The Impact of Forecasting Errors and Remedial Actions on Operational Security and Efficiency in Classical and Probabilistic Market Coupling

Sven C. Müller, Volker Liebenau, Sebastian Ruthe, Christopher Spieker, Chris Kittl, Stefan Dalhues, Daniel Mayorga, Valeri Franz, and Christian Rehtanz

Abstract—Managing uncertainties becomes a major challenge in power systems with a high penetration of volatile generation and load. On the contrary, the controllability of the transmission system increases due to the evolution of a smart grid and more flexible technologies. In this paper a methodology for analyzing the impact of uncertainties and operational flexibility in the context of different market coupling (MC) approaches is outlined. In particular, probability density functions of forecasting errors of renewable energy sources (RES) are evaluated and applied in a case study modeling MC in the CWE region. Further, a modeling approach for probabilistic constrained flow-based MC is presented as a more conservative alternative to classical flow-based MC. The simulation results underline that there is a trade-off between being conservative by constraining the dispatch in a tighter security-of-supply domain on the one hand and the economic costs and necessary curtailment of RES on the other hand. A key aspect being addressed is the consideration of remedial actions in the algorithms. Whereas accounting for uncertainties tightens the security-of-supply domain, the market results become less constrained when accounting for the ability to react to uncertainties and to (N-1)-cases.

Keywords—Capacity Allocation, Congestion Management, Market Coupling, Operational Security, Renewable Energies, Uncertainty Management

I. INTRODUCTION

CONGESTION management and capacity allocation play a key role for an efficient utilization of the European transmission grid. The fundamental problem is to determine which generation-load-configurations are permissible under the constraints of a secure network operation and to choose the configuration that maximizes social welfare.

Generally, the congestion management and capacity allocation problem occurs at different levels and at different time horizons. Looking at the ENTSO-E region, it can be distinguished between market platforms for forward, day-ahead and intraday markets on the one hand, and the operational planning and real-time operation by transmission system operators (TSOs) that finally bear the responsibility of a secure system operation on the other hand. The market platforms aim at obeying the network security constraints by limiting the tradeable exchanges between market zones. For this, absolute limits for cross-zonal trades (available transmission capacity - ATC) or flow-based models are used as constraints in the matching of bids at the market places. Naturally, these considerations have their limits as they rely on a single forecasted system state, selected transmission corridors and further assumptions simplifying the physical realities. If the market-driven generation dispatch would cause a system state that does not comply with operational security requirements (e.g., (N-1)-security), TSOs finally have to interfere with the market and apply changes like counter-trading or redispatch, thereby changing the generation-load-configuration in order to avoid overloads and to ensure a secure system operation.

In the following, two issues arising from the simplifications of the congestion management process on the market side are addressed. First, the technical constraints for choosing the generation dispatch are typically based on a single forecasted base case of feed-in by renewable energy sources (RES) and load that features significant uncertainties. Deviations from this forecast can lead to overloads and violating (N-1)-security constraints. Further, in flow-based approaches it can be accounted for operational flexibility in terms of remedial actions (e.g., fast power flow control in (N-1)-situations). Both forecasting errors and use of remedial actions are analyzed with respect to their impact on network security (resulting overloads in case of realization of uncertainties) and operational efficiency (generation costs and necessary curtailment of RES) under different congestion management approaches. Focusing on the Central Western European (CWE) region, classical ATC-based market coupling (MC), the recently introduced flow-based MC and a newly designed probabilistic flow-based MC approach are simulated.

This paper is structured as follows: after reviewing the state of the art in Section II, a methodology for quantifying nodal forecasting errors and resulting probability density functions (PDFs) of nodal deviations from forecasted RES feed-in and load are presented in Section III. Then, the mathematical models for the three MC approaches are described (Section IV). Next, simulation results for a case study in the CWE region are outlined in Section V analyzing the effect of forecasting errors and remedial actions considering the different MC algorithms. Finally, a conclusion is drawn and an outlook on future research is given.
II. STATE OF THE ART

After the introduction of the Trilateral Market Coupling (TLC) in France, Belgium and the Netherlands, ATC-based MC was launched in the CWE region in 2010: in this approach the physical grid is not modeled explicitly, instead exports from low price market zones are only allowed as long as cross-border exchanges do not exceed the limits determined typically ex-ante in long-term (yearly/monthly) scenario-based net transfer capacity (NTC) calculations. Security margins in form of Transmission Reliability Margins (TRM) are considered in the NTC calculations. Then, one day prior to intraday the ATC is determined by subtracting Already Allocated Capacity (AAC) from the possibly updated NTCs and making this capacity available for the spot market [1]. Additional capacity can be allocated following intraday ATC computations for the intraday market [2]. Further, also the 24 hours of a day are coupled in the MC by multiple-hours block orders [3].

In parallel to the ATC-based MC, the more complex but more efficient flow-based MC is investigated in simulations and results of external parallel runs have been published since early 2013. This approach is closer to the physical realities of the network as it models the power flows in the network and considers a likely operating point of the system: here, TSOs provide forecast files (Two-Days Ahead Congestion Forecasts - D2CF) for their respective part of the grid for each hour of the forecasted day. The D2CF files contain the best estimate for net exchanges with other zones, grid topology, planned outages, generation and load. Further, remedial actions (e.g., changing tap positions of phase shifting transformers (PSTs) or curative redispatch), generation shift factors (a mapping of changing net positions of a zone to the generating units), critical branches (branches to be monitored) and critical outages (branches to be considered as relevant (N-1)-cases) are included. Details on these necessary inputs for applying the flow-based MC algorithm can be found in [4]. Basing on these data a computation of power transfer distribution factors (PTDFs) is performed using linearized DC load flow assumptions [5]. Finally, a mixed-integer quadratic program (MIQP) is solved aiming at maximizing total welfare, here considered as the difference between the sum of the surplus of the consumers and the producers, plus the congestion revenue. The decision variables are the acceptance of orders, flows on transmission lines, and market as well as congestion prices. Further, both market (e.g. refuse order if its price is above the market clearing price) and network (e.g. keep line flow below available capacity) constraints are applied. For details on the algorithm see [3].

For the future, flow-based approaches are suggested for both day-ahead and intraday markets by ENTSO-E [6]. However, the model assumptions and their limits need to be well understood. First, the use of PTDFs based on linearized DC load flow assumptions is a key assumption as compared to the non-linear physics and AC load flow equations. Nonetheless, simulations in the former UCTE network have shown that DC-PTDFs fit PTDFs derived with an AC model reasonably well, whereas it was stressed that a nodal network should be used [7]. Second, as discussed above, the parameters for the MC algorithm rely on a single base case. Realizations of uncertainties need to be met by either security reserves or by countermeasures during intraday planning and real-time operation. An approach for incorporating meteorological uncertainties by use of probabilistic constraints was presented in [8]. The focus is set on capturing the influence of uncertainties on dynamic line rating in a dispatch model using a scenario-based methodology. Further research has been done in the field of robust optimal power flow (OPF) (e.g. [9], [10]). A third aspect that has been investigated little in the past is the impact of considering remedial actions in the algorithm. [11] and [12] present first results and methodologies for determining the effect of corrective use of power flow controllers on generation costs. However, analyses of the benefits of using fast redispatch as corrective actions and the interplay of remedial actions and uncertainties have not been addressed.

For analyzing uncertainties, models of the power system participants with a stochastic nature as well as information about the characteristics of the forecasting error are needed. Particularly, there is an increasing need for wind and solar power forecasts in addition to the well known load forecasting. For wind power prediction mainly three approaches can be found: Physical models describe the lower atmosphere and use power curves to transfer wind speed into expected power. Statistical or ‘black box’ methods utilize large quantities of past feed-in time series, whereas machine learning or ‘grey box’ methods try to learn relations between meteorological and power measurements [13]. A physical approach similar to that used in this paper is presented in [14]. Solar power forecasting is a relatively new field with different approaches, in particular it can be distinguished between satellite imagery of cloud coverage, forecasts based on numerical weather predictions (NWP), aggregated irradiance measurements, ‘Sky Imager Technology’ (observing cloud coverage from the ground) and utilization of irradiation measurements on plant-level (cp. [15]). For this paper an NWP-based model is used.

III. FORECASTING ERRORS

As mentioned above, forecasting errors need to be quantified in order to model potential deviations from a forecasted system state (in particular, the single base case in MC). Main components of the base case that feature uncertainty are the nodal values of electrical load as well as feed-in by wind energy converters (WEC) and photovoltaic installations (PV). This section presents a methodology for estimating the nodal forecasting error (NFE) and quantitative results in form of PDFs for these components.

The main procedure for quantifying the forecasting errors of RES feed-in is to use a physical model to transfer time series of both forecasted and measured meteorological values of the same time interval into power time series. Then, the difference between forecasted and ‘measured’ power is evaluated and summarized in a PDF. This is done for several forecasting horizons (e.g. 1 h, 24 h, 48 h ahead) and for various geographical locations. Here, RES generators are mapped to nodes in the transmission grids and the aggregation of these generators is modeled in a single model for each type of feed-in.
RES and for each node. The model derives the representative behaviour from an aggregated data set (e.g. aggregating power output curves as a function of wind speed for common on- or offshore WEC types). To reduce the requirements for the availability of input data a spatial correlation analysis is used building upon [16]. In the latter study data from the same NWP model as it is used in this paper is evaluated into RES feed-in forecasts and the correlation coefficient between each possible combination of geographical locations is calculated. The points with a correlation coefficient higher than a stipulated threshold are pooled in a cluster. Building on the assumption that the locations in a cluster are closely correlated, only a single location with available measurements and a corresponding meteorological situation in the whole cluster and thereon for every node within the cluster. As input data in the following analysis NWP forecasts by the COMSO-EU model [17] and measurements by Germany’s National Meteorological Service [18] and Photon Control [19] are used, each as hourly means.

As the NWP model provides data for different forecast horizons, their influence on the NFE can be assessed. Further, it can be investigated whether the forecasting error can be reduced when the NWP predictions are combined with the last available measurements and input to a linear extrapolation. The extrapolated forecast

\[ f_{\text{EXT}}(t_k) = \frac{m_{x,T_1} - m_{x,T_1}}{t_{T_2} - t_{T_1}} \cdot t_k + \frac{m_{x,T_1} \cdot t_{T_2} - m_{x,T_2} \cdot t_{T_1}}{t_{T_2} - t_{T_1}} \]

and the NWP forecast \( f_{x,NWP}(t_k) \) are linked applying the geometrical mean. An assessment of using this combined forecasting model using NWP values and recent measurements shows that the error of the power time series can be reduced upon a forecasting horizon of 6 h in the case of WEC and for up to 48 h in case of PV (with \( n_1 = 3 \), \( n_2 = 2 \)). For calculating the PDFs of forecasting errors in the following, this pre-processing is used for the aforementioned time ranges, where for the others the pure NWP predictions are used as input for the physical model.

The physical model is subdivided into a WEC and a PV-plant model. The WEC model simply acquires the wind speed predictions and measurements, corrects them to aggregated hub height and finally determines the wind power feed-in by applying the aggregated power curve for the WECs at the node. In the PV model, beam and diffuse irradiation are transferred into the global irradiation of the PV module plane. The model then computes the power curve of the aggregated module depending on the ambient temperature and irradiation. The inverter is assumed to be capable of perfectly keeping the PV module in its maximum power point (MPP).

Finally the NFE time series can be obtained by simply subtracting both forecasted and measured time series according to:

\[ \varepsilon(t_k) = P(F(t_k) - P(M(t_k)), \forall t_k \]

where \( F \) is a set of predicted and \( M \) of measured input data. The time series of deviations from the forecasts \( \varepsilon(t_k) \) are per unit values with the installed capacity of the RES type at a node as reference.

Example results are visualized in Fig.1 depicting discrete PDFs of the NFE. For the network security analysis later on, these PDFs can be used to generate probabilistic samples of forecasting errors. As the forecasting quality also depends on the situation to be forecasted (e.g. PV forecasts at night will be more accurate than in the daytime) conditional PDF (CPDF) with regard to the predicted feed-in are introduced. For wind power there are the classes zero, partial load and full load. The PDFs for PV are subdivided in zero and partial load. Fig.1b shows the CPDFs ‘partial load’ for PV feed-in. The different CPDFs are generated for different clusters in Germany and the four seasons. For nodes in neighbouring countries the PDFs of the nearest inland-cluster are used.

The PDF of the load forecasting error (cp. Fig. 1(c)) is the result of a study on improving demand forecasts in [20]. The study used an ARX-time-series model to forecast the demand of approximately 40,000 households in Germany based on historical input data. Assuming stochastic independency for two disjoint sets of households, the PDF can be approximated for regions with \( n = k \cdot 40,000 \) households and \( k \gg 1 \) by convoluting it \([k]\) times with itself.

IV. Market Coupling Modeling Approaches

In this section, three linear programming (LP) optimization problems are presented modeling classical ATC-based MC, classical flow-based MC and probabilistic flow-based MC. It should be stressed that these optimization problems are only simplified approaches for simulating market-driven dispatch configurations because they neither model the complex behaviour of sellers and buyers in a market environment (like gaming, cp. [21]) nor bidding and market clearing of bidding blocks. Instead, the objective function of all models presented in the following is the hourly maximization of social welfare by minimizing generation costs and assuming inelastic demand. Decision variables are the feed-in of generating units (representing sellers bidding at marginal costs) and operational measures available to the TSOs. The decisive differences are found in the set of constraints that restrict the space of permissible generation configurations in order to represent network security needs. This space is called security-of-supply domain in the following. Starting, ramping and shutting down
A. Classical ATC-Based Approach

As an LP, the ATC-based MC approach can be modeled as follows:

\[
\min_{P_g, \ld_g} \sum_{g \in M_g} c_g \cdot P_g \quad \text{(5)}
\]

s. t.

\[
\sum_{g \in M_g} P_g - \sum_{k \in M_k} \ld_k - \sum_{z \in M_z} P_{\text{ex}_{1,z}} = 0, \quad \forall z_1 \in M_z \quad \text{(6)}
\]

\[
P_{\text{ex}_{1,z}} = \frac{P_{\text{ex}_{2,z}}}{\beta_{k,b,n}} - \frac{P_{\text{ex}_{2,z}}}{\gamma_{x,b,n} \cdot X_{x,n}} \quad \forall z_1, z_2 \in M_z \quad \text{(7)}
\]

\[
P_{\min_g} \leq P_g \leq P_{\max_g}, \quad \forall g \in M_g \quad \text{(8)}
\]

\[
\text{ATC}_{\min_{z_1,z_2}} \leq P_{\text{ex}_{1,z_2}} \leq \text{ATC}_{\max_{z_1,z_2}}, \quad \forall z_1, z_2 \in M_z \quad \text{(9)}
\]

In this approach network restrictions are represented by restricting the power exchanges \( P_{\text{ex}_{1,z}} \) between two market zones \( z_1, z_2 \) (belonging to the set of all market zones \( M_z \)) to be only permissible within the minimal and maximal bounds \( \text{ATC}_{\min_{z_1,z_2}} \) and \( \text{ATC}_{\max_{z_1,z_2}} \) (Eq. (9)). Summing up the active power production \( P_g \) of each generator \( g \) (belonging to the set of all generators \( M_g \)) times its production costs \( c_g \) returns the total generation costs to be minimized as the objective (Eq. (5)). Further, the net total of generation, load \( \ld_k \) (with \( k \) belonging to the set of all nodes \( M_k \)) and exports in a country needs to be zero (active power balance, Eq. (6)). Also, the production of each generator \( g \) needs to be within its minimal and maximal bounds \( P_{\min_g} \) and \( P_{\max_g} \) (Eq. (8)).

B. Classical Flow-Based Approach

Modeling the classical flow-based MC approach, the following optimization problem can be formulated:

\[
\min_{P_g, X_{x,n}} \sum_{g \in M_g} c_g \cdot P_g \\
\text{s. t.} \\
\sum_{g \in M_g} P_g - \sum_{k \in M_k} \ld_k = 0 \quad \text{(10)}
\]

\[
| \sum_{g \in M_g} \alpha_{g,b,n} \cdot P_g - \sum_{k \in M_k} \beta_{k,b,n} \cdot \ld_k | + \sum_{x \in M_x} \gamma_{x,b,n} \cdot X_{x,n} \leq P_{\max_b}, \quad \forall b \in M_b, n \in M_n \quad \text{(11)}
\]

\[
P_{\min_g} \leq P_g \leq P_{\max_g}, \quad \forall g \in M_g
\]

In this approach, the active power balance is represented by a single constraint for balancing generation and load across the whole network (Eq. (10)). Instead of modeling power exchanges between zones and keeping these within fixed ATC-bounds, the network restrictions are modeled by a linearized representation of the power flow equations (Eq. (11)). Here, it has to be ensured that for each network branch \( b \) (belonging to the set \( M_b \) of all ‘critical branches’) the absolute value of the power flow on the branch is below its maximal power transmission capacity \( P_{\max_b} \). Using linearization assumptions (DC power flow or other linearized AC models), the power flow on a branch is modeled as a linear combination consisting of sensitivities and influential parameters on the power flow. The impact of a change of 1 MW of generator \( g \) on the power flow on branch \( b \) in network configuration \( n \) is represented by the sensitivity \( \alpha_{g,b,n} \) (in this case a DC-PTDF). Similarly, the PTDF \( \beta_{k,b,n} \) models the impact of the load at node \( k \) on the power flow on branch \( b \) in network configuration \( n \), and \( \gamma_{x,b,n} \) models the impact of the operational control action \( X_{x,n} \) on branch \( b \) in network configuration \( n \).

Two aspects deserve special attention in this model: First, this security-of-supply domain accounts for several network configurations in the same optimization problem. In particular the set \( M_n \) includes the network topologies for the (N)-case and for all or selected (N-1)-cases (post-contingency topologies...
after ‘critical outages’). In this paper, only line outages are considered as critical outages whereas generator outages are not included. Consequently, all types of sensitivities are dependent on the network configuration \( n \) and their values account for the changed topologies in the considered (N-1)-cases. Thus, this optimization problem has the characteristics of a security constrained optimal power flow (SCOPF). Second, the formulation allows for representing operational control actions \( X_{x,n} \), in particular modeling remedial actions. Thereby, it can be accounted for the operational flexibility of reacting to changing network configurations and for optimizing the operation by network-related measures in contrast to generator production being the only available decision variable. Specifically, the set of operating controls \( X_{x,n} \) can contain various operational measures like

- redispatch of generators and loads, and
- changes of set points of power flow controlling equipment like HVDC transmission systems, FACTS devices and PSTs.

The sensitivities \( \gamma_{x,b,n} \) corresponding to the operating controls depend on the type of control action, e.g. if the control \( X \) is a redispatch action, \( \gamma \) is a PTDF corresponding to the node where the redispatch is executed, and if \( X \) is a change of a PST, \( \gamma \) is a phase shifting distribution factor (PSDF, cp. [11]) corresponding to the respective PST. Naturally, operational controls are also subject to lower and upper bounds \( X_{\text{min},x,n} \) and \( X_{\text{max},x,n} \), e.g. minimal and maximal tap position of a PST or limited redispatch flexibility of generators and load (Eq. (12)).

\[
X_{\text{min},x,n} \leq X_{x,n} \leq X_{\text{max},x,n}, \quad \forall x \in M_x, \forall n \in M_n \tag{12}
\]

If redispatch is considered as an operational flexibility, it is also enforced that the sum of all redispatch is zero in order to keep the active power balance without consuming any dedicated control reserves for frequency control. Also, additional constraints can be added for further limiting the amount of operational controls to be accounted for, e.g. the redispatch flexibility of a generator might be dependent on the preceding operating point. One important factor to have in mind is that operating controls should only be integrated in the market model if they can be executed reliably in due time. E.g., ‘corrective’ controls (as a response to an (N-1)-case) should only be allowed as flexible decision variables if real-time support systems or reliable automated controls are available in network operation. Otherwise, these controls might only be considered as ‘preventive’, thus only a single optimized set point of these controls is chosen for all network configurations. This can be enforced by an additional constraint (Eq. (13)):

\[
X_{x,n} = X_{x,1}, \quad \forall n \in M_n \tag{13}
\]

The authors focus on the types of corrective actions mentioned above because they can be executed in an incremental way. As it is most critical that corrective actions do not risk system security and that their effect can be determined and verified reliably in real-time operation, smoothly controllable actions seem to be most suitable for real-time overload relief with limited risk. For completeness, it should be mentioned that also some corrective topological measures, like opening a line, could be considered in the model by use of discrete variables and sensitivities like Line Outage Distribution Factors (LODFs, cp. [23]). On the contrary, other topological actions, like switching of a network element from one bus to another, are difficult to include as decision variables in the optimization problem and could most conveniently be considered when they are precomputed for a specific topology.

### C. Probabilistic Flow-Based Approach

The classical flow-based approach is based on a single forecasted system state. Deviations from this state can risk (N-1)-security and can require countermeasures in network operation. Main uncertain parameters of the forecast are the variation of the RES production \( P_{\text{var,RES}} \) and the load \( P_{\text{var,ld}} \) at each node. Further, if the net total of all load and RES production forecasting errors is unbalanced, control reserves for frequency control \( P_{\text{var,fc}} \) are activated by changing the production of generators. These uncertainties can be modeled as a variable power \( P_{\text{var}} \) at each node \( k \) (equivalent to a positive or negative load) with \( P_{\text{var}} = P_{\text{var,RES}} + P_{\text{var,ld}} + P_{\text{var,fc}} \). However, there can be an infinite number of possible scenarios \( s \) of deviations from the forecasted system state resulting in an infinite number of possible nodal power variations \( P_{\text{var,s}} \).

With respect to system security and following the idea of [8] it can be of interest to keep the line loadings of the branches in the critical network topologies within the admissible limits even in case of realization of uncertainties. For this reason, a robust optimization approach based on probabilistic constraints is formulated in the following and analyzed as an alternative MC approach in the case study. The key idea is to permit market results \( P_g \) only if they do not cause overloads even in case of realization of uncertainties. As presented in [24], [25], probabilistic constraints can be approached by a scenario-based methodology: By sampling of the constraints (thus generating a set of scenarios \( M_S \)) a standard convex optimization problem can be formulated with a solution being approximately feasible for the typically infinite set of the original probabilistic constraints. The sampling of scenarios can be done following different approaches, in the case study a Monte Carlo method is used as discussed later on. The resulting robust MC formulation can be written as:

\[
\begin{align*}
\min_{P_g, X_{x,n,s}} \sum_{g \in M_g} c_g \cdot P_g \\
\text{s. t.} \\
\sum_{g \in M_g} P_g - \sum_{k \in M_k} P_{ld_k} = 0 \\
| \sum_{g \in M_g} a_{g,b,n} \cdot P_g - \sum_{k \in M_k} \beta_{k,b,n} \cdot (P_{ld_k} + P_{\text{var,k,s}}) | \\
+ \sum_{x \in M_k} \gamma_{x,b,n} \cdot |X_{x,n,s}| \leq P_{\text{max},b}, \quad \forall b \in M_b, n \in M_n, s \in M_S
\end{align*}
\]
\[ P_{\text{min},g} \leq P_g \leq P_{\text{max},g}, \quad \forall g \in M_g \]
\[ X_{\text{min},x} \leq X_{x,n,s} \leq X_{\text{max},x}, \quad \forall x \in M_x, \forall n \in M_n, s \in M_s \]

(15)

V. Case Study

In the previous sections, forecasting errors have been quantified and three algorithms for determining dispatch configurations under network constraints have been presented. Now, these results are used for a case study to analyze the impact of forecasting errors and remedial actions on network security and efficiency. The procedure for each scenario in the case study is as follows:

1) First, day-ahead market coupling is simulated using the algorithms presented in Section IV. The outcomes are market results (dispatch configurations \( P_g \)) and remedial actions \( X \) for each time step.

2) Second, the realizations of uncertainties (deviations of load and RES from the forecasted base case used in step 1) are simulated by Monte Carlo method considering the PDFs of forecasting errors presented in Section III. The outcomes are samples of nodal power variations \( P_{\text{var}} \) for each time step and for each Monte Carlo run.

3) Finally, the impact on network security and efficiency is analyzed, in particular power flows are calculated considering the dispatch (as determined in step 1) and superposing the nodal power variations of the Monte Carlo simulations (step 2). The final outcomes are the generation costs of the MC approaches and power flow distributions for each time step and for each network configuration.

A. Scenario Setup

The network model used for the case study is based on an aggregated model of the European transmission system described in [26] and is visualized in Fig. 2. As the focus of the analysis is set on the market coupling in the CWE region, only the sub-network consisting of Germany, the BENELUX countries, France and Austria is considered. In total 71 nodes, 329 lines and 6 PSTs are simulated. All cross-border lines are selected as both critical branches and critical outages. The hourly load values of the CWE region are taken from [27]. One quarter of the load is distributed to the nodes in proportion to the population density whereas three quarters are regionalized according to the gross domestic product. Due to the computational expensiveness of the simulations, 250 hours are simulated covering different month, daytimes etc. which have been found to be representative for a year. The data on installed capacity and the geographical distribution of RES generators in Germany are taken from [28]. The information about the installed capacity of RES in other countries of the CWE region is based on [29] and meteorological data and time series are derived from the regional COSMO-EU model available at [17]. As in practice D2CF files are used for the day-ahead MC, PDFs for forecasting errors are applied for a forecasting horizon of 48 hours and calculated as discussed in Section III. Finally, the power plant database bases on [30] and ATC values are taken from [31].

In total, 7 different scenarios are investigated. These include one ATC-based MC scenario (A), three classical flow-based MC scenarios (B) and three probabilistic flow-based MC scenarios (C). The variants of the flow-based scenarios result from investigating three different settings of remedial actions \( (M_s) \) being allowed to be applied in the algorithms: (i) no controls allowed, (ii) only corrective control of PSTs allowed and (iii) corrective control of PSTs as well as corrective redispatch allowed with an amount of 10\% of the feed-in or consumption of each generator or load. These settings mean that different levels of operational flexibility are already accounted for in the market procedure. As discussed above, available controls lead to additional degrees of freedom being available for reacting to (N-1)-cases \((M_n)\) and - in case of the probabilistic MC - to the uncertain scenarios \((M_s)\), thereby enlarging the security-of-supply domain of the dispatch configurations \( P_g \).

For simulating the uncertainties, 10,000 Monte Carlo runs are realized for each network situation. The Monte Carlo runs for generating the nodal power variations in the probabilistic flow-based scenarios consider deviations of up to 95\%. Further, only selected Monte Carlo runs are directly included as constraints in the probabilistic MC for reducing computational expensiveness. The selection is based on the \( p \)-norm \( \| L_b \|_p \) of the vector \( L_b \) containing the loading of all critical branches for each Monte Carlo run and each time step in all network topologies. For each time step, the forecasted system state and the Monte Carlo runs resulting in the greatest \( p \)-norm with \( p=4 \) are selected in the case study and used for parameterizing \( P_{\text{var},x,s} \). Thus, Monte Carlo runs resulting in high overloads are integrated as constraints in the probabilistic MC. Further, frequency control reserves \( (P_{\text{var},fc}) \) are assumed to be activated in proportion to the generating capacity by conventional power plants.

B. Results

In the following, the simulation results of the case study are presented. The computations have been performed on virtual machines each having allocated an Intel Xeon E7-8837 octa-core processor (2.67 GHz) and 64 GB RAM. Execution times for hourly time step have been approx. 5 s for ATC-based MC,
TABLE I: Simulation Results for Total Generation Costs and Necessary RES Curtailment for Different MC Approaches for $|M_s|=11$

<table>
<thead>
<tr>
<th></th>
<th>Generation Costs</th>
<th>RES Curtailment</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATC MC</td>
<td>A</td>
<td>+15.63 %</td>
</tr>
<tr>
<td>Classical</td>
<td>B(i)</td>
<td>base</td>
</tr>
<tr>
<td>Flow-based MC</td>
<td>B(ii)</td>
<td>−1.47 %</td>
</tr>
<tr>
<td></td>
<td>B(iii)</td>
<td>−4.46 %</td>
</tr>
<tr>
<td>Probabilistic</td>
<td>C(i)</td>
<td>+3.60 %</td>
</tr>
<tr>
<td>Flow-based MC</td>
<td>C(ii)</td>
<td>+2.26 %</td>
</tr>
<tr>
<td></td>
<td>C(iii)</td>
<td>−4.46 %</td>
</tr>
</tbody>
</table>

Table I shows the effect of the different MC approaches on the total generation costs and the necessary curtailing of available RES feed-in. The classical flow-based approach without corrective controls (setting B(i)) is chosen as a base case for the generation costs.

It can be seen that both the generation costs as well as the necessary curtailing of RES can be decreased in both classical and probabilistic flow-based MC with an increasing amount of operational flexibility being considered in the algorithms (increasing flexibility from settings (i) to (iii)). As expected, the consideration of multiple scenarios in the probabilistic flow-based MC case results in higher costs than in the classical flow-based MC. However, in scenario C(iii) (with the highest amount of controls considered) the constraining effect of the probabilistic scenarios was entirely compensated by the ability to react to the scenarios, for this reason the costs of B(iii) and C(iii) turn out to be almost equal. As the uncertainty of RES feed-in is represented in the probabilistic flow-based MC, the highest amount of RES curtailing is required for the case C(i) that does not consider any operational flexibility. The ATC-based approach shows significantly higher costs than the flow-based approaches as the ATCs contain long-term security margins.

For analysis of the effect on network security, the power flows for both the (N)-cases and the (N-1)-cases as determined by the MC algorithms are superposed by the effect of the uncertainties on the power flows deriving from the Monte Carlo runs. The analysis is only carried out for the algorithms without use of flexible controls as the controls would be chosen in adaptation to the realized system state. Based on the observations in the Monte Carlo runs, Table II shows the probability distribution of the maximum loading of the highest loaded branch being observed after accounting for uncertainties. It can be seen that in all MC algorithms overloads occur when uncertainties arise and even overloads above 150% can be observed. As discussed, these overloads need to be met by safety margins and operational reactions. The classical flow-based approach leads to a dispatch that in 16.3% of the Monte Carlo runs causes the overload of at least one line in the (N)-cases. The probability of overloads in the other MC approaches is less. In the ATC-based approach overloads occur less frequently due to the security margins. Also in the probabilistic approach significantly fewer occurrences of overloads can be observed than in the classical flow-based approach, however, there are still overload situations remaining. The power flow distributions in Fig. 3 illustrate that the operating points are shifted towards a more conservative system state in the probabilistic approach (cp. Fig. 3(b) and Fig. 3(c)). The results (Fig. 3(a) and Table II) also show that in the (N)-cases overloads only occur rarely, this is partly due to the fact that the (N-1)-criterion considered in the constraints has the effect of implicit security margins, in particular in case of parallel branches.

VI. CONCLUSION AND OUTLOOK

In the preceding sections modeling approaches for forecasting errors and MC approaches considering remedial actions
are described, and results for PDFs of forecasting errors for various sources of uncertainty as well as simulation results of a case study modeling MC in the CWE region are presented. The results of the case study underline that forecasting errors can lead to overloads in the electrical network, in particular in (N-1)-cases. These scenarios need to be manageable in operation in order to ensure system stability and the effect of forecasting errors will become more profound with a higher penetration of RES. For these reasons, further research will be dedicated to the question how to improve operational security at low economic costs, in particular in future systems with increasing uncertainties. Further, the simulation results point out that considering operational flexibility in the optimization can help to compensate the constraining effect of considering uncertainties. In this context, future work should also be dedicated to analyze which operational flexibility will be reliably available in future smart grids and to what extend this flexibility should be considered in MC and system operation. Finally, the considerations of uncertainties and operational flexibility similarly apply to intraday markets, operational OPF algorithms and in some contexts also to network planning. For each area a trade-off between computational expensiveness of OPF algorithms and in some contexts also to network planning.

REFERENCES


