)}$	Central moment of variable

$\mu_{(\cdot),(\cdot)}$	Variable mean
$\eta_{(\cdot)}$	Energy conversion efficiency
$\rho_{(\cdot),(\cdot)}$	Energy price
$\sigma_{(\cdot),(\cdot)}$	Variable standard deviation
Φ	Set of estimation points obtained by HM method

Matrices and vectors:

D	Vector of energy requirements for transportation
L	Vector of concentration locations
M	Vector of energy requirements in energy market
R	Vector of energy requirements for system regulation
W	Vector of concentration weights
X	Vector of input variables
ρ	Vector of electric energy prices

Abbreviations:

CDF	Cumulative distribution function
EDV	Electric-drive vehicle
EDVO	Electric-drive-vehicle operator
HM	Hong's 2-point + 1 estimation method
LP	Linear programming, linear program
MC	Monte Carlo
PDF	Probability distribution function
PE	Point estimation, point estimate
VaR	Value at Risk
V2G	Vehicle to grid

II. Introduction

TECHNOLOGICAL improvements in battery manufacturing, higher environmental awareness and high liquid fuel prices have brought into practical use electric-drive vehicles (EDVs), which requires a proper expansion of electric power grids as well as an upgrade of information and communication technology infrastructure. EDVs available in the market are powered by batteries, fuel cells or hybrid drive trains. Usually they enable electric energy storage and if equipped with appropriate connections, they also enable the supply of vehicle-to-grid (V2G) power to the network.

From the present perspective of the power-system, EDVs are passive elements, i.e. batteries that have to be charged after transportation, when they are parked. Since EDVs are still not a widespread solution in transportation, they are observed and controlled as individual units without coordinated charging. In the near future, the increasing number of EDVs will require the establishment of electric-drive-vehicle operators (EDVOs), responsible for ensuring the reliable operation, maintenance, and planning of the entire EDV infrastructure.

In the deregulated environment, EDVOs as regulated utilities will not participate in electric energy retailing. EDVs will present a business opportunity for electric energy suppliers, since available battery capacities of EDVs could be efficiently exploited in electricity markets. 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 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.

As reported in [1], [2], classical trading of V2G electric energy might not result in satisfactory revenues due to the low spreads between purchase and selling prices, high energy-conversion losses, etc. However, EDVs can serve as a fast-response capacity reserve in case of an unbalanced power system resulting from generation outages as addressed in [1]-[4]. In addition, EDVs can provide regulating power as an ancillary service in case of deviations from production or consumption plans, [5], [6]. When EDVs are paid for capacity reserve and for energy supplied to the grid due to regulation and system balancing, the revenues might be higher, making EDVs economically more attractive and investments into them economically justified. Finally, a better utilization of renewable energy sources is possible with intelligent charging of EDVs, [5], [6], resulting in lower CO_2 emissions.

Literature has long recognized the role of EDVs in energy markets, [1]-[6], and in provision of V2G power for different purposes [7], [8], e.g. frequency regulation, [9]-[11], unit commitment, [12], activation in virtual power plants [13] etc..

The closest references to the research presented in this paper are [1]-[4] since they address the opportunities of EDVs in the energy markets and the charging optimization with cost minimization. In [1], the provision of V2G power in the market is assessed with the conclusion that EDVs are not technically and economically appropriate for the base load provision, but can provide quick responses to balance load fluctuations. Reference [2] expands the research and suggests reconciling the complementary needs of EDV users and power system operators. V2G power could stabilize wind power by power injections and power storage. These two references provide some techno-economic calculations; give incentives for the research presented in this paper, but do not address the charging optimization. References [3], [4] provide a comprehensive overview of electricity markets, prices, EDVs and driving patterns. In Section III, the charging optimization with cost minimization is addressed applying the LP formulation. The proposed optimization does not take into account the stochastic nature of input data, e.g. energy prices, thus it is performed by deterministic methods under the assumption of perfect forecasts.

The main purpose of the paper is to present the advantages of EDV exploitation in the energy markets by energy suppliers that have to offer competitive energy prices to EDV users for transportation. Several uncertainties call for this problem to be addressed using the stochastic approach. The necessity of this approach is also recognized by [8]. Since the final energy prices cannot be deterministically calculated, the procedure proposes the risk-based approach applying Value at Risk (VaR) index.

Due to presented lack of the work performed in the past, the paper proposes a stochastic linear programming (LP) optimization algorithm of EDV charging and discharging in the market environment, with the possibility to exploit the remaining battery capacities in two markets: (i) electric-energy market, (ii) system regulation as an ancillary service. Related profits can compensate for the charging costs of EDVs, resulting in cheaper energy for transportation, which is – together with ensuring a reliable supply of EDVs – the main goal of the proposed optimization algorithm.

The rest of the paper is organized as follows: the optimization procedure is presented in Section III with Subsections III.A–III.E describing individual parts of the procedure. Section IV presents and discusses in detail three case studies, i.e. the possible exploitation of EDVs in the market environment. The conclusion drawn from the study is provided in Section V.

III. Optimization Procedure

The optimization procedure proposed in the paper consists of several tasks, presented in Fig. 1. The initial step is a stochastic assessment of input data: future energy requirements for transportation, energy requirements for trading and system regulation, and energy-purchase prices. Driving patterns are obtained by the analysis of the past transportation behavior, if the exiting EDVs are considered. Otherwise, for new EDVs, the Monte Carlo (MC) simulation is applied in order to produce a set of driving patterns. The procedure of data preparation considering EDVs is explained in detail in Subsection III.A. For other inputs a statistical assessment is performed and central moments are obtained used later in a point estimate (PE) procedure explained in Subsection III.C. The data preparation task also involves a definition of EDV technical parameters and contractual specifications for system regulation, such as a reserve capacity, capacity payment price, etc. The required parameters are explained in Subsection III.D, where the optimization algorithm is presented, as well.

In the real world, the optimization procedure of battery charging for numerous EDVs would have to be performed individually, which is not feasible due to problem complexity, thus the problem is reduced to the level of EDV fleets, [3], [4], i.e. clusters that merge EDVs with similar driving patterns. The clustering of driving patterns into a predefined number of fleets is outlined in Subsection III.B and the clustering method is explained in detail in [14], [15].

Once the input data are prepared, the PE procedure is performed as presented in Subsection III.C in order to allow for probabilistic nature of the problem. The Hong's 2-point + 1 estimation method (HM) is applied in order to define a set of input data points at which the output variables are deterministically evaluated and their statistical parameters are calculated by utilizing the optimization procedure with the algorithm presented in detail in Subsection III.D. It is important to note that for each input data point an independent and deterministic optimization is performed.

The final task of the proposed procedure is a calculation of prices of energy required by EDV users for transportation based on the charging cost and profit analyses. The energy suppliers have to offer the competitive prices to EDV users. As noted, these prices are actually calculated deterministically, but according to the applied HM method, they are presented stochastically by probability distribution functions (PDFs) and cumulative distribution functions (CDFs). Due to forecast uncertainties, the final prices for EDV users are calculated applying a risk-assessment approach that introduces VaR index. The idea is discussed in detail in Subsection III.E.

A. Input data preparation

In the open market, EDV users will choose the most competitive energy supplier that offers the lowest prices of electric energy needed for transportation. The proposed optimization procedure as a supporting tool for energy suppliers for price calculations involves uncertainties of input data, [16]. Some data have to be simply collected based on past observations, others statistically assessed or stochastically formulated as proposed later in the text. The following input data are proposed to be included in the procedure:

- future energy needs of consumers in the market and for system regulation as opportunities for energy suppliers to make additional profits by EDV exploitation,
- purchase energy prices for battery charging,
- future energy requirements of the existing EDVs derived from their driving patterns in the past and,
- energy requirements of new EDVs with driving pattern expectations.

For the future energy needs of consumers in the market and purchase energy prices a statistical analysis of the past data is performed and statistical central moments, i.e. the mean value and standard deviation (variance), are calculated. These parameters are directly considered in the calculation presented in Subsection III.C.

For the existing EDVs, it can be assumed that the future energy needs for transportation will follow the needs from the past. Thus, only the driving patterns in the past with no additional analysis have to be concerned in the EDV fleet assessment presented in Subsection III.B.

For new EDVs with no historical driving patterns a stochastic formulation and the MC simulation is proposed. Initially, the most expected driving patterns, $\delta_{(\cdot),(\cdot)}$, have to be defined. Due to uncertainties, a stochastic formulation includes two random components, i.e. $RU_{(\cdot),(\cdot),(\cdot)}$ with uniform distribution and $RN_{(\cdot),(\cdot),(\cdot)}$ with normal distribution. The random trajectory of the energy required for the transportation of EDV v, in hour h, in scenario k, $d_{v,h,k}$, is obtained as:

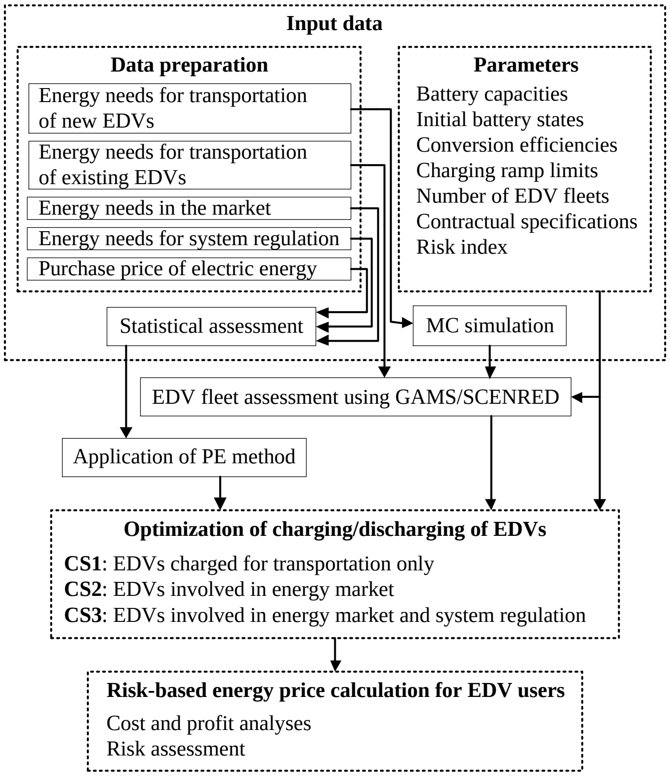

Fig. 1. Optimization procedure.

$$d_{v,h,k} = \left(\delta_{v,h} + RU_{v,h,k}\right)\cdot\left(1 + RN_{v,h,k}\right). \tag{1}$$

The random component with uniform distribution, $RU_{v,h,k}$, is required, since it allows for the possibility that EDV v is used in hour h although $\delta_{v,h} = 0$ is expected and most probable. For the random component with normal distribution, $RN_{v,h,k}$, the mean value and standard deviation are defined according to the expectations. If the formulation in (1) is not appropriate, some other distribution function that is expected to better describe behavior of the energy needs of new EDVs can be applied in the MC simulation.

It is important to notice, that the central moments of expected behavior of the energy needs of new EDVs could be directly defined from the applied distributions, but these moments are actually not required since the EDV fleet assessment as the next stage in the procedure requires scenarios and does not work with central moments. Thus the MC simulation is proposed to be performed in order to obtain required scenarios.

Instead of an ordinary MC simulation method, a low discrepancy MC simulation method (lattice) is applied in order to accelerate the convergence, which is discussed in detail in [17], [18], [19]. For instance, Fig. 2 presents a probabilistic forecast of hourly energy needs of EDV v for transportation, $d_{v,(\cdot),(\cdot)}$, with the forecast intervals. Obtained stochastic scenarios of driving patterns are further considered in the EDV fleet assessment.

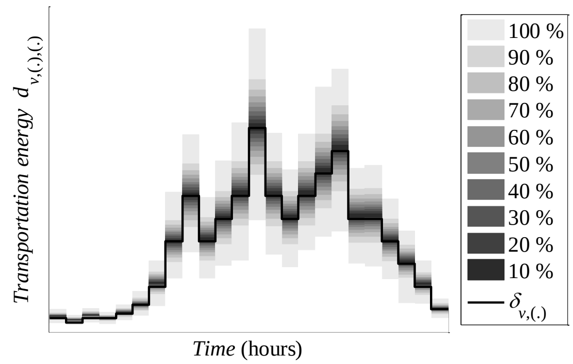

Fig. 2. Probabilistic forecast of energy requirements for transportation.

B. *EDV fleet assessment*

In real world applications of EDV charging management, an enormous changing set of EDVs has to be addressed, thus it is impossible to perform the optimization procedure efficiently for each EDV. Thus the proposed solution merges EDVs with similar driving patterns into fleets, which are further assessed in the optimization. In this way, the procedure is not directly affected by the changing number of EDVs in operation. The newcomers are included in the appropriate fleet according their driving patterns.

Allocation of the EDV driving patterns into a predefined number of fleets is performed with the GAMS/SCENRED tool, [14], [15], [17], based on the likelihood estimation, Fig. 3. Since the algorithms applied in this tool are scenario-based algorithms, the driving patterns are considered as stochastic scenarios and the fleets as a scenario subset of prescribed cardinality or accuracy. In the process, new probabilities to the preserved scenarios are assigned such that the corresponding reduced probability measure is the closest to the original measure in terms of a certain probability distance between them. The probability distance trades off scenario probabilities and distances of scenario values. In the context of stochastic power management models, the Kantorovich distance of (multivariate) probability distributions is used.

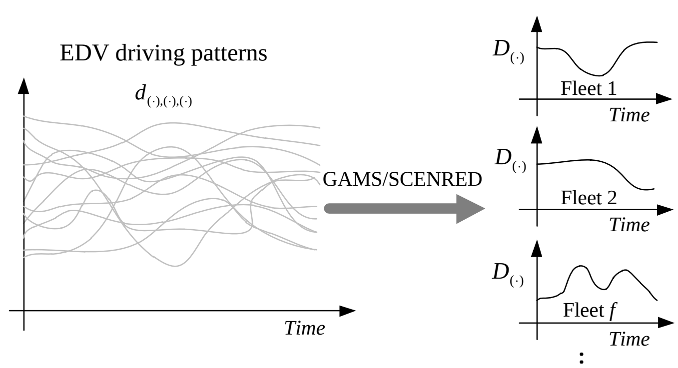

Fig. 3. Formation of EDV fleets.

Two conceptual strategies are applied here. In the first one called backward reduction, the optimal deletion of a single scenario is repeated recursively until a prescribed number of scenarios is deleted. The second strategy is appropriate if the number of preserved scenarios is small (strong reduction). The optimal selection of a single scenario is repeated recursively until a prescribed number s of preserved scenarios is selected. This strategy provides the basic concept of a second conceptual algorithm called forward selection. Both concepts are explained in detail in [14], [15].

Once the fleets are defined, the optimization procedure is applied as presented in Subsection III.D. However, additional coordination of charging and discharging processes among EDVs in a certain fleet is necessary. Appropriate smart metering, communication technology and control schemes with some additional local algorithms are required in order to perform all actions directed by the optimization.

It is also possible to improve the control schemes by merging EDVs into groups by their location patterns. This improvement would enable an efficient management of network loading and reliable energy supply for EDVs. The solution would require inclusion of additional, network constraints, e.g. a power balance equation, transmission line capacity limitations etc., in the optimization model presented in Subsection III.D. The paper is not focused on the network and reliability of supply, and addresses only the charging and discharging of EDVs.

C. Application of PE procedure

Since the problem is of stochastic nature, one possibility is to prepare a set of input data scenarios for the optimization procedure presented in Subsection III.D. The simplest solution would be applying the MC simulation of all input data resulting in b^a scenarios, where a represents the number of stochastic input data variables and b is the number of input data states. Due to numerous scenarios, the optimization process would be time consuming and its application in the real world would be questionable. The results have to be calculated quickly since the energy providers have to provide their offers to the EDV users and decide upon the exploitation of the batteries in the day-ahead market.

Thus, the acceptable solution is to step into the optimization with a completely different approach that is based on the application of the PE method. Instead of analyzing numerous combinations of different states of input variables it is possible to systematically define only few states of input data variables, i.e. points, and perform the optimization and assess the output variables. The number of calculations performed is smaller, but a reasonably good approximation of the original system is still retained. For this task, several different PE methods, [20]-[24], are available. They have been successfully applied in several engineering problems, such as a calculation of probabilistic power flows, [23], and energy prices [24].

Referenced methods in [20]-[24] apply different concentration schemes. The most widely used form of PE method employs “two points” scheme, [25], meaning that for each input variable two states are considered in the estimation procedure. In this paper, the HM method that applies “two points plus one” scheme is proposed, since it is reported in [22]-[24] as the most appropriate method when dealing with normal distributions and since it efficiently speed up the calculation. The goal of this method is to estimate a PDF of output variables by using the statistical information provided by the first few statistical central moments of input variables, i.e. the mean, the variance (standard deviation), the skewness, and the kurtosis. The first two moments provide information on the location and dispersion of a distribution. Skewness and kurtosis are the higher order central moments that provide information on the shape of a distribution, i.e. the symmetry of the shape and the flatness or peakedness of a distribution.

Let $\mathbf{X}$ denote the vector of a input variables $X_{(\cdot)}$ that are statistically assessed and required in the HM method, thus:

$$\mathbf{X} = \begin{bmatrix} \mathbf{M} \\ \mathbf{R} \\ \boldsymbol{\rho}_b \end{bmatrix}, \tag{2}$$

where $\mathbf{M} = [M_1, M_2, \ldots, M_h, \ldots, M_H]^{\mathrm{T}}$ and $\mathbf{R} = [R_1, R_2, \ldots, R_h, \ldots, R_H]^{\mathrm{T}}$ are the vectors of hourly energy requirements in the market and for system regulation, and $\boldsymbol{\rho}_b = [\rho_{b,1}, \rho_{b,2}, \ldots, \rho_{b,h}, \ldots, \rho_{b,H}]^{\mathrm{T}}$ is the vector of hourly purchase energy prices in the observed period with H hours. For each input variable only G data states, named concentrations, are needed for the optimization process. The g-th concentration, $g \in \{1, \ldots, G\}$, of the variable X_n, $(P_{n,g}, W_{n,g})$, $n \in \{1, \ldots, a\}$, is a pair that consists of the location $P_{n,g}$ and the weight $W_{n,g}$. The location is the value of the input variable at which the output variables are evaluated in the optimization process. The weight is a weighting factor which accounts for the relative importance of this evaluation in the output random variables. Fig. 4 presents the concentrations of the variable X_n on the x axis and the obtained output random variables $Y_{(\cdot)}$ with corresponding weights on the y axis.

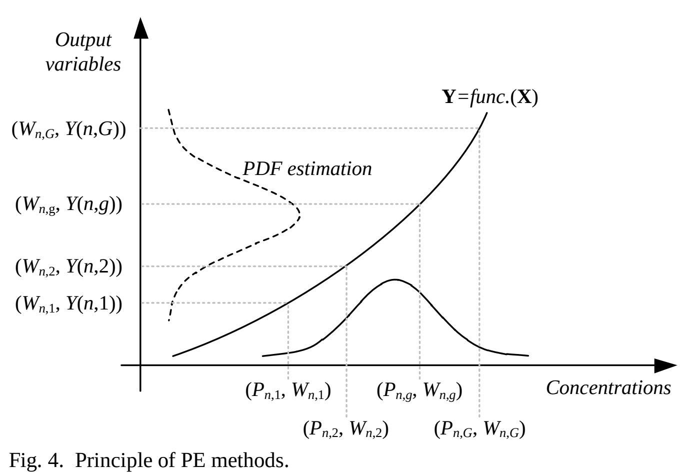

Fig. 4. Principle of PE methods.

As explained in [22], [23], if the HM method is applied, G is equal to 3 and the locations for the variable X_n are calculated applying:

$$P_{n,g} = \mu_{x,n} + \xi_{n,g} \cdot \sigma_{x,n} \qquad \forall g = 1, 2, 3, \tag{3}$$

where $\mu_{x,n}$ and $\sigma_{x,n}$ present the mean and standard deviation of the variable X_n. Symbol $\xi_{n,g}$ presents the standard location of g-th concentration of the variable X_n. These standard locations are obtained by solving the nonlinear system of equations as proposed in [22] and [23] and are calculated as:

$$\xi_{n,3} = 0\,, \tag{4}$$

$$\xi_{n,g} = \frac{\lambda_{n,3}}{2} + (-1)^{3-g} \sqrt{\lambda_{n,4} - \frac{3}{4}\lambda_{n,3}^2} \qquad \forall g = 1, 2\,, \tag{5}$$

where $\lambda_{n,3}$ and $\lambda_{n,4}$ present the skewness and the kurtosis of the variable X_n. Since $\xi_{n,3}$ is equal to zero, the location $P_{n,3}$ is equal to $\mu_{x,n}$.

The weights of all three concentrations of the variable X_n are calculated as:

$$W_{n,g} = \frac{(-1)^{3-g}}{\xi_{n,g}\left(\xi_{n,1} - \xi_{n,2}\right)} \qquad \forall g = 1, 2\,, \tag{6}$$

$$W_{n,3} = \frac{1}{a} - \frac{1}{\lambda_{n,4} - \lambda_{n,3}^2}\,. \tag{7}$$

Once the concentrations, i.e. locations and weights, of all $a = 3H$ input variables are calculated, the optimization process is performed for the set of all a points that is formed throughout the input variables and locations as:

$$\Phi = \left\{ \begin{matrix} \left(P_{1,1}, \mu_{x,2}, \mu_{x,3}, \ldots, \mu_{x,n}, \ldots, \mu_{x,a-2}, \mu_{x,a-1}, \mu_{x,a}\right) \\ \left(P_{1,2}, \mu_{x,2}, \mu_{x,3}, \ldots, \mu_{x,n}, \ldots, \mu_{x,a-2}, \mu_{x,a-1}, \mu_{x,a}\right) \\ \left(\mu_{x,1}, \mu_{x,2}, \mu_{x,3}, \ldots, \mu_{x,n}, \ldots, \mu_{x,a-2}, \mu_{x,a-1}, \mu_{x,a}\right) \\ \vdots \\ \left(\mu_{x,1}, \mu_{x,2}, \mu_{x,3}, \ldots, P_{n,1}, \ldots, \mu_{x,a-2}, \mu_{x,a-1}, \mu_{x,a}\right) \\ \left(\mu_{x,1}, \mu_{x,2}, \mu_{x,3}, \ldots, P_{n,2}, \ldots, \mu_{x,a-2}, \mu_{x,a-1}, \mu_{x,a}\right) \\ \left(\mu_{x,1}, \mu_{x,2}, \mu_{x,3}, \ldots, \mu_{x,n}, \ldots, \mu_{x,a-2}, \mu_{x,a-1}, \mu_{x,a}\right) \\ \vdots \\ \left(\mu_{x,1}, \mu_{x,2}, \mu_{x,3}, \ldots, \mu_{x,n}, \ldots, \mu_{x,a-2}, \mu_{x,a-1}, P_{a,1}\right) \\ \left(\mu_{x,1}, \mu_{x,2}, \mu_{x,3}, \ldots, \mu_{x,n}, \ldots, \mu_{x,a-2}, \mu_{x,a-1}, P_{a,2}\right) \\ \left(\mu_{x,1}, \mu_{x,2}, \mu_{x,3}, \ldots, \mu_{x,n}, \ldots, \mu_{x,a-2}, \mu_{x,a-1}, \mu_{x,a}\right) \end{matrix} \right\}, \tag{8}$$

Each point consists of one location of a certain input variable and the mean of the remaining a - 1 input variables. It is important to note that a points within the set Φ are identical, thus, in the optimization process, actually only one point out of these points has to be considered resulting in total $2 \cdot a + 1$ calculations. The weight of this specific point is calculated as:

$$W_{x,0} = \sum_{n=1}^{a} W_{x,n,3} = 1 - \sum_{n=1}^{a} \frac{1}{\lambda_{n,4} - \lambda_{n,3}^2}\,. \tag{9}$$

From a mathematical point of view, the applied $2 \cdot a + 1$ scheme is understood as a simplified version of the $3 \cdot a$ scheme. However, it can be recognized as a full $2 \cdot a$ scheme with one additional location defined by the mean of all input random variables. When $G \cdot a$ schemes are addressed, [23] and [25] that also considers PE methods point out a drawback of all $G \cdot a$ schemes, where the standard locations depend on the number of input random variables and consequently may take the values beyond their definition limits. This paper does not address this drawback exhaustively since in [23] it is showed that the $2 \cdot a + 1$ scheme is able to overcome it efficiently.

For each point from the set Φ in a combination with the energy requirement of EDV fleet, $\mathbf{D} = [D_1, D_2, \ldots, D_h, \ldots, D_H]^{\mathrm{T}}$, a deterministic optimization is run and the concentrations of F output variables $Y_{(\cdot)}$ are obtained resulting in the final, estimated PDFs of output variables Fig. 4.

The raw moments for each variable Y_m, $m \in \{1, \ldots, F\}$, are calculated applying:

$$E\left(Y_m^o\right) \approx \sum_{n=1}^{a} \sum_{g=1}^{G} W_{n,g} \cdot \left(Y_m(n,g)\right)^o \qquad \forall o = 1, 2\,. \tag{10}$$

The algorithm ends when all $2 \cdot a + 1$ concentrations of all F output variables are taken into account. Finally, the estimated raw moments of the output random variables are used to compute the desired statistical information. For the variable Y_m the mean and standard deviation are calculated as:

$$\mu_{y,m} = E\left(Y_m\right), \tag{11}$$

$$\sigma_{y,m} = \sqrt{E\left(Y_m^2\right) - \mu_{y,m}^2}\,. \tag{12}$$

These central moments enable a representation of output variables with PDFs and CDFs. In the results in Figs. 10 and 11, the price for transportation of EVDs, c, is assessed in this manner.

The advantage of the proposed usage of the HM method is reflected in the fact that the total number of required calculations is equal to $2 \cdot a + 1$ that is considerably less than b^a obtained by the Monte Carlo simulation.

It should be pointed out that the HM method can also be applied to near to normal or non-normal distributions if the final approximation error is acceptable. Otherwise some higher-order PE method, [22]-[24], should be applied to improve the precision, but the number of points would increase requiring longer calculation time.

D. Optimization of charging/discharging of EDVs in a fleet

Reliable usage of EDVs has to be provided by economically efficient and reliable supply of EDVs with electric energy. The unused battery capacities can be exploited in the market and used in system regulation as an ancillary service in order to maximize profits.

Fig. 5 presents the energy paths with the conversion efficiencies due to charging and discharging. In the proposed optimization model, all variables are observed at the level of the power system. Symbol $x_{h,p}$ presents the charged energy to EDVs in a fleet in hour p, which is used for transportation in hour $h \in \{p+1, \ldots, H\}$, where H is the number of hours in the assessed time period. Symbol $y_{h,p}$ presents the charged energy to EDVs in a fleet in hour p, which is sent back to the network via discharging V2G units in hour h, when it is sold to consumers in the market. Symbols η_c and η_d present charging and V2G efficiencies of EDVs, respectively. The same approach is applied to the other energy variables.

In general, the objective function of the optimization procedure is to minimize charging costs and maximize profits obtained from energy trading in the market and from the provision of reserved power and energy for system regulation.

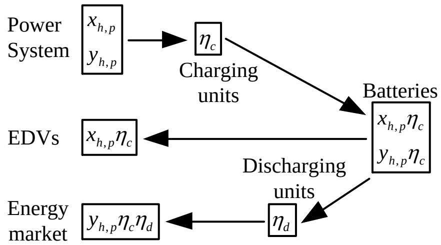

Fig. 5. Energy paths and energy conversion.

The optimization is deterministically performed for each EDV fleet and each point from the set Φ in (8), thus $2\cdot a + 1$ calculations are performed for each EDV fleet. When assessing the results, the calculated central moments in (11) and (12) are convenient for a presentation of the results with PDFs and CDFs.

The optimization problem is formulated as a linear program (LP) with the objective function J:

$$Min\{J = PC - MP - RP\}, \tag{13}$$

where:

$$PC = \sum_{h=1}^{H}\sum_{p=1}^{h-1}\left(x_{h,p} - b_{h,p}\right)\rho_{b,p}\ , \tag{14}$$

$$MP = \sum_{h=1}^{H}\sum_{p=1}^{h-1} y_{h,p}\left(\rho_{s,h}\eta_c\eta_d - \rho_{b,p}\right), \tag{15}$$

$$\begin{aligned} RP = &\sum_{h=1}^{H}\sum_{p=1}^{h-1} w_{h,p}\left(\rho_{e,h}\eta_c\eta_d - \rho_{b,p}\right) - \\ &- \sum_{p=1}^{h-1} z_{h,p}\Big|_{h=T}\rho_{b,p} + \sum_{h=T}^{H} P_h t \rho_{r,h} \end{aligned}, \tag{16}$$

s.t.

$$\sum_{p=1}^{h-1} x_{h,p}\eta_c - \sum_{p=1}^{h-1} b_{h,p}\eta_c = D_h \qquad \forall h = 1,\cdots,H\ , \tag{17}$$

$$\sum_{h=1}^{H}\sum_{p=1}^{h-1} b_{h,p}\eta_c = E\ , \tag{18}$$

$$\sum_{p=1}^{h-1} z_{h,p}\eta_c = P_h t \qquad \forall h = T\ , \tag{19}$$

$$w_{h+1,p}\eta_c\eta_d = R_h \qquad \forall h = T,\cdots,H, \forall p = h+1 \tag{20}$$

$$0 \le \sum_{p=1}^{h-1} y_{h,p}\eta_c\eta_d \le M_h \qquad \forall h = 1,\cdots,H\ , \tag{21}$$

$$\begin{aligned} &\sum_{h=p+1}^{H} x_{h,p}\eta_c + \sum_{h=p+1}^{H} y_{h,p}\eta_c \le C_p t - \\ &\quad - P_p t - E - \sum_{i=1}^{p-1}\sum_{h=i+1}^{H} x_{h,i}\eta_c + \qquad \forall p = 1,\cdots,H\ , \\ &+ \sum_{i=1}^{p-1}\sum_{h=i+1}^{H} b_{h,i}\eta_c - \sum_{i=1}^{p-1}\sum_{h=i+1}^{H} y_{h,i}\eta_c + \\ &+ \sum_{i=1}^{p-1} D_i + \sum_{i=1}^{p-1}\sum_{j=1}^{i-1} y_{i,j}\eta_c \end{aligned} \tag{22}$$

$$\begin{aligned} &\sum_{h=p+1}^{H} x_{h,p}\eta_c + \sum_{h=p+1}^{H} y_{h,p}\eta_c + \sum_{h=p+1}^{T-1} z_{h,p}\eta_c + \\ &+ w_{p,p}\Big|_{p\ge T+1}\eta_c \le L_p C_p t \qquad \forall p = 1,\cdots,H \end{aligned}, \tag{23}$$

$$x_{h,p} \ge 0 \qquad \forall h = 2,\cdots,H, \forall p = 1,\cdots,h-1\ , \tag{24}$$

$$x_{h,p} = 0 \qquad \forall h = 1,\cdots,H, \forall p = h,\cdots,H\ , \tag{25}$$

$$y_{h,p} \ge 0 \qquad \forall h = 2,\cdots,H, \forall p = 1,\cdots,h-1\ , \tag{26}$$

$$y_{h,p} = 0 \qquad \forall h = 1,\cdots,H, \forall p = h,\cdots,H\ , \tag{27}$$

$$b_{h,p} \ge 0 \qquad \forall h = 1, \forall p = 1\ , \tag{28}$$

$$b_{h,p} = 0 \qquad \forall h = 1, \forall p = h+1,\cdots,H\ , \tag{29}$$

$$b_{h,p} \ge 0 \qquad \forall h = 2,\cdots,H, \forall p = 1,\cdots,h-1\ , \tag{30}$$

$$b_{h,p} = 0 \qquad \forall h = 2,\cdots,H, \forall p = h,\cdots,H\ . \tag{31}$$

$$z_{h,p} \ge 0 \qquad \forall h = 2,\cdots,T, \forall p = 1,\cdots,h-1\ , \tag{32}$$

$$z_{h,p} = 0 \qquad \forall h = 1,\cdots,T-1, \forall p = h,\cdots,H\ , \tag{33}$$

$$z_{h,p} = 0 \qquad \forall h = T,\cdots,H, \forall p = 1,\cdots,H\ , \tag{34}$$

$$w_{h+1,p} = 0 \qquad \forall h = 1,\cdots,H, \forall p = 1,\cdots,h,h+2,\cdots,H\ . \tag{35}$$

$$w_{h+1,p} \ge 0 \qquad \forall h = T,\cdots,H, \forall p = h+1\ . \tag{36}$$

The first term in the objective function (13) presents the purchase costs of electric energy for EDVs, PC. Symbol $x_{h,p}$ in (14) presents the purchased and charged energy at hour p, required for the transportation of EDVs in hour h, and symbol $b_{h,p}$ presents the already available energy in the batteries of EDVs that is used in hour h substituting the energy that should be purchased in hour p for the needs in hour h, $x_{h,p}$, if there would be no accumulated energy in the batteries. Since there is no need to purchase the energy in the market in hour p due to adequate stored energy quantities, the charging costs are reduced. Symbol $\rho_{b,p}$ in (14) presents the purchase energy price in hour p. The second term in the objective function (13) presents the profits from energy trading of EDVs in the market, MP. Symbol $y_{h,p}$ in (15) presents the energy that is bought and charged to EDVs in hour p at price $\rho_{b,p}$ and sold in the market in hour h at price $\rho_{s,h}$. Apart from market participation, the energy supplier can obtain profits in hour h, RP, also by providing reserved capacity, P_h, and energy for system regulation, R_h, when requested. The first term in (16) presents the profits from system regulation that requires energy $w_{h,p}$, which is bought and charged in hour p at price $\rho_{b,p}$ and provided back to the power system in hour h when required at the price contracted for regulation, $\rho_{e,h}$. The second term in (16) presents the costs of the first charging of reserved capacity, P_h, that has to be available for system regulation in hour $h = T$, when the contract is signed. Symbol $z_{h,p}$ presents the charged energy of the first charging. The last term in (16) presents the income from reserved capacity payments in contractual time, i.e. $h \in \{T, \ldots, H\}$, with the hourly prices $\rho_{r,h}$ that are usually set to a fixed value.

The equality constraint (17) stands for the energy requirement for transportation of EDVs in hour h, D_h, in order to ensure reliable energy supply to EDV users. In the initial stage, a certain amount of energy, E, in the equality constraint (18) is already available in the batteries and can be used when most appropriate.

The equality constraint (19) is added in order to ensure the fully charged capacity reserved for system regulation, P_h, with energy, $z_{h,p}$, in the moment of activation of this ancillary service. The equality constraint (20) stands for compulsory system regulation defined in the contract. The energy regulation requirement in hour h, R_h, has to be covered by EDVs in the following hour, h+1, as the contractual call duration of this service is presumed to equal one hour. The number of calls per observed period is not limited.

The inequality constraint (21) enables EDVs to participate in the energy market, if profitable. In hour h, the energy requirement of consumers in the market, which can be covered by EDVs, is denoted by M_h.

The right-hand side of constraint (22) presents the available battery capacity of EDVs in hour p for charging $x_{h,p}$ and $y_{h,p}$. The total battery capacity of EDVs in hour p, C_p, decreases by the reserved capacity for regulation, P_p, the amount of energy in the battery in the initial stage, E, and for purchased and charged energy in hours $i \in \{1, \dots, p\text{-}1\}$ prior to hour p, $x_{h,i}$, $y_{h,i}$. Energy discharged from the battery in hours $i \in \{1, \dots, p\text{-}1\}$ before hour p, $b_{h,i}$, $y_{i,j}$, and D_i, increase the available battery capacity in hour p.

Constraint (23) introduces the charging-speed limitation with the charging ramp-rate limit of EDVs in hour p L_p.

Constraints (24)-(36) present limitations of all applied variables. For example, constraints (24) and (25) ensure that $x_{h,p}$ can be bought and charged only in hours $p \in \{1, \dots, h\text{-}1\}$ prior to hour h, when it is consumed. Due to limitation of call duration to one hour, a special bounding is defined in (35) and (36) for variable $w_{h+1,p}$, which is different from zero only in the hours that follow the hours with the regulation requirement, R_h, thus $p = h + 1$ in the mentioned constraints and in (20).

Fig. 6 presents the optimization variables and their roles to clarify the optimization model. The total battery capacity $C_{(\cdot)}$ is presumed to be constant in all hours. At hour T when the contract for system regulation is signed, EDVs have to start with the provision of system regulation. The capacity $C_{(\cdot)}$ is thus reduced for $P_{(\cdot)}$ that presents the reserved capacity for system regulation. The remaining capacity $C_{(\cdot)} - P_{(\cdot)}$ is still available for transportation purposes and energy trading in the market presented in Fig. 6 by $x_{(\cdot),(\cdot)}$ and $y_{(\cdot),(\cdot)}$, respectively. The reserved capacity $P_{(\cdot)}$ has to be fully charged with the energy presented by $z_{(\cdot),(\cdot)}$ in earlier hours and prepared for regulation in hour T. Another set of variables used in the system regulation provision is $w_{(\cdot),(\cdot)}$. As presented in Fig. 6, this is the energy that has to be charged immediately after the system regulation is performed in order to have fully available capacity P for new call. Variables $w_{(\cdot),(\cdot)}$ can be actually excluded from the optimization since they are not really optimized due to heavily constrained region by (20), (35) and (36) with only one feasible solution. In spite of this, the variables $w_{(\cdot),(\cdot)}$ are included in the model in order to calculate the profit RP and the objective function J correctly.

Since E is not equal to zero in Fig. 6, the available energy in the battery can be used when most appropriate. The consumption of this energy is presented by $b_{(\cdot),(\cdot)}$ in Fig. 6. This energy is welcomed since it replaces the energy that should be purchased in the market and therefore reduces the charging costs.

As presented, the battery charging is covered by four different sets of variables, i.e. $x_{(\cdot),(\cdot)}$, $y_{(\cdot),(\cdot)}$, $z_{(\cdot),(\cdot)}$, and $w_{(\cdot),(\cdot)}$, since each set has its specific role. For example, variables $x_{(\cdot),(\cdot)}$ and $y_{(\cdot),(\cdot)}$ both present the charged energy, but for different purposes. They cannot be merged into one set due to different parameters in the objective function J. In this aspect, variables $x_{(\cdot),(\cdot)}$ and $z_{(\cdot),(\cdot)}$ could be presented as one set, but in this case the profit RP cannot be explicitly calculated.

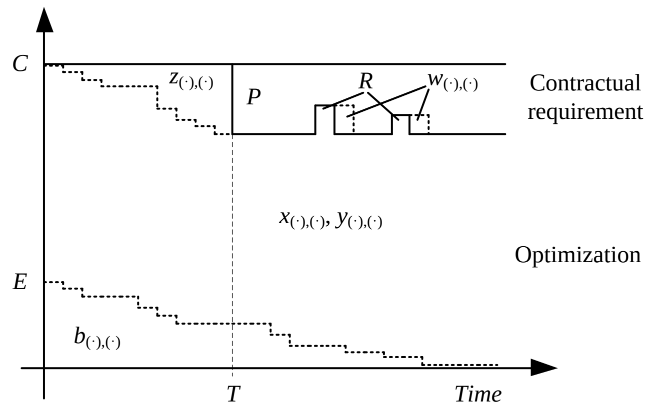

Fig. 6. Role of optimization variables.

In the presented optimization model, the total battery capacity is exploited. However, with a proper modification of constraint (22) it is possible to reserve some additional capacity exclusively for EDV users in order to ensure a reliable use of EDVs for transportation, as suggested in [1].

It is important to note that each EDV fleet is considered independently in the optimization and the energy requirements $M_{(\cdot)}$ and $R_{(\cdot)}$ are allocated among the fleets in advance. A better solution that would provide a global optimum would be to consider in the optimization all EDV fleets jointly, which requires a minor modification of the optimization model. By this improvement the question of the optimization architecture is raised, e.g. numerous EDV fleets considered in one optimization could not be manageable and would require their aggregation to EDV super fleets, the question of optimal number of EDV fleets, etc.. Since the paper does not address the optimization architecture, the proposed optimization procedure is focused on EDVs individually.

Also worth mentioning is that the equipment degradation costs, especially the additional costs of the extensive use of batteries in the market, are not included in the objective function (13).

E. Risk-based energy price offers for EDV users

Applying the proposed optimization model, the charging costs, PC, are minimized and profits, MP and RP, maximized in order to provide the lowest energy prices to users of EDVs, c. If it is presumed that the price c covers only the total costs, $J = PC - MP - RF$, it is calculated as:

$$c = \frac{J}{f\sum_{h=1}^{H} l_h}, \quad (37)$$

where l_h is the driving distance of EDVs in hour h and f the number of EDVs in a fleet.

Since the problem is of a stochastic nature, price c in (37) presents the expected cost of transportation per distance unit in a fleet and can be depicted by a normal PDF. Fig. 7 presents PDFs of price c for all three cases in the optimization procedure presented in Fig. 1. The costs and consequently the price are the lowest in the third case, since the profit obtained in the energy market, *MP*, and the profit from system regulation, *RP*, compensate for the charging costs *PC*.

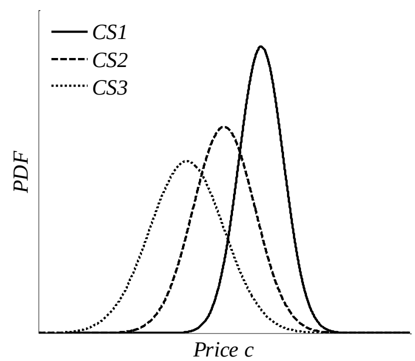

Fig. 7. PDF of price c for all three cases.

Finally, the energy supplier should offer only one price for the energy required for transportation of EDV users in each fleet, c^*. The price is set according to the company's risk policy and its acceptable level of risk, $r \in (0, 1)$, under which the selected price, c^*, does not ensure the coverage of the total costs J. The offered price to EDV users is calculated from:

$$1 - r = \int_{-\infty}^{c^*} pdf(c) \cdot dc \,. \quad (38)$$

where $1 - r$ presents VaR index commonly used in financial risk management. Function in (38) takes the form of CDF as presented in Fig. 8. It is clearly shown that at the same risk level r the price c^* is the lowest in case CS3, when EDVs participate both in the energy market and system regulation procurement.

It should be mentioned that the proposed optimization is performed on the fleets' level and the obtained results should actually be followed and realized by EDVs, thus an appropriate coordination scheme for EDVs within the fleets has to be implemented. Nevertheless, a certain level of risk that the expected results would not be achieved is always present. This risk is not addressed in the paper since the goal of each energy supplier is to estimate the potential of the charging cost reduction by the EDV market involvement and to assess the final price for EDV users. It is assumed that the coordination among EDVs and control are properly performed on the operational level.

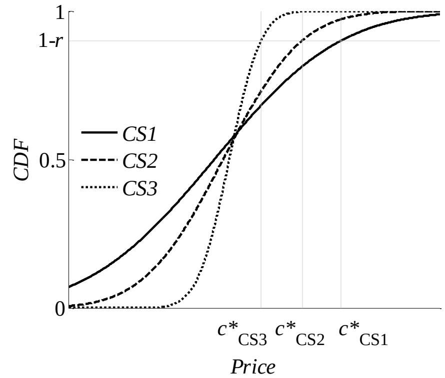

Fig. 8. CDF of price c for all three cases.

IV. Case Studies

The proposed optimization method is, further, tested in three case studies, Fig. 1: (**CS1**) EDVs do not participate in the day-ahead energy market or system regulation, (**CS2**) EDVs participate in the day-ahead energy market, and (**CS3**) EDVs participate in both the day-ahead energy market and system regulation. In all cases, 24 hours of the next day are chosen as a test time frame for which the prices for energy required for transportation of EDVs are assessed.

In all cases, for the simulation purposes twenty EDV daily driving patterns $\delta_{(\cdot),(\cdot)}$ presented in Table I are considered as a basis for the scenario preparation. To simulate behavior uncertainties, 500 scenarios are created for each driving pattern with the MC simulation, resulting in a total of 10,000 scenarios. The settings of random components with uniform and normal distributions, $RU_{(\cdot),(\cdot),(\cdot)}$ and $RN_{(\cdot),(\cdot),(\cdot)}$, are presented in Table II. The conversion efficiency of 6 km/kWh is presumed for all EDV patterns. Other parameters of EDVs are presented in Table III. Each EDV battery has a capacity of 25 kW and has 3 kWh of stored energy available for use. Energy is charged and discharged with 90 % and 93 % efficiency, respectively. Charging speed is limited to 50 % of the total capacity per hour, meaning that the empty batteries are fully charged in two hours.

Instead of optimizing 10,000 driving patterns, their clustering into three EDV fleets is proposed and applied by the GAMS/SCENRED tool, [14], [15]. The resulting driving patterns of fleets are presented in Fig. 9 together with the number of EDVs allocated to each fleet.

It is important to note that in case only one EDV is allocated to a certain fleet, the proposed optimization algorithm has to be slightly modified in order to prevent from simultaneous charging and discharging of the battery. As already explained, if more EDVs are members of a certain fleet, simultaneous charging and discharging on the fleet's level are allowed since the appropriate coordination scheme should control and manage the processes on the EDVs' level.

Table IV presents the central moments of the energy requirements of consumers in the market, the energy requirements for system regulation and the purchase energy prices. These energy requirements are allocated among the fleets according to their size, i.e. 20 % of requirements can be covered by fleet 1, 20 % by fleet 2, and 60 % by fleet 3.

TABLE I
DAILY DRIVING PATTERNS IN KM

Hour h	EDV requirements $\delta_{v,h}$ (km)																			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	3	0	20	15	0	2	0	0	0	0	1	14	0	2	15	0	1	16	17
2	0	2	0	19	16	0	2	0	0	0	0	1	12	0	0	11	0	2	13	12
3	0	3	0	18	17	0	2	0	0	0	1	0	13	2	1	13	1	1	14	14
4	0	3	0	17	14	0	2	0	0	0	0	1	13	0	0	15	1	2	16	12
5	0	4	3	18	15	0	2	0	10	0	3	10	13	2	11	12	1	13	11	14
6	10	6	6	19	14	0	2	5	50	10	8	53	12	9	52	14	10	54	15	12
7	14	10	12	14	13	0	2	7	80	10	13	82	15	12	83	15	11	80	15	15
8	18	20	18	19	12	0	2	9	50	0	20	49	12	21	48	15	22	52	14	13
9	0	30	25	0	14	30	2	5	0	0	29	1	13	28	2	16	27	1	15	14
10	0	20	40	0	15	40	2	0	0	15	40	0	14	41	0	15	38	0	16	17
11	0	25	55	0	16	35	2	0	0	20	56	0	16	57	0	15	58	0	17	14
12	6	30	60	0	15	25	2	0	0	0	59	0	16	60	1	13	59	0	14	15
13	6	45	65	0	14	35	2	0	0	0	63	1	12	62	0	10	61	2	14	13
14	0	30	52	0	15	15	2	0	0	0	52	1	16	53	2	18	50	2	17	16
15	0	25	46	0	16	10	2	0	0	10	44	0	16	43	0	18	45	0	19	14
16	10	30	72	0	14	0	2	5	50	10	71	49	17	72	50	15	70	52	14	17
17	18	35	58	0	15	0	2	6	80	0	63	76	16	64	75	16	61	78	16	16
18	12	40	32	0	16	0	2	6	60	0	31	63	17	30	64	15	27	65	14	18
19	0	25	25	0	13	0	2	0	0	0	24	0	13	25	0	15	22	0	12	11
20	10	25	20	5	17	0	2	0	0	10	21	1	14	20	2	15	23	2	16	17
21	11	20	12	10	15	0	2	0	10	10	10	12	12	11	11	12	13	10	14	13
22	0	15	2	15	16	0	2	0	5	0	3	5	19	2	6	19	3	4	19	19
23	0	10	0	20	14	0	2	0	0	0	1	1	13	2	2	12	2	3	11	13
24	0	5	0	22	15	0	2	0	0	0	1	1	16	0	1	15	1	1	17	17

TABLE II
PARAMETERS OF RANDOM COMPONENTS RU AND RN OF NEW EDVS

Interval for *RU*	Mean of *RN*	Stand. dev. of *RN*	No. of scenarios
[0, 0.15 kWh]	0	0.2	500

TABLE III
PARAMETERS OF EDVS

Parameters	$C_{v,(\cdot)}$	E_v	η_c	η_d	$L_{v,(\cdot)}$
Values	25 kW	3 kWh	90 %	93 %	50 % of $C_{v,(\cdot)}$ per hour

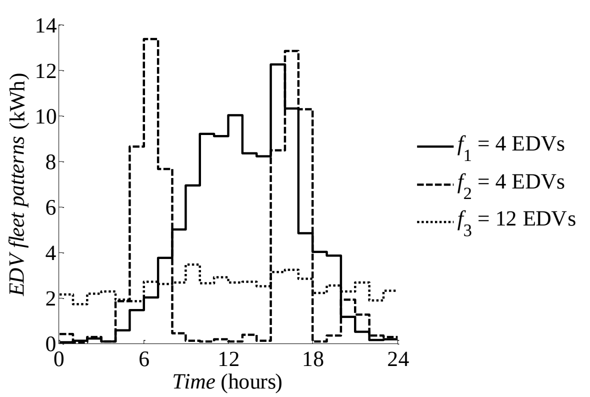

Fig. 9. EDV fleet driving patterns.

If EDVs provide system regulation, it is presumed that the regulation energy has to be provided in the fourth hour, $T = 4$, and later as defined in the contract for regulation provision. Call duration of this service is equal to one hour and the number of calls per observed period is not limited. Reserved capacity for regulation, P_h, equals 5 kW. The price of capacity reservation, $\rho_{r,(\cdot)}$, equals 10 EUR/MW/h in all hours, and the price of regulated energy, $\rho_{e,(\cdot)}$, equals75 EUR/MWh.

TABLE IV
CENTRAL MOMENTS OF INPUT DATA

Hour h	Market requirement (kWh)		Regulation requirement (kWh)		Purchase price (EUR/MWh)	
	Mean	Std	Mean	Std	Mean	Std
1	1.9506	0.1379	0.0000	0.0000	46.6412	3.3012
2	20.1669	1.4277	0.0000	0.0000	42.2284	2.9846
3	41.9212	2.9633	0.0000	0.0000	54.1746	3.8422
4	60.9017	4.3105	0.0000	0.0000	42.0157	2.9691
5	80.7470	5.7084	19.9998	1.4147	50.1401	3.5436
6	61.9460	4.3810	1.1371	0.0806	53.7486	3.8008
7	200.8008	14.1768	39.9999	2.8244	58.0511	4.1019
8	201.6101	14.2365	2.7463	0.1942	58.9805	4.1726
9	241.0191	17.0520	50.0001	3.5341	58.9026	4.1709
10	140.8472	9.9516	4.9545	0.3500	71.8268	5.0864
11	161.7333	11.4463	5.8545	0.4144	67.8828	4.7991
12	120.2548	8.5153	29.9999	2.1251	62.7472	4.4348
13	41.7017	2.9516	0.6483	0.0459	53.4147	3.7776
14	20.7995	1.4747	30.0000	2.1272	41.3896	2.9319
15	101.5343	7.1799	6.9264	0.4891	57.1082	4.0402
16	40.0304	2.8329	0.6580	0.0467	56.1951	3.9681
17	241.3354	17.0460	0.9386	0.0664	66.0166	4.6710
18	240.1802	16.9739	50.0010	3.5362	60.2017	4.2691
19	200.1573	14.1490	5.9959	0.4236	69.0069	4.8823
20	200.5465	14.1902	100.0026	7.0916	71.4677	5.0541
21	200.1531	14.1949	4.4187	0.3123	50.5963	3.5771
22	81.9050	5.7878	8.5594	0.6048	45.6382	3.2254
23	41.9904	2.9671	5.4621	0.3867	49.3461	3.4915
24	20.2383	1.4328	0.0000	0.0000	43.1162	3.0552

In general, the energy requirement for system regulation cannot be planned in advance or predicted, thus the energy supplier should consider in the analysis of the profit *RP* the worst case scenario when the reserves $P_{(\cdot)}$ are not activated at all. However, based on the past experience, several activations can be expected and included in the analysis. Thus, CS3 presumes some energy requirements for system regulation presented in Table IV. This assumption affects the variables $w_{(\cdot),(\cdot)}$ and the profit *RP* only, but does not affect other optimization variables and results as explained in Fig. 6.

The energy for transportation, trading in the market and system regulation is purchased in the market at hourly market prices, $\rho_{b,(\cdot)}$, which are stochastically modeled, since they cannot be precisely forecasted due to uncertainties. Table IV provides in the last two columns the central moments of the purchase prices. The selling hourly prices of V2G energy, $\rho_{s,(\cdot)}$, are set at 65 EUR/MWh.

The proposed optimization procedure results in energy prices for EDV transportation presented in Fig. 10 as PDFs for all EDV fleets and all case studies. It shows that EDVs' participation in the market and system regulation reduces energy prices for EDV users offered by the energy supplier that performs optimization of charging and discharging of EDV batteries.

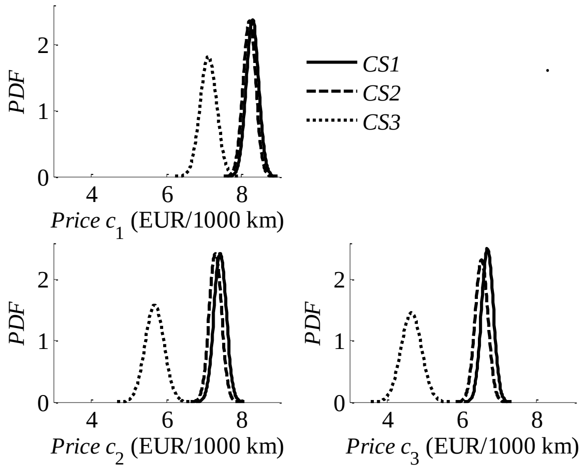

Fig. 10. PDFs of prices c in EUR/1000 km for all fleets in all cases.

To show the effectiveness of the HM method, the results obtained with this method are compared with the results obtained with the MC simulation. For this purpose, the input data in Table IV are presented by 500 scenarios that require 500 calculations. Since the HM method requires only $2 \cdot a + 1 = 2 \cdot 3 \cdot 24 + 1 = 145$ calculations, it is, in these case studies, approximately 3.44 times faster than the MC simulation, but the question is whether the error made in the HM estimation procedure is acceptable. Fig. 11 graphically compares PDFs of the prices c for EDVs in fleet 1 in the CS1, obtained using the MC simulation and the HM method. The incurred errors (in %) of the PDF mean (in EUR/1000 km) as well as standard deviations for all fleets and all case studies are presented in Table V. The average error for the mean is -0.23 % and for the standard deviation -8.87 %.

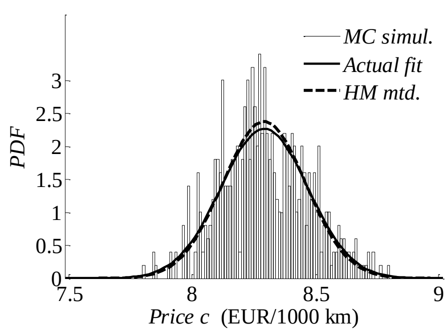

Fig. 11. Comparison of prices' PDFs obtained using the MC and HM methods.

The accuracy of the proposed solution is additionally assessed in the calculation of energy prices for transportation c^* at risk level $r = 0.1$. According to Fig. 8 that explains the meaning of the risk level r, the value 0.1 means that the price c^* at that risk value is expected to cover the associated costs J in 90 % of the simulated cases. Fig. 12 presents CDFs of the price for EDV transportation in fleet 3 in CS2 calculated using the MC and HM methods. This is the case with the highest discrepancy between CDFs at risk level $r = 0.1$. The exact error values for all fleets in all case studies are presented in Table VI and take the values between -1.18 % and -0.14 % with the average at -0.58 %. In addition, Fig. 13 presents the price errors for all fleets in all case studies for different risk levels. Since the errors range between -1.83 % and 1.29 %, they can be neglected and since the errors are so insignificant, this justifies the use of the HM method.

TABLE V
ACCURACY OF HM METHOD, MEAN IN EUR/1000 KM, ERRORS IN %

Case study	Method	Fleet 1		Fleet 2		Fleet 3	
		Mean	Std	Mean	Std	Mean	Std
CS1	MC	8.2928	0.1761	7.4496	0.1848	6.7029	0.1756
	HM	8.2923	0.1680	7.4320	0.1645	6.6835	0.1587
	Error	-0.0067	-4.5864	-0.2361	-10.9881	-0.2892	-9.6608
CS2	MC	8.2114	0.1789	7.3276	0.1937	6.5407	0.1989
	HM	8.2107	0.1688	7.3075	0.1643	6.5227	0.1718
	Error	-0.0086	-5.6515	-0.2754	-15.1533	-0.2753	-13.6347
CS3	MC	7.1274	0.2307	5.7073	0.2714	4.6770	0.2976
	HM	7.1213	0.2194	5.6903	0.2522	4.6499	0.2732
	Error	-0.0852	-4.8927	-0.2974	-7.0688	-0.5776	-8.1984

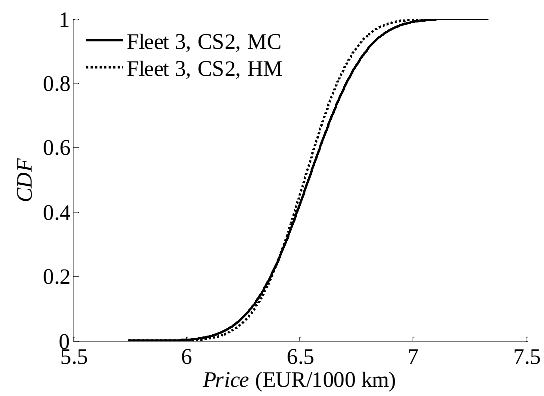

Fig. 12. CDFs of EDV prices obtained using the MC and HM methods.

TABLE VI
ACCURACY OF HM METHOD, PRICES IN EUR/1000 KM, ERRORS IN %

Case study	Method	Price c^*, $r = 0.1$		
		Fleet 1	Fleet 2	Fleet 3
CS1	MC	8.5182	7.6862	6.9276
	HM	8.5059	7.6418	6.8855
	Error	-0.1447	-0.5771	-0.6084
CS2	MC	8.4404	7.5756	6.7954
	HM	8.4261	7.5174	6.7417
	Error	-0.1696	-0.7670	-0.7904
CS3	MC	7.4227	6.0547	5.0579
	HM	7.4019	6.0113	4.9984
	Error	-0.2797	-0.7172	-1.1769

If the risk level $r = 0.1$ is presumed, the final EDV prices, c^*, are calculated as proposed in (38) and Fig. 8. Results are presented in Table VII. In simulated case studies, prices are reduced by 0.94 % to 2.09 % if EDVs participate in the market and by 13.10 % to 27.99 % if they participate in the market as well as system regulation.

In order to show the advantage of the proposed optimization procedure and the EDV involvement in the markets, the results of a simple procurement strategy of the energy required for transportation are presented in Fig. 14. In this primitive, passive strategy, it is presumed that (i) no optimization tool is available and (ii) EDVs are not involved in the markets and consequently do not provide V2G service. Since there is no optimization applied, it is also presumed that (iii) the batteries are fully pre-charged in the initial hour and (iv) are charged regardless to the prices right after their energy is used for transportation, i.e. in the next hour. The results in Fig. 14 are obtained with the same input data and procedure described in Subsection III without applying the optimization. The final PDFs of the prices *c* for EDVs in all fleets have the means equal to 11.36 EUR/1000 km, 11.63 EUR/1000 km, and 12.26 EUR/1000 km, respectively. Compared to the results in Fig. 10, the prices are higher due to the higher, unoptimized charging costs and lack of market profits *MP* and *RP*. It can be concluded that the proposed procedure applied in CS1-CS3 significantly reduces the prices for EDVs, also in CS1, where only optimal charging is performed without any market involvements.

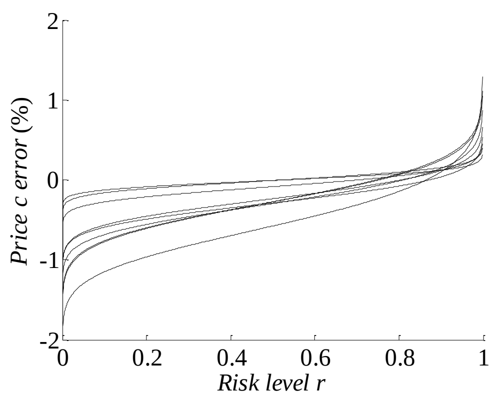

Fig. 13. Price *c* errors.

TABLE VII
FINAL PRICES IN EUR/1000 KM, REDUCTIONS IN %

Case study	Fleet 1		Fleet 2		Fleet 3	
	Price *c**	Reduction	Price *c**	Reduction	Price *c**	Reduction
CS1	8.5059	-	7.6418	-	6.8855	-
CS2	8.4261	0.94	7.5174	1.63	6.7417	2.09
CS3	7.4019	13.10	6.0113	21.69	4.9984	27.99

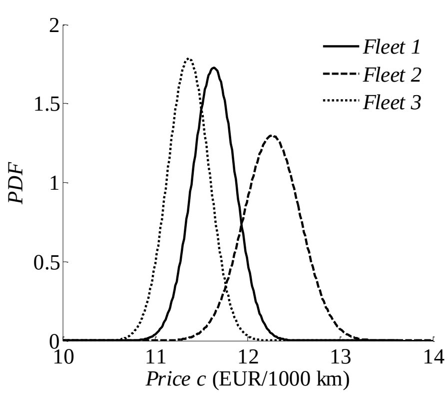

Fig. 14. Prices of a simple procurement strategy.

V. CONCLUSIONS

The paper proposes the stochastic optimization of EDV charging/discharging patterns used in the risk-based assessment of the energy prices for transportation offered by the energy supplier to EDV users. To enable the practical implementation of the proposed model, the paper introduces EDV fleets obtained with the GAMS/SCENRED tool. The proposed optimization is performed on the fleets' level, but the obtained results should actually be followed and realized by EDVs, thus an appropriate coordination scheme for EDVs within the fleets is required. It is presumed that the coordination among EDVs and control are properly performed on the operational level, otherwise additional financial risks have to be assessed. The HM method is applied in order to generate input data points that are deterministically analyzed in the optimization. Even though the problem is of stochastic nature, it is solved applying a sequence of deterministic calculations instead of a stochastic programming, since this simple approach is efficiently used in several engineering problems. The effectiveness of the proposed formulation is demonstrated by three case studies, which consider different levels of EDVs' involvement in the markets. The results of these case studies are compared with the results of one additional case study with a primitive, passive charging strategy. Simulations show that market participation of EDVs enables lower energy prices for EDV users and a better position of energy supplier applying the proposed optimization in the competitive market. Due to the errors involved being insignificant, the HM method used in the process makes the proposed optimization procedure applicable in practice. The future work will focus on the equipment degradation costs, especially on the batteries' costs, due to their extensive exploitation in the market. Also coordination of EDVs within the fleets and their control schemes have to be addressed in the future.

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VII. Biography

Miloš Pantoš (M'00) was born in 1977 in Slovenia. He became Bachelor and Ph.D. in Electrical Engineering at the Faculty of Electrical Engineering, University of Ljubljana, Slovenia, in 2001 and 2005, respectively. He is currently an associate professor at this Faculty. In 2009, he was a Fulbright visiting researcher at Illinois Institute of Technology, Chicago, USA. His main research field includes power-system operation and control, the power market and ancillary services.