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The Impact of Uncertainty and Time Structure on Optimal Flexibility Scheduling in Active Distribution Networks

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ABSTRACT The authors focus on a model for system operators that uses centralized scheduling of multiple flexibility assets and services to minimize the cost of managing problems with grid congestion, voltages, and losses. The model schedules flexibility assets using stochastic optimization for AC optimal power flow in an active distribution network. The novelty of the contribution lies in its focus on how the dynamic capabilities of the flexibility resources are defined with regard to how uncertainty is resolved in the model. The impact of uncertainty is studied by using well-known quality measures from stochastic programming, such as the value of the stochastic solution. Moreover, the authors introduce a new measure related to the impact of representing uncertainty and flexibility when considering reactive power. By changing the time attributes of flexibility assets, the authors show the impact of uncertainty and time structure on a scheduling problem. The uncertainties considered are price and load levels. The findings reveal that the quality of the scheduling of each flexibility resource depends on using a stochastic model with a rigorous consideration of time and uncertainty.

INDEX TERMS Flexibility, active distribution networks, optimal power flow, scheduling, stochastic programming, uncertainty.

NOMENCLATURE

Abbreviations:

ADN	Active Distribution Network
CB	Shunt capacitor banks
DER	Distributed Energy Resource
DSO	Distribution System Operator
DVSS	Deviated value of stochastic solution
EEV	Expected value of expected solution
FSP	Flexibility Service Provider
ICT	Information-communication technologies
LV	Low-voltage
MV	Medium-voltage
OLTC	On load tap changer
PV	Photo-voltaic module
RP	Recourse problem
SDP	Semi-definite programming
SO	System operator
SOP	Soft open point
SOS2	Special Ordered Sets of type 2
SVC	Static VAR compensators
TSO	Transmission System Operator
VoLL	Value of lost load
VSS	Value of stochastic solution

Parameters:

$\beta_{s,t}$	Power price from the grid parameter
η_c, η_d	Battery charge and discharge coefficients parameters

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σ_k The percentage of load considered in correspondence of breakpoint k
$L^p_{s,i,t}$ Active load demand from node i, at time t, in scenario s
$L^q_{s,i,t}$ Reactive load demand from node i, at time t, in scenario s
P^{max}_g,P^{min}_g Upper and lower limits of active power purchase from the grid.
Q^{max}_g,Q^{min}_g Upper and lower limits of reactive power purchase from the grid.
R_s Probability of the occurrence for a scenario
SoC_{max} Parameter for maximum state of charge in batteries
VC_k Variable cost of load shifting parameter
Z_i Multiplying parameter for minimum battery capacity

Sets:
$g \in G$ Set of generators with index g
$i \in I$ Set of buses in network with index i
$j \in J$ Set of buses in network with index j
$k \in K$ Set of breakpoints with parameter index k
$s \in S$ Set of scenarios with index s
$t \in T$ Set of periods with hourly resolution with index t
$t_{shift} \in T$ Load shifting time index

Variables:
$\delta_{i,t}$, $\theta_{s,i,j,t}$ Voltage angles between buses i and j
ϵ_{t+1} Prediction error
$\hat{L}_{t+1}$ Forecasted load level
$\lambda_{s,i,t,k}$ Continuous variable between 0 and 1
ϕ_m, α AR(N)-process coefficients
$AF_{s,i,j,t}$ Active power flow between nodes i and j
$B_{i,j}$ Line reactance value in DC-OPF model
$C_{s,i,t}$,$C_{i,t}$ Costs of load shifting
$DP^+_{s,g,t}$, $DP^-_{s,g,t}$ Active power import or export from an external grid
$DQ^+_{s,g,t}$, $DQ^-_{s,g,t}$ Reactive power import or export from an external grid
L_{t+1} Historical load data for forecasting
$P^{char}_{s,i,t}$, $P^{dis}_{s,i,t}$ Charging and discharging amount of a battery
$P^{shed}_{s,i,t}$ Amount of active power curtailment
$P^{shift}_{s,i,t_{shift}}$ Amount of active power shift
$P_{s,g,t}$, $Q_{s,g,t}$ Active and reactive of scheduled production from a generator
$Q^{shed}_{s,i,t}$ Amount of reactive power curtailment
$Q^{shift}_{s,i,t_{shift}}$ Amount of reactive power shift
$RF_{s,i,j,t}$ Reactive power flow between nodes i and j
$S_{i,j}$ Current flow between nodes i and j
$SoC_{i,t}$ State of charge for a battery
$V_{s,i,t}$ Voltage magnitude
$Y_{s,ij}$ Impedance value in AC-OPF model

I. INTRODUCTION

The penetration of Distributed Energy Resources (DER), located close to where electricity is consumed, e.g., households or commercial buildings is increasing considerably in the last years. However, due to the often-intermittent nature of DERs, as well as variations in demand, such developments can also cause several problems in low-voltage (LV) grid designs such as voltage variations (drops/rises), grid congestion, and network losses. Increases in electricity load are likely to continue in the future [1]. To solve these problems at grid level, distribution system operators (DSOs) have shifted from traditional passive and unidirectional distribution networks to bidirectional active distribution networks (ADNs).

An ADN can be described as a network system with control over its distributed generation resources. Some of the enabling technologies for ADNs are storage resources, demand-response programs, dynamic line ratings, and voltage/power control technologies [2].

In this regard, *flexibility* refers to the ability of a power system to respond to changes in demand and supply [3]. Based on recent developments in ICT, different levels of demand-side flexibility resources based on demand response programs and technologies could contribute to the efficiency of the ADNs by activating end users and their flexibility assets [4]–[6]. In this paper, we focus on the grid-relevant issues, including network congestion, voltage variation problems, and network losses, and investigate the impact of time and uncertainty on the activation of required flexibility services.

Several studies have reported on the traditional use of active management resources, such as on-load tap changers (OLTCs), static VAR compensators (SVCs), shunt capacitor banks (CBs), and standard operating procedures (SOPs), to deal with grid operational challenges(e.g., [7]). However, traditional solutions require significant investments in grid infrastructure and therefore flexible electricity resources can contribute to deferral of such investments. In this study, we focus on flexible electricity resources such as demand-response programs, change in supply, and batteries, which do not require additional investments in grid infrastructure and technology [8].

A. RESEARCH METHOD

In a traditional power market, grid congestion, voltage variations, network losses, and frequency deviations are handled by a system operator (SO) using ancillary services. Recent developments in DERs and demand-side flexibility (response) programs [9], [10] suggest that low-voltage grid issues resulting from high demand or high levels of local power generation could be dealt with at the distribution networks level [11]. In this context, traditional passive distribution networks are transformed into ADNs. Different flexibility assets, such as demand-side flexibility resources, batteries, and DERs are considered local flexibility assets in the ADN. Most of the aforementioned resources are stochastic in nature [12], but they can still play a crucial role in demand-side management and low-voltage grid operation. This is particularly the case when central operators have the possibility to shift or curtail loads over a particular period or to use energy storage or batteries when necessary. Therefore, the SO needs to assess possible future developments in terms of uncertainties and time.

In this paper, we study the impact of time and uncertainty on the decision processes of SOs in ANDs [13]. An SO uses centralized scheduling of multiple flexibility assets and services to minimize the cost of managing problems relating to network congestion, voltage variations, and network losses. A number of authors have studied uncertain parameters such as price, load, renewable generation, and fault situations in distributional grids in connection with optimal response to system or market conditions [14]. The novelty in this paper is our focus on how the dynamic capabilities of the flexibility resources (e.g.,) time are defined, how uncertainty is resolved in our optimal scheduling model, and the characteristics of the flexible assets. Two important parameters for optimal decision-making at the operational level are activation (response) time and duration of the flexibility provided by the assets. Fig. 1 shows the characteristics of a flexibility resource (asset), in which the SO procures a certain amount of flexibility from flexibility service providers (FSPs).

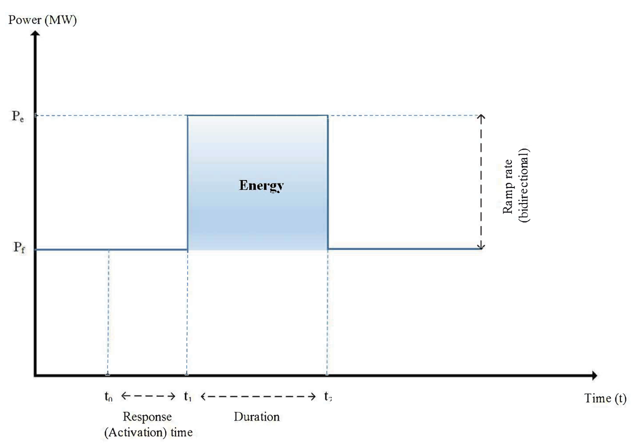

FIGURE 1. Characteristics of a flexibility resource base for time and power [15].

To study the impact of uncertainty representation when scheduling flexible assets in ADN management, we use well-known quality measures from stochastic programming, including the value of the stochastic solution. We also introduce a new measure related to uncertainty and flexibility when considering reactive power. By varying the characteristics relating to activation time and duration of flexibility provision from these assets, our analysis shows that the presentation of uncertain information regarding load and price in a model is very important when considering the value of flexibility.

A stochastic two-stage AC optimal power flow (AC-OPF) model is used in the analyses. The results can be generalized to a multistage setting. However, two stages are deemed sufficient to illustrate the importance of the information structure of the model, namely the time when uncertainty is resolved and how that affects decisions and the representation of flexibility in the available assets regarding activation time and duration of the flexibility supply. In peak load situations in which voltage drops and/or network congestion problems occur, the SO implements dynamic scheduling of a portfolio of flexible assets. The primary objective is to present the impact of uncertainty representation and timing on both active and reactive power. Accordingly, a moving interval approach is used, whereby both the first stage decisions and the recourse decisions in the second stage of the stochastic model are affected by the response and duration times of the assets. Fig. 2 shows the moving interval method, which uses load shifting for flexibility.

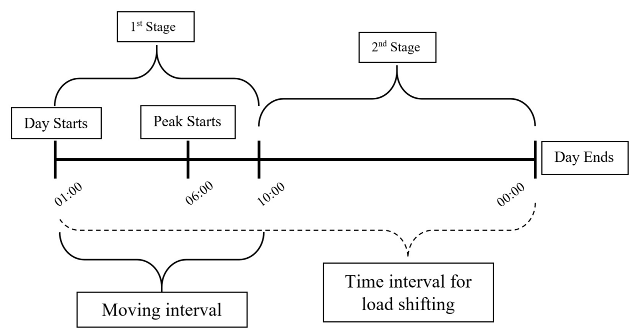

FIGURE 2. Timeline of the moving interval method.

B. LITERATURE REVIEW AND CONTRIBUTIONS

Authors in [16] investigated time aspects of flexibility provision through a qualitative survey-based study of different companies. They found that timing-based business models could perform in very short time intervals to complement traditional power generation capabilities when managing changes in generation or consumption plans.

An SO needs to choose between grid upgrades and using flexibility products by considering the time dimension of the network configuration and demand-side flexibility. Different factors such as response time, duration, and power amount of the demand-side flexibility, affect the ability to use flexibility assets to replace or delay network upgrades [8].

The time characteristics of some flexibility assets (technologies) could enable the assets to provide value in multiple time intervals. The authors in [15] conducted a survey to evaluate different flexibility technologies with respect to their time dimension and found that for optimal valuation and usage of flexibility resources, the decision-maker (in our case the SO) needs to know the time characteristics of the scheduled flexible asset before physical delivery of the flexibility services. The literature provides examples of stochastic models for scheduling flexible assets at the level of microgrids, DSOs, and transmission system operators (TSOs), based on central control [17], [18]. Often, such modeling approaches are based on optimal power flow models for scheduling and flexibility procurement [19], [20]. The importance of duration and activation times for flexibility assets (time characteristics) are discussed by [15], [21], but the authors do not present quantitative studies of flexibility in grid operations and the impact of uncertainty on flexibility services and assets. To our knowledge, no studies to date have used stochastic programming to examine both uncertainty and characteristics of flexibility (e.g., duration, activation time, and their relationships) in a dynamic schedule. This article makes a contribution in this respect.

In the case of ADNs, some studies present methods to deal with DERs and uncertain loads in cases of network congestion and voltage variation problems. Besides active management resources in ADNs, an SO or centralized management could use economic incentives and market-based approaches to mitigate such problems. As one approach, [22] present a congestion management strategy with a market-based mechanism and SOPs. Since original SOP-based congestion management is a non-convex problem, they applied convex relaxation, namely semidefinite programing (SDP). They specifically did not use demand-side flexibility such as load shifting and shedding. In another approach, authors in [23] used flexible demand and storage systems for an ADN with dynamic OPF modeling. Their results showed the efficiency of the use of flexible demand and storage systems for ADNs. In a recent study, [24] present a method for two-stage hierarchical congestion management in ADNs with SOPs, tie switches, DERs, and a microgrid. They used SOPs and switches as direct control mechanisms, while DERs contributed through a market. The above-discussed studies demonstrate the efficiency of flexibility in ADN management, but without emphasizing the impact of time and uncertainty in scheduling and decision making.

The authors in [25] and [26] discuss reactive power provision from DERs via market designs (optimal reactive power dispatch). Both sets of authors state the importance of uncertainty from the DER perspective. However, they do not discuss the provision of reactive power from demand-side flexibility assets for grid operations according to the time dimension. Our stochastic flexibility provision framework, which is the second contribution of this paper, includes the reactive power component.

Recent research on flexibility usage has focused on demand uncertainty [27], uncertainty in renewable resource generation [28], PV generation and ambient temperature uncertainties [17], and uncertain reserves from demand response [29]. In this paper, we mainly discuss uncertainties regarding resources and their availability in a binary manner (i.e., the power resource is either available at a certain level or not), rather than representing duration and time lags for activation (response).

The contributions of this paper are summarized as follows:

- We investigated the impact of uncertainty in decision-making and the importance of how to represent the time dimension (i.e., duration and activation (response) time) when scheduling flexibility assets and services as well as how uncertainty is resolved in optimal scheduling model.
- A new quality measure is introduced to evaluate the significance of representing uncertainty about availability of the usage in different assets, with a focus on reactive power.
- The impact of uncertainty and time when scheduling each flexibility asset is examined by applying two variants of our optimal scheduling model.

Our evaluations use both this new quality measure and traditional ones such as the Value of the Stochastic Solution [30].

The paper is structured as follows. Section II discusses the concept and the different flexible assets. Section III describes the mathematical model. Section IV explains the representation of stochasticity and scenario generation. Section V introduces a case study from Norway and the results of optimal scheduling. Section VI explains quality measures and the impact of how uncertainty is represented with regard to the activation time and the duration characteristics of the flexible assets.

II. FLEXIBILITY ASSETS AND SERVICES

Our study includes two primary demand-side flexibility resources: demand response in terms of load curtailment and load shifting; demand response in terms of storage.

A. DEMAND-SIDE FLEXIBILITY SERVICES-LOAD SHIFTING AND CURTAILMENT

Load curtailment is defined as a reduction in the maximum load (peak shaving) for a predefined duration and payment for a prosumer/consumer. As a flexibility asset, load curtailment is prepared for immediate use by the central system operator. The cost of using load curtailment could be too high in some circumstances and therefore the duration of this asset is less than other assets. However, the response time is shorter than that of other measures due to an immediate cut in consumption.

Load shifting differs from load curtailment in terms of cost, duration, and activation time. The main condition for shifting any flexible load is that it is possible to meet total demand after the shift. An SO or asset owner could shift the consumption within a time interval for specific **load volumes**. The load profile can be changed, but the total energy delivered over the planning horizon must be preserved. Alternatively, the whole **load profile** can be shifted. In this paper, we discuss the first approach with load preservation within a planning horizon. For a further discussion of the load shifting, see [31].

The duration and response time of load shifting, time dimensions illustrated in Fig. 1, are important attributes concerning its timing. The provision for flexibility through load shifting needs careful consideration, as it must include enough time to shift the volume as well as to meet the total power demand. Moreover, the load shifting should remain in the solution process for sufficient time for cost-efficient solution (duration).

Demand-side flexibility assets such as load shifting and load curtailment include uncertainty about their duration response time and load amount. Any changes in the time dimensions of these assets will also change the degree of uncertainty during the flexibility usage for grid problems.

B. STORAGE FLEXIBILITY- BATTERIES

The use of batteries allows for flexibility without incurring any operating costs. The reactive power compensation capability of PV inverters can be used to regulate the voltage magnitude [32]. In this paper, we discuss only active power sourced from batteries.

Batteries are flexible with respect to timing and managing uncertainty. An SO can plan exactly how long a battery should remain in flexibility usage process and batteries can be activated whenever the SO needs them to provide power.

C. SYSTEM ARCHITECTURE

Our proposed power system architecture has a central SO that can procure flexibility services from flexibility assets connected to an LV grid within limits defined by bilateral contracts with the asset owner. The contracts specify how the load can be shifted or curtailed within predefined limits and how batteries can be used to address grid operational issues. The central SO procures flexibility from the FSPs at a pre-agreed cost that reflects the batteries' disutility. The assets are located in residential areas, but the flexibility is controlled by the operator. The architecture of the suggested solution is shown in Fig. 3.

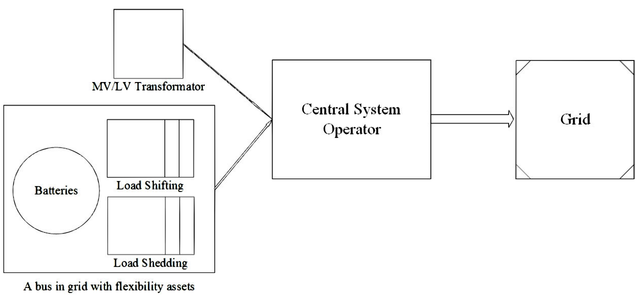

FIGURE 3. Proposed power system architecture.

1) COSTS OF FLEXIBILITY ASSETS

In the studied case from Norway, load curtailment is a voluntary action. Therefore, the cost is set at 1500 EUR/MWh, which is lower than the normal value of lost load (VoLL). The disutility cost [31] used for load shifting is shown as a piecewise-linear cost curve. The shifting is based on voluntary actions and therefore the cost is assumed to be lower than the VoLL, but it will increase with volume.

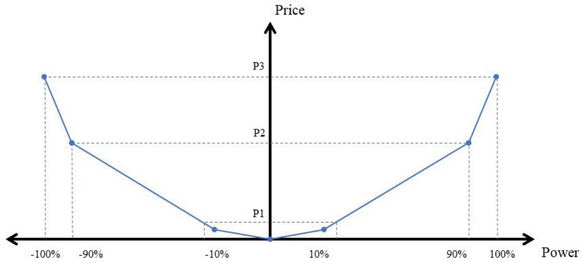

FIGURE 4. Piecewise-linear cost curve with four increments.

The disutility cost curve for load shifting includes four increments and five breakpoints on the cost curve, as presented in Fig. 4. Breakpoints in the cost function, as well as other details, are defined based on studies of variable costs of end-user appliances [33], [34].

III. MATHEMATICAL MODEL: STOCHASTIC TWO-STAGE AC OPTIMAL POWER FLOW

In this section, we present the stochastic two-stage AC-OPF model with demand-side and storage flexibility. The background information on load shifting was sourced from [31], whereas the AC-OPF model is based on the work of [35]. For comparison, both in terms of solution times and solution quality, we consider an AC formulation and an alternative DC relaxation formulation of power flow for the second-stage of the stochastic model.

We used a two-stage stochastic program to model the uncertainty in demand and prices [36]. The two stages, the uncertainties, and the decision-making process are all shown in Fig. 5. In the first 10 periods, all scheduling and load/supply balances are performed without knowing which of the scenarios will occur at $t = 11$ hence without knowing the realizations of load and prices from that point until the end of the problem's time horizon. Before $t = 11$, the parameters such as load and prices are deterministic. At $t = 11$ one of the scenarios will be realized and scheduling of flexible assets will be scenario-contingent from thereon. The main purpose

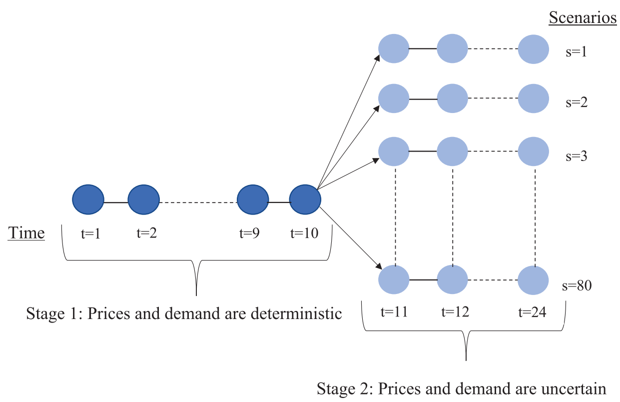

FIGURE 5. Two-stage decision-making structure with uncertainties.

of the stochastic program is to minimize the expected costs for all periods, considering the uncertainty process.

A. OBJECTIVE FUNCTION

The objective function in (1) aims to minimize the total system cost. There are four terms in the expression. The first two represent the deterministic first-stage decisions. The third and fourth terms represent exactly the same costs in the second stage and therefore variables are scenario-dependent, indexed by s, and the terms are multiplied by probability R_s. The first term includes the cost of electricity imported from the medium-voltage (MV) grid. $DP^+_{g,t}$, $DP^-_{g,t}$ are active power import and export from external grid and β_t is the electricity price. The second term consists of the active power load curtailment $P^{shed}_{i,t}$ as well as the cost of load shifting at time t in bus i, $C_{i,t_{shift}}$.

$$\begin{aligned} \text{minimize} & \sum_{t\in T}\sum_{g\in G}\left[DP^+_{g,t}\beta_t + DP^-_{g,t}\beta_t\right] \\ & + \sum_{i\in I}\sum_{t\in T}\left[\text{VoLL} * P^{shed}_{i,t} + C_{i,t_{shift}}\right] \\ & + \sum_{s\in S} R_s\left[\sum_{t\in T}\sum_{g\in G}\left[DP^+_{s,g,t}\beta_{s,t} + DP^-_{s,g,t}\beta_{s,t}\right]\right. \\ & \left. + \sum_{i\in I}\sum_{t\in T}\left[\text{VoLL} * P^{shed}_{s,i,t} + C_{s,i,t_{shift}}\right]\right] \end{aligned} \tag{1}$$

B. CONGESTION CONSTRAINTS

To prevent grid congestion, the equation 2 is added to the optimization problem with active power flow $AF^2_{s,t,i,j}$, reactive power flow $RF^2_{s,t,i,j}$ and upper limit of the line usage, S^2_{ij}, between buses i and j.

$$AF^2_{s,t,i,j} + RF^2_{s,t,i,j} \leq S^2_{ij} \tag{2}$$

In the variant model with DC power flow, grid congestion is modeled in (3). The equation provides an upper limit for active power flow between buses i and j. The impacts of equations (2) and (3) are discussed in Section VI.

$$AF_{s,t,i,j} \leq S_{ij} \tag{3}$$

C. IMPORT AND EXPORT CONSTRAINTS FROM AN EXTERNAL GRID

These import and export constraints in equations (4) and (5) represent the imported active power, $P_{s,g,t}$, and imported reactive power, $Q_{s,g,t}$, from the external grid. In our case study, the external grid is connected to the first bus in the LV grid and can be considered as a source of an external flexibility asset.

$$P_{s,g,t} = DP^+_{s,g,t} - DP^-_{s,g,t} \tag{4}$$
$$Q_{s,g,t} = DQ^+_{s,g,t} - DQ^-_{s,g,t} \tag{5}$$

D. POWER FLOW CONSTRAINTS

The AC power flow constraints enforces the active and reactive power balance at each bus in the LV grid for voltage regulations, $V_{s,i,j,t}$, at each bus.

$$\begin{aligned} AF_{s,i,j,t} &= V^2_{s,i,t}Y_{ij}cos\theta_{s,ji} \\ &\quad - V_{s,i,t}V_{s,j,t}Y_{ij}cos\left(\delta_{s,i,t} - \delta_{s,j,t} + \theta_{s,ij}\right) \end{aligned} \tag{6}$$
$$\begin{aligned} RF_{s,i,j,t} &= V^2_{s,i,t}Y_{ij}sin\theta_{s,ji} \\ &\quad - V_{s,i,t}V_{s,j,t}Y_{ij}sin\left(\delta_{s,i,t} - \delta_{s,j,t} + \theta_{s,ij}\right) \\ &\quad - \frac{bV^2_{i,t}}{2} \end{aligned} \tag{7}$$

In some the following formulations we use a DC optimal power flow equation in case we want to see the impact of uncertainty on just the active power balance (without considering voltage regulations):

$$AF_{s,i,j,t} = B_{i,j}\left(\theta_{s,i,t} - \theta_{s,j,t}\right) \tag{8}$$

E. LOAD BALANCE CONSTRAINTS

For each bus in our grid topology, equations (9) and (10) represent net demand, including flexibility for active and reactive power from all flexibility assets in the grid. In equation (9), we obtain active power from batteries, demand-side assets and services, and the main grid. In equation (10), we obtain reactive power from demand-side assets and the main grid only. The last two equations (11 and 12) show the upper and lower limits of purchases from the MV grid.

$$\begin{aligned} AF_{s,t,i,j} &= \sum_{g\in G_i} P_{s,i,g,t} + \left(P^{dis}_{s,i,t} - P^{chr}_{s,i,t}\right) \\ &\quad + P^{shift}_{s,i,t,t_{shift}} - L^p_{s,i,t} + P^{shed}_{s,i,t} \end{aligned} \tag{9}$$
$$\begin{aligned} RF_{s,t,i,j} &= \sum_{g\in G_i} Q_{s,i,g,t} \\ &\quad + Q^{shift}_{s,i,t,t_{shift}} + Q^{shed}_{s,i,t} - L^q_{s,i,t} \end{aligned} \tag{10}$$
$$P^{min}_g \leq P_{s,t,g} \leq P^{max}_g \tag{11}$$
$$Q^{min}_g \leq Q_{s,t,g} \leq Q^{max}_g \tag{12}$$

F. BATTERY CONSTRAINTS

Equations (13)–(16) represent the state of charge (SoC) in the batteries ($SoC_{s,i,t}$), the limits of the SoC, and the maximum and minimum charging capacities, respectively.

$$SoC_{s,i,t} = SoC_{s,i,(t-1)} + P^{char}_{s,i,t} * \eta_c - \frac{P^{dis}_{s,i,t}}{\eta_d} \tag{13}$$
$$SoC^{min} \leq SoC \leq SoC^{max} \tag{14}$$
$$0 \leq P^{char}_i \leq Z_i \cdot SoC^{max}_i \tag{15}$$
$$0 \leq P^{dis}_i \leq Z_i \cdot SoC^{max}_i \tag{16}$$

G. LOAD CURTAILMENT CONSTRAINTS

In equations (18) and (19) the amount of load curtailment is limited by $L^p_{s,i,t}$ for active power demand, and $L^q_{s,i,t}$ for reactive power demand in each bus (the power factor in (17) is assumed to be constant at each bus).

$$Q^{shed}_{s,i,t} = P^{shed}_{s,i,t}\, tan(\theta_{s,i}) \quad (17)$$
$$0 \leq P^{shed}_{s,i,t} \leq L^{p}_{s,i,t} \quad (18)$$
$$0 \leq Q^{shed}_{s,i,t} \leq L^{q}_{s,i,t} \quad (19)$$

H. LOAD SHIFTING CONSTRAINTS

The load shifting formulation is based on [31] and states that the total load volume could be reallocated in any period within the planning horizon: $t_{shift} \in \left[t^{down}_{shift}, t^{up}_{shift}\right] \subset T$. Within t_{shift}, our model is obliged to satisfy all demands at each bus.

Four equations represent the convex cost function of load shift, and in Fig. 4 they are depicted as the cost curve. The reference equation (20) gives the amount of load shifting ($P^{shift}_{s,i,t_{shift}}$), and equation (21) gives the cost of load shifting ($C_{s,i,t_{shift}}$) as the function equation. The convexity equation (22) creates a convex combination of auxiliary variables $\lambda_{s,i,t_{shift},k}$ with one of the variable's immediate neighbors. In a minimization problem with a convex and piecewise linear cost curve, such a formulation leads to an exact formulation without resorting to the formulation of Special Ordered Sets of type 2 (SOS2) variables. Equation (23) is used to calculate the load profile balance, which ensures that the shifted load is energy preserving at the end of the interval. Equation (24) calculates the shifted reactive power load.

$$P^{shift}_{s,i,t_{shift}} = \sum_{k\in K} \lambda_{s,i,t_{shift},k} L^{p}_{s,i,t}\sigma_k \quad (20)$$

$$C_{s,i,t_{shift}} = \sum_{k\in K} \lambda_{s,i,t_{shift},k} L^{p}_{s,i,t}\sigma_k VC_k \quad (21)$$

$$\sum_{k\in K} \lambda_{s,i,t_{shift},k} = 1, \quad 0 \leq \lambda_{s,i,t_{shift},k} \leq 1 \quad (22)$$

$$\sum_{t_{shift}} P^{shift}_{i,t_{shift}} + \sum_{t_{shift}} P^{shift}_{s,i,t_{shift}} = 0,$$
$$t^{down}_{shift} \leq t_{shift} \leq t^{up}_{shift} \quad (23)$$
$$Q^{shift}_{s,i,t} = P^{shift}_{s,i,t} * tan(\theta_{s,i}) \quad (24)$$

where σ_k represents the percentage of load considered in correspondence of breakpoint k. After exceeding 10% and 90% respectively of the total load in each bus, different variable costs and increments in the cost function are activated. Concerning the $\lambda_{s,i,t_{shift},k}$ value, reference row increments will be activated and will give the cost of a load shift according to the related variable cost, γ_k. For the 10% shift and 90% shift, are EUR 10/MWh and EUR 50/MWh respectively based on [33].

I. VOLTAGE ANGLE AND MAGNITUDE LIMITS

The following equation (25) gives the magnitude limits for voltages:

$$0.9 \leq V_{s,i,j,t} \leq 1.1 \quad (25)$$

IV. STOCHASTICITY AND SCENARIO GENERATION

The main analysis is performed with a two-stage stochastic model in which load and electricity power prices are deterministic to describe scenarios representing the second-stage uncertainty, a scenario generation algorithm based on a combination of forecasting and *moment-matching* of residuals [37], [38] is used. This is similar to the approach used by [39]. Our method, which is based on articles by [37]–[39], collects the historical data, establishes (parameterizes) an autoregressive forecast model for load in the buses and prices, and combines estimated realizations for these into a scenario tree representing the realizations.

Probability distributions for the errors (residuals) in the load and price forecasts are used as a basis for modeling the uncertainty. For each error distribution, we estimate moments such as mean, variance, skewness, and kurtosis. Next, we use an algorithm for moment-matching scenario generation to estimate joint error distributions for prices and the 80 buses for all periods in the second stage. The approach captures both temporal correlations (through the forecasts) and inter-variable correlation (through the moment matching). The main feature of the scenario generation algorithm is to combine the time series information for the load in the 80 buses and price with the generated error distributions from the moment matching, thus enabling us to capture both the time correlation and inter-variable correlation. The scenario generation method is convenient to use in short-term scenario tree constructions [40], as described in the following six steps:

Step 1: Forecast the load in each bus. For each bus, use an $\mathbf{N}^{th}$ order, AR(N)-process to forecast load:

$$\hat{L}_{t+1} = \alpha + \sum_{m=1}^{N} \phi_m L_{t+1-m} + \epsilon_{t+1} \quad (26)$$

where L_{t+1} is the historical load data, $\hat{L}_{t+1}$ is forecasted load level, ϵ_{t+1} is the residual or prediction error and ϕ_m and α are AR(N)-process coefficients. This is parameterized based on historical data.

Step 2: Calculate the historical residuals of the forecasted parameters. This residual distribution will be the basis for all scenarios in all periods as the error processes are stationary.

Step 3: Calculate the statistical properties of the error distributions. Calculate the mean ($\bar{\epsilon}_{t+1} \sim$), variance ($Var(\epsilon_{t+1} \sim)$), skewness ($Skew(\epsilon_{t+1} \sim)$), and kurtosis ($Kurt(\epsilon_{t+1} \sim)$) and correlations between the residual series ($Corr(\epsilon_{t+1})$)

Step 4: Create a joint error distribution. It should be noted that this is valid in all periods because the errors are stationary. Use Høyland *et al.*'s moment-matching algorithm [37] to create a discrete joint scenario tree with error distribution for price and load in all the buses. The joint distribution approximates the four moments and correlations using s outcomes for the residuals (ϵ^{s}_{t+1}). In our case, the number of scenarios in the distribution is $s = 80$. The spatial (inter-variable) correlations of variables in scenarios are captured by the moment-matching algorithm. It should be noted that our algorithm captures the correlation of forecast model residuals, not the variables themselves.

Step 5: Create the first stage of the scenario tree. A scenario tree can be made by first using the forecasting methods directly for the first t_1 periods in a *rolling window* approach where in if t is the last observed period and $t+1$ is the first forecasted period, we will have

$$\hat{L}_{t+1} = \alpha + \sum_{m=1}^{N} \phi_m L_{t+1-m} \tag{27}$$

Then, proceed with

$$\hat{L}_{t+2} = \alpha + \phi_1 \hat{L}_{t+1} + \sum_{m=2}^{N} \phi_m L_{t+2-m} \tag{28}$$

until

$$\hat{L}_{t+t_1} = \alpha + \sum_{m=1}^{N} \phi_m \hat{L}_{t+t_1-m} \tag{29}$$

Step 6: Create the second stage of the scenario tree. For each second stage scenario s, we follow the same procedure, but, add the term ϵ_t^s, which is a sample of the error in period t used in scenario s. It is sampled from the s outcomes from Step 4 (without replacement), such that all S outcomes are used in a scenario within a period. This is then repeated for $t = t_1, \ldots, t_2$. The variables in each of the second stage scenarios can then be represented as

$$\hat{L}_{t+1}^s = \alpha + \sum_{m=1}^{N} \phi_m L_{t+1-m} + \epsilon_t^s \tag{30}$$

$$\hat{L}_{t+2}^s = \alpha + \hat{L}_{t+1}^s + \sum_{m=2}^{N} \phi_m L_{t+2-m} + \epsilon_t^s \tag{31}$$

until

$$\hat{L}_{t+t_2}^s = \alpha + \sum_{m=1}^{N} \phi_m \hat{L}_{t+t_2+1-m}^s + \epsilon_t^s \tag{32}$$

where $s = 1, \ldots, S$.

Without loss of generality, the above assumes that $m \leq t_1$ and $m \leq t_2$.

In our research, we parameterize 17 different (S)ARIMA load models, one for each bus in the grid. The same procedure is used to generate separate scenarios for the grid power price. Thereafter, the load and price scenarios are combined randomly, so that on expectation the expected correlation between the load and price is zero. We generate 80 joint scenarios for loads at every bus and the grid price. We capture the spatial correlation of model residuals because the load profiles of each variable are located in the same place, and they have similar time-series patterns. Furthermore, variables do not affect the national grid prices. Our model calculates in-sample accuracy simultaneously while generating scenarios at out-of-sample.

V. CASE STUDY FROM SOUTHERN NORWAY

In this section, we analyze the results of our case study of the islands that constitute Hvaler Municipality in southern Norway, in January 2016. The municipality has approximately a population of 4100, in 2016, whereas on warm summer days there can be ca. 40,000 people due to the number of second homes [41]. Consumers locate in the area are commercial buildings, two- to four-family houses, and Norwegian holiday homes. In addition to the second homes, there are two-family and to four-family residential buildings and commercial buildings.

The 22kV and 230V radial grid structure in this study is synthetically generated based on Hvaler Municipality, and it contains 26 buses, of which 17 buses have electricity demand and they represent households. The network is an LV grid and therefore we expect to see voltage problems and congestion. The radial topology of the grid is presented in Fig. 6. Red buses are end users with demand-side flexibility capacities. The first bus is the connection point to the MV grid with a transformer. Therefore, possible congestion might occur on the line between buses 1 and 26.

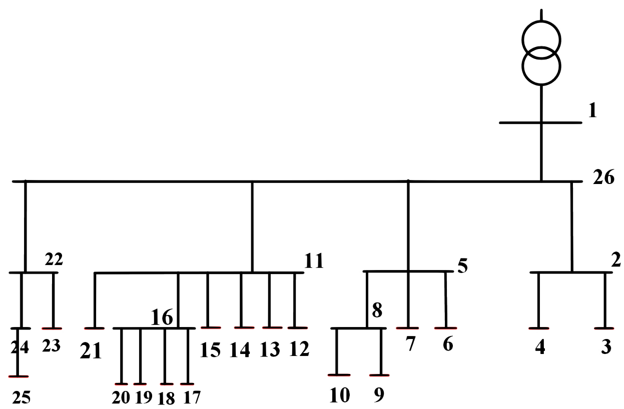

FIGURE 6. Radial grids structure based on Hvaler Municipality.

The anonymous data and demand-side flexibility parameters were provided by a distribution system operator (DSO). The data are observations of the grid participants and include the load profiles of 17 end users from January 1, 2014 to December 31, 2016. We used MATPOWER[1] to conducted power flow analysis in order to identify existing voltage and congestion problems on a predetermined day. Based on power flow analysis, the active and reactive power demands from each bus are represented in Fig. 7 and Fig. 8, respectively.

There are five batteries with 14 kW capacities connected to buses 6, 10, 13, 18, 23 (battery sites). In cases of immediate load curtailment, the system operator pays the VoLL to end users.

We use two main approaches in this research for optimal scheduling of flexibility assets. First, by using historical data, we solve a deterministic AC-OPF problem. Later,

[1] https://matpower.org/

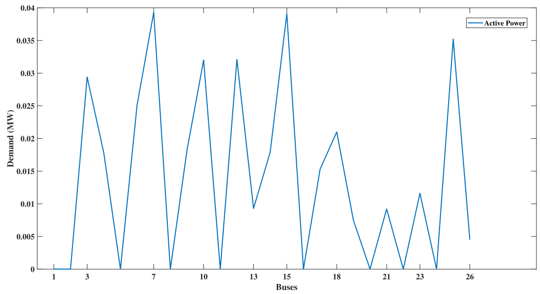

FIGURE 7. Fixed active power demand from each bus (MW).

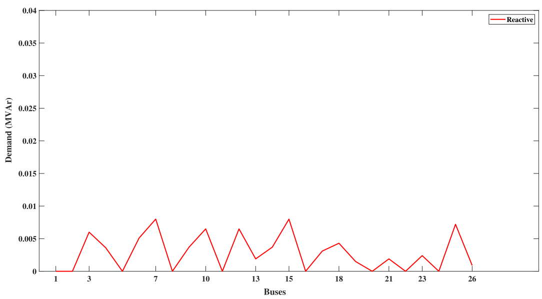

FIGURE 8. Fixed reactive power demand from each bus (MVAr).

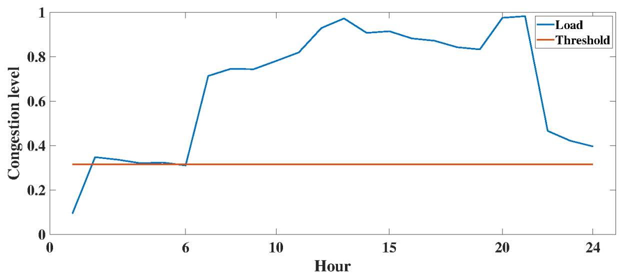

FIGURE 9. Congestion level on the predetermined sample day (hourly) in the case study.

to observe the impact of uncertainty in load and prices, we apply the two-stage stochastic AC-OPF model. The problems are solved using KNITRO and GAMS on a computer with Intel(R) Core(TM) i7-7500U processor at 2.70GHz and with 16GB RAM. The total run time for the deterministic case is 33 seconds, and for the stochastic case is 15 minutes.

A. GRID PROBLEMS

1) CONGESTION PROBLEM

Congestion in an LV grid results from pushing the physical limits of network lines, such as voltage limits, stability limits, and thermal limits [42]. The level of congestion in the case study on the predetermined sample day is presented in Fig. 9.

2) VOLTAGE VARIATIONS

If there is insufficient reactive power from system participants, a voltage variation problem will occur [42]. In our case study, the problem was a voltage drop due to high demand on the sample day (see Fig. 10).

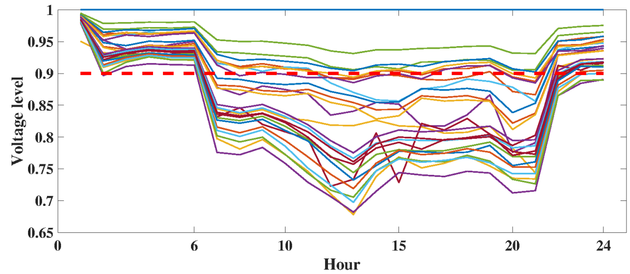

FIGURE 10. Voltage profiles on the sample day (hourly) in the case study.

B. DETERMINISTIC RESULTS

For the deterministic part of our study we used a single scenario AC-OPF model to schedule flexibility assets to keep the voltage within the required interval. In equations (6) and (7) buses are kept within the voltage interval, and grid congestion at the MV/LV transformer is prevented with Eq. (2). The results of the imported power from the MV grid, the state of charge (SoC) of the batteries, and the load shifting amount are respectively presented in Fig. 11, Fig. 12, Fig. 13.

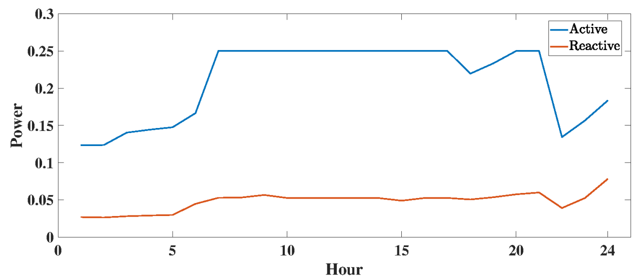

FIGURE 11. Power from the main grid (MWh).

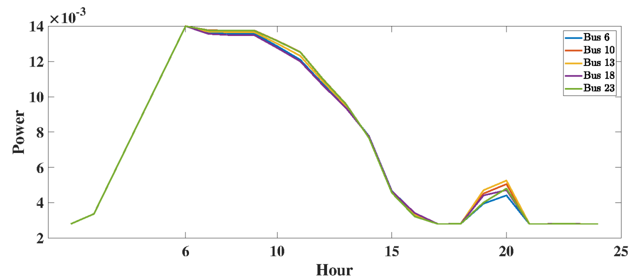

FIGURE 12. Battery SoC in the deterministic solution (MWh).

1) DISCUSSION OF DETERMINISTIC RESULTS

The deterministic case observes a significant impact of flexible assets when managing peak load hours. The main observation from Fig. 11 and Fig. 12 is that the feed from the main grid is used for charging batteries until 06:00 in the morning. Until peak hours start, the batteries are fully charged. As shown in Fig. 9, heavy congestion starts at 06:00. Between 06:00 and 21:00, load shifting is used to resolve voltage and congestion problems (see Fig. 13).

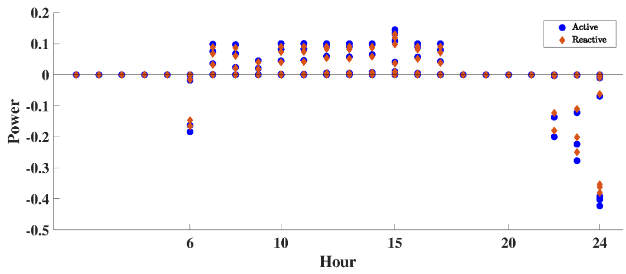

FIGURE 13. Load shifting in the deterministic solution (MWh).

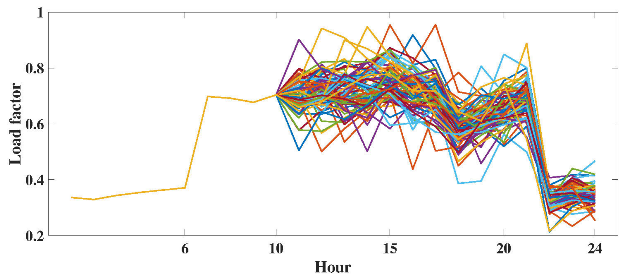

FIGURE 14. Load factor in the grid for 80 scenarios.

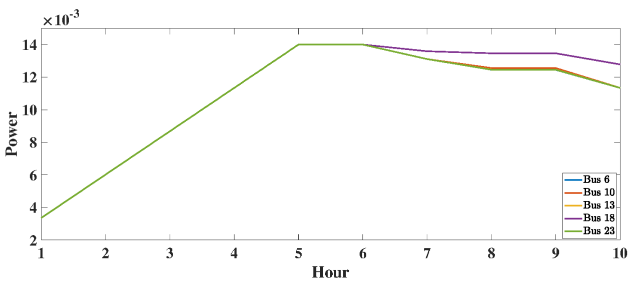

FIGURE 15. Battery state of charge at the first stage of AC-OPF (MWh).

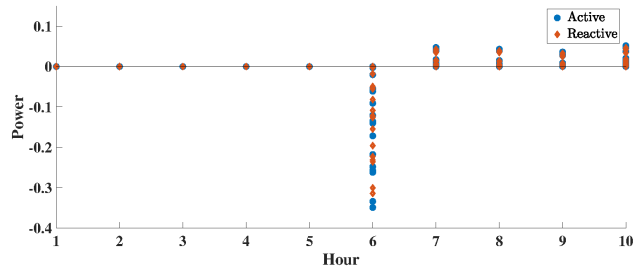

FIGURE 16. Load shifting at the first stage of AC-OPF (MWh).

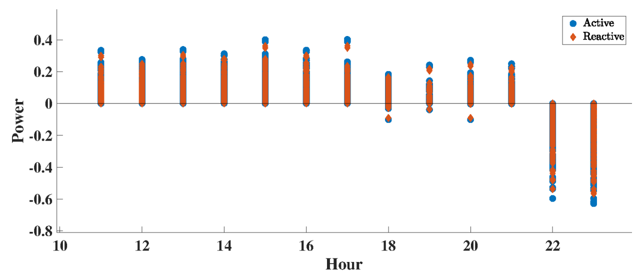

FIGURE 17. Load shifting at the second stage of AC-OPF (MWh).

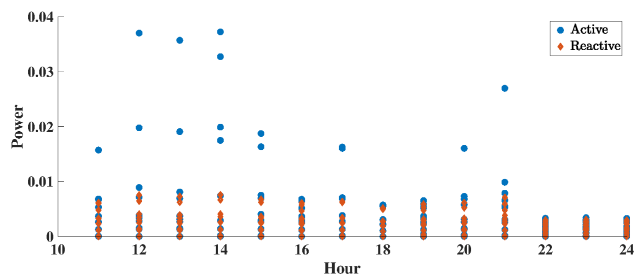

FIGURE 18. Load curtailment at the second stage of AC-OPF (MWh).

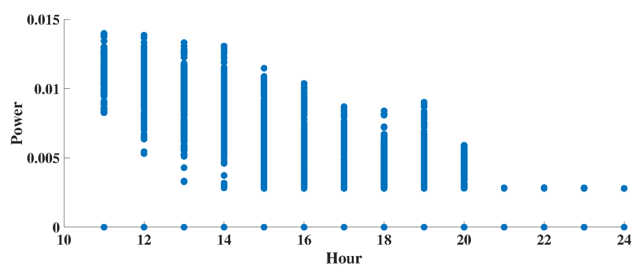

FIGURE 19. Battery state of charge at the second stage of AC-OPF (MWh).

C. STOCHASTIC RESULTS FOR WINTERTIME

The stochastic case includes 80 scenarios at the second stage for loads and prices. The results of the scenario generation are presented in Fig. 14 as *load factor* in the grid, i.e., $\left(\frac{\text{peak load}}{\text{max. poss. load}}\right)$, with an assumption of constant maximum load for every bus.

In the stochastic case, the AC-OPF model with all scenarios provides different results from the deterministic case. The peak period or increase in demand starts at 06:00. During the first stage of our AC-OPF model, the observations presented in Fig. 15 show that batteries are charging themselves from the main grid, and load shifting occurs at the same time (Fig. 16).

For the second stage, starting at 10.00, we observe load shifting (Fig. 17), load curtailment (Fig. 18), and battery power (Fig. 19). All these assets are contribute to grid operations.

1) DISCUSSION OF STOCHASTIC RESULTS

The 80 scenarios at the second stage of our AC-OPF model represent different paths in our LV grid. The results contain individual scenario responses to the uncertainty in load and price levels. Similar to the deterministic case, we observe that batteries are charging until 06:00 and discharging after that (see Fig. 19) In addition, we also see load shifting in the active and reactive power balance at the first stage Fig. 16.

In the second stage, the discharging process in the batteries to provide active power to the grid can be observed (Fig. 19), The load shifting shown in Fig. 17 shows different load patterns between peak hours (06:00–21:00) and off-peak hours (after 21:00). Moreover, load curtailment is observed (see Fig. 18). Although it is not substantial at each hour, it increases the cost of the solution compared with in the deterministic case.

The use of load curtailment is related to the interval used for load shifting. Load shifting is available between peak load hours, 06:00 to 21:00, and spans both stages. When the applied model cannot shift enough load to off-peak hours, the next option is to curtail the load. The difference between the deterministic and the stochastic cases will become more visible during the use of load curtailment. When uncertainty both occurs and is non-negligible, the system will require additional flexibility assets and services (i.e., additional to batteries) in order to fix voltage drops and congestion problems, such as load curtailment and shifting. In the next section, we discuss the relationship between uncertainty, time, peak loads, and reactive power.

VI. THE IMPACT OF UNCERTAINTY AND TIME

In this section we study the effect of time structures on our model's solution. We measure the effect of varying time characteristics of demand response assets. Moreover, we investigate how the timing of uncertainty is resolved and affects flexible scheduling.

The value of the stochastic solution (VSS) measures the expected difference between using the deterministic model (replacing uncertainty with expected values) and the stochastic model when the stochastic model is considered the true model. We calculate the expected value of the expected value solution (EEV). We start by replacing all stochastic variables with their mean and solve the deterministic model. The EEV will be the expected value of using this deterministic first stage solution in the true stochastic model, and the corresponding optimal second-stage responses are calculated. VSS is the difference between the optimal solution value for the stochastic model (recourse problem-RP) and the EEV [30].

Besides VSS, we define another measure in order to discuss the impact of uncertainty related to the relevance of modeling reactive power: *deviated value of stochastic solution* (DVSS). To calculate DVSS, we first need to model an AC/DC model that is a two-stage OPF model with AC-OPF first stage and DC-OPF second stage. For this purpose, we use equation (8) instead of equation (6). As is the case with VSS, we start to calculate DVSS first by solving the AC/DC model (model M1). Then, we solve the AC/AC model with fixed first-stage decision variables (model M2) corresponding to M1. Next, we solve the regular AC/AC model (model M3) and calculate DVSS as the difference between the objective function values of models M3 and M2. If DVSS is small enough, it will be possible to use the two-stage AC/DC model and obtain faster results, also allowing for decomposition methods, such as Benders' decomposition method (e.g., [43]), and utilizing the fact that the second stage is convex.

Furthermore, to see the relationship between the recourse actions, load shifting/curtailment, and uncertainty in load and prices, we apply a *moving interval* method to study load shifting. The availability interval of the load shifting changes in every instance of a problem in the moving interval. The beginning of the load shift interval changes between 01:00 and 10:00, but we keep the end of the interval at 24:00 as a fixed point, as shown in Fig. 2.

Furthermore, we investigate the VSS and DVSS values for two different instances in order to observe the impact on flexibility assets individually. In Variant 1, we use both types of flexibility assets (i.e., demand-side flexibility and storage) simultaneously in the solution process of the grid operations. Table 1 presents the changes in the values for VSS and DVSS as a result of a change in the uncertain parameters.

VSS increases in particular instances when load curtailment is a major part of the EEV, since the deterministic solution is not able to meet the load in some scenarios, mainly after 05:00. For both EEV and RP, the cost of load shifting and the cost of purchase from the main grid to charge batteries are almost the same. The main cost difference between RP and EEV is due to load curtailment. The SO activates the load curtailment if there is not enough time to shift the load in the available time interval for load shifting, thus demonstrating the importance of load shifting interval width. When the load shifting interval is too short, the applied model needs to shed load to deal with load uncertainty. The opposite case is also true: if the load shifting time interval is long enough, the central optimizer will not need to activate load curtailment and the cost of flexibility procurement will be lower than using the deterministic solution, hence the VSS will be lower. In that case, the value of using the stochastic model will be higher when solving a problem in which there is less flexibility.

DVSS measures the error of using the AC/DC model instead of AC/AC. When this value is small enough, it is possible to use AC/DC approximation instead of the AC/AC model. Table 1 shows that, as in VSS, DVSS is mainly impacted by load curtailment. In this case though, when the load shifting interval is longer, the value of using an AC/AC model will increase, and the AC/DC approximation will not represent the flexibility adequately. It is important to represent the AC power flow to utilize flexibility efficiently. The difference between the two approaches indicates the importance of reactive power and the impact of uncertainty. Similar to the VSS results, the DVSS results indicate that to fix voltage problem or insufficient reactive power problem at the grid, SO should consider the time of availability for reactive power flexibility resources. Otherwise, reactive power provision could cost more than usual for the SO due to lack of the activation time.

TABLE 1. The impact of uncertainty and time in Variant 1.

Load shift interval (hours)	VSS percentage	DVSS percentage
1-24	26	38
2-24	26	38
3-24	26	38
4-24	27	38
5-24	28	38
6-24	30	34
7-24	0	0
8-24	0	0
9-24	0	0
10-24	0	0

TABLE 2. The impact of uncertainty and time in Variant 2.

Load shift interval (hours)	VSS percentage	DVSS percentage
1-24	29	35
2-24	29	38
3-24	29	38
4-24	30	35
5-24	33	35
6-24	27	20
7-24	0	0
8-24	0	0
9-24	0	0
10-24	0	0

In Variant 2, we observe that the VSS and DVSS values change when demand-side flexibility, such as load shifting and load curtailment assets, is possible. We observe a similar result without the use of batteries. In the absence of batteries, that are controllable, demand-side assets such as load shifting and curtailment provide a solution to grid problems with regard to their availability time and uncertainty. These results are presented in Table 2.

In both variants of the case study from Norway, it is critical for the quality of the solution that the hour when uncertainty is resolved (the second stage starts) is within the load shifting interval, rather than at the beginning of the peak load hours. Then, load shifting will be the only flexibility asset with a recourse possibility. If the load shifting interval does not involve a stage break, both VSS and DVSS values will erroneously indicate that the impact of uncertainty will be insignificant. For an SO, this will require careful consideration of the time structure of the stochastic model, the related uncertainty structure, and, importantly, the representation of time characteristics of the flexibility assets.

VII. CONCLUSION AND OUTLOOK

In this paper we have studied the scheduling of a portfolio of flexibility assets to solve voltage variation and grid congestion problems in an ADN. The main results indicate the importance of considering the timing of decisions, the time characteristics of the flexibility assets, and the representation of uncertainty in the stochastic AC-OPF model in this research. Representation of flexibility assets, especially demand-side flexibility assets, must include information on duration and activation (response) times for those assets to have optimal impact on flexibility provision. In order for the assets to be effective for flexibility provision, the load shifting interval of an asset must be seen in relation to the time when uncertainty is resolved.

There are three main observations. First, if the available load shifting capacity is available in a wide enough time window to overlap with both the first and second stages of our model, the stochastic model will be better than the deterministic model. Second, the narrower the duration time interval, the more important the use of a stochastic model will become. Third, we observe that the greater the amount of flexibility available in the duration of the load shifting interval, the more important it will be to use an AC model, also for the second stage, to capture the value of this flexibility.

Future research topics for optimal flexibility scheduling under uncertainty might include risk-neutral or risk-averse actors in a power market setting to investigate the efficiency of the usage of the flexibility assets for grid operations. Another approach would be to include the use of active management technologies such as soft open point, on load tap changer, and static VAR compensators in an integrated way with flexibility assets. Furthermore, value could be added by including the customer's perspective in a market design in cases where more solar power and wind power are available.

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