Stochastic Optimal Charging of Electric-Drive Vehicles with Renewable Energy

Miloš Pantoš

University of Ljubljana, Faculty of Electrical Engineering, Tržaška 25, SI-1000, Ljubljana, Slovenia
E-mail: milos.pantos@fe.uni-lj.si, Tel.: +386 1 4768241, Fax: +386 1 4264651

Abstract

The paper presents the stochastic optimization algorithm that may eventually be used by electric energy suppliers to coordinate charging of electric-drive vehicles (EDVs) in order to maximize the use of renewable energy in transportation. 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 production of renewable energy sources (RESs) are presented by statistical central moments that are further considered in Hong's 2-point + 1 estimation method in order to define estimate points considered in the optimization. Case studies illustrate the application of the proposed optimization in achieving maximal exploitation of RESs in transportation by EDVs.

Keywords

Electric-drive vehicles, linear programming, optimization, renewable energy sources.

I. Nomenclature

Indices:

g	Subscript index for concentration
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 RES
s	Subscript index for scenario
v	Subscript index for EDV
x	Subscript index for input variable
y	Subscript index for output variable
ρ	Subscript index for energy price
0	Subscript index for scenario 0
*	Superscript index for determined value

Variables and functions:

$b_{(\cdot),(\cdot)}$	Energy used from the battery
$X_{(\cdot)}$	Input data variable
$x_{(\cdot),(\cdot)}$	Charged energy for transportation
$Y_{(\cdot)}$	Output data variable

Parameters and Constants:

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	Energy-distance conversion factor
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
H	Number of hours
J	Objective function
$K_{(\cdot)}$	Optimization parameter
$l_{(\cdot)}$	Expected driving distance

$L_{(\cdot)}$	Charging ramp-rate limit
$L_{(\cdot),(\cdot)}$	Concentration location
NC	Number of concentrations
NG	Number of renewable energy sources
NI	Number of input data states
NV	Number of input data variables
o	Parameter in central moment calculation
$P_{(\cdot)}$	Production of RES
$pdf(\cdot)$	Probability distribution function
r	Risk level
$RN_{(\cdot),(\cdot),(\cdot)}$	Random component with normal distribution
$RU_{(\cdot),(\cdot),(\cdot)}$	Random component with uniform distribution
s	RES share in transportation
T	Time of activation of system regulation service
$t_{(\cdot)}$	Part of s function
$W_{(\cdot),(\cdot)}$	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 variance
Φ	Set of scenarios obtained by HM method

Matrices and vectors:

$\mathbf{D}$	Vector of energy requirements for transportation
$\mathbf{L}$	Vector of concentration locations
$\mathbf{P}$	Vector of production of RES
$\mathbf{W}$	Vector of concentration weights
$\mathbf{X}$	Vector of input variables
$\boldsymbol{\rho}$	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.

However, 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. 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]-[10], unit commitment, [12], activation in virtual power plants [13] etc.. As reported in [1], [2], 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. EDVs can also 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]. 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.

To mitigate climate change and reduce dependence on external energy supplies, many countries have adopted policies to increase energy conservation, the share of renewable energy resources (RESs), and the share of combined heat and power, [6]. As simulated in [5], [6], a better utilization of RESs is possible with intelligent charging of EDVs resulting in lower CO_2 emissions. Beside the share increase of RESs, in [6], it is reported that EDVs with vehicle to grid (V2G) technology can help to better utilize and stabilize fluctuating, intermitted RESs and to maintain a balance between supply and demand.

Although the energy suppliers are focused in their profits, EDVs that extensively exploit RESs present green transportation technology and could serve as a good promotion of the companies as eco-friendly companies and could help to raise public environmental awareness.

The paper presents the optimization procedure for coordinated charging of EDVs that maximize the use of renewable energy in transportation. Its main advantages comparing to the existing solutions presented in [5], [6] are:

- a clear presentation of the optimization model for EDV charging applying simple linear programming (LP),
- a formation of EDV fleets based on an assessment of driving patterns applying the GAMS/SCENRED tool that performs the scenario reduction method presented in [14], [15], [17],
- consideration of uncertainties of the RES production and the energy price in the market requiring stochastic optimization modeling, and
- an application of a point estimate (PE) procedure for easier assessment of the problem, where Hong's 2-point + 1 estimation method (HM), [22]-[24], is utilized.

Besides the algorithm, the main purpose of the paper is to show that charging of EDVs with the energy from RESs to a feasible extent could lead to the higher transportation costs since in this case the optimization is not focused on the energy price in the market and the charging cost minimization. Higher transportation costs for EDV users present a tradeoff for the cleaner environment. The assessment of this tradeoff concludes a discussion in the paper. It compares three different possibilities of EDV charging: (**CS1**) passive approach to EDV charging without any charging strategy, i.e. the batteries are charged immediately after transportation, (**CS2**) charging of EDVs that maximizes the share of RESs in transportation, (**CS3**) charging of EDVs with cost minimization as the main goal of energy providers in the competitive market.

It is important to stress that in all case studies it is assumed that EDVs enable battery recharging that can be coordinated and managed by intelligent control schemes. Actual application of the proposed solution would also require appropriate smart metering, communication technology and some additional algorithms engaged on the operational level in order to perform all actions directed by the optimization. Although EDVs with automatic night recharging present a significant share among EDVs in reality, they are not considered in the research since their charging is performed automatically at nights and it is not driven by the optimization.

The rest of the paper is organized as follows: the optimization procedure is presented in Section III with Subsections III.A–III.D describing individual parts of the procedure. Section IV presents and discusses in detail three case studies, i.e. the assessment of possible charging strategies. 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 Figure 1. The initial step is a stochastic assessment of input data:

- expected electric energy production of RESs,
- purchase prices of energy in the market, and
- energy requirements for transportation of EDVs.

For production of RESs and energy prices, their central moments, i.e. the means and standard deviations, are forecasted by the analysis of the behavior in the past. These central moments are used later in a scenario preparation procedure presented in Subsection III.A, where scenarios with their probabilities are defined applying a PE procedure, i.e. HM method. These scenarios are further considered in the optimization procedure with the algorithm presented in detail in Subsection III.C. It is important to note that for each scenario independent and deterministic optimization is performed.

For the existing EDVs, driving patterns are obtained by the analysis of the past transportation behavior. Otherwise, for new EDVs, the Monte Carlo (MC) simulation is applied in order to produce a set of driving patterns. The procedure is explained in detail in Subsection III.B.

Once the patterns are available, the optimization can be performed. In the real world, the optimization procedure of battery charging would have to be performed for numerous EDVs 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].

The data preparation task also involves a definition of EDV technical parameters. They are explained in Subsection III.C, where the optimization algorithm is presented.

The final task of the proposed procedure presented in Subsection III.D is a calculation of prices of energy required by EDV users for transportation based on the charging cost analysis and an assessment of a share of RESs exploited in transportation to a feasible extent. It is expected that exploitation of RESs could lead to the higher transportation costs since in this case the optimization is not focused on the charging cost minimization but on the maximization of RESs in transportation. Higher transportation costs for EDV users present a tradeoff for the cleaner environment.

A. Scenario preparation procedure

Input data are divided into two groups. The first group consists of the expected electric energy production of RESs and the purchase prices of energy in the market. For this group of input data, the scenario preparation procedure presented in this Subsection is applied. The second group addresses the EDV transportation patterns that are considered in the proposed EDV fleet assessment presented in Subsection III.B.

Considering the RES production and the energy prices from the first group, several uncertainties due to forecast errors call for this problem to be addressed using the stochastic approach. The necessity of this approach is also recognized by [8]. If a scenario-based solution is applied, a set of scenarios has to be prepared for the optimization procedure presented in Subsection III.C. The simplest solution would be applying the MC simulation of all input data resulting in NI^{NV} scenarios, where NV represents the number of stochastic input data variables and NI 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 for transportation has to be purchased in the day-ahead market according to the chosen charging strategy.

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 speeds 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 NV input variables $X_{(\cdot)}$ that are statistically assessed and required in the HM method, thus:

$$\mathbf{X} = \left[\mathbf{P}_1, \mathbf{P}_2, \ldots, \mathbf{P}_r, \ldots, \mathbf{P}_{NG}, \boldsymbol{\rho}\right], \tag{1}$$

where $\mathbf{P}_r = [P_{r,1}, P_{r,2}, \ldots, P_{r,h}, \ldots, P_{r,H}]^{\mathrm{T}}$ is the vector of hourly productions of RES r, and $\boldsymbol{\rho} = [\rho_1, \rho_2, \ldots, \rho_h, \ldots, \rho_H]^{\mathrm{T}}$ is the vector of hourly purchase energy prices in the observed period with H hours. For each input variable only NC data states, named concentrations, are needed for the optimization process. The g-th concentration, $g \in \{1, \ldots, NC\}$, of the variable X_n, $(L_{n,g}, W_{n,g})$, $n \in \{1, \ldots, NV\}$, consists of the location $L_{n,g}$ 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. Figure 2 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.

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

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

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:

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

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

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 $L_{n,3}$ is equal to $\mu_{x,n}$.

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

$$W_{n,g} = \frac{(-1)^{3-g}}{\xi_{n,g}\left(\xi_{n,1} - \xi_{n,2}\right)} \qquad \forall g = 1, 2, \tag{5}$$

$$W_{n,3} = \frac{1}{a} - \frac{1}{\lambda_{n,4} - \lambda_{n,3}^2}. \tag{6}$$

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

$$\Phi = \begin{Bmatrix} \left(L_{1,1}, \mu_{x,2}, \mu_{x,3}, \ldots, \mu_{x,n}, \ldots, \mu_{x,NV-2}, \mu_{x,NV-1}, \mu_{x,NV}\right) \\ \left(L_{1,2}, \mu_{x,2}, \mu_{x,3}, \ldots, \mu_{x,n}, \ldots, \mu_{x,NV-2}, \mu_{x,NV-1}, \mu_{x,NV}\right) \\ \left(\mu_{x,1}, \mu_{x,2}, \mu_{x,3}, \ldots, \mu_{x,n}, \ldots, \mu_{x,NV-2}, \mu_{x,NV-1}, \mu_{x,NV}\right) \\ \vdots \\ \left(\mu_{x,1}, \mu_{x,2}, \mu_{x,3}, \ldots, L_{n,1}, \ldots, \mu_{x,NV-2}, \mu_{x,NV-1}, \mu_{x,NV}\right) \\ \left(\mu_{x,1}, \mu_{x,2}, \mu_{x,3}, \ldots, L_{n,2}, \ldots, \mu_{x,NV-2}, \mu_{x,NV-1}, \mu_{x,NV}\right) \\ \left(\mu_{x,1}, \mu_{x,2}, \mu_{x,3}, \ldots, \mu_{x,n}, \ldots, \mu_{x,NV-2}, \mu_{x,NV-1}, \mu_{x,NV}\right) \\ \vdots \\ \left(\mu_{x,1}, \mu_{x,2}, \mu_{x,3}, \ldots, \mu_{x,n}, \ldots, \mu_{x,NV-2}, \mu_{x,NV-1}, L_{NV,1}\right) \\ \left(\mu_{x,1}, \mu_{x,2}, \mu_{x,3}, \ldots, \mu_{x,n}, \ldots, \mu_{x,NV-2}, \mu_{x,NV-1}, L_{NV,2}\right) \\ \left(\mu_{x,1}, \mu_{x,2}, \mu_{x,3}, \ldots, \mu_{x,n}, \ldots, \mu_{x,NV-2}, \mu_{x,NV-1}, \mu_{x,NV}\right) \end{Bmatrix}, \tag{7}$$

Each point consists of one location of a certain input variable and the mean of the remaining $NV - 1$ input variables. It is important to note that NV 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 $2 \cdot NV + 1$ calculations. The weight of this specific point is calculated as:

$$W_0 = \sum_{n=1}^{NV} W_{n,3} = 1 - \sum_{n=1}^{NV} \frac{1}{\lambda_{n,4} - \lambda_{n,3}^2}. \tag{8}$$

From a mathematical point of view, the applied $2 \cdot NV + 1$ scheme is understood as a simplified version of the $3 \cdot NV$ scheme. However, it can be recognized as a full $2 \cdot NV$ scheme with one additional location defined by the mean of all input random variables. When $NC \cdot NV$ schemes are addressed, [23] and [25] that also considers PE methods point out a drawback of all $NC \cdot NV$ 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 $2\cdot NV + 1$ scheme is able to overcome it efficiently.

For each point from the set Φ in a combination with the hourly energy requirements 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 Figure 2.

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

$$E\left(Y_m^o\right) \approx \sum_{n=1}^{NV} \sum_{g=1}^{NC} W_{n,g} \cdot \left(Y_m(n,g)\right)^o \qquad \forall o = 1, 2\,. \tag{9}$$

The algorithm ends when all $2\cdot NV + 1$ 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:

$$\mu_{y,m} = E\left(Y_m\right), \tag{10}$$

$$\sigma_{y,m} = \sqrt{E\left(Y_m^2\right) - \mu_{y,m}^2}\,. \tag{11}$$

These central moments enable a representation of output variables with PDFs and CDFs. In the results in Figures 8 and 9, the price for transportation of EVDs, c, and the share of RESs in transportation, s, are 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 $2\cdot \mathrm{NV} + 1$ that is considerably less than NI^{NV} 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 estimation method, [22]-[24], should be applied to improve the precision, but the number of scenarios would increase requiring longer calculation time.

B. Driving pattern and EDV fleet assessment

The second group of input data consists of the EDV driving patterns. For new EDVs with no history a stochastic formulation and the MC simulation is proposed to generate a set of possible driving patterns. For this task, the most expected driving patterns, $\delta_{(\cdot),(\cdot)}$, have to be defined initially applying some forecasting of EDV behaviour. 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 s, $d_{v,h,s}$, is obtained as:

$$d_{v,h,s} = \left(\delta_{v,h} + RU_{v,h,s}\right) \cdot \left(1 + RN_{v,h,s}\right). \tag{12}$$

The random component with uniform distribution, $RU_{v,h,s}$, 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, $RN_{v,h,s}$, 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 the behavior of EDVs can be applied in the MC simulation.

It is important to note, 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, Figure 3 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.

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.

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.

Once the optimization is preformed, additional coordination of charging 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.

Allocation of the EDV driving patterns into a predefined number of fleets is performed with the GAMS/SCENRED tool that applies the scenario reduction method described in [14], [15], [17], which is based on the likelihood estimation, Figure 4. 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.

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 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.C.

C. Optimization of EDV fleet charging

EDVs require reliable supply with electric energy in order to ensure reliable transportation. Besides this requirement, it is possible to optimize the battery charging in the way that would minimize the charging costs and ensure the lowest prices for EDV users which is of crucial importance in the market environment. Another possibility is to charge the batteries in the way the impact on the environment would be minimal. This goal is achieved if RESs are utilized to a feasible extent.

The optimization model presented in the paper is formulated as a linear program (LP) and enables both possibilities by setting the optimization parameters $K_{(\cdot)}$ in the objective function J properly:

$$Min\left\{ J = \sum_{h=1}^{H}\sum_{p=1}^{h-1}\left(\left(x_{h,p} - b_{h,p}\right)\cdot\left(K_\rho \rho_p - \sum_{r=1}^{NG} K_r P_{r,p} \right)\right)\right\}, \tag{13}$$

where symbol $x_{h,p}$ 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 H presents the number of hours in the assessed time period. The production of RES r in hour p among NG RESs is denoted by $P_{r,p}$ and symbol ρ_p presents the purchase energy price in the market in hour p. Symbols K_ρ and K_r present the optimization parameters that regulate the objective function J:

- **CS3**: if parameters are set to $K_\rho = 1$ and $K_r = 0$, the objective is to minimize the charging costs,
- **CS2**: if parameters are set to $K_\rho = 0$ and $K_r = 1$, the objective is to maximize the RES exploitation.

The optimization constraints are:

$$\sum_{p=1}^{h-1} x_{h,p}\eta - \sum_{p=1}^{h-1} b_{h,p}\eta = D_h \qquad \forall h = 1,\cdots,H\ , \tag{14}$$

$$\sum_{h=1}^{H}\sum_{p=1}^{h-1} b_{h,p}\eta = E\ , \tag{15}$$

$$0 \le \sum_{h=p+1}^{H} x_{h,p}\eta \le C_p - \sum_{i=1}^{p-1}\sum_{h=1}^{i-1} x_{h,i}\eta + \sum_{i=1}^{p-1} D_i - E + \sum_{i=1}^{p-1}\sum_{h=1}^{i-1} b_{h,i}\eta \qquad \forall p = 1,\cdots,H\ , \tag{16}$$

$$0 \le \sum_{h=p+1}^{H} x_{h,p}\eta \le L_p C_p \qquad \forall p = 1,\cdots,H\ , \tag{17}$$

$$x_{h,p} \ge 0 \qquad \forall h = 2,\cdots,H, \forall p = 1,\cdots,h-1\ , \tag{18}$$

$$x_{h,p} = 0 \qquad \forall h = 1,\cdots,H, \forall p = h,\cdots,H\ , \tag{19}$$

$$b_{h,p} \ge 0 \qquad \forall h = 1, \forall p = 1\ , \tag{20}$$

$$b_{h,p} = 0 \qquad \forall h = 1, \forall p = h+1,\cdots,H\ , \tag{21}$$

$$b_{h,p} \ge 0 \qquad \forall h = 2,\cdots,H, \forall p = 1,\cdots,h-1\ , \tag{22}$$

$$b_{h,p} = 0 \qquad \forall h = 2,\cdots,H, \forall p = h,\cdots,H \ . \tag{23}$$

The equality constraint (14) 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 (15) is already available in the batteries and can be used when most appropriate. Symbol η presents the charging efficiency of EDVs. The right-hand side of constraint (16) presents the available battery capacity of EDVs in hour p for charging $x_{h,p}$. The total battery capacity of EDVs in hour p, C_p, decreases by the amount of energy in the battery in the initial stage, E, and for purchased and charged energy in hours $i \in \{1, \ldots, p\text{-}1\}$ prior to hour p, $x_{h,i}$. Energy discharged from the battery in hours $i \in \{1, \ldots, p\text{-}1\}$ before hour p, $b_{h,i}$, and D_i, increase the available battery capacity in hour p. Constraint (17) introduces the charging-speed limitation with the charging ramp-rate limit of EDVs in hour p L_p. Constraints (18)–(23) present limitations of all applied variables. For example, constraints (18) and (19) ensure that $x_{h,p}$ can be bought and charged only in hours $p \in \{1, \ldots, h\text{-}1\}$ prior to hour h, when it is consumed.

It is important to note that the optimization is deterministically performed for each EDV fleet and each point from the set Φ in (7), thus $2\cdot NV + 1$ calculations are performed for each EDV fleet. Calculated central moments in (10) and (11) are convenient for a presentation of the results with PDFs and CDFs.

D. Risk-based energy price offers for EDV users and RES shares in transportation

In the market, each energy supplier has to provide offers to EDV users for the energy required for transportation, since EDV users do not autonomously purchase the energy in the market due to high exposure to the risks, e.g. the price volatility. More convenient is to be supplied by the energy supplier who purchases the energy in the market for all its customers and appropriately manages the risks. Also EDV users expect to have a flat rate in a certain time frame, a constant price for the energy required for transportation that does not change hourly. If the goal of the energy supplier is to provide the most competitive offers, SC3 in Figure 1 has to be applied in the proposed optimization since the charging costs are minimized resulting in the lowest energy prices to users of EDVs, c. If it is presumed that the price c covers only the total costs J, it is calculated as:

$$c = \frac{J}{f\sum_{h=1}^{H} l_h} , \tag{24}$$

where l_h is the expected driving distance of EDVs in hour h directly obtained from the energy requirement for transportation D_h taking into consideration the energy-distance conversion factor e, thus $l_h = e\cdot D_h$. Symbol f in (24) presents the number of EDVs in a fleet. The price c in (24) should assure sufficient revenue to the energy supplier at least for covering the expected costs of transportation.

Another goal of the energy supplier could also be a promotion of green transportation achieved by maximal possible exploitation of RESs for battery charging. In this case, the share of RESs in the charged energy that is required for transportation, s, can be used as a measure of the environmental acceptance of transportation with EDVs. This measure is calculated as:

$$s = \frac{\sum_{p=1}^{H} t_p \sum_{r=1}^{NG} P_{r,p}}{\sum_{p=1}^{H} \sum_{h=p+1}^{H} x_{h,p}} \cdot 100\,\% , \tag{25}$$

where:

$$t_p = \begin{cases} \dfrac{\sum_{h=p+1}^{H} x_{h,p}}{\sum_{r=1}^{NG} P_{r,p}}; & \text{if } \sum_{h=p+1}^{H} x_{h,p} \le \sum_{r=1}^{NG} P_{r,p} \\ 1; & \text{if } \sum_{h=p+1}^{H} x_{h,p} > \sum_{r=1}^{NG} P_{r,p} \end{cases} . \tag{26}$$

Since the problem is of a stochastic nature, price c in (24) can be depicted by a normal PDF. Figure 5 presents PDFs of price c for all three cases in the optimization procedure presented in Figure 1. The costs and consequently the price are the lowest in CS3, since the charging costs are minimized. Similar conclusions can be drawn about the RES share since it can also be presented by PDF and compared among case studies.

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:

$$1 - r = \int_{-\infty}^{c^*} pdf(c) \cdot dc \,. \tag{27}$$

where $1 - r$ presents VaR index commonly used in financial risk management. Function in (27) takes the form of CDF as presented in Figure 6. It is clearly shown that at the same risk level r the price c^* is the lowest in case CS3.

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. It is assumed that the coordination among EDVs and control are properly performed on the operational level.

IV. Case Studies

The proposed optimization method is tested in three case studies, Figure 1: (**CS1**) charging of EDVs without any charging strategy, i.e. charging immediately after transportation, (**CS2**) charging of EDVs that maximizes the share of RESs in transportation, and (**CS3**) charging of EDVs with cost minimization resulting in minimal prices for EDV users. Although EDVs with automatic night recharging are very common in reality, they are not considered in these case studies since their charging is performed automatically and it is not controlled by the optimization. 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 and the RES shares in transportation are assessed.

In all cases, a set of ten new EDVs with daily driving patterns $\delta_{(\cdot),(\cdot)}$, presented in Table 1, are considered. The energy-distance conversion factor e of 6 km/kWh is presumed for all EDVs. Due to behavior uncertainties, 1,000 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 2. Other parameters of EDVs used in case studies are presented in Table 3. Each EDV battery has a capacity of 25 kWh and has 3 kWh of stored energy available for use. Energy is charged with 90 % efficiency. 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 with incorporated the scenario reduction method presented in [14], [15], [17]. The resulting driving patterns of fleets are presented in Figure 7 together with allocated numbers of scenarios. These numbers should be understood as the number of EDVs making up fleets.

Table 4 presents the central moments of the energy produced by photovoltaic power plants and wind power plants. This energy is available for EDVs and it can be purchased in the market at hourly market prices, $\rho_{(\cdot)}$, which are stochastically modeled, since they cannot be precisely forecasted due to uncertainties. Table 4 provides in the last two columns the central moments of the purchase prices.

The proposed optimization procedure results in energy prices for EDV transportation presented in Figure 8 as PDFs for all EDV fleets and all case studies. It shows that the prices are the highest in CS1, where no optimization is applied. If the charging costs are minimized as in CS3 the prices are efficiently reduced. CS2 results in the average prices since the focus is moved from cost minimization to maximization of renewable energy exploitation in transportation. Figure 9 presents the results from the aspect of the RES exploitation. The highest shares are obtained in CS3 since the RES exploitation is maximized to the limit.

Table 5 presents the final EDV prices, c^*, at the risk level $r = 0.5$, i.e. the mean values, and the price reductions in CS2 and CS3 that range between 24.1 % and 47.8 %. Table 6 presents the mean values of the RES shares in transportation for each fleet in each case study. To raise the purpose of the proposed optimization method, Table 6 shows the share increases among case studies according the worst case study. For example, the RES share for fleet 1 in CS2 is increased for 30.06 % according to the share in CS1 that is the worst case study for that fleet with the lowest RES share.

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 4 are presented by 1,000 scenarios that require 1,000 calculations. Since the HM method requires only $2 \cdot NV + 1 = 2 \cdot 3 \cdot 24 + 1 = 145$ calculations, it is, in these case studies, approximately seven times faster than the MC simulation, but the question is whether the error made in the HM estimation procedure is acceptable. The incurred errors (in %) of the PDF mean (in EUR/1000 km) as well as standard deviations for all fleets and all scenarios are presented in Table 7. The average error for the mean is -0.39 % and for the standard deviation -3.89 %.

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 Figure 6 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 scenarios. Figure 10 presents CDFs of the price for EDV transportation in fleet 2 in CS2 calculated using the MC and HM methods. This is the case with the highest discrepancy between CDFs at risk level $r = 0.1$. In addition, Figure 11 presents the price errors for all fleets in all case studies for different risk levels. Since the errors range between -2.48 % and 0.79 %, they can be neglected and since the errors are so insignificant, this justifies the use of the HM method.

V. Conclusions

The paper proposes the stochastic optimization of EDV charging patterns that enables maximization of RES exploitation in transportation or can be 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 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 stochastic scenarios that are analyzed in the optimization. The effectiveness of the proposed formulation is demonstrated by three case studies, which consider different optimization criteria. Simulations show that higher transportation costs for EDV users present a tradeoff for the cleaner environment as a result of more intensive RES exploitation in transportation. 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 coordination of EDVs within the fleets and their control schemes.

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FIGURE CAPTIONS

TABLE CAPTIONS

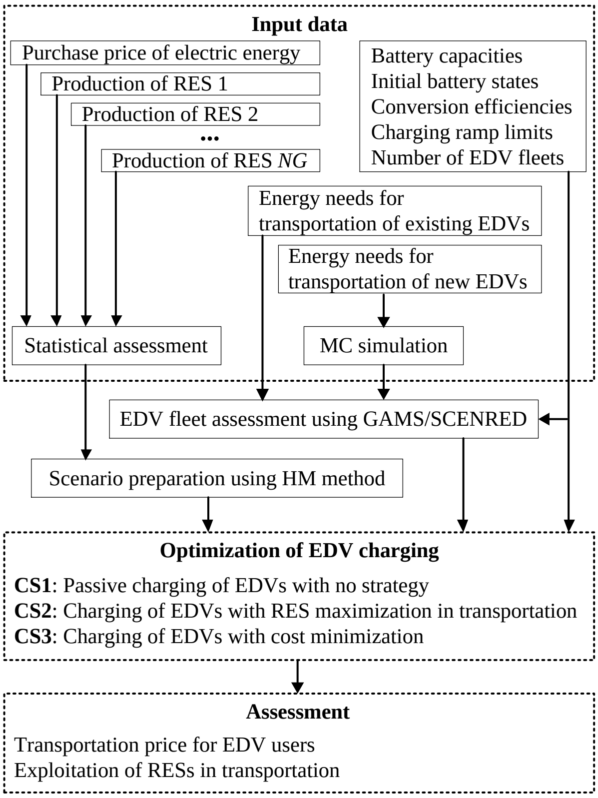

Figure 1: Optimization procedure

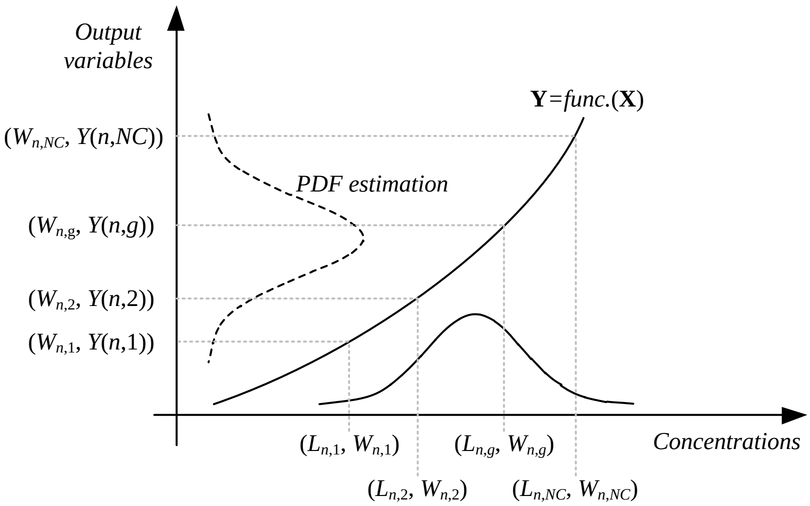

Figure 2: Concentrations of the input variable X_n

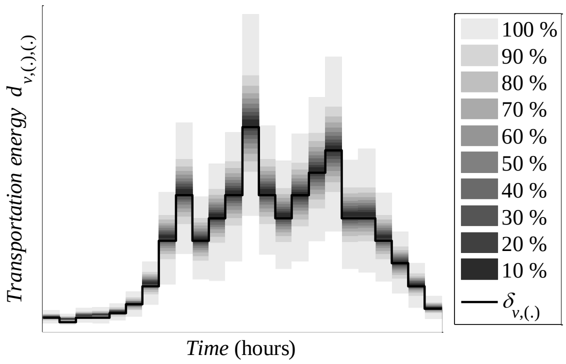

Figure 3: Probabilistic forecast of energy requirements for transportation

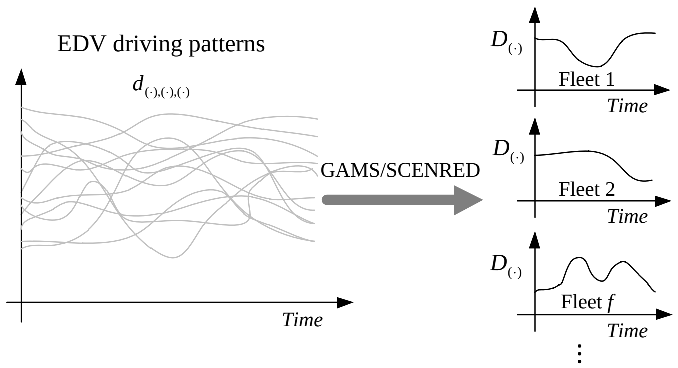

Figure 4: Formation of EDV fleets

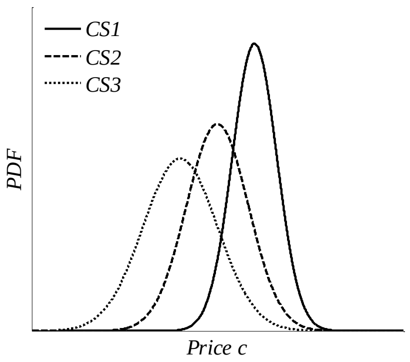

Figure 5: PDF of price c for all three cases

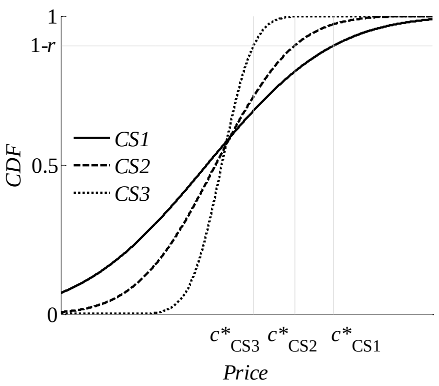

Figure 6: CDF of price c for all three cases

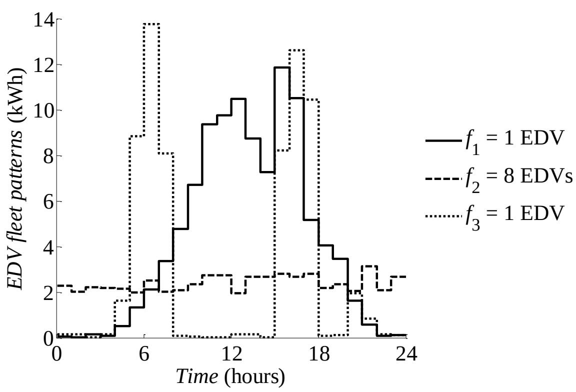

Figure 7: EDV fleet driving patterns

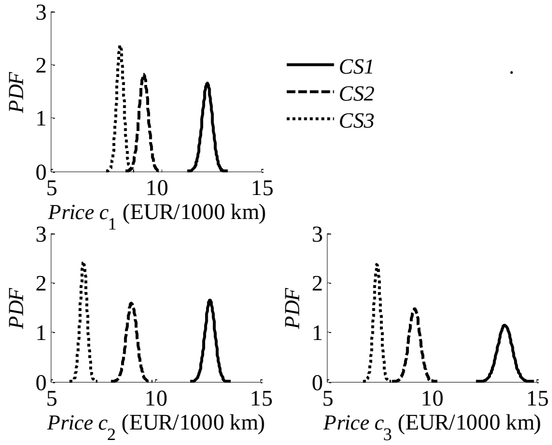

Figure 8: PDFs of prices *c* in EUR/1000 km for all fleets in all cases

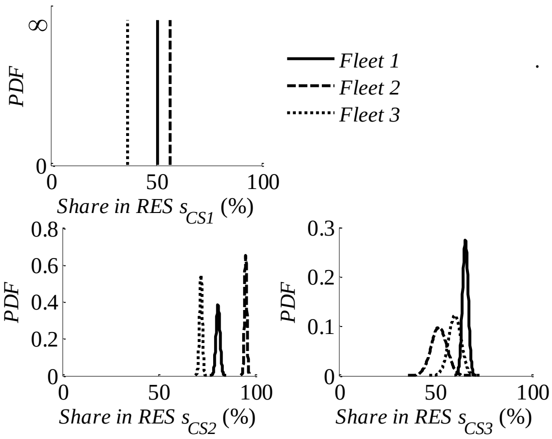

Figure 9: PDFs of RES shares in transportation for all fleets in all cases

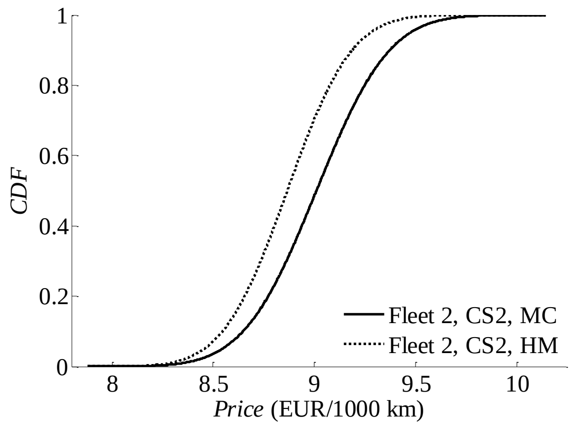

Figure 10: CDFs of EDV prices obtained using the MC and HM methods

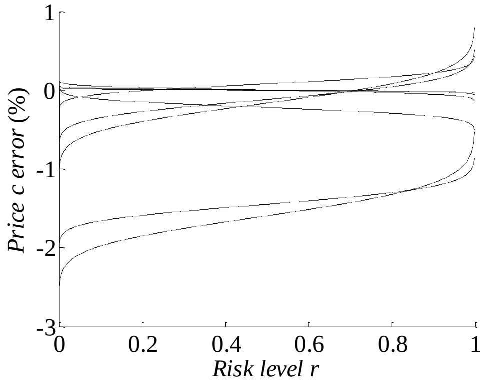

Figure 11: Price *c* errors

Table 1: Daily driving patterns in km

Hour h	EDV requirements $\delta_{v,h}$ (km)									
	1	2	3	4	5	6	7	8	9	10
1	0	3	0	20	15	0	2	0	0	0
2	0	2	0	19	16	0	2	0	0	0
3	0	3	0	18	17	0	2	0	0	0
4	0	3	0	17	14	0	2	0	0	0
5	0	4	3	18	15	0	2	0	10	0
6	10	6	6	19	14	0	2	5	50	10
7	14	10	12	14	13	0	2	7	80	10
8	18	20	18	19	12	0	2	9	50	0
9	0	30	25	0	14	30	2	5	0	0
10	0	20	40	0	15	40	2	0	0	15
11	0	25	55	0	16	35	2	0	0	20
12	6	30	60	0	15	25	2	0	0	0
13	6	45	65	0	14	35	2	0	0	0
14	0	30	52	0	15	15	2	0	0	0
15	0	25	46	0	16	10	2	0	0	10
16	10	30	72	0	14	0	2	5	50	10
17	18	35	58	0	15	0	2	6	80	0
18	12	40	32	0	16	0	2	6	60	0
19	0	25	25	0	13	0	2	0	0	0
20	10	25	20	5	17	0	2	0	0	10
21	11	20	12	10	15	0	2	0	10	10
22	0	15	2	15	16	0	2	0	5	0
23	0	10	0	20	14	0	2	0	0	0
24	0	5	0	22	15	0	2	0	0	0

Table 2: 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	1000

Table 3: Parameters of EDVs

Parameters	$C_{(\cdot)}$	E	η	e	$L_{(\cdot)}$
Values	25 kWh	3 kWh	90 %	6 km/kWh	50 % of $C_{(\cdot)}$ per hour

Table 4: Central moments of input data

Hour h	PV energy (kWh)		Wind energy (kWh)		Purchase price (EUR/MWh)	
	Mean	Std	Mean	Std	Mean	Std
1	0.0000	0.0000	3.0000	0.1062	46.6412	3.3012
2	0.0000	0.0000	4.0000	0.1415	42.2284	2.9846
3	0.0000	0.0000	5.0000	0.1767	54.1746	3.8422
4	0.0000	0.0000	6.0000	0.2119	42.0157	2.9691
5	0.2000	0.0071	6.5000	0.2301	50.1401	3.5436
6	1.0000	0.0354	7.0000	0.2475	53.7486	3.8008
7	1.2000	0.0424	6.5000	0.2302	58.0511	4.1019
8	3.5000	0.1240	6.3000	0.2228	58.9805	4.1726
9	4.6000	0.1627	6.2000	0.2191	58.9026	4.1709
10	5.0000	0.1775	6.0000	0.2132	71.8268	5.0864
11	6.0000	0.2119	5.0000	0.1772	67.8828	4.7991
12	6.2000	0.2195	4.5000	0.1591	62.7472	4.4348
13	6.2000	0.2192	4.2000	0.1484	53.4147	3.7776
14	5.8000	0.2054	3.3000	0.1170	41.3896	2.9319
15	5.0000	0.1769	3.0000	0.1064	57.1082	4.0402
16	3.2000	0.1130	2.5000	0.0883	56.1951	3.9681
17	1.2000	0.0424	1.5000	0.0531	66.0166	4.6710
18	0.8000	0.0283	1.0000	0.0354	60.2017	4.2691
19	0.2000	0.0071	0.1000	0.0036	69.0069	4.8823
20	0.0000	0.0000	0.0000	0.0000	71.4677	5.0541
21	0.0000	0.0000	0.0000	0.0000	50.5963	3.5771
22	0.0000	0.0000	0.0000	0.0000	45.6382	3.2254
23	0.0000	0.0000	0.0000	0.0000	49.3461	3.4915
24	0.0000	0.0000	0.0000	0.0000	43.1162	3.0552

Table 5: Mean prices in EUR/1000 km and reductions in %

Case study	Fleet 1		Fleet 2		Fleet 3	
	Mean price c	Reduction	Mean price c	Reduction	Mean price c	Reduction
CS1	12.4415	-	12.6060	-	13.5002	-
CS2	9.4414	24.1142	9.0097	28.5288	9.3247	30.9295
CS3	8.2985	33.2998	6.5843	47.7686	7.4149	45.0757

Table 6: Mean RES shares in % and increases in %

Case study	Fleet 1		Fleet 2		Fleet 3	
	Mean RES share s	Increase	Mean RES share s	Increase	Mean RES share s	Increase
CS1	50.8889	-	56.4504	4.4039	36.4357	-
CS2	80.9487	30.0599	95.2894	43.2429	72.0503	35.6146
CS3	65.7593	14.8705	52.0465	-	60.2631	23.8273

Table 7: 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	12.4415	0.2398	12.6060	0.2411	13.5002	0.3432
	HM	12.4415	0.2421	12.6060	0.2424	13.5002	0.3486
	Error	0.0000	0.9388	0.0000	0.5598	0.0000	1.5803
CS2	MC	9.4414	0.2111	9.0097	0.2826	9.3247	0.2928
	HM	9.4206	0.2187	8.8660	0.2499	9.1895	0.2726
	Error	-0.2203	3.5786	-1.5950	-11.5644	-1.4489	-6.9133
CS3	MC	8.2985	0.1776	6.5843	0.1774	7.4149	0.1897
	HM	8.3052	0.1690	6.5764	0.1649	7.4027	0.1683
	Error	0.0803	-4.8417	-0.1191	-7.0583	-0.1643	-11.3166