Uncertainty Management in Power System Operation

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***Abstract*—This paper summarizes the prevailing power system operation methods for managing the uncertainty brought by large-scale integration of renewables and active load demand. From the perspective of power system operations, uncertainty management is an important problem. In this paper, the mathematical models used for handling uncertainty are discussed, along with the pros and cons as well as future development efforts of four different operation methods. The study concludes that it is difficult to adopt a universal operation theory for mitigating the uncertainty in power system operations. Instead, it is necessary to choose the most feasible operation method that matches the specific operation requirement.**

***Index Terms*—Management, power system operation, robust optimization, stochastic optimization, uncertainty.**

I. INTRODUCTION

THE uncertainty in power systems is a persistent issue. In power systems, generally, the uncertainty is a state for all the system operation, components, and the objective environment, where it is impossible to exactly describe the existing state, a future outcome, or more than one possible outcome due to limited knowledge. Due to uncertainty, the power system can be exposed to potential safety issues as well as economic loss. Mitigating the uncertainty is desirable, and therefore, an important research topic.

The North American Electric Reliability Corporation (NERC) has published a report stating that uncertainty must be addressed in long-term planning, calling for more robust and flexible systems [1]. During short periods, however, the uncertainty is absorbed by the power system operation. The *Reliability Assessment Guidebook*, for instance, requires that the uncertainty should be addressed within the assumptions, such as load variation, generation dispatch, the effect of loop flows as well as the status of transmission elements [2]. Intuitively, it is more complex and critical to handle the uncertainty in system operation rather than in planning. In system planning, the uncertainty prediction is typically inaccurate, often far from the actual situation, thus requiring a rough approximation of uncertainty that is acceptable. The deviation of uncertainty prediction in the planning stage can be "rescued" in the operation stage. However, the price of uncertainty in the operation stage is higher than in the planning stage. There are a variety of methods and theories on uncertainty in power system operation that have emerged requiring continuous study and improvement.

In traditional power systems, the uncertainty mainly exists in the electric component outages, such as unit outage, transmission line breakdown, and breaker faults. Based on the highly controllable power generation and accurate load forecast, the system is operated by unit commitment (UC) and economic dispatch (ED) with N-1 contingency [3], which greatly reduce the uncertainty from the outage. Furthermore, to meet the increased uncertainty, traditional systems adopt deterministic dispatch or worst-case dispatch methods that have been developed by acquiring substantial capacity reserves, but which can also increase the energy cost and emissions [4]. In most cases, these methods guarantee power system security, while seeing substantial improvement over the course of their use.

In recent years, with the emergence of the smart grid, a number of stochastic factors have begun to play an important role in both the generation and demand side of power systems. From the generation side, renewables, such as wind power and solar power, are remarkably integrated into power grids. According to the U.S. National Renewable Energy Laboratory (NREL), renewable energy contributed approximately 10% of total power-sector U.S. electricity supply in 2010 [5]. Among European countries, Ireland has achieved 50% instantaneous wind penetration with no energy storage. Denmark receives about 20% of its electricity from wind power. Germany's wind-energy penetration has reached 7% of power generation capacity and has produced as much as 22 MW of solar power to serve about one-third of energy demand during peak hours [6]. In China, the National Energy Administration (NEA) announced that the total installed capacity of wind power and photovoltaic power is 77,160 MW [7], and 19,420 MW in 2013 [8], respectively. Meanwhile, the demand side is likewise becoming increasingly active [9], [10]. Thus, enhancements of forecasting tools, operation practices and techniques and tools are necessary to allow the system operator to handle increased uncertainty related to large-scale integration of variable generation and active demand [11].

This paper discusses diverse operation techniques and methods that have emerged in recent years. The remainder of the

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paper is organized as follows. Section II is an overview of some critical concepts in power system operation, supported by diagrams explaining major modifications of different operation paradigms. Section III provides general mathematical models. Section IV presents the various operation methods based on these models, including the stochastic dispatch based on scenario reduction, the look-ahead dispatch, the risk-limiting dispatch (RLD) and the robust optimization (RO). Finally, Section V concludes this study.

II. Overview of Power System Operation

A crucial objective in power system operation is to ensure its reliability at all times, where the power balance is the most fundamental requirement, as shown in (1).

$$s(t) = d(t), \tag{1}$$

where $s(t)$ and $d(t)$ are the power supply and power demand at time t, respectively. Additional operational constraints may also be necessary in different operation cases. The second critical objective of power system operation is economic benefits, achieved by reducing operational costs.

To accomplish the above two goals, power systems are generally operated in the context of timeframes: seconds-to-minutes, minutes-to-hours, hours-to-days, days-to-one week and beyond, shown in Fig. 1. In the seconds-to-minutes timeframe, bulk power system reliability is almost entirely controlled by automatic equipment and control systems, e.g., Automatic Generation Control (AGC). In the minutes-to one-week timeframe, system operators are in charge of committing and dispatching units to balance the bulk power system.

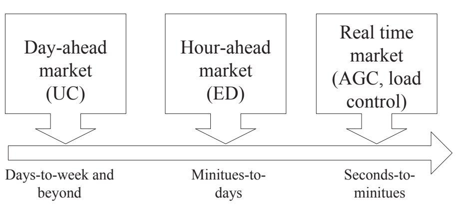

Fig. 1. Timeframe for power system operation.

In the past, the major uncertainty in the day-ahead timeframe has been in component outages, which is typically smoothed by security constrained UC (SCUC) under N-1 contingency. In the hours-to-days timeframe, the uncertainty is reduced by security constrained ED (SCED) under N-1 contingency. The implementation framework for Independent System Operators (ISOs) is shown in Fig. 2 [3].

Now, the high penetration of large-scale renewables and the active load demand lead to the injection of large amounts of randomness into the power supply and demand side, so the power balance equation (1) should be a stochastic equation, rather than the deterministic one, shown in (2).

$$s_{\mathrm{d}}(t) + s_{\mathrm{s}}(t) = d_{\mathrm{d}}(t) + d_{\mathrm{s}}(t), \tag{2}$$

where $s_{\mathrm{d}}(t)$ and $d_{\mathrm{d}}(t)$ are the deterministic supply and demand, while $s_{\mathrm{s}}(t)$ and $d_{\mathrm{s}}(t)$ are the stochastic parts.

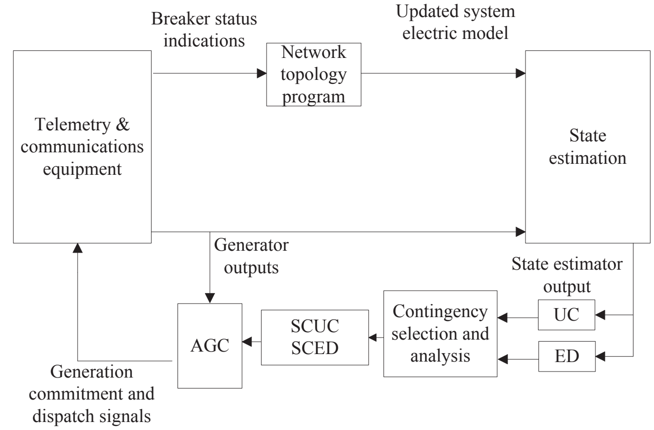

Fig. 2. Traditional operation framework.

Therefore, the crucial problem in current operation paradigms is how to manage the stochastic components. The uncertainty in the system, fortunately, is not a chaotic mass because it can be either forecasted by a probability distribution function (PDF), or restricted in a certain interval. Based on the availability of prediction, actions such as unit commitment and dispatch, and reserve procurement and demand side resource management, should be undertaken to reduce the increased uncertainty [9]. According to this requirement, the new operation paradigm is constructed, shown in Fig. 3.

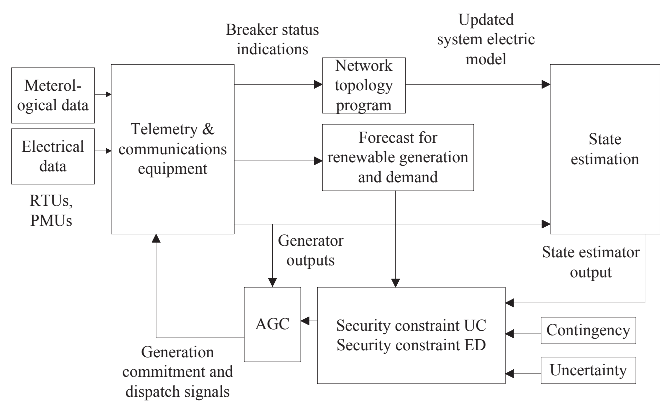

Fig. 3. New operation paradigm dealing with uncertainty.

Fig. 3 shows the counterpart operation paradigm in which there are three major changes: First, meteorological and electrical data are required and must be updated by the Supervisory Control and Data Acquisition (SCADA) systems in state-of-the-art forecasting. Second, SCUC and SCED must be modified to accommodate renewable units that are uncontrollable. Finally, N-1 contingency analysis must be replaced by new SCUC and SCED dealing with uncertainty.

Among the three major changes in the new operation paradigm, forecast technology (especially for variable generation resources) is the foundation of the latter two changes, which is highly supported by both the public and private sectors. For example, the Independent Electricity Service of Ontario (IESO) has established a near-term forecasting method, while the Alberta Electric System

Operator (AESO) has initiated a wind power forecasting pilot project in the summer of 2006 [9].

The next two changes in Fig. 3 are in relation to specific operating and dispatch criteria and methods, which are all formulated upon the same mathematical principle. Thus, before elaborating the operation methods, the following section illustrates the general mathematical models.

III. General Mathematical Models

The objective of operations is to ensure the safety and security of power systems, and to obtain higher economic benefits. Mathematically, this objective can be converted to an optimization problem, where safety and security are the constraints, and economic benefit the objective function, shown in (3).

$$\begin{aligned}&\text{minimize} \quad f(\boldsymbol{x},\widetilde{\boldsymbol{y}})\\&\text{s.t.} \quad h_i(\boldsymbol{x},\widetilde{\boldsymbol{y}}) \le 0, \forall i \in \{1,\cdots,n\},\end{aligned} \tag{3}$$

where $\boldsymbol{x}$ and $\widetilde{\boldsymbol{y}}$ are the vector for deterministic and stochastic variables, respectively. $f(\cdot)$ is the cost function, and $h_i(\cdot)$ is the i^{th} constraints.

The stochastic elements in constraints are often tackled by stochastic programming, and robust optimization [12].

In stochastic programming, two common methods are used. One is the discretization for the stochastic variable, usually by Monte Carlo simulation. The general model in (3) can be transformed into (4). The continuous variable $\widetilde{\boldsymbol{y}}$ is sampled into m discrete variables, denoted by $\boldsymbol{y}_j$ with probability p_j respectively. Thus, the objective function is altered in expectation form, and the constraints must be matched in each scenario. Related technology is discrete sampling and scenario reduction.

$$\begin{aligned}&\text{minimize} \quad \sum_{j=1}^{m} p_j \times f(\boldsymbol{x},\boldsymbol{y}_j)\\&\text{s.t.} \quad h_i(\boldsymbol{x},\boldsymbol{y}_j) \le 0, \forall i \in \{1,\cdots,n\}, \forall j \in \{1,\cdots,m\}.\end{aligned} \tag{4}$$

The second method is to take advantage of the cumulative distribution function, where the constraints are commonly transferred into probability constraints with an acceptable probability level η, while the objective function is changed to an expectation, shown in (5).

$$\begin{aligned}&\text{minimize} \quad E[f(\boldsymbol{x},\widetilde{\boldsymbol{y}})]\\&\text{s.t.} \quad \text{prob}(h_i(\boldsymbol{x},\widetilde{\boldsymbol{y}}) \le 0) \ge \eta_i, \forall i \in \{1,\cdots,n\}.\end{aligned} \tag{5}$$

In robust optimization, the constraints and objective function are often expressed as (6).

$$\begin{aligned}&\underset{\boldsymbol{x}}{\text{minimize}} \quad \sup\{f(\boldsymbol{x},\widetilde{\boldsymbol{y}}) | \widetilde{\boldsymbol{y}} \in \varepsilon\}\\&\sup\{h_i(\boldsymbol{x},\widetilde{\boldsymbol{y}}) | \widetilde{\boldsymbol{y}} \in \varepsilon\} \le 0,\end{aligned} \tag{6}$$

where ε is the interval of $\widetilde{\boldsymbol{y}}$.

Obviously, in stochastic programming, there is a small probability that the constraints are not met, and thus are less reliable; however, they have significant economic benefits. In robust optimization, the reliability can be guaranteed definitely, with the price being worse economic benefits.

Thus, in realistic operation processes, the mathematical model that is adopted depends on the trade-off between economic benefits and reliability, according to different operation requirements. The specific operation methods based on these models are illustrated in detail in the next section.

IV. Uncertainty Management with Operation Methods

A. Scenario-based Stochastic Programming

The scenario-based stochastic programming is generally modeled using the steps in [13]–[16]. The discretization of stochastic components is the first step. For straightforward illustration, we regard the stochastic components, denoted by net load $l(t)$, to be one dimension, shown in (7). It is easy to be extended into the high dimension.

$$l(t) = d(t) - s(t). \tag{7}$$

Based on Monte Carlo simulation, the continuous PDF for net load is sampled into $N(t)$ discrete points with different probabilities, and each discrete point is denoted by $l_i(t)$ $(i \in \{1,\cdots,N(t)\})$.

For the second step, a scenario tree is formed [13], [16], [17]. If the operation is concerned about the next $t(t \in \{1,\cdots,T\})$ hours, for each period t, step one is repeated. Thus, for the whole time horizon, the scenario tree is formed, and each trajectory is called one scenario. For example, provided that $T = 2, N(1) = 2$, and $N(2) = 3$, the scenario tree is shown in Fig. 4.

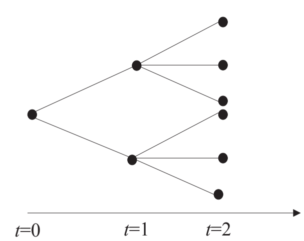

Fig. 4. Illustrated scenario tree.

The next step is the problem formulation [13], [14], [17]–[19]. For simplification, only the power balance is considered as the constraint.

$$\begin{aligned}&\text{minimize} \quad c_0 s_0 + \sum_{t=1}^{T} \sum_{i=1}^{N(t)} p_i c_i s_i(t)\\&\text{s.t.} \quad s_0 = d_0\\&\qquad s_i(t) - d_i(t) = 0\\&\qquad \forall t \in \{1,\cdots,T\}, \forall i \in \{1,\cdots,N(t)\},\end{aligned} \tag{8}$$

where c_0, s_0 and d_0 are operating cost, dispatch power, and demand at the initial time period. $p_i, c_i, s_i(t)$, and $d_i(t)$ are the probability, operating cost, dispatch power, and demand in scenario i. Thus, the objective function is composed of a deterministic part in the initial stage and a stochastic part in the subsequent stage; this is the so-called two-stage problem.

In the initial stage, the real dispatch strategy is generated. In the next stage, operators wait and see which scenario truly happens, and choose the operation strategy, accordingly.

Finally, the conventional solution algorithm is decomposition techniques, such as Benders decomposition [20], [21]. Using such techniques, we can take full advantage of the parallel computation capabilities of computers because scenarios are decomposed into several separate ones, which can be dealt with equally by computers.

This original operation method, however, suffers from three problems. First, there is computation complexity resulting from the exponential growth of scenario numbers. The countermeasure for this is scenario reduction, which cuts some branches in the scenario trees [16], [22]–[24]. The merit of scenario reduction is that computations are fast; the weakness, on the other hand, is the potential operation bias compared to the one generated from the complete scenario tree due to the nonlinear characteristic of the mapping between scenarios and operation strategy. A potential improvement is to develop the scenario reduction based on the final operation goals, rather than to simply approximate the complete scenario trees.

The second problem is that continuous PDF is not used, which may lead to loss of important information. The countermeasure for this is to utilize the chance-constraint in place of the discrete scenario based constraint.

Finally, the operation strategy is static, where recourse decisions are not considered. The forecast errors are smoothed by fast start units and load shedding [20], while the economic benefits are sacrificed. The countermeasure is to adopt dynamic operation strategies, shown in the next part.

B. Look-ahead Dispatch

The principle of look-ahead dispatch is model predictive control (MPC) [25]–[29]. The MPC approach deals with the dynamic receding horizon optimization control problem [30]. Usually, MPC systems employ a stochastic model for the uncertainty. In this way, the systematic stochastic terms can be effectively compensated by the decisions of the system. In addition, proper inclusion of integration in the model can eliminate steady state error from the system outputs. The mathematical model of look-ahead dispatch is shown in (9).

$$\begin{aligned} &\text{minimize} \quad f(\boldsymbol{u}) \\ &\text{s.t.} \quad x_{k+1} = g(x_k, u_k), \forall k \in \{1, \cdots, N\} \\ &\qquad h(x_k, x_{k+1}, u_k) \leq 0, \forall k \in \{1, \cdots, N\} \\ &\qquad x_0 = Z(k), \end{aligned} \tag{9}$$

where k is the index of the time period, N is the whole time horizon, x_k is the state variable in period $k, \boldsymbol{u} = [u_1, \cdots, u_k]$ is the vector of control variables.

In each time period, the predictions for the whole time horizon are made, expressed by the first constraint in (9). Based on the predictions, the control strategies are generated by optimization (9), but only the strategy for the current period is realized. When the time comes to the next period, a similar control is duplicated, up until the final period. In sum, there are k optimization problems solved.

The look-ahead dispatch is the implementation of MPC in system operation [28]. At each operation stage, the operators do not just wait and see, but rather they compute the optimal operation repeatedly with updated information. The dispatch process can be illustrated in Fig. 5. In each period, the operators look n steps ahead, and decide the operation for the current stage, where a two-stage problem is solved. As time passes, the two-stage problems are solved by rolling forward [25], [26]. The improvement of look-ahead dispatch is prominent. First, by on-line dynamic rolling, the updated prediction information can be used. The operators do not have to wait and see, thus the emergencies resulting in start-up of fast response units and load shedding can be greatly decreased. In addition, the optimization model is not limited to scenario based, but can be extended to integrate continuous PDF by introducing chance-constraint [31], [32].

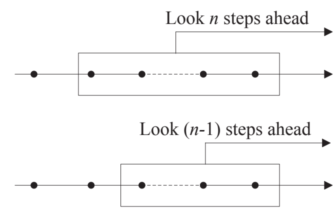

Fig. 5. Rolling operation in look-ahead dispatch.

In sum, the look-ahead dispatch dynamically operates the system by rolling the two-stage stochastic optimization. Due to the constant change of renewables, the time scale of two-stage prediction is usually not long [27]. In other words, it generally deals with short-term operation, such as ED, but not for long-term, such as UC. In addition, because it assumes that the system model in the following steps remains the same, the solution of look-ahead dispatch is not global optimal, which is one of the major concerns in risk-limiting dispatch.

C. Risk-limiting Dispatch

The risk-limiting dispatch is also a dynamic sequential operation method. The fundamental idea of risk-limiting dispatch is to restrict the risk for the final operation objective through stages of operation [4], [9], [33]–[35]. Therefore, in risk-limiting dispatch, there are a series of recourse decisions inserted between the initial stage and the final goal stage, and the final goal stage can be either a single time point, or a time horizon. Furthermore, the global optimal scheduling strategy can be found in risk-limiting dispatch, providing enough prediction information.

To specify the major features, Fig. 6 shows the operation strategies for the whole time horizon. Here the final operation goal is the power balance for real time t. At the initial stage, the operation strategy, either a UC or ED, is generated. As time goes by, at the recourse stages, the operation strategies are made with the updated prediction information that can be viewed mathematically as the conditional probability. Then, in real time, the final strategy prevents potential emergencies. The mathematical model is shown in (10).

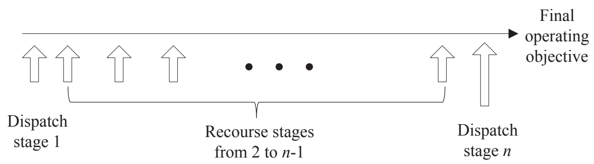

Fig. 6. Risk-limiting dispatch with recourse decisions.

$$\begin{aligned} &\text{minimize} \quad E\{\sum_{i=1}^{n} c_i s_i\} \\ &\text{s.t.} \quad p\{\sum_{i=1}^{n} s_i + w = d|Y_n\} \geq \eta, \end{aligned} \tag{10}$$

where s_i is the dispatch power in stage i, Y_n is the prediction information in stage n, η is the risk level, d is the load, and w is the wind power.

For the first feature of the model, shown in (10), theoretically, the risk constraints for each stage should be added into the optimization model; however in [9], it has been proven that the risk bounds in previous stages are the subset of the ones in the final stage. In other words, considering the risk constraint in the final stage is enough, which greatly reduces the computation complexity. Moreover, the risk index can be varied according to specific operation requirements. Thus, the feature of using risk constraint brings about more flexibility to the operating problem.

For the second feature, [9], [35] and [36] use dynamic programming to arrive at the analytical solution, where the solution form is very simple and elegant. Furthermore, [35] and [36] have given the analytical solution for the time horizon including n recourse stages. Ideally, the increasing frequency of recourse stages leads to more accurate and economically beneficial operation decisions because recourse decisions can largely reduce the expensive and fast start-up units as well as load shedding.

In the last feature, the operation strategy is global optimal, as long as the prediction information provides the conditional probability for the distribution of renewables [9]. The objective function of risk-limiting dispatch is a conditional expectation, varying with the conditional probability; thus the global optimal solution can be found by dynamic programming, in which the specific or fixed objective function is not required.

As with the current risk-limiting dispatch model in [9], there are two main simplifications. First, the risk constraint LOLP is set to be 0; thus the probability constraint is regressed. If the confidence level can be reduced a little, the dispatch cost must be decreased. Even under extreme circumstances, while the net load can be matched by flexible emergency measures, such as load shedding, the expectation dispatch cost will reduce. Second, the current theory is being realized on a single bus system, whereas the network influence is regressed. In realistic systems, the network constraint limits the output of controllable generation, which calls for improvement.

In [37], an analytical solution is found when the units' generation bound is taken into consideration, while the transmission capacity is still neglected. In [38]–[40], the influence of the network is considered. Assuming there is at most one congestion line, the network can be replaced by a single bus system, plus the two buses, and one line system; the analytical solution can then be derived. The model is a two-stage stochastic form, where the recourse stage is not considered, and the operation reliability and economics are determined in a day-ahead market. Thus, they are not as reliable and cost-saving as multi-stages dispatch, and the probability constraint is also regressed.

Despite the restriction of current risk-limiting dispatch, their merits are remarkable, and thus the idea of risk-limiting has been extended in different topics [41]–[45]. Reliability and flexibility are balanced well, which in turn helps to realize the basic operational goal: safety and economic benefits.

D. Robust Optimization

Since RO only requires moderate knowledge of the uncertainty and its solution immunizes against any realization of the uncertainty set, RO applications in power system operation have been extensively studied. Due to the consideration of computational tractability, robust linear programming (RLP) has become an area of interest. Normally, rather than the basic non-adjustable RLP, the more complex Adjustable Robust Linear Optimization (ARLP) [46] is employed to reduce the degree of conservatism and to cooperate with the multistage nature of problems in power systems. ARLP includes some "here and now" decisions to be determined before the uncertainty reveals itself, and some "wait and see" decisions to be determined after the uncertain data are known. Usually, a two-stage optimization problem is modeled. Benders decomposition is one of the major algorithms for solution methodology development.

In power system operation, robust unit commitment might be the most extensively studied topic among RO applications [47]–[53]. In [47], an adaptive robust unit commitment that has two stages is proposed. First, the nodal net injection uncertainty is considered in which decisions are divided into two groups, binary variables of commitment related decisions and continuous variables of dispatch related decisions. "Budget of uncertainty" is then used to control the extent of conservatism. As the "budget" reduces, the solution becomes less conservative since a smaller uncertainty set is considered. However, the robustness against uncertainty also decreases, and the problem of how to determine a reasonable "budget" arises. Some publications propose similar models with additional considerations. In [49], wind uncertainty correlations are included. In [52], especially the uncertainty of wind power and the buffer effect of pumped storage hydro are handled. And in [54], natural gas congestion is considered in the wind-thermal system. Readers can refer to [53] for more modeling details of robust unit commitment.

Although the application of ARLP already decreases the conservativeness compared to the non-adjustable ALP, many studies to further reduce the conservativeness of RO are executed. Reference [48] discusses multiple approaches of uncertainty set construction, aiming at reducing the conservativeness while maintaining the same degree of robustness.

It points out that the spatial and temporal correlations between uncertain parameters, and split uncertainty set can be modeled. However, according to [55], this is more a tradeoff between robustness and conservatism.

References [50] and [56] apply a different decision-making philosophy, i.e., the maximum regret criterion, to evaluate a robust feasible solution to select the robust optimal solution. The regret of a decision in a specific scenario is its cost minus the least cost among all decisions; moreover, the maximum regret of a decision is introduced since there exist plenty of possible scenarios. This can be a meaningful modification since the same level of robustness against uncertainty is maintained. However, according to [56], compared with the normal maximum cost criterion, the performance of this method depends on the construction of an uncertainty set and the preference of the decision-maker. In [51], a unified stochastic and robust unit commitment model is proposed that will take advantage of the two optimization methodologies and overcome their respective limitations, namely, computational challenges for stochastic optimization (SO) and conservatism for RO. The objective function consists of stochastic and robust parts with adjustable weights in this work. Based on preference, one can adjust the weights. More attention, however, should be paid to the combination of SO and RO for more investigations.

With respect to the potential development, the very first one is the construction of the uncertainty set. Until now, the basic box set, ellipsoidal set, split uncertainty set, and discrete scenario-based uncertainty set could be handled with additional considerations such as spatial and temporal correlations. Methods for uncertainty set construction of different problems could also be found. Nevertheless, there is a need for more studies on this topic to more accurately represent the actual information, as methods for uncertainty set construction also greatly influence the level of conservatism. Moreover, the possible combination of SO and RO is worth studying due to their complementary characteristics. Reference [51] provides one kind of possible combination. Another opportunity is that the theory of RO can provide computationally tractable approximations for chance-constrained uncertain linear programming problems.

Finally, to justify the application of RO, more precise interpretations of the robust optimal solution obtained by RO should be presented based on the detailed situations of the actual problems and when compared to other methodologies.

V. CONCLUSION

Power system operation is always a battle between reliability and economic benefits, especially with the influx of uncertainty resulting from the high penetration of renewables generation. For the four prevailing operation methods, the weight between reliability and economic benefits are different. In scenario-based stochastic programming, the reliability method can be secured exhaustively in all selected scenarios. In the look-ahead dispatch, the operation method is conducted dynamically, which reduces the dispatch cost through fast response units and load shedding. As with the risk-limiting dispatch method, by introducing stages of recourse decision, operation strategies can become more economical, flexible, and user-friendly as UC and ED are combined, and risk is customized. Finally, robust optimization ensures system safety and security at the price of expensive operating costs. Accordingly, creating a universal operation theory is hardly feasible. Rather, dispatch methods should be matched to the specific operation requirements.

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