The following publication X. Lu, K. W. Chan, S. Xia, X. Zhang, G. Wang and F. Li, "A Model to Mitigate Forecast Uncertainties in Distribution Systems Using the Temporal Flexibility of EVAs," in IEEE Transactions on Power Systems, vol. 35, no. 3, pp. 2212-2221, May 2020 is available at https://doi.org/10.1109/TPWRS.2019.2951108

A Model to Mitigate Forecast Uncertainties in Distribution Systems Using the Temporal Flexibility of Electric Vehicle Aggregators

Xi Lu, Ka Wing Chan, *Member, IEEE*, Shiwei Xia, *Member, IEEE*, Xian Zhang, *Student Member*, *IEEE*, Guibin Wang, *Member, IEEE,* Furong Li, *Senior Member*, *IEEE*

***Abstract*— Electric vehicles (EVs) provide new options for energy balancing of power systems. One possible way to use EVs in energy balancing is to let each distribution system mitigate its forecast uncertainties through the flexibility of EVs. In consideration of the difficulties to directly govern a large number of EVs, it is more reasonable for distribution systems to dispatch electric vehicle aggregators (EVAs). Without influencing driving activities of EVs in the next day, a model is established for distribution systems to make use of EVAs, whose contributions are delaying uncertainties through their temporal flexibility and thus creating opportunities for uncertainties from different hours to offset each other. In the established model, a scheme of uncertainty transferring is proposed to relieve interruption to EVAs and distributionally robust optimization is adopted to evaluate the operation plans' average performance with temporal and spatial uncertainty correlations considered. Comprehensive case studies are carried out based on charging demands of EVAs simulated from real traffic data to verify the effectiveness of the proposed model.**

***Index Terms*-- Distribution system, electric vehicle aggregator, uncertainty mitigation, day-ahead planning, temporal flexibility, distributionally robust optimization.**

NOMENCLATURE

Sets, decision variables and uncertainties are printed in italics while others are in non-italics. Decision variables depending on uncertainty realizations are marked with tildes.

A. Sets

$\mathcal{N}$	Set of all nodes in the distribution system
$\mathcal{N}_{\mathrm{AVR}}$	Set of nodes that AVRs are connected to
$\mathcal{N}_{\mathrm{EVA}}$	Set of nodes that EVAs are connected to
$a(i)$	Parent node of node i
$\mathcal{B}(i)$	Set of child nodes of node i

B. Parameters

$\Delta\mathrm{t}$	Duration of a time period, i.e. an hour
T	Number of time periods in a day
$\mathrm{c}_i^{\mathrm{r,del}}$, $\mathrm{c}_i^{\mathrm{r,adv}}$	Price of reserve capacity for delayed, advanced charging of the EVA at node i
$\mathrm{c}_i^{\mathrm{in,del}}$, $\mathrm{c}_i^{\mathrm{in,adv}}$	Regular compensation rate to the EVA at node i for delayed, advanced charging
$\mathrm{c}_i^{\mathrm{out,del}}$, $\mathrm{c}_i^{\mathrm{out,adv}}$	Punitive compensation rate to the EVA at node i for delayed, advanced charging
$\mathrm{c}^{\mathrm{pen,+}}$, $\mathrm{c}^{\mathrm{pen,-}}$	Penalty coefficient for positive, negative deviations of distribution systems' energy consumptions
v_0	Base voltage
$\mathrm{R}_{i,j}$, $\mathrm{X}_{i,j}$	Resistance, reactance of the feeder between node i and j
$\mathrm{p}_{t,i}^{\mathrm{d}}$, $\mathrm{q}_{t,i}^{\mathrm{d}}$	Active, reactive load at node i in hour t
$\mathrm{e}_{t,i}^{\mathrm{EVA,p}}$	Planned charging demand of the EVA at node i in hour t
β_i	Power factor of the EVA at node i
$\mathrm{e}_{t,i}^{\mathrm{cap,del}}$, $\mathrm{e}_{t,i}^{\mathrm{cap,adv}}$	Dispatchable range for delayed, advanced charging of the EVA at node i in hour t
$\mathrm{q}_i^{\mathrm{AVR,cap}}$	Capacity of the AVR at node i

C. Uncertainties

$\xi_{t,i}$	Uncertain deviation of the charging demand of the EVA at node i in hour t from the forecast
$\boldsymbol{\xi}$	Vector of $\xi_{t,i}$ for all EVAs and all hours
N_{ξ}	Dimension of $\boldsymbol{\xi}$
$\boldsymbol{\mu}$	Statistical mean of $\boldsymbol{\xi}$
$\boldsymbol{\Sigma}$	Statistical covariance matrix of $\boldsymbol{\xi}$
f_{ξ}	Distribution of $\boldsymbol{\xi}$
D	Family of distributions that satisfies the statistical mean and covariance matrix of $\boldsymbol{\xi}$

D. Decision variables

e_t^{p}	Planned energy consumption of the distribution system in hour t
$r_{t,i}^{\mathrm{del}}$, $r_{t,i}^{\mathrm{adv}}$	Reserve capacity purchased from the EVA at node i for delayed, advanced charging in hour t
$\tilde{p}_{t,i}^{\mathrm{EVA}}$, $\tilde{q}_{t,i}^{\mathrm{EVA}}$	Active and reactive charging power of the EVA at node i in hour t

This work was supported by the Hong Kong Polytechnic University under Project G-UA3Z, in part by Research Studentship RUH5, in part by the Jiangsu Basic Research Project (Natural Science Foundation BK20180284) and in part by the Fundamental Research Funds for the Central Universities (2019MS007) *(Corresponding authors: Shiwei Xia and Ka Wing Chan).*

X. Lu, K. W. Chan and X. Zhang are with the Department of Electrical Engineering, The Hong Kong Polytechnic University, Hung Hom, Hong Kong SAR (e-mail: harry.lu@connect.polyu.hk; eekwchan@polyu.edu.hk; eexianzhang@outlook.com).

S. Xia is with the School of Electrical and Electronic Engineering, North China Electric Power University, Beijing 102206, China (e-mail: s.w.xia@ncepu.edu.cn).

G. Wang is with the College of Mechatronics and Control Engineering, Shenzhen University, Shenzhen 518060, China (e-mail: wanggb@szu.edu.cn).

F. Li is with the Department of Electrical Engineering, University of Bath, Claverton Down, 386416, UK (e-mail: f.li@bath.ac.uk).

$\tilde{e}_{t,i}^{\mathrm{EVA,dev}}$ Accumulated interruption to the charging of the EVA at node i in hour t

$\tilde{q}_{t,i}^{\mathrm{AVR}}$ Reactive power output of the AVR at node i in hour t

$\tilde{p}_{t,i,j}^{\mathrm{fl}}$, $\tilde{q}_{t,i,j}^{\mathrm{fl}}$ Active, reactive power flow from node i to node j in hour t

$\tilde{p}_{t}^{\mathrm{in}}$, $\tilde{q}_{t}^{\mathrm{in}}$ Active, reactive power input from the main grid in hour t

$\tilde{v}_{t,i}$ Voltage of node i in hour t

$\alpha_{\hat{t},j}^{t,i}$ Proportion of the uncertainty of the EVA at node i in hour t allocated to the EVA at node j in hour $\hat{t}$

I. Introduction

IN power systems, energy supplies and demands need to be balanced all the time. To maintain the balance under forecast uncertainties, reserve needs to be prepared, which is traditionally achieved through generators and hydropower stations [1-2].

Nowadays, EVs are becoming increasingly popular. A salient feature of EVs is that their connection times to power systems are usually longer than the times needed to fulfill their charging requirements. As a result, instead of keeping constant charging rates, adjusting their energy consumption patterns is possible. In other words, EVs are able to provide temporal flexibility, which can be used in maintaining the energy balance of power systems. In some deregulated power systems, EVs can participate in energy balancing through regulation markets [3-4]. While for power systems without regulation markets, other mechanisms need to be designed. As EVs are connected to distribution systems, one possible alternative is to let each distribution system mitigate its forecast uncertainties [5-6]. Then, each distribution system becomes a balance responsible party and can be penalized if its actual energy consumption fails to match the plan [7]. With each distribution system mitigating its own uncertainties, the transmission system operator needs to prepare less reserve.

The flexibility of EVs has been widely utilized in distribution system operation. For example, a receding horizon optimization model is established in [8] to shift charging demands of EVs to off-peak hours. In [9], a scheduling scheme is designed to maintain the voltage profile under high EV penetration. [10] proposes a charging strategy to regulate fluctuations of wind generation. These works all achieve their targets by taking circumstances of specific EVs into consideration. However, it will be very difficult for future system operators to directly govern a large number of EVs because the computation requirement for taking every EV into consideration and the investment requirement for collecting all necessary information will be too demanding [11]. Instead, it is more reasonable to have EVs controlled by EVAs and then the system operator dispatches EVAs rather than EVs. Such hierarchical scheme is used in [11] to improve wind power utilization. In [12], EVAs are dispatched as a whole to maximize the hosting capacity of distribution systems for their charging demands.

Because EVAs can make use of the temporal flexibility of EVs, EVAs also possess temporal flexibility in terms of accepting delayed and advanced charging to some extent. Besides, as a result of unpredictable behaviors of EVs, charging demands of EVAs may deviate from the forecast or in other words, there are uncertainties in charging demands of EVAs. Because of the large volume of charging demands of EVAs in the future, their potential deviations from forecast can be considerable although they have relatively predictable patterns. But in use of the temporal flexibility of EVAs, their charging rates can be kept as scheduled at the cost of their delayed or advanced charging depending on the signs of their uncertainty realizations and then their uncertainties are compensated by themselves.

To mitigate forecast uncertainties in distribution systems, different facilities have been used in literature. In [13], energy storage (ES) is adopted. [5] resorts to both ES and distributed generators (DGs). However, models using ES and DGs cannot be directly applied to distribution systems with EVAs because of the following distinct features of EVAs. Firstly, as stated above, EVAs possess uncertainties in their charging demands, while ES and DGs do not. Secondly, primary tasks of EVAs are guaranteeing energy requirements of EVs' driving activities, instead of facilitating distribution system operation as ES and DGs. Thirdly, costs of ES and DGs result from their operation. In contrast, costs of EVAs are incurred when their charging is interrupted. Apart from ES and DGs, load curtailment is another option and is used in [14], which is effective only when demands surpass supplies but not vice versa. While EVAs are applicable for both cases. In view of the particularity of EVAs, a tailored model is established in this paper to use temporal flexibility of EVAs to mitigate forecast uncertainties in distribution systems. Charging demands of EVAs are required to be fulfilled at the end of the day in order to guarantee driving activities of EVs in the next day. As a result, delayed and advanced charging of EVAs incurred from mitigating uncertainties should be recovered later in the day. So, contributions of EVAs in mitigating uncertainties are actually delaying uncertainties. Then, the deviation of the energy consumption of the distribution system from the plan in an hour depends on uncertainties from different hours, which may offset each other.

Components of distribution systems can have intertemporal constraints, such as those on ramping rates of DGs, state of charge of ES and accumulated interruption to the charging of EVAs. With these constraints, earlier decisions influence later operation. Therefore, it is necessary to take real-time recourse operation into consideration when making operation plans. In [5], to tackle uncertainties in energy supplies, reserve capacities are scheduled from DGs and ES. But the real-time operation is not considered when scheduling reserve capacities and thus DGs and ES are poorly coordinated. Different from [5], [14] considers real-time operation in advance through a two-stage framework. But the second stage of the framework assumes that real-time decisions at all times are made simultaneously knowing realizations of uncertainties at all times, which neglects the fact that earlier decisions are made without knowing realizations of later uncertainties. As a consequence, operational infeasibility may be encountered. To consider real-time operation without violating temporal sequences of uncertainty realizations, linear decision rules (LDR) are adopted in this paper, which assumes that real-time decisions are affine functions of realizations of earlier uncertainties. Details about LDR will be given in Section III.B.

As stated above, charging rates of EVAs can be kept as scheduled in use of their temporal flexibility, which is equivalent to having each EVA to mitigate its own uncertainties. Then, charging of different EVAs is interrupted independently. Without any influence on total energy consumptions of distribution systems, a scheme of uncertainty transferring is proposed based on LDR. Under this scheme, EVAs can transfer their uncertainties to each other. Or, in other words, an EVA can mitigate uncertainties of other EVAs. Then, interruption to the charging of an EVA depends on uncertainties of different EVAs and may be relieved because uncertainties of different EVAs may offset each other. This scheme also has other potential benefits, which will be further discussed in Section III.B.

For problems involving uncertainties, how to deal with uncertainties is an important issue. When uncertainties cannot be observed directly or accurately, fuzzy theory can be used [15-16]. Uncertainties concerned in this paper are from energy demands and supplies in distribution systems and their historical samples can be accurately recorded. In terms of handling this kind of uncertainties, [17] focuses on the worst uncertainty realization through interval analysis and optimization. However, pursuing the best performance in mitigating forecast uncertainties in distribution systems under the worst uncertainty realization may lead to over-conservative operation plans and result in inferior performance under most possible uncertainty realizations. Instead, it is more reasonable to optimize the average performance of the operation plans. For this reason, distributionally robust optimization (DRO) is adopted in this paper, which is a newly developed approach and has been shown to be effective [18-19]. The statistical mean and covariance matrix of uncertainties can be calculated from historical samples. By using DRO techniques, the proposed model considers all possible uncertainty distributions satisfying the statistical mean and covariance matrix and makes decisions with respect to the worst possible distribution. Distributional information of uncertainties is thus well utilized in optimizing the average performance of the operation plans and risks of having unexpected average performance are avoided as well. Besides, because movements of EVs possess distinct spatial-temporal features [20], uncertainties in charging demands of EVAs may have prominent temporal and spatial correlations, which can also be well considered by the proposed model as the statistical covariance matrix is used to depict uncertainty distributions.

The following are the main contributions of this paper.

(1) A model is proposed to use the temporal flexibility of EVAs to mitigate forecast uncertainties in distribution systems without influencing driving activities of EVs in the next day. Contributions of EVAs are delaying uncertainties and thus making it possible for uncertainties from different hours to offset each other.

(2) In consideration of the temporal sequences of uncertainty realizations, LDR is used to model real-time operation. Based on LDR, a scheme of uncertainty transferring is proposed, which can relieve interruption to the charging of EVAs.

(3) DRO is used to evaluate the average performance of the operation plans with temporal and spatial uncertainty correlations considered through the statistical covariance matrix.

(4) Real traffic data is used to simulate charging demands of EVAs, whose spatial and temporal correlations are qualitatively shown. Effectiveness of the proposed model is verified through comprehensive case studies based on the simulated charging demands of EVAs.

This paper is organized as follows. Section II presents settings on distribution system operation. Formulation of the proposed model and its deterministic transformation are given in Section III. In Section IV, the simulation of charging demands of EVAs is introduced. Case studies are conducted in Section V and further discussions are made in Section VI. At last, conclusions are drawn in Section VII.

II. Settings on Distribution System Operation

It is assumed that energy consumptions of the distribution system at different hours in a day should be planned in advance. Similar to [13, 21], penalties are assumed to be applied on deviations of the distribution system's energy consumptions from the plan. In terms of dispatching EVAs, the distribution system is assumed to purchase reserve capacities from EVAs ahead of time. Then during operation, the part of interruption to the charging of EVAs within purchased capacities is compensated by the distribution system at regular rates and the part beyond purchased capacities is compensated at punitive rates, which are higher than regular rates.

The interaction mechanism between the distribution system and EVAs is as follows. First, EVAs plan their charging demands by collecting information from EV owners. Then, based on energy requirements of EVs, revenue from the distribution system and potential compensations to EVs, EVAs decide their dispatchable ranges for the distribution system. Planned charging demands and dispatchable ranges of EVAs are reported to the distribution system. After that, the distribution system decides its energy consumption plans and its dispatching plans for EVAs and purchases reserve capacities from EVAs. Knowing the reserve capacities purchased by the distribution system, EVAs can make plans on controlling EVs. At last, as uncertainties realize in real-time operation, the distribution system gives dispatch to EVAs within their dispatchable ranges, and EVAs control EVs to follow the dispatch of the distribution system.

The above-discussed EVAs can be operators of EV parking lots or providers of smart-charging service to EVs at home. They can also be affiliated departments of the distribution system. In the latter case, it is equivalent to simplifying distribution system operation by adopting hierarchical dispatching schemes. This paper focuses on distribution system operation under the above interaction mechanism between the distribution system and EVAs. Operation models of EVAs and the interaction mechanism between EVAs and EVs are beyond the scope of this paper.

III. MODEL FORMULATION AND TRANSFORMATION

In this section, the formulation of the proposed model is given first. Then, LDR and the uncertainty transferring scheme are discussed. At last, the proposed model is transformed into a deterministic second-order conic program.

A. Formulation of the proposed model

The proposed model optimizes the operation plans by balancing costs of dispatching EVAs and penalties for deviations of the distribution system's energy consumptions from the plan at the same time of guaranteeing system security. Its formulation is given in (1). The first item in the objective (1.1) is the cost of purchasing reserve capacities from EVAs. The second term is the worst expected sum of compensations to EVAs and penalties for energy deviations of the distribution system over all considered uncertainty distributions. (1.2) and (1.3) are penalties when deviations of the energy consumptions of the distribution system from planned values are positive and negative, respectively. (1.4) and (1.5) are compensations to EVAs when the delayed charging of EVAs is within and beyond purchased reserve capacities, respectively. (1.6) and (1.7) are compensations to EVAs when the advanced charging of EVAs is within and beyond purchased reserve capacities, respectively. (1.8) and (1.9) indicate the active and reactive power imported from the main grid, respectively. The node connecting the main grid is numbered as 0. (1.10) and (1.11) ensure active and reactive power balance, respectively. Automatic voltage regulators (AVRs) are installed at certain nodes to supply reactive power in order to maintain voltage profiles. (1.12) describes the relationship between the voltage of adjacent nodes. (1.13) prevents voltage profiles from exceeding the lower and upper boundary. (1.14) limits the output of AVRs. (1.15) ensures the charging power of EVAs to be non-negative. (1.16) is the relationship between the active and reactive charging power of EVAs. (1.17) describes the accumulated interruption to the charging of EVAs. Positive values indicate delayed charging and negative values indicate advanced charging. (1.18) avoids the dispatchable ranges of EVAs from being violated. (1.19) requires that charging demands of EVAs are fulfilled at the end of the day to guarantee driving activities of EVs in the next day.

$$\begin{aligned}\min \quad & \textstyle\sum_{t=1,\dots,\mathrm{T}}\sum_{i\in\mathcal{N}_{\mathrm{EVA}}}\left(\mathrm{c}_i^{\mathrm{r,del}}\cdot r_{t,i}^{\mathrm{del}}+\mathrm{c}_i^{\mathrm{r,adv}}\cdot r_{t,i}^{\mathrm{adv}}\right)\\ & +\sup_{f_{\xi}\in\mathrm{D}}\mathrm{E}\Big[\textstyle\sum_{t=1,\dots,\mathrm{T}}\max\limits_{k=1,2} f_k\left(\tilde{p}_t^{\mathrm{in}},e_t^{\mathrm{p}}\right)\\ & +\textstyle\sum_{t=1,\dots,\mathrm{T}}\sum_{i\in\mathcal{N}_{\mathrm{EVA}}}\max\limits_{k=1,2,3,4} g_k\left(\tilde{e}_{t,i}^{\mathrm{EVA,dev}}\right)\Big]\end{aligned} \tag{1.1}$$

s. t.

$$f_1\left(\tilde{p}_t^{\mathrm{in}},e_t^{\mathrm{b}}\right)=\mathrm{c}^{\mathrm{pen},+}\cdot\left(\tilde{p}_t^{\mathrm{in}}\cdot\Delta\mathrm{t}-e_t^{\mathrm{p}}\right) \tag{1.2}$$

$$f_2\left(\tilde{p}_t^{\mathrm{in}},e_t^{\mathrm{b}}\right)=\mathrm{c}^{\mathrm{pen},-}\cdot\left(e_t^{\mathrm{p}}-\tilde{p}_t^{\mathrm{in}}\cdot\Delta\mathrm{t}\right) \tag{1.3}$$

$$g_1\left(\tilde{e}_{t,i}^{\mathrm{EVA,dev}}\right)=\mathrm{c}_i^{\mathrm{in,del}}\cdot\tilde{e}_{t,i}^{\mathrm{EVA,dev}} \tag{1.4}$$

$$g_2\left(\tilde{e}_{t,i}^{\mathrm{EVA,dev}}\right)=\mathrm{c}_i^{\mathrm{out,del}}\cdot\left(\tilde{e}_{t,i}^{\mathrm{EVA,dev}}-r_{t,i}^{\mathrm{del}}\right)+\mathrm{c}_i^{\mathrm{in,del}}\cdot r_{t,i}^{\mathrm{del}} \tag{1.5}$$

$$g_3\left(\tilde{e}_{t,i}^{\mathrm{EVA,dev}}\right)=-\mathrm{c}_i^{\mathrm{in,adv}}\cdot\tilde{e}_{t,i}^{\mathrm{EVA,dev}} \tag{1.6}$$

$$g_4\left(\tilde{e}_{t,i}^{\mathrm{EVA,dev}}\right)=\mathrm{c}_i^{\mathrm{out,adv}}\cdot\left(-\tilde{e}_{t,i}^{\mathrm{EVA,dev}}-r_{t,i}^{\mathrm{adv}}\right)+\mathrm{c}_i^{\mathrm{in,adv}}\cdot r_{t,i}^{\mathrm{adv}} \tag{1.7}$$

$$\tilde{p}_t^{\mathrm{in}}=\textstyle\sum_{i\in\mathcal{B}(0)}\tilde{p}_{t,0,i}^{\mathrm{fl}}\quad\forall\boldsymbol{\xi},\forall t \tag{1.8}$$

$$\tilde{q}_t^{\mathrm{in}}=\textstyle\sum_{i\in\mathcal{B}(0)}\tilde{q}_{t,0,i}^{\mathrm{fl}}\quad\forall\boldsymbol{\xi},\forall t \tag{1.9}$$

$$\tilde{p}_{t,a(i),i}^{\mathrm{fl}}=\mathrm{p}_{t,i}^{\mathrm{d}}+\tilde{p}_{t,i}^{\mathrm{EVA}}+\textstyle\sum_{j\in\mathcal{B}(i)}\tilde{p}_{t,i,j}^{\mathrm{fl}}\quad\forall\boldsymbol{\xi},\forall i\in\mathcal{N}/\{0\},\forall t \tag{1.10}$$

$$\tilde{q}_{t,a(i),i}^{\mathrm{fl}}=\mathrm{q}_{t,i}^{\mathrm{d}}+\tilde{q}_{t,i}^{\mathrm{EVA}}-\tilde{q}_{t,i}^{\mathrm{AVR}}+\textstyle\sum_{j\in\mathcal{B}(i)}\tilde{q}_{t,i,j}^{\mathrm{fl}}\quad\forall\boldsymbol{\xi},\forall i\in\mathcal{N}/\{0\},\forall t \tag{1.11}$$

$$\tilde{v}_{t,a(i)}-\left(\mathrm{R}_{a(i),i}\cdot\tilde{p}_{t,a(i),i}^{\mathrm{fl}}+\mathrm{X}_{a(i),i}\cdot\tilde{q}_{t,a(i),i}^{\mathrm{fl}}\right)/\,\mathrm{v}_0=\tilde{v}_{t,i}\quad\forall\boldsymbol{\xi},\forall i\in\mathcal{N}\,/\,\{0\},\forall t \tag{1.12}$$

$$0.95\cdot\mathrm{v}_0\le\tilde{v}_{t,i}\le1.05\cdot\mathrm{v}_0\quad\forall\boldsymbol{\xi},\forall i\in\mathcal{N},\forall t \tag{1.13}$$

$$0\le\tilde{q}_{t,i}^{\mathrm{AVR}}\le\mathrm{q}_i^{\mathrm{AVR,cap}}\quad\forall\boldsymbol{\xi},\forall i\in\mathcal{N}_{\mathrm{AVR}},\forall t \tag{1.14}$$

$$\tilde{p}_{t,i}^{\mathrm{EVA}}\ge0\quad\forall\boldsymbol{\xi},\forall i\in\mathcal{N}_{\mathrm{EVA}},\forall t \tag{1.15}$$

$$\beta_i\cdot\tilde{q}_{t,i}^{\mathrm{EVA}}=\sqrt{1-\beta_i{}^2}\cdot\tilde{p}_{t,i}^{\mathrm{EVA}}\quad\forall\boldsymbol{\xi},\forall i\in\mathcal{N}_{\mathrm{EVA}},\forall t \tag{1.16}$$

$$\tilde{e}_{t,i}^{\mathrm{EVA,dev}}=\textstyle\sum_{\hat{t}=1,\dots,t}\left(\mathrm{e}_{\hat{t},i}^{\mathrm{EVA,p}}+\xi_{\hat{t},i}\right)-\sum_{\hat{t}=1,\dots,t}\Delta\mathrm{t}\cdot\tilde{p}_{\hat{t},i}^{\mathrm{EVA}}\quad\forall\boldsymbol{\xi},\forall i\in\mathcal{N}_{\mathrm{EVA}},\forall t \tag{1.17}$$

$$-\mathrm{e}_{t,i}^{\mathrm{cap,adv}}\le\tilde{e}_{t,i}^{\mathrm{EVA,dev}}\le\mathrm{e}_{t,i}^{\mathrm{cap,del}}\quad\forall\boldsymbol{\xi},\forall i\in\mathcal{N}_{\mathrm{EVA}},\forall t \tag{1.18}$$

$$\textstyle\sum_{t=1,\dots,\mathrm{T}}\tilde{p}_{t,i}^{\mathrm{EVA}}\cdot\Delta\mathrm{t}=\sum_{t=1,\dots,\mathrm{T}}\left(\mathrm{e}_{t,i}^{\mathrm{EVA,p}}+\xi_{t,i}\right)\quad\forall\boldsymbol{\xi},\forall i\in\mathcal{N}_{\mathrm{EVA}} \tag{1.19}$$

B. Linear decision rules approximation and the uncertainty transferring scheme

In (1), optimal values of variables with tildes are influenced by realizations of uncertainties. As uncertainty realizations cannot be foreseen, uncertainty-affected variables are decided only with information about earlier realized uncertainties but not future ones. Because there are many time periods in (1) and the relationship between the optimal values of variables and realizations of earlier uncertainties can be very complicated [22-23], problem (1) is very difficult to solve. Therefore, to make problem (1) solvable, proper approximations are necessary. In this respect, LDR is widely used to approximate multi-period problems with uncertainties [22-25]. With LDR, instead of considering the actual relationship between the optimal values of variables and realizations of earlier uncertainties, affine relationships are assumed to hold in order to reduce the complexity, coinciding with the idea of automatic generation control [25]. This is equivalent to allocating uncertainties to different hours in advance through determining the uncertainty coefficients of LDR. Then, the charging power of EVAs will be as (2) if each EVA mitigates its own uncertainties. It should be noted that uncertainties can only be allocated to later hours but not earlier ones as uncertainty realizations cannot be foreseen. Besides, uncertainties in an hour can be allocated to more than one later hour.

$$\tilde{p}_{t,i}^{\mathrm{EVA}}=p_{t,i}^{\mathrm{EVA,con}}+\textstyle\sum_{\hat{t}=1,\dots,t}\alpha_{t,i}^{\hat{t},i}\cdot\xi_{\hat{t},i}\quad\forall i\in\mathcal{N}_{\mathrm{EVA}},\forall t \tag{2}$$

As discussed in Section I, without influencing total energy consumptions of the distribution system, EVAs can transfer their uncertainties to each other. Then, the charging power of EVAs will be as (3) and interruption to the charging of an EVA depends on uncertainties of different EVAs. Because uncertainties of different EVAs may offset each other, interruption to the charging of EVAs may be relieved. Apart from this, the uncertainty transferring scheme has other potential benefits as well. First, uncertainties of EVAs that are more expensive to dispatch can be transferred to cheaper EVAs, which is equivalent to having uncertainties of expensive EVAs mitigated by cheaper EVAs. Then, the distribution system needs to pay less to EVAs in total. Furthermore, it is possible that when one EVA reaches its dispatchable ranges, the others do not. Then, uncertainties of this EVA can be transferred to other EVAs to make use of their spare dispatchable capacities and thus potential deviations of the distribution system's energy consumptions from the plan may further decrease.

$$\tilde{p}_{t,i}^{\mathrm{EVA}} = p_{t,i}^{\mathrm{EVA,con}} + \sum_{j\in\mathcal{N}_{\mathrm{EVA}}} \sum_{\hat{t}=1,\dots,t} \alpha_{t,i}^{\hat{t},j} \cdot \xi_{\hat{t},j} \quad \forall i \in \mathcal{N}_{\mathrm{EVA}}, \forall t \tag{3}$$

To further illustrate the idea of allocating uncertainties to different hours and different EVAs in advance, the implication of (1.19) on the uncertainty coefficients of LDR for the charging power of EVAs is discussed here. According to (1.19), the total energy that any EVA is charged with at the end of the day should be the sum of its uncertainties and planned demands. Therefore, for any uncertainty of any EVA, its allocation (LDR) coefficients to its EVA at all hours should sum to one, leading to (4). Also, (1.19) implies that the energy that any EVA is charged with at the end of the day should not be influenced by uncertainties of other EVAs. So, for any uncertainty of any EVA, its allocation (LDR) coefficients to any other EVA at all hours should sum to zero, which results in (5).

$$\sum_{\hat{t}=t,\dots,\mathrm{T}} \alpha_{\hat{t},i}^{t,i} = 1 \quad \forall i \in \mathcal{N}_{\mathrm{EVA}}, \forall t \tag{4}$$

$$\sum_{\hat{t}=t,\dots,\mathrm{T}} \alpha_{\hat{t},j}^{t,i} = 0 \quad \forall j \in \mathcal{N}_{\mathrm{EVA}}/\{i\}, \forall i \in \mathcal{N}_{\mathrm{EVA}}, \forall t \tag{5}$$

Similar to the charging power of EVAs, all other uncertainty-affected variables are also assumed to be affine functions of earlier uncertainty realizations under LDR. Then, different time periods in (1) can be regarded as being squeezed together and (1) becomes a mathematically single-period problem, which is easier to handle. Decision variables to be solved are the constants and uncertainty coefficients of LDR and reserve capacities purchased from EVAs.

C. Deterministic transformation of the proposed model

To solve problem (1), it still needs to be transformed into deterministic forms. In (1), (1.13)-(1.15) and (1.18) are linear inequality constraints involving uncertainties, which can be replaced by their deterministic counterparts through robust optimization [26-27]. There are linear equality constraints involving uncertainties in (1) as well. To ensure these constraints to be satisfied with respect to all considered uncertainty realizations, the additive coefficient for each uncertainty in each constraint needs to be zero, forming corresponding constraints on uncertainty coefficients of LDR. After removing these uncertainty-related terms, the original equality constraints in (1) become deterministic.

To handle uncertainties in the objective, DRO is adopted. As shown in (6), the family of distributions satisfying the statistical mean and covariance matrix of uncertainties is considered and represented as D. The worst expectation of a specific family of piecewise-linear utility functions over all possible distributions in D can be transformed into deterministic forms as (7), where w_1, w_2, w_3 and w_4 are slack variables [28]. $\boldsymbol{y}'$ represents the transpose of $\boldsymbol{y}$. However, there are summations of piecewise-linear functions within the expectation operator in the objective (1.1), impeding the direct application of (7). To overcome this difficulty, the objective (1.1) is approximated by (8), where the original worst expectation is replaced by its upper bound. The conservatism of such approximation is shown to be acceptable in [29]. After the manipulations stated earlier and substituting worst expectations in the approximated objective (8) by (7), the proposed model becomes a deterministic second-order conic program and can be solved by off-the-shelf solvers.

At the same time of depicting uncertainty distributions by the statistical expectation and covariance matrix, DRO can also bound the range of uncertainty realizations by ellipsoidal sets as done in [2]. With such DRO technique, the conservatism level of the proposed model can be adjusted by varying the sizes of the ellipsoidal sets, but also, semidefinite programs will be resulted, which are challenging and time-consuming to solve. To avoid heavy computational burden, the DRO technique from [28] rather than that from [2] is adopted.

$$\mathrm{D} = \left\{ f_{\xi} \left| \begin{array}{l} \Pr(\boldsymbol{\xi} \in \mathbb{R}^{\mathrm{N}_{\xi}}) = 1 \\ \mathrm{E}[\boldsymbol{\xi}] = \boldsymbol{\mu} \\ \mathrm{E}[(\boldsymbol{\xi}-\boldsymbol{\mu})\cdot(\boldsymbol{\xi}-\boldsymbol{\mu})'] = \boldsymbol{\Sigma} \end{array} \right. \right\} \tag{6}$$

$$\begin{aligned} &\sup_{f_{\xi}\in \mathrm{D}} \mathrm{E}\left[\max_{k=1,\dots,\mathrm{K}} \{m_k(y_0 + \boldsymbol{y}'\boldsymbol{\xi}) + n_k\}\right] \\ &= \inf\ w_4 - w_3 \\ &\quad \mathrm{s.t.}\ w_3 \le -m_k(y_0 + \boldsymbol{y}'\boldsymbol{\mu}) - n_k - m_k{}^2 w_1 - m_k w_2 \quad \forall k \\ &\quad\quad\ w_1 + w_4 \ge \sqrt{\boldsymbol{y}'\boldsymbol{\Sigma}\boldsymbol{y} + w_2{}^2 + (w_1 - w_4)^2} \\ &\quad\quad\ w_1 \ge 0 \end{aligned} \tag{7}$$

$$\begin{aligned} &\sum_{t=1,\dots,\mathrm{T}} \sum_{i\in\mathcal{N}_{\mathrm{EVA}}} \left(\mathrm{c}_i^{\mathrm{r,del}} \cdot r_{t,i}^{\mathrm{del}} + \mathrm{c}_i^{\mathrm{r,adv}} \cdot r_{t,i}^{\mathrm{adv}}\right) \\ &\quad + \sum_{t=1,\dots,\mathrm{T}} \sup_{f_{\xi}\in\mathrm{D}} \mathrm{E}\left[\max_{k=1,2} f_k\left(\tilde{p}_t^{\mathrm{in}}, e_t^{\mathrm{p}}\right)\right] \\ &\quad + \sum_{t=1,\dots,\mathrm{T}} \sum_{i\in\mathcal{N}_{\mathrm{EVA}}} \sup_{f_{\xi}\in\mathrm{D}} \mathrm{E}\left[\max_{k=1,2,3,4} g_k\left(\tilde{e}_{t,i}^{\mathrm{EVA,dev}}\right)\right] \end{aligned} \tag{8}$$

IV. Simulation of the Charging Demands of EVAs

As charging demands of EVAs are greatly influenced by the travel of EVs, a travel survey in Atlanta [30] with 119480 trip records is used to simulate the daily operation of EVs, which is then used to simulate charging demands of EVAs. Instead of accurate and complex analysis, simple settings are adopted because the charging demands simulated here are only used to validate the effectiveness of the proposed model. In actual operation, real data will be used.

The simulation here focuses on charging at home by assuming that the simulated EVAs are in residential areas. From the 119480 trip records of the survey, 26617 home-to-home (h2h) trips are sorted out, each of which may be made up of itself or several connected non-h2h trips. The 26617 h2h trips further constitute 18553 records of daily operation, forming the database. Each simulated EV is assigned with a random daily operation record from the database. The energy consumption rate of EVs is assumed to be 0.22 kWh per mile. Charging demands of EVAs are calculated by assuming that EVs are charged at the maximum rate once they arrive home until they are fully charged. The charging efficiency is assumed to be 90%. The maximum charging rate is assumed to be 6 kW. Charging demands of EVAs at each hour are measured in kWh. As there is a relatively large number of EVs under each EVA, different energy consumption rates, charging efficiencies and maximum charging rates are not considered. 10000 sets of simulated daily charging demand of an EVA with 450 EVs are presented in Fig. 1 and used in Section V.A to Section V.C.

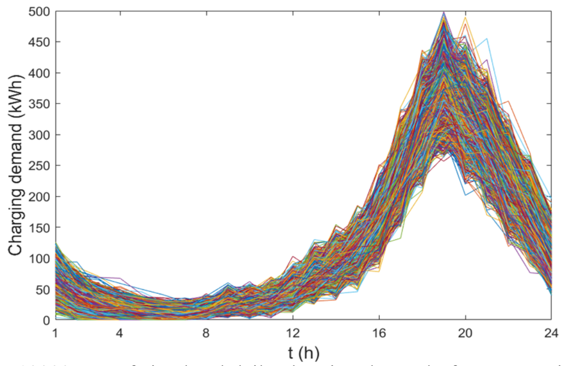

Fig. 1. 10000 sets of simulated daily charging demand of an EVA with 450 EVs.

Traffic congestion is further considered in simulation to reflect spatial correlations of the charging demands of EVAs. Again, as the simulated data is just used for validating the proposed model, only the influence of traffic congestion on travel speeds of EVs is considered with simple settings. The congestion period is assumed to be the 18th to 20th hour in the day. As the travel routes of EVs from the same distribution system are generally near to each other, a random variable γ_t is generated to reflect the overall congestion level of this area in hour t. For every single EV, another random variable $\lambda_{t,i}$ is generated to reflect the specific influence of traffic congestion on its travel speed. A simple assumed relationship between congestion levels and travel speeds of EVs is adopted as (9), where $s_{t,i}$ and $\hat{s}_{t,i}$ are the original speed and the speed under congestion of EV i in hour t, respectively. The smaller γ_t and $\lambda_{t,i}$ become, the slower EVs travel. 10000 sets of simulated daily charging demand of an EVA with 450 EVs considering traffic congestion are presented in Fig. 2 and used in Section V.D.

$$\hat{s}_{t,i} = \gamma_t \cdot \lambda_{t,i} \cdot s_{t,i} \tag{9}$$

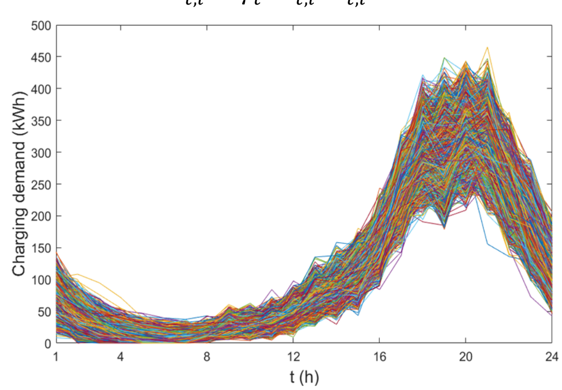

Fig. 2. 10000 sets of simulated daily charging demand of an EVA with 450 EVs considering traffic congestion.

V. CASE STUDIES

Four sets of case studies are presented in this section. General performance of the proposed model is shown first. Then, the second set discusses the effects of the temporal flexibility of EVAs in mitigating forecast uncertainties in distribution systems. After that, benefits of the uncertainty transferring scheme are illustrated. At last, temporal and spatial correlations of the charging demands of EVAs are qualitatively shown and the effectiveness of the proposed model in considering them is verified.

The IEEE 33-bus distribution system from [31] is adopted for case studies with the following base case settings. Three EVAs are assumed to be connected to Bus 16, 22 and 32 with 450, 450 and 600 EVs, respectively. Dispatchable ranges for delayed and advanced charging of the EVA at Bus 16, 22 and 32 at all hours are set to 450, 450 and 600 kWh, respectively. Power factors of all EVAs are set to 0.8. AVRs are assumed to be installed at Bus 6, 9, 15, 20, 23, 27 and 31. Each has a capacity of 500 kVar. Prices of reserve capacities of all EVAs for delayed and advanced charging at all hours are set to 0.2¢ per kWh. Regular compensation rates to all EVAs for delayed and advanced charging at all hours are set to 1¢ per kWh. Punitive compensation rates to all EVAs for delayed and advanced charging at all hours are set to 5¢ per kWh. Penalty rates for positive and negative deviations of energy consumptions of the distribution system from planned values at all hours are set to 15¢ per kWh. For all case studies, 10000 sets of charging demands are simulated to calculate the statistical mean and covariance matrix of uncertainties in charging demands of EVAs, based on which the operation plan of the distribution system is solved by the proposed model. Then, another 10000 sets of data are simulated independently to test the performance of the obtained operation plan.

A. General performance of the proposed model

Case studies here are conducted by varying penalty rates. Relevant results are recorded in Table I. Costs recorded in all subsequent tables are incurred from distribution system operation in the considered day. Average costs are computed based on actual outcomes under simulated charging demands of EVAs. With the increase of penalty rates, using EVAs to mitigate uncertainties becomes relatively cheaper and thus EVAs are resorted to more extensively. As a result, costs of reserve capacities from EVAs and average compensations to EVAs increase. Besides, average penalties grow with the rise of penalty rates. But the increased percentage of average penalties is less than that of penalty rates, which is also because that EVAs are used more extensively. To conclude, the proposed model can successfully give proper operation plans under a wide range of penalty rates.

TABLE I
GENERAL PERFORMANCE OF THE PROPOSED MODEL

Penalty rates (¢/kWh)	5	10	15*	20
Reserve costs ($/day)	2.64	4.36	4.80	5.16
Average compensations to EVAs ($/day)	3.95	6.55	7.21	7.74
Average penalties ($/day)	22.03	38.09	55.89	73.60
Average total costs ($/day)	28.61	49.00	67.91	86.50

* base case

B. Effects of EVAs in mitigating forecast uncertainties in distribution systems

In this part, case studies are first conducted by using EVAs to mitigate uncertainties and not, respectively. The average penalty at each hour under both cases are presented in Fig. 3. When EVAs are not used, the curve of average penalties reflects the level of uncertainties in each hour and basically matches the trend of the charging demands of EVAs. When EVAs are used, average penalties at some hours are close to zero because uncertainties in these hours are mainly mitigated by EVAs. In some other hours, delayed or advanced charging of EVAs incurred from mitigating uncertainties are recovered, and thus the average penalty is high. Therefore, the dashed curve in Fig. 3 fluctuates more severely than the solid curve. With the temporal flexibility of EVAs, uncertainties from different hours can be delayed to the same hour and thus may offset each other. As a result, the average penalty is lower in most hours when EVAs are used to mitigate uncertainties.

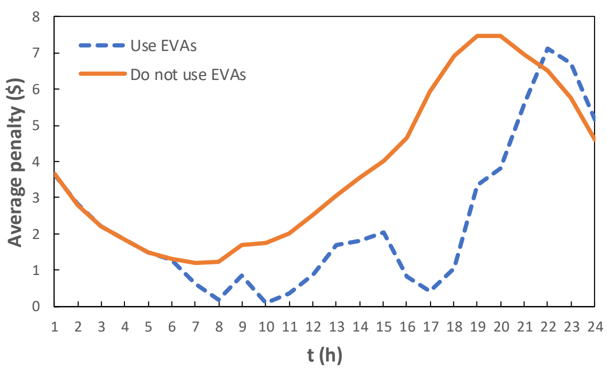

Fig. 3. Average penalty at each hour when EVAs are used to mitigate uncertainties and not

Case studies are also conducted by increasing cost coefficients of EVAs to 2 to 4 times of the original setting and relevant results are recorded in Table II. When EVAs are used to mitigate uncertainties, there are corresponding reserve costs and compensations to EVAs. But at the same time, average penalties decrease compared with the case that EVAs are not used, resulting in lower average total costs. When cost coefficients of EVAs increase, EVAs are used less extensively because using them becomes less economical. As a result, average penalties and average total costs increase and get closer to the values when EVAs are not used. Reserve costs and average compensations to EVAs increase first because of higher cost coefficients but then decrease as EVAs are rarely used. When cost coefficients are high enough, the result will be the same as when EVAs are not used to mitigate uncertainties.

TABLE II
CASE STUDIES ON DIFFERENT COST COEFFICIENTS OF EVAS

Using EVAs to mitigate uncertainties	Yes				No
Cost coefficients of EVAs	1*	2	3	4	-
Reserve costs ($/day)	4.80	7.72	7.91	5.43	0
Average compensations to EVAs ($/day)	7.21	11.59	11.81	8.10	0
Average penalties ($/day)	55.89	59.11	66.09	76.10	90.65
Average total costs ($/day)	67.91	78.42	85.84	89.65	90.65

* base case

C. Benefits of the uncertainty transferring scheme

Three potential benefits of the uncertainty transferring scheme are discussed in Section III.B and will be further illustrated here. Case studies are conducted with and without the uncertainty transferring scheme. As shown in Table III, with uncertainty transferring, savings in reserve costs and average compensations to EVAs are about 50% because now interruption to the charging of an EVA depends on uncertainties of several EVAs, which may offset each other. The other two benefits of the uncertainty transferring scheme are not significant under current parameters. To illustrate them more clearly, the above case studies are repeated with specific parameters modified. The original setting is represented as Setting 1, based on which Setting 2 and Setting 3 are created. In Setting 2, cost coefficients of the EVA at Bus 32 are set to half of their original values. In Setting 3, dispatchable ranges of the EVA at Bus 16 at all hours are set to 0. Setting 3 implies that the EVA at Bus 16 is non-dispatchable.

Results under Setting 2 are summarized in Table IV. Apart from relieving interruption to the charging of EVAs, the uncertainty transferring scheme can make use of the low cost coefficients of the EVA at Bus 32 by transferring uncertainties of other EVAs to it. As a result, savings in reserve costs and average compensations to EVAs brought by the uncertainty transferring scheme are about 76% and are higher than those under Setting 1.

Results under Setting 3 are given in Table V. Without the uncertainty transferring scheme, uncertainties of the EVA at Bus 16 cannot be mitigated as it is now non-dispatchable. In contrast, its uncertainties can be transferred to other EVAs to make use of their spare dispatchable capacities under the uncertainty transferring scheme and thus can be mitigated. Therefore, when the uncertainty transferring scheme is applied, reserve costs and average compensations to EVAs are higher but average penalties are much lower. The saving in average penalties increases from 3.02% under Setting 1 to 26.77% under Setting 3.

TABLE III
BENEFITS OF UNCERTAINTY TRANSFERRING IN RELIEVING INTERRUPTION TO THE CHARGING OF EVAS

With uncertainty transferring	No	Yes*	Savings brought by uncertainty transferring (%)
Reserve costs ($/day)	7.20	4.80	49.77
Average compensations to EVAs ($/day)	10.85	7.21	50.47
Average penalties ($/day)	57.58	55.89	3.02
Average total costs ($/day)	75.62	67.91	11.36

* base case

TABLE IV
BENEFITS OF UNCERTAINTY TRANSFERRING IN MAKING USE OF EVAS WITH LOWER COST COEFFICIENTS

With uncertainty transferring	No	Yes	Savings brought by uncertainty transferring (%)
Reserve costs ($/day)	6.21	3.51	76.88
Average compensations to EVAs ($/day)	9.34	5.30	76.49
Average penalties ($/day)	56.43	55.46	1.76
Average total costs ($/day)	71.98	64.26	12.02

TABLE V
BENEFITS OF UNCERTAINTY TRANSFERRING IN RELIEVING LIMITATION FROM THE DISPATCHABLE RANGES OF EVAS

With uncertainty transferring	No	Yes	Savings brought by uncertainty transferring (%)
Reserve costs ($/day)	4.02	4.54	-11.5
Average compensations to EVAs ($/day)	6.05	6.82	-11.3
Average penalties ($/day)	72.78	57.41	26.77
Average total costs ($/day)	82.85	68.78	20.46

D. Temporal and spatial correlations of the charging demands of EVAs and effectiveness of the proposed model in considering them

Simulated charging demands of EVAs with traffic congestion considered are adopted here. Instead of proving correlations between the charging demands of EVAs, simulation here is only to illustrate possible correlations. For space-saving purposes, temporal and spatial correlations of the charging demands of EVAs are illustrated through sub-matrices of the complete statistical covariance matrix. The statistical covariance matrix of charging demands of the EVA at Bus 16 from the 18th to 20th hour is represented as $\mathbf{\Sigma}_1$ and shown in (10). Significant positive temporal correlations between charging demands in adjacent hours can be observed, which is because the charging of EVs may not finish in the hour when EVs arrive home and may last to the following hour. The statistical covariance matrix of charging demands of all EVAs in the 19th hour is represented as $\mathbf{\Sigma}_2$ and shown in (11). There are significant positive spatial correlations between charging demands of different EVAs because traffic conditions pose similar influences on the travel of EVs from different EVAs and thus on charging demands of different EVAs as well.

$$\mathbf{\Sigma}_1 = \begin{bmatrix} 1031.7 & \mathbf{555.3} & 46.7 \\ \mathbf{555.3} & 1520.1 & \mathbf{513.9} \\ 46.7 & \mathbf{513.9} & 1150.3 \end{bmatrix} \tag{10}$$

$$\mathbf{\Sigma}_2 = \begin{bmatrix} 1520.1 & \mathbf{555.0} & \mathbf{735.7} \\ \mathbf{555.0} & 1554.6 & \mathbf{728.0} \\ \mathbf{735.7} & \mathbf{728.0} & 2313.4 \end{bmatrix} \tag{11}$$

Because temporal and spatial correlations of the charging demands of EVAs can be significant, it is crucial to consider them when making operation plans. Otherwise, sub-optimal solutions may be obtained. Case studies are conducted here to show the necessity of considering the correlations of charging demands of EVAs and the effectiveness of the proposed model in this aspect. A modified covariance matrix is generated by setting all covariance terms in the original statistical covariance matrix to zero. The proposed model is solved to obtain operation plans with the original and the modified covariance matrix, respectively. The average performance of obtained operation plans is recorded in Table VI. Under positive correlations, it is easier for interruption to the charging of EVAs to be greater than purchased reserve capacities given a fixed amount of purchased reserve capacities as the possibility that uncertainties offset each other decreases. Therefore, reserve capacities should be properly purchased from EVAs to avoid excessive compensations to them, in which regard the proposed model is effective. Overall, the average total cost is lower when uncertainty correlations are properly considered by the proposed model.

TABLE VI
CASE STUDIES WITH UNCERTAINTY CORRELATIONS CONSIDERED AND NOT

Considering uncertainty correlations	Yes	No
Reserve costs ($/day)	5.76	5.52
Average compensations to EVAs ($/day)	8.48	14.17
Average penalties ($/day)	58.66	60.38
Average total costs ($/day)	72.90	80.07

VI. FURTHER DISCUSSIONS

By setting the dispatchable ranges of EVAs to zero as shown in Section V.C, the proposed model can consider EVAs that choose to not follow the dispatch of the distribution system or have no flexibility. Other loads with uncertainties can also be considered by the proposed model as they are the same as non-dispatchable EVAs from the perspective of the distribution system. Besides, the proposed model can incorporate renewable energy sources as well. Uncertainties of these system components can be mitigated by dispatchable EVAs through the proposed uncertainty transferring scheme. The methodology adopted to solve the proposed model remains valid with respect to such modifications.

Although the discharging mode of EVAs is not considered in the current work, the proposed model can be extended to incorporate it. Then, EVAs may be able to provide greater flexibility as their dispatchable ranges may become larger. Power losses incurred by the discharging of EVAs can be evaluated through average discharging efficiencies of EVAs. When EVAs discharge, the influence of their uncertainties on energy consumptions of distribution systems are alleviated because of power losses caused by discharging, which will affect the distribution system's scheduling for the uncertainties of EVAs. Besides, binary variables need to be added for EVAs to avoid their simultaneous charging and discharging.

Linearized power flow equations for distribution networks from [14] are adopted in this paper, which neglects non-linear terms of power losses. As power losses are much smaller than power flows in distribution networks [14], neglecting them has tiny influences on the result but can greatly reduce the computational complexity. To further improve the accuracy of the proposed model, the linearized equations from [12] can be employed, which approximates the non-linear terms of power losses by piecewise-linear functions.

VII. CONCLUSIONS

In this paper, a comprehensive model is established to mitigate forecast uncertainties in distribution systems by using EVAs. With their temporal flexibility, uncertainties from different hours can be delayed to the same hour and thus may offset each other. The established model solves the operation plans by balancing costs of dispatching EVAs and penalties for deviations of distribution systems' energy consumptions from planned values. Therefore, as dispatching EVAs becomes cheaper, they will be used more extensively. Various benefits of the proposed uncertainty transferring scheme for the established model are verified through case studies.

Furthermore, the adopted distributionally robust optimization technique is shown to be effective in avoiding unnecessary costs by taking temporal and spatial correlations of the charging demands of EVAs into consideration.

References

[1] W. Wei, F. Liu and S. Mei, "Distributionally Robust Co-Optimization of Energy and Reserve Dispatch," in IEEE Transactions on Sustainable Energy, vol. 7, no. 1, pp. 289-300, Jan. 2016.

[2] Y. Chen, W. Wei, F. Liu, and S. Mei, "Distributionally robust hydro-thermal-wind economic dispatch," Applied Energy, vol. 173, pp. 511-519, 2016.

[3] S. I. Vagropoulos, D. K. Kyriazidis and A. G. Bakirtzis, "Real-Time Charging Management Framework for Electric Vehicle Aggregators in a Market Environment," in IEEE Transactions on Smart Grid, vol. 7, no. 2, pp. 948-957, March 2016.

[4] S. Li, M. Brocanelli, W. Zhang and X. Wang, "Integrated Power Management of Data Centers and Electric Vehicles for Energy and Regulation Market Participation," in IEEE Transactions on Smart Grid, vol. 5, no. 5, pp. 2283-2294, Sept. 2014.

[5] A. Saint-Pierre and P. Mancarella, "Active Distribution System Management: A Dual-Horizon Scheduling Framework for DSO/TSO Interface Under Uncertainty," in IEEE Transactions on Smart Grid, vol. 8, no. 5, pp. 2186-2197, Sept. 2017.

[6] N. Holjevac, T. Capuder, N. Zhang, I. Kuzle, and C. Kang, "Corrective receding horizon scheduling of flexible distributed multi-energy microgrids," Applied Energy, vol. 207, pp. 176-194, 2017.

[7] M. Sanchez ´ et al., “Regulatory recommendations for the deployment of flexibility,” Smart Grid Task Force, Brussels, Belgium, EU SGTF-EG3 Report, 2015.

[8] J. de Hoog, T. Alpcan, M. Brazil, D. A. Thomas and I. Mareels, "Optimal Charging of Electric Vehicles Taking Distribution Network Constraints Into Account," in IEEE Transactions on Power Systems, vol. 30, no. 1, pp. 365-375, Jan. 2015.

[9] X. Luo and K. W. Chan, "Real-time scheduling of electric vehicles charging in low-voltage residential distribution systems to minimise power losses and improve voltage profile," in IET Generation, Transmission & Distribution, vol. 8, no. 3, pp. 516-529, March 2014.

[10] S. Xia, S. Q. Bu, X. Luo, K. W. Chan and X. Lu, "An Autonomous Real-Time Charging Strategy for Plug-In Electric Vehicles to Regulate Frequency of Distribution System With Fluctuating Wind Generation," in IEEE Transactions on Sustainable Energy, vol. 9, no. 2, pp. 511-524, April 2018.

[11] Q. Huang, Q. Jia and X. Guan, "A Multi-Timescale and Bilevel Coordination Approach for Matching Uncertain Wind Supply With EV Charging Demand," in IEEE Transactions on Automation Science and Engineering, vol. 14, no. 2, pp. 694-704, April 2017.

[12] J. Zhao, J. Wang, Z. Xu, C. Wang, C. Wan and C. Chen, "Distribution Network Electric Vehicle Hosting Capacity Maximization: A Chargeable Region Optimization Model," in IEEE Transactions on Power Systems, vol. 32, no. 5, pp. 4119-4130, Sept. 2017.

[13] Y. Zheng, Z. Y. Dong, F. J. Luo, K. Meng, J. Qiu and K. P. Wong, "Optimal Allocation of Energy Storage System for Risk Mitigation of DISCOs With High Renewable Penetrations," in IEEE Transactions on Power Systems, vol. 29, no. 1, pp. 212-220, Jan. 2014.

[14] C. Zhang, Y. Xu, Z. Y. Dong and J. Ma, "Robust Operation of Microgrids via Two-Stage Coordinated Energy Storage and Direct Load Control," in IEEE Transactions on Power Systems, vol. 32, no. 4, pp. 2858-2868, July 2017.

[15] B. Zeng, X. Wei, D. Zhao, C. Singh, and J. Zhang, "Hybrid probabilistic-possibilistic approach for capacity credit evaluation of demand response considering both exogenous and endogenous uncertainties," Applied energy, vol. 229, pp. 186-200, 2018.

[16] G. Sadikoglu, "Modeling of Consumer Buying Behaviour Using Z-Number Concept," Intelligent Automation & Soft Computing, pp. 1-5, 2017.

[17] A. T. Saric and A. M. Stankovic, "An application of interval analysis and optimization to electric energy markets," in IEEE Transactions on Power Systems, vol. 21, no. 2, pp. 515-523, May 2006.

[18] X. Lu, K. W. Chan, S. Xia, B. Zhou and X. Luo, "Security-Constrained Multiperiod Economic Dispatch With Renewable Energy Utilizing Distributionally Robust Optimization," in IEEE Transactions on Sustainable Energy, vol. 10, no. 2, pp. 768-779, April 2019.

[19] Y. Zhang, S. Shen and J. L. Mathieu, "Distributionally Robust Chance-Constrained Optimal Power Flow With Uncertain Renewables and Uncertain Reserves Provided by Loads," in IEEE Transactions on Power Systems, vol. 32, no. 2, pp. 1378-1388, March 2017.

[20] D. Tang and P. Wang, "Probabilistic Modeling of Nodal Charging Demand Based on Spatial-Temporal Dynamics of Moving Electric Vehicles," in IEEE Transactions on Smart Grid, vol. 7, no. 2, pp. 627-636, March 2016.

[21] D. T. Nguyen and L. B. Le, "Optimal Bidding Strategy for Microgrids Considering Renewable Energy and Building Thermal Dynamics," in IEEE Transactions on Smart Grid, vol. 5, no. 4, pp. 1608-1620, July 2014.

[22] A. Lorca, X. A. Sun, E. Litvinov, and T. Zheng, "Multistage adaptive robust optimization for the unit commitment problem," Operations Research, vol. 64, no. 1, pp. 32-51, 2016.

[23] A. Lorca and X. A. Sun, "Multistage robust unit commitment with dynamic uncertainty sets and energy storage," IEEE Transactions on Power Systems, vol. 32, no. 3, pp. 1678-1688, 2017.

[24] J. Warrington, P. Goulart, S. Mariéthoz, and M. Morari, "Policy-based reserves for power systems," IEEE Transactions on Power Systems, vol. 28, no. 4, pp. 4427-4437, 2013.

[25] R. A. Jabr, "Adjustable robust OPF with renewable energy sources," IEEE Transactions on Power Systems, vol. 28, no. 4, pp. 4742-4751, 2013.

[26] J. Li, Z. Xu, J. Zhao and C. Wan, "A Coordinated Dispatch Model for Distribution Network Considering PV Ramp," in IEEE Transactions on Power Systems, vol. 33, no. 1, pp. 1107-1109, Jan. 2018.

[27] A. Ben-Tal, L. El Ghaoui, and A. Nemirovski, Robust optimization. Princeton University Press, 2009.

[28] K. Natarajan, M. Sim, and J. Uichanco, "Tractable robust expected utility and risk models for portfolio optimization," Mathematical Finance, vol. 20, no. 4, pp. 695-731, 2010.

[29] C. Wang, R. Gao, F. Qiu, J. Wang and L. Xin, "Risk-Based Distributionally Robust Optimal Power Flow With Dynamic Line Rating," in IEEE Transactions on Power Systems, vol. 33, no. 6, pp. 6074-6086, Nov. 2018.

[30] Metropolitan Travel Survey Archive. 2016. [Online]. Available: http://www.surveyarchive.org/

[31] B. Venkatesh, R. Ranjan and H. B. Gooi, "Optimal reconfiguration of radial distribution systems to maximize loadability," in IEEE Transactions on Power Systems, vol. 19, no. 1, pp. 260-266, Feb. 2004.

Xi LU received the B.Eng. degree in Electrical Engineering from North China Electric Power University in Beijing, China in 2015. He is currently pursuing the PhD degree in Electrical Engineering at The Hong Kong Polytechnic University, Hong Kong. His research interests include applications of robust optimization and distributionally robust optimization in power systems.

Ka Wing Chan (M’98) received the B.Sc. (Hons) and Ph.D. degrees in electronic and electrical engineering from the University of Bath, U.K., in 1988 and 1992, respectively. He currently is an Associate Professor and Associate Head in the Department of Electrical Engineering of the Hong Kong Polytechnic University. His general research interests include power system stability, analysis and control, power grid integration, security, resilience and optimization, demand response management, etc.

Shiwei Xia (M'12) received the B.Eng. and M.Eng. degrees in electrical engineering from Harbin Institute of Technology, Harbin, China, in 2007 and 2009, respectively, and the Ph.D. degree in power systems from The Hong Kong Polytechnic University, Hung Hom, Hong Kong, in 2015. He then stayed with the department and worked as a Research Associate and subsequently as a Postdoctoral Fellow in 2015 and 2016. Currently, he is with the State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources, School of Electrical and Electronic Engineering, North China Electric Power University, Beijing, China. His research interests include security and risk analysis for power systems with renewable energies, distributed optimization and control of multiple sustainable energy sources in smart grid.

Xian Zhang received the B.Sc. degree from North China Electric Power University, China, in 2009, the M.Sc. degree from Tsinghua University, China, in 2012, and the Ph.D. degree from The Hong Kong Polytechnic University, in 2019, all in electrical engineering. Her main fields of interest include smart grid and electric vehicle.

Guibin Wang received his B.E. and Ph.D. degrees in electrical engineering from Shandong University, Jinan, China and Zhejiang University, Hangzhou, China, in 2009 and 2014, respectively. From 2011 to 2014, he was also a Research Assistant in the Department of Electrical Engineering, Hong Kong Polytechnic University, Hong Kong. He is currently an Associate Research Professor in Smart Grid Institute, Shenzhen University, Shenzhen, China. His main research interests lie in electric vehicles and renewable energy.

Furong Li (SM'09) received the B.Eng. degree in electrical engineering from Hohai University, Nanjing, China, in 1990, and the Ph.D. degree in electrical engineering from Liverpool John Moores University, Liverpool, U.K., in 1997, with a dissertation on applications of genetic algorithms in optimal operation of electrical power systems.

She is currently a Professor and the Director of the Center for Sustainable Power Distribution, University of Bath, Bath, U.K. Her major research interests include the area of power system planning, analysis, and power system economics.