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Review

Uncertainty in Unit Commitment in Power Systems: A Review of Models, Methods, and Applications

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Abstract: The unit commitment problem (UCP) is one of the key and fundamental concerns in the operation, monitoring, and control of power systems. Uncertainty management in a UCP has been of great interest to both operators and researchers. The uncertainties that are considered in a UCP can be classified as technical (outages, forecast errors, and plugin electric vehicle (PEV) penetration), economic (electricity prices), and "epidemics, pandemics, and disasters" (techno-socio-economic). Various methods have been developed to model the uncertainties of these parameters, such as stochastic programming, probabilistic methods, chance-constrained programming (CCP), robust optimization, risk-based optimization, the hierarchical scheduling strategy, and information gap decision theory. This paper reviews methods of uncertainty management, parameter modeling, simulation tools, and test systems.

Keywords: chance-constrained programming; hierarchical scheduling strategy; information gap decision theory; probabilistic methods; risk-based optimization; robust optimization; stochastic pro-gramming; unit commitment problem; uncertainty

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1. Introduction

A UCP involves the optimization of the ON/OFF states of generation units by minimizing the total operational cost while considering different constraints, in a particular period, generally one day/week. This problem arises mainly from the changing nature of human activities, which result in frequent load changes in each interval (minute, hour, day). Changes in load patterns require a change in available generation power plants. Mathematically, this problem is to optimize a set of completely mixed and nonlinear integer equations under different constraints to minimize the operational cost by solving the optimal combination of units from all possible scenarios.

In the last century, the UCP has continued to be significant, on account of developments and other changes in the power industry. Environmental policies, restructuring, privatization of the grid, penetration of RE, and the advent of smart grids have resulted in many changes and randomness in the power grid.

Uncertainties associated with various input parameters in the grid have raised several operational issues for system operators and other stakeholders. According to Ebeed et al. [1], the uncertainties of the parameters can be classified into two general categories: — uncertainties of technical parameters and those of economic parameters. The COVID – 19 pandemic has resulted in an unexpected global economic and social dilemma [2], leading to the identification of a third category of "epidemics, pandemics, and disasters", all of which have techno-socio-economic effects on the energy sector.

Uncertainty affects schedules and may raise new challenges for the power grid. Various techniques and methods have been studied and employed to control the consequences of uncertainties associated with parameters.

Different studies and reviews were published considering uncertainty management. Uncertainty management can be implemented using different decision – making techniques [3] and various system optimization algorithms [4–7]. Abujarad et al. [5] discussed different optimization approaches for a UCP considering intermittent renewable energy resources. Dai et al. [6] provided a summary of different SP applications in a UCP. Lastly, Jurković et al. [7] highlighted the advantages and disadvantages of commonly used methods (stochastic, robust, and interval) in UCPs for uncertainty management. Unlike previous studies, this paper will focus on a review of previously implemented methods such as stochastic programming, probabilistic methods, CCP, RO, risk-based optimization, hierarchical scheduling strategy, and IGDT in uncertainty management considering technical, economical, and "epidemics, pandemics, and disasters" parameters.

The objectives of this paper are as follows:

1. Delve into research that has considered uncertainty in the unit commitment problem.
2. Discuss models, methods, test systems, and simulation tools that are used for uncertainty management.
3. General comparison of different methods in terms of hardware specification, solver, run – time, and results.

This paper is structured as follows: Section 2 formulates the general unit commitment problem. Section 3 shows the modeling of different uncertainties that are considered in relation to unit commitment. Section 4 briefly reviews methods or techniques that are used to address these uncertainties. Section 5 addresses the different constraints that are applied in each method as well as the implemented test systems and simulation tools. Section 6 presents general notes on reviewed methods or techniques in addressing uncertainties. Lastly, Section 7 concludes by presenting the most important findings.

2. Unit Commitment Formulation

A UCP is a high-dimensional, mixed-variable, and complex problem because of its combinatorial behavior. The UCP involves the minimization of cost or maximization of profit. The formulation in this section involves all commonly used cost functions and constraints from various studies. Section 5 will summarize them.

2.1. Objective Function

The general expression of the objective function in the UCP is minimizing the total cost of running all the units for a given time. The difference between TC and TR is defined as,

$$\begin{gathered}\text{Minimize } \sum_{i}^{N_g}\sum_{t}^{T}\left(TC_i^t\text{-}TR_i^t\right)\\ \text{or}\\ \text{Maximize } \sum_{i}^{N_g}\sum_{t}^{T}\left(TR_i^t\text{-}TC_i^t\right)\end{gathered} \tag{1}$$

where TC, or total operation cost, is specified mainly in terms of fuel cost, shutdown, start-up, emissions, and social welfare cost. TR represents the total revenue because of market involvement. The essential parameter that affects TR is the payment method, which is specified in terms of market operations and market-clearing mechanisms. All of these must be optimized by taking into account the constraints that govern the problem. In the classical UCP, TR is not considered because the market is regulated.

2.2. Different Terms of Objective Function

Section 2.2 presents the terms associated with TC and TR.

2.2.1. Total Cost Terms

The five cost terms are fuel, start-up, shutdown, emission, and social welfare cost functions.

TC is calculated as,

$$\mathrm{TC_i^t} = \sum_{i=1}^{N_g}\sum_{t=1}^{T} \mathrm{F_i}\left(\mathrm{P_{gi}^t}+\mathrm{R_{gi}^t}\right)\mathrm{X_i^t} + \mathrm{SUC_i}\mathrm{X_i^t} + \mathrm{SDC_i}\left(1-\mathrm{X_i^t}\right) \quad (2)$$

The social welfare and emission functions are not directly included in the TC term and will be considered in a multi-objective optimization framework.

Fuel Cost Function

The fuel cost function of a thermal generator is given in quadratic form. The conventional form of this function is as follows.

$$\mathrm{F_i}\left(\mathrm{P_{gi}^t}+\mathrm{R_{gi}^t}\right) = \mathrm{a_i} + \mathrm{b_i}\left(\mathrm{P_{gi}^t}+\mathrm{R_{gi}^t}\right) + \mathrm{c_i}\left(\mathrm{P_{gi}^t}+\mathrm{R_{gi}^t}\right)^2 \quad (3)$$

Emission Function

Emission function is presented in a non-linear form as follows.

$$E_{\mathrm{i}}\left(\mathrm{P_{gi}^t}+\mathrm{R_{gi}^t}\right) = \alpha_{\mathrm{i}} + \beta_{\mathrm{i}}\left(\mathrm{P_{gi}^t}+\mathrm{R_{gi}^t}\right) + \gamma_{\mathrm{i}}\left(\mathrm{P_{gi}^t}+\mathrm{R_{gi}^t}\right)^2 + \xi_i e^{\lambda_i\left(\mathrm{P_{gi}^t}+\mathrm{R_{gi}^t}\right)} \quad (4)$$

Social Welfare Function

Social welfare function involves the so-called penalty cost function. Social welfare is maximized when this penalty cost function is minimized. Table 1 shows the different models of this function and the studies that consider them.

Table 1. Different Models of Penalty Cost (Social Welfare) Function.

Study	Model
[8–41]	Load Shedding
[10,24,27,30–33,39,40,42–47]	Wind Spillage
[12,48]	Fuel Consumption
[12,32,48]	Emission Allowance
[12,18,31,41,49–52]	Replacement Reserve Penalty
[12,18,31,41,49–51,53]	Spinning Reserve Penalty
[15–18]	Transmission Capacity/Ramp – Rate Limit Violations
[25,29]	RE Curtailment
[44]	BESS Charge and Discharge Index

Start-Up Cost

In a thermal power plant, the start-up cost varies on fuel and emission prices, along with depreciation costs. These costs vary on off-time and therefore on a generator's temperature at the time when it is started up again. Mostly, a basic approach is implemented to specify the start – up cost. This cost is a function of the operational status of the thermal generator and can be allocated into cold and hot start – up costs, as follows.

$$\mathrm{SUC_i} = \begin{cases} \mathrm{HSUC_i} & \mathrm{T_{i(OFF)}^t} \le \mathrm{T_{i(down)}^t} + \mathrm{T_{i(cold)}^t} \\ \mathrm{CSUC_i} & \mathrm{T_{i(OFF)}^t} > \mathrm{T_{i(down)}^t} + \mathrm{T_{i(cold)}^t} \end{cases} \text{ for all thermal units over all time intervals} \quad (5)$$

The start – up cost of a thermal generator is modeled as,

$$SUC_i = CSSMC_i + CSUC_i\left(1\text{-}e^{\left(\frac{SX_{i(OFF)}^{t}}{CC_i}\right)}\right) \quad (6)$$

Shutdown Cost

Most of the time, the shutdown cost is constant. This cost is developed as a constant term for each thermal generator, which is shut down in a specified hour.

2.2.2. Total Revenue of Generation Companies

The total revenue is taken from the sales of power. The three main approaches for payment are PPD, PRA, and PPRP. Abdi reviewed these methods [54].

2.3. Problem Constraints

This subsection presents the primary constraints in the UCP.

2.3.1. System Constraints

System constraints, known as global constraints, are important in the UCP. The main system constraints are as follows.

System Energy Balance or Real Power Constraints

$$\sum_{i=1}^{N} P_{gi}^{t} X_i^t \leq P_d^t \qquad t=1,\ldots,T \quad (7)$$

Energy Constraints

$$E_i^{min} \leq \sum_{i=1}^{N} P_{gi}^{t} X_i^t \leq E_i^{MAX} \quad (8)$$

Reserve Constraints

$$\sum_{i=1}^{N} R_{gi}^{t} X_i^t \geq SR^t \qquad t=1,\ldots,T \quad (9)$$

Transmission Losses

The transmission losses are considered as follows.

$$P_{loss}^{t} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P_{gi}^{t} B_{i,j} P_{gj}^{t} + \sum_{i=1}^{N_g} B_0 P_{gi}^{t} + B_{00} \quad (10)$$

2.3.2. Unit Constraints (Local Constraints)

Unit constraints are the local constraints that are considered on each generating unit. They are as follows.

Power Unit Limits

$$P_{gi}^{min} \leq P_{gi}^{t} \leq P_{gi}^{MAX}, \quad i=1,\ldots,N \quad (11)$$

Reserve Unit Limits

$$0 \leq R_{gi}^{t} \leq P_{gi}^{MAX} - P_{gi}^{min}, \ i=1,\ldots,N \quad (12)$$

$$P_{gi}^{t}+R_{gi}^{t}\leq P_{gi}^{MAX},\ i=1,\ldots,N \tag{13}$$

Unit Minimum Up/Down Times (MUT/MDT)

$$U_i^t=\begin{cases} 1;\ T_{i(ON)}^{t-1}\leq T_i^{up} \\ 1;\ T_{i(OFF)}^{t-1}\leq T_i^{down} \\ 1 \text{ or } 0;\text{otherwise} \end{cases} \tag{14}$$

Ramp Rate Limits (RRLs)

$$P_{gi}^{t}-P_{gi}^{t-1}\leq UR_i \tag{15}$$

$$P_{gi}^{t-1}-P_{gi}^{t}\leq DR_i \tag{16}$$

Unit Status Limits

Several units may be needed to be online at a specified duration (must run) or may become offline due to scheduled maintenance or forced outages (must not run), due to reliability issues, economic factors, or operating limitations.

2.3.3. Security Constraints

In the SCUCP, security constraints are developed as follows.

AC Power Flow Constraints

$$P_{Bgp}^{t}-P_{Bdp}^{t}-V_{p}^{t}\sum_{q=1}^{N_g}V_{q}^{t}\left(G_{pq}\cos\theta_{pq}+B_{pq}\sin\theta_{pq}\right)=0 \quad p\epsilon(N_B\text{-}1)\ \ t=1,..,T \tag{17}$$

$$Q_{Bgp}^{t}-Q_{Bdp}^{t}-V_{p}^{t}\sum_{q=1}^{N_g}V_{q}^{t}\left(G_{pq}\sin\theta_{pq}-B_{pq}\cos\theta_{pq}\right)=0 \quad p\epsilon N_{PQ}\ \ t=1,..,T \tag{18}$$

Transmission Line MVA Flow Limits

$$MVAflow_{pq}^{t}\leq MVAflow_{pq}^{MAX} \tag{19}$$

Bus Voltage Constraints

$$V_q^{min}\leq V_q^t\leq V_q^{MAX} \tag{20}$$

3. Modeling of Uncertainty

The challenges that are raised by uncertain parameters in the power grid have encouraged operators to use different uncertainty modeling techniques to prepare for their consequences and to make the best decisions. Table 2 shows works concerning each category of uncertainty.

Table 2. Studies Concerning Uncertainty Parameters in Unit Commitment Problem.

Category	Description	Related Works
1 (Technical)	outage or failure of any element (lines, generators, or others)	[20,21,28,46,53,55–72]
	load demand alteration/load growth	[9–12,17,18,21,23–25,27–34,41,43,47–50,53,55–58,60–64,66,70–85]
	renewable output (wind, PV, etc.)	[9,10,12–17,22–35,38–45,47,49,51,53,55,57,58,60,65–76,78,79,81–111]
	Fluctuation	[11,13,24,35,44,50,65,74,76,112,113]
	uncertain penetration of PEVs	[55,70,72,75,86,87,104,114]
2 (Economic)	variations in electricity market price	[11,16,18,19,24,43,61,81,83,84,103,109,115]
3	epidemics, pandemics, and disasters	[36,100,116]

The uncertainties of parameters can be classified as technical, economic, and "epidemics, pandemics, and disasters". The following subsection will describe each model of uncertain parameters in the power system.

3.1. Outage or Failure of Any Element (Lines, Generators, or Others)

The uncertain parameter in the power system considering failure or outages is obtained using different reliability indices. These reliability indices can be classified as deterministic or probabilistic. Table 3 identifies each parameter, based on the work of Albrecht *et al.* [117].

Table 3. Various Reliability Indices in Power System.

Deterministic Indices	Probabilistic Indices
Percent reserve based on peak load Percent reserve based on installed capacity Reserve equal to several large units Maximum load not supplied Maximum energy not supplied Minimum load supplying capability Minimum simultaneous interchange capability Maximum line flow	HLOLE LOLE/LOLP POPM Q PLOL EENS XLNS/XLOL FLOL DLOL BPII BPECI

3.2. Load Demand Uncertainty Model

The uncertainty of load demand can be developed using Gaussian or normal PDFs. The PDF of load demand can be stated as follows. [9,24,30,34,53,60,64,66,73,81]

$$f_L(P_D)=\frac{1}{\sqrt{2\pi\sigma_D}}e^{\left(-\frac{(P_D-\mu_D)2}{2\sigma_D^2}\right)} \tag{21}$$

3.3. Wind Energy Uncertainty Model

Wind speed is an important parameter in determining wind energy output. The distribution of wind speeds can be modeled as a Weibull PDF or as Rayleigh PDF. Equations (22) and (23) describe the Weibull PDF and Rayleigh PDF of wind speed [23], respectively.

$$f_\omega(\omega)=\left(\frac{\beta}{\alpha}\right)\left(\frac{\omega}{\alpha}\right)^{\beta-1}e^{\left(-\left(\frac{\omega}{\alpha}\right)^{\beta}\right)} \qquad 0\leq V<\infty \tag{22}$$

$$f_{\omega}(\omega)=\left(\frac{2\omega}{\alpha^2}\right)e^{\left(-\left(\frac{\omega^2}{\alpha^2}\right)\right)} \quad (223)$$

A Weibull PDF with $\beta=2$ is called a Rayleigh PDF.

The output wind power can be expressed by means of various models. Table 4 presents commonly used models.

Table 4. Models for Determining Wind Energy Output.

Model	Study
$P_W(\omega)=\begin{cases}0 & \text{for } \omega<\omega_i \text{ and } \omega>\omega_o\\ P_r\left(\frac{\omega-\omega_i}{\omega_r-\omega_i}\right) & \text{for } (\omega_i\leq\omega\leq\omega_r)\\ P_r & \text{for } (\omega_r<\omega\leq\omega_o)\end{cases}$	[42,118–123]
$P_W(\omega)=\frac{1}{2}\rho AV^3C_p$	[29,110,124]
$P_W(\omega)=\begin{cases}0 & \text{for } \omega<\omega_i \text{ and } \omega>\omega_o\\ P_r\left(\frac{\omega^3-\omega_i^3}{\omega_r^3-\omega_i^3}\right) & \text{for } (\omega_i\leq\omega\leq\omega_r)\\ P_r & \text{for } (\omega_r<\omega\leq\omega_o)\end{cases}$	[49,125]
$P_W(\omega)=\begin{cases}0 & \text{for } \omega<\omega_i \text{ and } \omega>\omega_o\\ P_r\left(\frac{\omega^2-\omega_i^2}{\omega_r^2-\omega_i^2}\right) & \text{for } (\omega_i\leq\omega\leq\omega_r)\\ P_r & \text{for } (\omega_r<\omega\leq\omega_o)\end{cases}$	[126]

3.4. PV Energy Uncertainty Model

The PV energy output is affected by the irradiance at the location. The probability distribution of irradiance is represented as a lognormal PDF as follows [127–129].

$$f_S(G_S)=\frac{1}{SI\sigma_S\sqrt{2\pi}}e^{\left(-\frac{(\ln(SI)-\mu_S)^2}{2(\sigma_S)^2}\right)} \quad (234)$$

The probability distribution of solar irradiance can also be expressed using the Beta distribution function as follows.

$$f_T(T)=\begin{cases}\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)+\Gamma(\beta)}\times SI^{\alpha-1}\times(1--SI)^{\beta-1} & \text{if } 0\leq -SI\leq 1,\ \ 0\leq\alpha,\beta\\ 0 & \text{otherwise}\end{cases} \quad (245)$$

where β and α are parameters in the beta probability function. The parameter of the Beta PDF can be assessed using the standard deviation and mean of the random variable [128,129]:

$$\beta=(1-\mu_S)\times\left(\frac{\mu_S\times(1+\mu_S)}{\sigma_S^2}\right)-1 \quad (256)$$

$$\sigma_S=(1-\mu_S)\times\left(\frac{\mu_S\times\beta}{1-\mu_S}\right)-1 \quad (27)$$

The output PV power can be expressed using different models. Table 5 presents commonly used models.

Table 5. Models for Determining PV Power Output.

Model	Study
$P_{PV,out}=\begin{cases} P_{sr}\left(\frac{SI_{S-}^{2}}{G_{std}\times X_{c}}\right) & \text{for } 0<-SI\leq G_{std} \\ P_{sr}\left(\frac{SI}{G_{std}}\right) & \text{for } -SI\geq X_{C} \end{cases}$	[119,123]
$P_{PV,out}=\begin{cases} P_{sr}\left(\frac{SI}{G_{std}}\right) & \text{for } 0<SI\leq G_{std} \\ P_{sr} & \text{for } SI\geq G_{std} \end{cases}$	[121,122]
$P_{a}(SI)=\int P(SI)\cdot f(SI)\cdot dSI$	[78,129]
$P_{PV,out}=\zeta_{PV}\times A_{PV}\times SI$	[110,130]
$P_{PV,out}=N_{S}\times N_{P}\times FF\times V_{OC}\times I_{SC}$ $V_{OC}=\frac{V_{NOC}}{1+c_{2}\ln\left(\frac{G_{std}}{SI}\right)}\left(\frac{\tau_{N}}{\tau_{a}}\right)$ $I_{SC}=I_{NSC}\left(\frac{G_{std}}{SI}\right)^{c}$ $FF=\left(1-\frac{G_{std}}{\left(\frac{V_{OC}}{I_{SC}}\right)}\right)\left(\frac{\frac{V_{OC}}{nK\tau/q}-\ln\left(\frac{V_{OC}}{nK\tau/q}+0.72\right)}{1+\frac{V_{OC}}{nK\tau/q}}\right)$	[118]
$P_{PV,out}=N_{S}\times N_{P}\times FF\times V_{OC}\times I_{SC}$ $I=G_{a}[I_{SC}+K_{i}(\tau_{C}-25)]$ $V=V_{oc}-K_{v}\times\tau_{c}$ $FF=\frac{V_{mpp}\times I_{mpp}}{V_{oc}\times I_{oc}}$	[127,128]
$P_{PV}(t)=\frac{SI(t)}{1000}\times P_{sr}\times\eta_{PV}\times\left[1-\beta_{T}(\tau_{C}-25)\right]$ $\tau_{C}=25+(NOCT-20)\times\frac{SI(t)}{800}$	[74,125]

3.5. PEVs Uncertainty Model

The random nature of PEVS were considered and modeled using normal or Gaussian PDFs [127,131]. Table 6 presents various random variables that are related with PEVs. The PEV's daily arrival time is a common random variable that can be considered in the modeling uncertainties associated with PEV.

Table 6. Random Variables Concerning PEVs.

Random Variable	Study
daily arrival time (initial parking time)	[55,70,75,86,114,127]
initial state of charge (SOC) of the EV battery	[72,86,87,127,131]
vehicle travel (distance)	[55,70,75,86,87]
charge and discharge power of the EV	[55,72,87,125,131]

3.6. Load Growth Uncertainty Model

Load growth is essential information in the research of a power system; it is also considered to be a random parameter. $P_{L}(0)$ denotes the initial load in the base year while $\Delta P_{L}(y)$ is the incremental load growth in year *y*. Therefore, the load in year *y* is $P_{L}(y)=P_{L}(0)+\Delta P_{L}(y)$. Its PDF can be expressed as follows [122]:

$$f_{\Delta P_L}(\Delta P_L)=\frac{1}{\sigma_{\Delta P_L}\sqrt{2\pi}}e^{\left(-\frac{\left(\Delta P_L-\mu_{\Delta P_L}\right)2}{2\left(\sigma_{\Delta P_L}\right)^2}\right)} \quad (268)$$

3.7. Electricity Price Uncertainty Model

Electricity price bought from the grid can also cause uncertainties in power system operation. The PDF of the electric price can be expressed as follows. [120,132]

$$f_{EP}(EP)=\frac{1}{\sigma_{EP}\sqrt{2\pi}}e^{\left(-\frac{\left(EP-\mu_{EP}\right)^2}{2(\sigma_{EP})^2}\right)} \quad (29)$$

3.8. Epidemics, Pandemics, and Disasters

Natural disasters such as typhoons, droughts, tsunamis, and earthquakes may generate uncertainty in the power grid. No base model exists for this category as each type of disaster can have certain consequences in the system (it can cause outages of power system components, a deficiency of supply, or excess supply). Huang et al. modeled the spillage of water from hydropower plants as an uncertain parameter [100]. Arab et al. proposed a post-disaster model that considered whether a component was "damaged" or "functional" [116]. Components that are classified as "damaged" undergo repairs for a specified time, and the VOLL is included in the UCP. Zhao et al. considered the worst load forecasting and line failure scenario in the UCP after a hurricane has occurred [36]. Pandemics and epidemics are presently highly significant,—specifically due to the COVID-19 pandemic [2]. This category will motivate new studies and modeling techniques since it influences the energy sector not only techno-economically but socially as well.

4. Different Methods Used for Uncertainty in Unit Commitment

The previous section considered the models of different uncertain parameters in the power grid. Different methods are required to solve the UCP with these uncertain parameters. Ebeed et al. [1] and Majidi et al. [133] classified these methods as possibilistic, probabilistic, hybrid possibilistic – probabilistic, IGDT, robust optimization, and interval analysis. This section discusses the methods considered in the literature review.

4.1. Stochastic Programming

SP is an approach that is risk-neutral and optimizes the expected outcome over a known probability distribution. Li et al. provided a brief history and review of stochastic programming methods [134]. They also discussed instances of SP, such as two – stage SP, multistage SP, multistage SP that goes through endogenous uncertainty, and scenario tree generation that is data-driven. Table 7 presents studies in which stochastic programming was used and the uncertain parameters modeled.

Table 7. Studies that Use Stochastic Programming.

Uncertainty Model	Ref.	Remarks
Demand	[11]	➢ MCS is performed to generate possible outcomes. ➢ SAA replaces the expected value function. ➢ The chance constraint is substituted by MILP reformulation. ➢ The price – elastic demand curve can be acquired by historical and simulation data analysis.
Demand	[17]	➢ A low expected total cost results from the novel unified stochastic and RUC model while ensuring system robustness.

Wind Power	[12]	➢ The WILMAR model is used. This model consists of two parts: — the scheduling model and STT. ➢ The main use of STT is to create scenarios used as inputs to the scheduling model. ➢ The STT is used to generate scenarios that are used as inputs to the scheduling model. ➢ The required wind and load scenarios are generated through the MCS of the wind and load forecast error coming from and based on an auto-regressive moving average model that illustrates the wind speed forecast error. ➢ The varied probable scenarios generated are then reduced in number using a scenario reduction approach. ➢ A stochastic, mixed – integer optimization model is applied for the scheduling model.
Wind Power	[33]	➢ Wind generation uncertainty is presented using different scenarios that capture all feasible realizations of the stochastic process. ➢ An appropriate set of scenarios were generated using a time series model. ➢ SP by market – clearing model was used to calculate the required reserve levels and their associated costs on a daily time horizon.
Wind Power	[34]	➢ Proposes analytical EENS and LOLP indices to which wind power uncertainties contribute, using the Q – function approximation.
Wind Power	[42]	➢ Weibull PDF was proposed to characterize the stochastic wind speed characteristic. ➢ WECS is included in the ED problem model. ➢ Together with the classic ED factors, other factors that account for both the overestimation and the underestimation of available wind power are included.
Wind Power	[43]	➢ This model optimizes the dispatch and commitment of power generating units in the electricity system by minimizing operating costs. ➢ The scenario tree approach is used to model wind power uncertainty.
Wind Power	[51]	➢ The potential value of ESU in power systems with renewable penetration are determined using a two – step framework. ➢ The first step uses a stochastic unit commitment with energy storage and wind power generation forecast uncertainty. ➢ In the second step, the stochastic unit commitment solution is applied to obtain a flexible schedule for energy storage in economic dispatch with a limited look-ahead horizon. ➢ GP regression is applied to generate the wind scenarios which account for the errors in the NWP.
Wind Power	[58]	➢ Stochastic unit commitment including input and rolling planning scenarios, based on wind forecasts, is proposed. ➢ STT is established that allows forecast error statistics to be modified and simplifies the study of the impacts of statistics on system operation and UC.
Wind Power	[73]	➢ The proposed scheme differs from already known unit commitments in such a way of explicitly modeling the day – ahead predicted residual demand PDF, including the effect of wind power curtailment.
Wind Power	[89]	➢ The forecasted sporadic wind power generation is included in the UCP and solved in the master problem. ➢ Benders' cuts are generated and combined with the master problem to revise the commitment solution if the dispatch fails.

		➢ Possible scenarios are simulated by MCS to represent wind power volatility. ➢ The computational requirement for simulating many scenarios are reduced by the scenario reduction technique.
Wind Power	[91]	➢ Describes a computational framework that combines an advanced NWP model in economic dispatch/stochastic unit commitment formulations. ➢ Enhances the NWP model with an ensemble – based uncertainty quantification approach that is realized in a distributed – memory parallel computing architecture.
Wind Power	[92]	➢ Comparison of interval optimization and scenario – based approaches to stochastic SCUC are presented. ➢ Monte Carlo simulation is used for scenario – based approach. ➢ Lower and upper bounds are utilized in interval optimization. ➢ The stochastic SCUC problem is formulated as an MILP problem.
Wind Power	[95]	➢ Development of an Artificial Neural Network – based wind forecast model that considers wind generation uncertainty by using the probabilistic concept of a confidence interval.
Wind Power	[96]	➢ The stochastic bottom – up electricity market model optimizes unit commitment taking into account five kinds of market and considering the prediction error and stochastic behavior of wind power generation. ➢ It can be used to evaluate varying electricity prices and system costs because of wind power integration and to study integration measures.
Wind Power	[97]	➢ Wind power is approximated using a normal PDF. ➢ Many scenarios are generated by MCS in describing the stochastic nature of wind power output. ➢ The generated scenarios are separated into three types (typical, normal, extreme) using CFSDP. ➢ Extreme scenarios are discovered to establish the on/off states of generators, and the typical scenarios are utilized to solve the day – ahead SCED problem.
Wind Power	[107]	➢ Novel formulation of FDCUCP. ➢ The impact of wind uncertainty on FDCUCP is considered using interval – based optimization. ➢ The original nonlinear model is reformulated to an MILP problem using the reformulation – linearization technique.
Wind Power and Demand	[30]	➢ The optimal schedule of generation units and the required flexible ramp and spinning reserves on a daily horizon are implemented on a proposed stochastic NCUC model that includes uncertainties of demand and wind power. ➢ Reduction of scenarios in modeling demand and wind power uncertainties is implemented using PEM. ➢ Worst – case scenarios that are based on regional wind and demand variations are defined and incorporated into the proposed model together with the PEM scenarios.
Wind Power and Demand	[57]	➢ This paper formulates a short – term forward electricity market clearing problem with stochastic security that is capable of accounting for variable and non – dispatchable wind power generation sources. ➢ Demand is modeled using a normal distribution function. ➢ Wind speed is modeled using a Rayleigh distribution function.
Renewable Energy	[44]	➢ Establishes a stochastic gas – power – network-constrained unit commitment model that considers both combined – cycle units and gas networks. ➢ ADP is proposed to prevent the curse of dimensionality.

		➢ Renewable energy output is modeled using a probabilistic distribution function.
Renewable Energy and Demand	[111]	➢ A stochastic programming model of the short – term peak shaving operation of a photovoltaic – wind – hydro hybrid system is implemented. ➢ The renewable energy production and load demand uncertainties are simulated using scenario trees and synthetic ensemble forecasts.
Solar, Wind, and Demand	[123]	➢ RTED is carried out every 5 – 15 min using static snapshot forecast data. ➢ The minute-to-minute variability of wind, PV, and demand on a given scheduling period is considered in the evaluation of "best-fit" PFs. ➢ The Weibull probability density function is obtained from the wind and solar profiles. ➢ Load demand is modeled using a normal PDF.
PEV	[86]	➢ Suggests a new stochastic framework based upon UT in modeling uncertainties related with PEVs' behaviors in considering the correlated WTs' power generation.
PEV, Demand and Wind Power	[72]	➢ MCS is utilized in the proposed stochastic model. ➢ PEV energy consumption patterns, load forecast errors, and the number of PEVs in a fleet are characterized by truncated normal PDFs. ➢ Wind speed variations are simulated by the Weibull PDFs, diurnal pattern, and auto correlation factor, and wind generation is found by incorporating it to a wind turbine power curve and wind speed at wind sites. ➢ Forward backward and forward algorithms are created to reduce the number of scenarios while providing acceptable accuracy.
PEV, Demand and PV	[75]	➢ The scheduling of local electricity flows is presented using a central planner – decentral operator method. ➢ The central planner performs a two-stage optimization to derive the demand limit and a corresponding battery schedule. The decentral operator, on the other hand, applies the battery schedule and heuristically reacts to unforeseen deviations between the actual and forecasted generation and demand. ➢ The reserve capacity and relaxation factor of the battery are derived from MCS that considers underlying uncertainties.
PEV and Wind Power	[87]	➢ Utilizes three coordinated PEV – wind energy dispatching methods in the V2G context (variable – rate energy dispatching, interruptible, and valley searching) to encourage user demand response by optimizing the utilization efficiency of wind power generation and meet dynamic power demands. ➢ These approaches are addressed in a stochastic framework, considering the uncertainties. ➢ A comparative study involves numerical simulation experiments that cover adequate system scenarios using scenario generation and reduction techniques.
Electricity Price	[19]	➢ Scenario trees are used to generate the scenarios for electricity price uncertainty. ➢ Power trading is included in the stochastic UC model. ➢ Fuel constraints and prices are considered in the model that may change with electricity prices and demand. ➢ Lagrangian relaxation and Bender's decomposition are applied in the MILP model.
Electricity Price Wind, Solar, and Demand	[81]	➢ A scenario-based technique is used in modelling the uncertainties of PV and WT output power, demand forecast errors, and grid bid changes for the optimal energy management of microgrid.

		➢ MBA is used to optimize the energy management of the grid-connected microgrid with large uncertainties.
Electricity Price (Investment) Load Growth	[83]	➢ The day-ahead reserve and energy markets, and real time operation are implemented using a proposed two – stage SP. ➢ Scenario tree is used to generate the investment and load growth model.
Electricity Price Wind Power	[103]	➢ Scenario generation (Roulette Wheel) is used to model uncertainty. ➢ The initial scenarios are reduced using SCENRED. ➢ A multi – objective offering strategy is proposed.
Electricity Price Renewable Energy	[113]	➢ An innovative formulation for UBFUCC^{DRRs} is suggested. ➢ The price – elasticity of electrical consumption is modeled, as an uncertain, unavailable, and hard – to – estimate parameter using Z numbers in a possibilistic – probabilistic method. ➢ Supply-side resource uncertainty is considered using MCS.
Electricity Price Load Growth PEV	[120]	➢ MCS is used to model uncertainty.
Outages of Generation Units	[20]	➢ Random disturbances are modeled using scenario trees. ➢ The failure probability law used is binomial. ➢ The use of an augmented Lagrangian technique provides the decomposition algorithm with satisfactory convergence properties.
Outages of Generation Units Demand Electricity Price	[21]	➢ Scenario generation is used to model the uncertainty.
Outages of Generation Units and Transmission Lines Demand	[48]	➢ Uncertainty modeled using scenario trees via MCS. ➢ The scenario aggregation method and scenario reduction are used to reduce computation time.
Outages of Generation Units Demand	[56]	➢ Compares the reserve and stochastic approach and evaluates the benefits of a combined method for the efficient management of uncertainty in the unit commitment problem. ➢ Two-state Markov process is implemented in modeling the state of generation resources. ➢ Uncertainty in the demand is handled by the addition of the stochastic forecast error.
Outages of Generation Units Demand and Wind Power	[60]	➢ Load is modeled using a normal distribution function. ➢ The 2 – state capacity model is used to represent generator availability. ➢ ARMA is used to model wind speed variations.
Outages of Generation Units Wind, PV, and Demand	[67]	➢ The uncertainties due to generator outages, PV, wind, and demand forecast errors are incorporated into the proposed optimization problem using EUE and LOLP reliability indices.

4.2. Probabilistic Methods

A PDF is identified for each random input parameter. Numerical and analytical methods are the commonly known category of probabilistic approaches or uncertainty modeling methods.

4.2.1. Numerical Methods

Numerical methods are mathematical tools used to find the uncertain input parameter. The main drawback of this method, also known as the conventional or purely mathematical method, is its high dimensionality and computing time. The following subsection will discuss MCS and MCMCS.

Monte Carlo Simulation

The MCS is applied to develop the probabilities of several outcomes of a process that cannot easily be predicted owing to the involvement of random variables. This is used to understand the impact of uncertainty and risk in forecasting and prediction models. Table 8 lists studies in which the MCS method was used and the uncertain parameters that were modeled in them. Most studies that use this method focus on renewable energy and demand as sources of uncertainty for the power grid.

Table 8. Studies In Which MCS Is Used.

Ref.	Uncertainty Model
[11]	Demand
[12]	Wind Power
[48]	Demand
[60]	Demand and Wind Power
[75]	Demand, PEV and PV
[89]	Wind Power
[92]	Wind Power
[97]	Wind Power
[113]	RE
[120]	Load Growth, Electricity Price and PHEV

Markov Chain MCS

MCMCS is a dynamic variation of the MCS method that is utilized to manage the uncertainty of parameters of a system. In this method, MCMCS is used to generate the samples based on the probability distribution, in which the probability of creating a unique state in the chain is based only on the present state.

In the MCMCS implementation, the probability of change is defined using the Metropolis method, which states that transition probability from state m to $\overline{m}$, is $q(m,\overline{m})$ while the probability of the accepted state is $\alpha(m,\overline{m})$ [1].

Table 9 presents studies in which the MCMS method has been used and the uncertain parameters that are modeled in them.

Table 9. Studies In Which MCMS Is Used.

Ref.	Uncertainty Model
[46]	Outages of Generation Units and Transmission Lines
[56]	Outages of Generation Units
[60]	Outages of Generation Units

4.2.2. Analytic Methods

Different analytical methods (scenario – based and PDF approximation) are established for calculation with PDFs of uncertain input parameters.

Scenario-Based Method

The scenario – based method is a simple and efficient method for developing probabilistic uncertainties in which the continuous space of an uncertain function is converted into discrete scenarios with subsequent probabilities, and the PDF curve is divided into subregions [1]. Each region denotes a scenario that has a particular probability. Suppose that the divided regions have k = 1,2, 3…, N and their subsequent probabilities are $p_1, p_2, p_3, \ldots, p_N$. The expected output value is given by,

$$E(y)=\sum_{k=1}^{N} p_k \times f(x) \tag{30}$$

The scenario-based method approximates and provides the expected values of the output functions.

Table 10 lists studies in which a scenario – based method is used, and the associated uncertain parameters. Scenario Trees are most used in the scenario-based method. Other methods include the WILMAR model, the PEM, GP regression, and the Roulette Wheel.

Table 10. Studies In Which Scenario-based Is Used.

Ref.	Uncertainty Model	Approach/Technique
[12]	Wind Power	WILMAR Model
[19]	Electricity Prices	Scenario Trees
[21]	Outages of Generation Units Demand Electricity Price	Scenario Generation (not stated)
[30]	Wind Power and Demand	PEM
[43]	Wind Power	Scenario Trees
[48]	Demand	Scenario Trees
[51]	Wind Power	GP Regression
[58]	Wind Power	Scenario Trees
[81]	Wind, Solar, and Demand Electricity Price	The Scenario – Based Technique (not stated)
[83]	Load Growth Electricity Price (Investment)	Scenario Trees
[103]	Electricity Price Wind Power	Scenario Generation (Roulette Wheel)
[111]	Renewable Energy and Demand	Synthetic Ensemble Forecasts and Scenario Trees

PDF Approximation

Approximate methods provide a simple description of the uncertain parameters by random variables. The main advantage of these methods is the use of deterministic routines for solving the UCP. In addition, approximate methods are computationally more efficient than other probabilistic methods.

Table 11 presents studies in which the PDF approximation method was used, the uncertain parameters modeled, and the type of technique considered. This method has been mostly applied to uncertainties with demand and renewable energy.

Table 11. Studies In Which PDF Approximation Is Used.

Ref.	Uncertainty Model	Approach/Technique
[36]	Disaster (Hurricane)	Fast Kernel Density Estimation Algorithm
[74]	PV	Cornish – Fisher Expansion
[75]	PV and Demand PEV	Kernel Distribution Estimation
[78]	PV and Demand	Gaussian Copula
[86]	PEV	Unscented Transformation
[104]	RE and Demand	Maximum Entropy and Gram – Charlier Probability Density Function Reconstructions
[112]	Wind Power	Nonparametric Density Estimators

4.3. Chance Constrained Programming

The core idea of conventional CCP is to permit constraint violation. The probability violation must be smaller than a predefined risk level (confidence interval). A general form of a chance constraint is as follows. [40]

$$\Pr\{f_i(x,\xi)\le B_i\}\ge 1\text{-}A_i \quad (31)$$

The symbol "Pr{•}" indicates the value of a probability.

CCP is regarded as solving a stochastic problem with some probabilistic constraints, such that certain constraints that are related to some uncertain parameters are fulfilled with a given probability.

Table 12 presents different studies in which CCP is used and the uncertain parameters modeled. A significant number of studies uses CCP to deal with uncertainties that are generated by wind power and demand.

Table 12. Studies In Which CCP Is Used.

Uncertainty Model	Ref.	Remarks
Wind Power	[9]	➢ This paper suggests an expected value and chance constrained stochastic optimization approach to solve the UCP with uncertain wind power output. ➢ The model utilizes the wind power generation by varying the utilization rate in the proposed expected value constraint. ➢ In the model, the utilization of wind power can be adjusted by changing the utilization rate in the proposed expected value constraint. ➢ The chance constraint is imposed to inhibit the probability of load imbalance. ➢ The expected value and chance constraint, and the objective function are transformed using SAA.
Wind Power	[14]	➢ The problem is formulated as CCTS stochastic program. ➢ The two-stage stochastic and chance – constrained stochastic program features were included in the given model. ➢ The model is effectively solve using a combined SAA algorithm.
Wind Power	[40]	➢ A novel CCGP model was proposed to optimize the risk adjustable UCP. ➢ A tractable MILP resulted to the transformation of the proposed model using a deterministic equivalent and piecewise linearization.
Wind Power	[45]	➢ MILP – based chance – constrained optimization model is proposed to establish efficiently the optimal wind power output ranges, which are quantified using maximum and minimum wind generation levels in a certain time interval. ➢ The developed wind power range is then used to create dynamic uncertainty intervals for the robust SCUC model.
Wind Power	[99]	➢ Transforms the conventional UC model into a chance – constrained stochastic problem to satisfy the optimal schedule objective. ➢ The non – convex problem is solved by introducing the PSO algorithm and BB technique; PSO is initialized using simplex algorithms.
Wind Power	[108]	➢ A novel method for solving GRCC – RTD with wind power uncertainty is proposed.
Wind Power Demand	[64]	➢ A new approach for reserve scheduling and joint energy and reserve scheduling and unit commitment under reliability constraints for the day – ahead market is provided. ➢ The proposed method includes a novel $n-K$ criterion under which load must be satisfied with a specified probability under any instantaneous loss of K generating units. ➢ A chance – constrained method is proposed with an α-quantile measure to determine the confidence level, where demand is met under K simultaneous contingencies.

		➢ The chance – constrained optimization problem CCP is recast as a MILP optimization problem.
Wind Power Demand	[79]	➢ The UCP is devised as a chance – constrained two – stage stochastic programming problem where the chance constraint is applied to limit the probability of load imbalance. ➢ Presents the bilinear mixed – integer formulation of the chance constraint, and then derives its linear equivalent using the McCormick linearization method. ➢ Develops a bilinear variant of Benders' decomposition method, which is an easy-to-implement algorithm, to answer the resulting large – scale linear equivalent.
Wind Power Electricity Price	[13]	➢ An optimal bidding strategy for independent power producers in a deregulated electricity market is proposed. ➢ The problem is devised as a two – stage stochastic price – based UCP with chance constraints to ensure wind power operation. ➢ The 1st stage decision includes unit commitment and the amount of electricity submitted to the day-ahead market. ➢ The 2nd stage outcome includes actual usage of wind power, generation dispatch, and energy imbalance among the day – ahead and real – time markets. ➢ The chance constraint is utilized to guarantee a specific percentage of wind power operation to satisfy renewable energy utilization regulations. ➢ SAA is applied to solve the problem.
Renewable Energy	[52]	➢ The problem is devised as a chance – constrained two – stage stochastic programming model. ➢ Three different policies are used to guarantee that the utilization of renewable energy is high in microgrid operations. ➢ The 1st policy imposes a specific percentage of renewable energy utilization for the full interval while the 2nd and 3rd policies impose renewable energy utilization for certain hours and all operating hours, respectively. ➢ A combined SAA algorithm is used in solving the proposed model.
Renewable Energy	[110]	➢ The method uses CCP to manage uncertainties in power that are generated by renewable resources. ➢ The design variables are the PV panel area, the number of batteries, and the rotor's swept area.
Renewable Energy Demand	[107]	➢ The total storage power and energy constraints are presented as chance constraints, for which conservative convex approximations are used for tractability.
Fluctuation	[65]	➢ Formulates a stochastic optimization program with chance constraints that determine the probability of fulfilling the transmission capacity constraints on generation and the lines limits. ➢ The steady – state behavior of the secondary frequency controller is considered to incorporate a reserve decision scheme. ➢ Deployed reserves are taken as linear function of the total generation-load mismatch. ➢ They are proposed for tractability. ➢ A scenario – based approach and an approach that considers only the quantiles of the stationary distribution of the wind power error are used in dealing the chance constraint.
Electricity Price	[85]	➢ A new electricity market – clearing structure based on LMPs is provided for assessing the uncertain generation and load. ➢ U – LMP is developed from a distributionally robust chance – constrained optimal power flow model where only the 1st order and 2nd order moments of the uncertain sources' probability distribution are required.
PEV Wind Power Demand	[106]	➢ Uses a fuzzy CCP that considers wind power forecasting errors. ➢ The demand response and PEVs may change the demand curve to solve the mismatch problem.

PEV Wind Power PV Power	[122]	➢ A new method is introduced to manage uncertainties (Wind, PV, and PEVs) in the optimal sizing of DGs. ➢ A mathematical model of CCP is created with the minimization of the DGs' maintenance cost, network loss cost, capacity adequacy cost, operating cost, and the investment cost as the objective function, security limitations as constraints, and the sizing and siting of DGs as optimization variables. ➢ An MCS – embedded genetic – algorithm – based method is used in solving the developed CCP model.

4.4. Robust Optimization

RO methods are commonly used for uncertainty management in power systems. For instance, RO methods are used to solve the optimization problem with the worst scenario concerning the uncertain parameters.

Table 13 lists studies in which robust optimization is used and how this method is implemented for uncertain parameters. Different studies consider the uncertainty set to have fixed limits [15–18,22], while others model it as a flexible one [25,27,31]. MCS [17,94], PSO [82], and historical data [15,22,29,114,115] are commonly used to generate the uncertainty set for the reviewed studies.

Table 13. Studies In Which Robust Optimization Method Is Used.

Ref.	Method Implementation	Remarks
[15]	➢ The random wind power output is model with an uncertainty set. ➢ The assumed uncertain wind power output is within a given lower and upper limit. ➢ The lower and upper limit can be found based on an interval forecast or historical data.	➢ Proposes an RO approach to accommodate wind output uncertainty, and, to provide an RUC schedule for the thermal generators in the day-ahead market that minimizes the total cost in the worst wind power output scenario. ➢ RO is used to model the randomness using an uncertainty set that includes the worst-case scenario and keeps this scenario under the minimal increment of costs.
[16]	➢ The uncertain wind power output is based on the uncertainty set with limit set at 0.95 and 0.05 quantiles. ➢ The demand response uncertainty set can be formulated using the price – elastic demand curve.	➢ A multi-stage robust MIP problem. ➢ An exact solution that uses Benders' decomposition is developed to obtain the optimal robust unit commitment schedule for the given problem.
[17]	➢ In generating the uncertainty set for the robust optimization part, the assumed demand at each time in each bus is between an upper and a lower bound, which can be set as the 5th and 95th percentiles of random demand.	➢ A novel unified robust and stochastic UC model can attain a low expected total cost while ensuring system robustness. ➢ Introduces weights of the components for the robust and stochastic parts in the objective function, SO can adjust the weights according to preferences. ➢ The model is solved using Benders' decomposition algorithm. ➢ For the stochastic part, MCS is performed to generate scenarios for load uncertainty (stochastic part).
[18]	➢ The uncertainty model in an RO formulation is not a probability distribution, but rather a deterministic set. ➢ In this paper, the uncertain parameter is the nodal net injection.	➢ Proposes a two – stage adaptive RUC model for the SCUCP with nodal net injection uncertainty. ➢ The proposed model is more practical compared to other models since it requires only a deterministic uncertainty set rather than a hard – to – obtain probability distribution of uncertain parameters.

		➢ Develops a practical solution method using a combination of Benders' decomposition and the outer approximation technique.
[22]	➢ The uncertain wind power injections are assumed to be changeable within a polyhedron. ➢ This polyhedron is specified by the deterministic confidence bounds for each uncertain variable over the time horizon, which can be computed using statistical inference techniques based on historical data.	➢ An RUC model is proposed for hybrid AC/DC transmission grids. ➢ Full decomposition of network feasibility evaluation improves scalability. ➢ Nonanticipativity is maintained using robust generator-wise reserve margins. ➢ Improves hosting capacity and loadability for RES.
[25]	➢ The operation risk of load shedding and RE curtailment is reduced through the participation of DR when the RE falls out of the adjustable uncertainty set.	➢ The uncertainty of RE in UC is dealt by the proposed adjustable uncertainty set. ➢ DR is co-optimized to reduce the operational risk of RE curtailment and load shedding.
[26]	➢ Linear decision rules are used as an effective estimate to solve the multistage robust model, where decision variables are assumed to depend linearly on uncertain parameters.	➢ Implements a rolling look-ahead UC scheme in a joint PDN and DHN to exploit the operational flexibility of rapid – response CHP units under substantially variable RES power output. ➢ The scheme is formulated as a multistage distributionally robust commitment model that the non-anticipativity of decision variables for sequential revelations of uncertainties.
[27]	➢ The uncertainty set in the proposed model is relevant and variable to the availability of system flexible resources. ➢ The position and scale of the variable uncertainty set depend on the flexible reserve capacity and the system operation state.	➢ Proposes a flexible robust risk-constrained UC formulation where energy storage is allocated to cope with the uncertainty of wind power. ➢ The model creates an adjustable and flexible uncertainty set. ➢ The model balances the operational risk and the operational costs.
[29]	➢ Uncertainty set is described as the convex hull of a set of multivariate points representing RE profiles. ➢ Historical daily profiles are used as scenarios, thus embedding relevant information about the true underlying uncertainty process in each vertex of the uncertainty set.	➢ Two – stage RUC models use an alternate scenario – based framework to characterize uncertain renewable power generation by a polyhedral uncertainty set. ➢ The data – driven RUC protects against the convex hull of realistic scenarios empirically capturing the time – varying and complex intra – day spatial and temporal interdependencies between renewable units.
[31]	➢ The formation of the partition – combine uncertainty set can be separated into three steps. ➢ First, the box set surrounding all the historical data is divided into subsets. ➢ Second, the subsets with new developed boundaries are combined to reformulate the new uncertainty set. ➢ Third, the inner subsets are found to reduce the scale of uncertainty variables.	➢ RUC is conducted using the partition – combine – method to create the minimal uncertainty set with erratically distributed historical data.
[32]	➢ The wind power system is assumed to receive no dispatch signals and generate unlimited power, whereas other energy systems are considered dispatchable.	➢ An RUC model for multiple energy sources based on the optimal uncertainty set is proposed. ➢ The RUC model is used to elucidate the effect of wind power fluctuations on power system scheduling.

	➢ The uncertainty set contains three scenarios for wind power output. (predicted, error and extreme)	
[35]	➢ The 1st and 2nd order moments of stochastic parameters can be assumed from historical data, and then employed to model the set of probability distributions. ➢ The resulting problem is a two – stage distributional RUC with 2nd order moment constraints, and it can be recast as MI – SDP with finite constraints.	➢ The UC problem considering uncertainties of RES is examined using a distributionally robust optimization approach. ➢ The solution algorithm of the problem solves a series of relaxed MI-SDPs and includes a subroutine of vertex generation and feasibility checking.
[36]	➢ In the 1st stage, the energy, reserves and commitment of generators are pre – scheduled to minimize the operational cost, responding to the line failure scenario and worst load forecasting in a day of operations. ➢ The 2nd stage constraint set includes the scheduling of generators, power flow, load shedding, generation curtailment after the realization of load forecasting errors and transmission line operating status.	➢ A resilient UC problem is created as a two-stage DR&RO problem. ➢ The formulated DR&RO problem is resolved using the column – and – constraint generation scheme and hybrid Benders' decomposition.
[37]	➢ Zonal disaster – specific uncertainty sets are used to capture the dynamic behaviors of windstorms. ➢ The unavailability uncertainties of N-K contingencies, as well as the forecast uncertainties of wind power, PV power, and demand are considered.	➢ A robust – resilient operational schedule for active distribution networks against windstorms is proposed. ➢ Instead of committing microturbines and ESS in the 1st stage (here – and – now) of the decision-making process, the proposed model considers related commitment decisions in the 2nd stage (wait – and – see) of the decision – making process. This approach is more reliable with the short response time of these units. ➢ A new solution that is based on LS and BCD techniques is suggested to solve the bi – level problem.
[38]	➢ A data – driven, distance – based ambiguity set can be constructed to capture the uncertainty of wind power distribution.	➢ Develops DDRC UC model. ➢ The two – stage UC model aims on the commitment decision and dispatch plan in the 1st stage and considers the worst – case expected cost for a possible power imbalance or re – dispatch in the 2nd stage.
[59]	➢ The upper – level agent (the SO) determines the schedule of reserves and power so that the overall cost is minimized. This cost minimization problem is subjected to the worst – case contingency in each period and is modeled by the lower – level optimization. ➢ The lower – level determines the combination of out – of – service generators so that the available post – contingency power output in each period is minimized.	➢ A new approach for solving contingency – constrained single – bus UCP is presented ➢ The proposed model explicitly incorporates an $n-K$ security criterion by which the power balance is guaranteed under any contingency state that involves the simultaneous loss of up to K generation units. ➢ The resulting model is a particular instance of bilevel programming and is solved by transforming it into an equivalent single – level MIP problem.
[82]	➢ Different wind penetration levels are generated using PSO. ➢ In addition, 10%, 15%, 20%, 25%, 30% and 35% wind penetration are considered.	➢ A PSO – based scenario reduction and generation algorithm is used to model uncertain parameters. ➢ The stochastic UCP is solved using a new parameter – free self – adaptive PSO algorithm.

[85]	➢ The 1st and 2nd order moments of the forecast errors for demand and wind power generation are needed, which are obtained from historical data instead of the predefined uncertainty sets. ➢ The transmission power flow limits and generation output constraints are developed as chance constraints in which a flexible coefficient uses the robustness of the chance constraints to the forecast errors. ➢ The LMP uncertainty components for the transmission overloading and the generation violations are derived from the Lagrangian function. ➢ These uncertainty components in the LMP represent the marginal contribution of the uncertainty in variable sources such as demand and wind power on the system cost.	➢ A new electricity market – clearing mechanism that is based on LMPs is provided for pricing uncertain demand and generation. ➢ U – LMP is developed from a distributionally robust chance – constrained optimal power flow model in which only the 1st order and 2nd order moments of the uncertain sources' probability distribution are required.
[93]	➢ Implementation and development of two algorithms within a two – level framework. ➢ The 1st stage decision variables should be made day-ahead while the 2nd stage decision variables should be made after wind power uncertainty is shown.	➢ A two – stage robust UC model yields day-ahead generator schedules; wind uncertainty is captured by a polytropic uncertainty set. ➢ Includes a DR strategy such that both generator schedules and price levels are obtained for the following day.
[94]	➢ Feasibility and optimality cuts in Bender's decomposition are considered. ➢ MCS is used to find the lower bound and upper bound of the wind power forecast.	➢ Introduces an innovative min – max regret UC model to minimize the maximum regret of the day – ahead decision scheduling from the actual realization of the uncertain wind power generation. ➢ Benders' decomposition is developed to solve the problem.
[108]	➢ Wind power forecast errors follow a normal distribution, and their first and second – order moments are allowed to change within predetermined regions.	➢ A novel solution method of GRCC – RTD, considering wind power uncertainty, is proposed.
[114]	➢ The robustness of the PHEV transition model is examined with respect to perturbations in electricity prices. ➢ The performance of the robust solution as a function of the protection level for an emission cost/credit. ➢ Data uncertainty from both electricity grid and transport sector are considered (54 parameters).	➢ The method is based on comprehensive RO planning that considers the constraints associated with both the transport sector and the electricity grid.
[115]	➢ Offering curves are done based on price-taker producer. The effectiveness of these curves aim to achieve high profit. ➢ Electricity prices are obtained using ARIMA method.	➢ Provides a technique for building hourly offering curves for a price – taking producer that participates in a pool. ➢ The technique relies on solving a sequence of robust MILP problems. ➢ Price confidence intervals are considered.

4.5. Risk-Based Optimization

Risk-based optimization is based on the definition of risk measures and associated optimization problem formulation that accounts for the risk induced in system-level outputs by uncertain parameters.

Table 14 presents studies in which risk-based optimization is used, and the risk considered. Risk-based optimization is performed by adding a penalty term in the objective function [10,98], or by including the risk to constraints in the UCP [28,84], or by doing both [39,49,50,77]. Additional constraints are defined in [77,84] while others integrate the risk in the energy balance [98] and reserve constraint [28,49,50]. Wind power [10,28,39,49,98], demand [10,50,84], and failure of units [28,49,77] are considered as uncertain parameters in the risk-based optimization.

Table 14. Studies In Which Risk-Based Optimization Is Used.

Ref.	Risk Considered	Remarks
[10]	➢ The risk considered are EENS, EWPC and EOB. ➢ EENS considers the load uncertainty parameter. ➢ EWPC considers the wind power uncertainty. ➢ EOB considers the power flow uncertainty. ➢ EENS, EWPC and EOB are considered to the objective function as the penalty cost.	➢ Presents a novel RBDAUC model considering the risks of the wind curtailment, branch overflow and loss of load. ➢ The risks are expressed in using the probabilistic distributions of the wind power generation forecast that are found in the objective function and the constraints. ➢ The RUC model is shown to be convex and is transformed into a MILP problem using relaxation and piecewise linearization.
[28]	➢ The PDF of the residual demand can be obtained by the convolution of the PDFs of the demand and the post curtailment wind generation. ➢ The residual demand is considered as the operating risk and is integrated in the reserve constraints. ➢ N—1 security stochastic criterion is also considered in the reserve constraints.	➢ A new bi – objective PRCBUC model is developed to simultaneously minimize the risks and operational costs. ➢ The novel formulation of PRCBUC offers a new power redispatch procedure to comply with the up – and – down ramp rate constraints. ➢ A new operational – cycles – based UC algorithm is developed. ➢ The approach uses a new nondominated sorting backtracking search optimization algorithm for extracting the Pareto-optimal set.
[39]	➢ CVaR is adopted to specify the risk loss when the wind power output falls outside the predefined uncertainty set. ➢ CVaR is defined as wind spillage and load shedding cost and integrated in the objective function.	➢ A risk – based two – stage RUC model is developed to analyze the admissibility of wind power generation. ➢ ESS is utilized to manage wind power uncertainty and reduce the risk of loss.
[49]	➢ Cost of the down – spinning reserve is the penalty cost due to wind power (unavailability) and demand uncertainty (overestimating). ➢ Cost of the up – spinning reserve is the penalty cost due to wind power uncertainty (overestimating) and generation outage. ➢ The risk constraint of load shedding is based on the up – spinning reserve. ➢ The risk constraint of wind energy waste is based on the down – spinning reserve. ➢ N-1 condition is also considered in terms of the total up and down – spinning reserve.	➢ A modified ED optimization model with wind power penetration is developed. ➢ Underestimation and overestimation of the available wind power are offset by using up and down – spinning reserves. ➢ Risk-based up and down – spinning reserve constraints are presented considering not only the uncertainty of available wind power generation but also the load forecast error and generator outage rates. ➢ The predictor – corrector primal – dual interior – point (IP) method is applied to solve the ED model.

[50]	➢ The reserve capacity constraint integrates the demand uncertain parameter in terms of RMSE. ➢ The RMSE considers the line flow and power/required reserve. ➢ The negative and positive reserve capacities are integrated into the objective function as the penalty cost.	➢ A risk-based approach is presented to find the stochastic solution of NCUC when additional uncertainties are incorporated into the power system scheduling. ➢ The NCUC problem is formulated as a single – stage – 2nd order cone program which is a convex algorithm. ➢ The proposed method provides efficient solutions to large – scale stochastic problems and aids to accommodate DER variabilities in economic and secure operations of power systems.
[77]	➢ The UC risk considers the failure of generators, failure of lines, and risk of responsive demand. ➢ The UC risk is defined as a penalty cost in the objective function.	➢ The Day-Ahead Demand Response Program is implemented as an incentive – based in providing the spinning reserve. ➢ A certain number of demands are selected based on a sensitivity analysis and simulated as a virtual generation unit. ➢ The reserve market is cleared for spinning reserve allocation using a probabilistic technique. ➢ A comparison is made concerning economics and reliability between the absence and use of a Day – Ahead Demand Response Program.
[84]	➢ A reliability constraint is accommodated directly in terms of the power balance between supply and demand.	➢ RLD is a new framework that integrates complex inputs and allows decision-makers to balance tradeoffs and quantify benefits that arise from increased flexibility and improved forecasting.
[98]	➢ The curtailment of wind power is included in the energy balance constraint. ➢ The curtailment cost of wind turbine is integrated in the objective function.	➢ Addresses a generic continuous – time risk – based model for sub – hourly scheduling of energy generating units and bulk ESUs in the day – ahead UCP. ➢ The continuous – time risk – based UCP is modeled using Bernstein polynomials and considers ESU constraints. ➢ The continuous – time risk – based model ensures that the generating units and ESUs track the sub – hourly variations of WPG, and the generation and demand are stable in each sub-hourly interval.

4.6. Hierarchical Scheduling Strategy

A hierarchical scheduling strategy is the process of scheduling components or entities according to rank of importance. In a UCP, it can be carried out concerning committed generation units or reserve allocation [23,24], [88].

Table 15 presents studies in which the hierarchical scheduling strategy is used and how this method is implemented for uncertain parameters modeling. Power trading is implemented in [23] to manage the uncertainty of renewable energy and demand. In this study, the penalty cost of power trading between microgrids is implemented through the hierarchical approach considering the least cost. In [24], the author emphasize that the tie-line schedule is solved first before considering the generation schedule when a power interchange occurs during load uncertainty. Lastly, in [88], the study implements a hierarchical scheduling strategy considering generation reserve, ramping reserve, and transmission reserve. This method is implemented in the UCP using the energy balance constraint and penalty cost function.

Table 15. Studies In Which The Hierarchical Scheduling Strategy Is Used.

Ref.	Method Implementation	Remarks
[23]	➢ ATC method is used to minimize the penalty cost of power trading from different microgrids due to uncertainty of demand and renewable energy (PV and WP).	➢ Solves the optimal operation problem for IMS in a market environment with uncertainty. ➢ Establishes a hierarchical distributed framework for cloud – edge coordination. ➢ Proposes a bi – level distributed optimization model with a fair price mechanism. ➢ ATC and augment Lagrange method are integrated. ➢ The diagonal quadratic approximation is used to yield a parallel solution.
[24]	➢ The hierarchical solution method considers net load uncertainties for several interconnected power systems. ➢ An initial tie – line schedule and generation schedule for each area is derived. When a power interchange occurs, the tie – line schedule becomes the upper – level problem followed by the generation schedule as the lower – level problem.	➢ The problem is devised as a multi-area robust SCUC model, with a novel uncertainty set that is specified in terms of the variance of the system netload. ➢ A modified outer approximation algorithm is developed to obtain a higher quality solution using bilinear programming.
[88]	➢ The hierarchical scheduling strategy considers both traditional and emergency operations. ➢ The strategy separates the wind power output into two intervals based on confidence levels and applies various scheduling strategies in different intervals of wind power output.	➢ HUC model is presented to keep system security by scheduling power system reserves with high penetration of wind power generation. ➢ The reserves in the HUC model include the generation reserve, transmission reserve, and ramping reserve.

4.7. Information Gap Decision Theory (IGDT)

IGDT identifies the extent to which an uncertain parameter can function while ensuring that the minimum income is received by the decision – maker. Its two essential features are robustness and opportuneness. A detailed review of this approach can be found in the paper by Majidi et al. [133].

Table 16 presents the studies in which the IGDT method is used and how this method is implemented for uncertain parameters. The studies discussed in Table 16 consider a robust function wherein the uncertainty level is maximum when the function is maximized. The IGDT may be applied to the UCP by adding a penalty cost to the objective function; the IGDT's robust function is integrated into the energy balance constraint.

Table 16. Studies In Which IGDT Method Is Used.

Ref.	Method Implementation	Remarks
[70]	➢ IGDT is implemented modeling the load demand and wind power generation uncertainty by envelope bound method. ➢ The uncertainty level is maximum when the robust function is maximized. ➢ The robust function is subjected to the energy balance constraint wherein the minimum wind power level and highest demand level are considered.	➢ Presents a new framework, using IGDT, for the multi-objective robust SCUC of generating units that are connected to gridable vehicles and wind farms. ➢ A bi – objective model is used in considering the uncertainties cause by demand and wind power. ➢ Normal boundary intersection technique is used to solve the problem.
[80]	➢ IGDT is implemented by maximizing the uncertainty horizon of demand.	➢ Proposes a robust framework using IGDT for the SCUC of generating units and lithium – ion BESS.

➢ The model is subjected to the energy balance constraint wherein the highest load level is considered.	➢ The cost of the degradation of the BESS is considered in the objective function as an element that strongly influences the BESS operation. ➢ The framework is independent of PDFs or the membership of sets and allows the SO to modify the operating strategy (between over – conservative and reckless) against the demand uncertainty. ➢ The day – ahead scheduling problem is modeled as SCUC using MILP.

4.8. Discussion of Reviewed Methods

A comprehensive review of the different studies and the method implementation were discussed in Sections 4.4–4.7. These include SP, probabilistic methods, CCP, RO, risk-based optimization, hierarchical scheduling strategy, and IGDT. SP is a method that optimizes the expected outcome on a risk-neutral perspective using a probability distribution. Commonly used PDFs are Gaussian, Rayleigh, Weibull, and Beta Distribution. In most cases, this method is transformed into a deterministic approach making it much simpler and easily implemented. Renewable energy and demand uncertainty are the most common areas of study that implement this method. The PDF can be formulated using historical data, forecasted data, or simulation results. Aside from using a given PDF, other ways of generating input are numerical and analytic methods which fall under the second discussed method which is the probabilistic method. This method together with SP has been applied by many studies involving outages, demand, and renewable uncertainty. Unfortunately, using these two methods may lead to an infeasible solution due to the constraint violation. In this case, the use of IGDT and CCP methods can be applied. These two methods can relax constraint violations by augmenting a penalty factor when these violations are relaxed.

CCP is an approach wherein a constraint violation is allowed. When these constraints are violated, a penalty cost is introduced on the UCP. Commonly used penalty costs are related to the load shedding and wind spillage of renewable energy spillage. Like the SP and probabilistic methods, the expected outcome can be compared over a known PDF or interval. Unfortunately, CCP does not consider the given interval or known PDF, resulting in a limitation of its flexibility and robustness. IGDT, on the other hand, like the CCP, allows constraint violations. The difference is that a robust function is implemented in IGDT. In this method, the framework is independent of the PDF or membership set and it allows the SO to vary the operating strategy easily.

The risk-based method, unlike the SP, optimizes the UCP using a risk-level approach. Most of the studies that applied this method involve the wind power and demand uncertainty. Unlike the SP, the reserve allocation in the UCP is fixed and cannot be adjusted; the risk-based optimization allows violations on constraints at a given risk level. Some risk-based methods consider the penalty cost while others just integrate it in the energy balance constraint or in the reserve constraint.

The other two methods discussed in Section 4 are the hierarchical scheduling strategy and RO. The hierarchical scheduling strategy is, unlike SP, CCP, and IGDT, a hierarchical process which is implemented to mitigate the effect of uncertainty. Reserve allocation is the common application of this method. RO solves the UCP by considering the worst-case scenario which may not be considered by the previous methods.

Lastly, since more uncertainty parameters in the UCP can be considered, it results in more data and variables to be considered. Different methods may be integrated together to increase computational efficiency.

5. Evaluation of Constraints, Test System, and Simulation Tools of Different Studies

Table 17 gives an outline of studies on the UCP that consider uncertainty. The constraints that are applied in the problem, along with the test system and the applied simulation tools, are shown in each scenario.

Table 17. Methods For UCP With Uncertainty Management.

Ref.	Constraints												Uncertainty Considered	Studied System	Simulation Tool
	EB	EC	RR	TL	PULs	RULs	MUT/MDT	RRLs	USLs	ACPF	TLF	BVC			
[9]	•	•			•		•	•	•		•		Wind Power	6 Bus System IEEE 118 Bus System	C+ with CPLEX 12.1
[10]	•	•	•		•	•	•	•	•	•	•		Wind Power	IEEE RTS79 System (24 h)	CPLEX 12.5 using MATLAB
[11]	•		•		•	•	•	•	•	•	•		Demand	IEEE 118 Bus System	NS
[12]	•		•		•	•			•				Wind Power	Irish System in 2020	CPLEX
[13]	•	•					•	•					Wind Power	3 Generator System Complicated System Multi-Bus System (24 h)	C+ with CPLEX 12.1
[14]	•		•		•	•	•	•	•				Wind Power	6 Bus System IEEE 118 Bus System (24 h)	C+ with CPLEX 12.1
[15]	•	•			•		•	•	•		•		Wind Power	6 Bus System IEEE 118 Bus System (24 h)	CPLEX 12.1
[16]	•	•			•		•	•	•		•		Wind Power Demand Electricity Price	IEEE 118 Bus System 118 TW System (24 h)	CPLEX 12.1
[17]	•				•		•	•	•		•		Demand	IEEE 118 Bus System (24 h)	C+ with CPLEX 12.1
[18]	•		•	•	•	•	•	•	•	•	•		Electricity Price Demand	ISO New England Inc. (24 h)	GAMS with CPLEX 12.1
[19]	•	•	•		•	•	•	•	•				Electricity Price	Electric Utility in the midwestern United States (168 h)	Optimization Subroutine Library of IBM (OSL)
[20]					•				•				Outages of Generation Units	Thermal generation mix of Electricite de France (24 h)	NS
[21]					•				•				Outages of Generation Units Demand	Michigan Electric Power Coordination Center (168 h)	C

													Electricity Price		
[22]	•	•	•	•	•	•	•	•	•	•	•	•	Renewable Energy	2383 Bus Test Case—Polish Transmission Grid (24 h)	CPLEX and MATLAB
[23]	•	•			•								Renewable Energy Demand	IM (Interconnected Microgird) system consisting of three MGs (Microgrids) and an IMO (Integrated Microgrid System Operator) in a DN (Distributed Network) (24 h)	MATLAB 2019 and Gurobi
[24]	•	•			•		•	•	•	•	•		Demand	2 Area 157 Bus System (IEEE 39 and 118) (24 h)	CPLEX 12.5
[25]	•				•		•		•		•		Renewable Energy	IEEE 6 Bus System IEEE 30 Bus System IEEE 300 Bus System (24 h)	MATLAB with YALMIP and Gurobi
[26]	•				•		•	•	•				Renewable Energy	Barry Island Multicarrier Energy System (2 h)	CPLEX
[27]	•	•	•		•	•	•	•	•	•	•		Wind Power	IEEE 39 Bus System (24 h)	YALMIP toolbox in MATLAB and CPLEX 12.8
[28]	•				•			•	•				Wind Power Demand Outages of Generation Units	10 Unit Test System IEEE 118 Bus System (24 h)	FORTRAN Power Station
[29]	•				•		•	•	•				Renewable Energy Demand	4 Bus System IEEE 118 Bus System (24 h)	Gurobi 7.0.2 under JuMP (Julia 0.5)
[30]	•	•	•		•	•	•	•	•	•	•	•	Wind Power Demand	IEEE 118 Bus System (24 h)	GAMS with CPLEX
[32]	•	•	•		•	•	•	•					Renewable Energy Demand	Power Grid of Southern Island	CPLEX 12.1
[33]	•		•		•	•	•	•	•	•	•		Wind Power	3 Bus System (4 h)	CPLEX 10.2.0 under GAMS
[34]	•	•	•		•						•		Wind Power	IEEE 39 Bus System	GAMS

[35]	•				•		•	•	•		•		Renewable Energy	IEEE 6 Bus System (24 h and 30 days)	GUROBI 8.1.1 and MOSEK8.1
[36]	•		•		•	•		•	•		•		Disaster (Hurricane)	IEEE RTS IEEE RTS-96 (24 h)	CPLEX
[37]	•	•			•				•	•	•	•	Disaster (Windstorms) Wind Power PV Power Demand	IEEE 33 Bus System (24 h)	GAMS using CPLEX
[38]	•				•		•	•	•		•		Wind Power	IEEE 6 Bus System IEEE 118 Bus System (24 h)	MATLAB with YALMIP toolbox using GUROBI
[39]	•				•		•		•	•	•		Wind Power	6 Bus System IEEE 118 Bus System (24 h)	CPLEX 12.8
[40]	•		•		•	•	•	•	•	•	•		Wind Power	IEEE 39 Bus System (24 h)	MATLAB and GAMS with CPLEX
[42]	•			•	•								Wind Power	NS	MATLAB Optimization toolbox
[43]	•	•	•		•	•	•	•	•				Wind Power	NS (48 h)	NS
[44]	•	•	•		•	•	•	•	•		•		Renewable Energy	IEEE RTS-24 System with 20 node gas network (24 h)	CPLEX 12.5
[45]	•		•		•		•	•	•		•		Wind Power	6 Bus System IEEE 118 Bus System (24 h)	CPLEX 12.4
[47]	•				•		•	•	•				Wind Power	Isolated Power System (8760 h)	NS
[48]	•				•		•	•					Outages of Generation Units and Transmission Lines Demand	6 Bus System IEEE 118 Bus System 1168 Bus System	NS
[49]	•		•		•	•							Wind Power Demand Outage of Generation Units	Test System with 10 conventional generator and 1 windfarm	NS
[50]	•		•	•	•	•	•	•	•	•	•		Demand	IEEE RTS-96 System IEEE 300 Bus System (24 h)	Gurobi 7.5.1

[51]	•	•	•		•	•	•	•	•		•		Wind Power	IEEE RTS 24 Bus System (24 h)	NS
[52]	•	•			•		•	•	•				Renewable Energy	NS	Python with GUROBI 6.5.1
[53]	•	•	•		•	•	•	•	•				Demand Wind Power Outages of Generation Units	Simplified Illinois Power System (744 h)	NS
[54]	•	•	•		•	•	•	•	•				Outages of Generation Units Demand	IEEE Reliability Test System (48 h)	NS
[58]	•	•	•	•	•	•	•	•	•	•	•	•	Wind Power	Portfolio 5 of All Island Grid Study (24 h)	GAMS with CPLEX 12
[59]	•	•	•		•	•		•	•				Outage of Generation Units	3 Generator Unit System Case Study built on a Base Test System with 10 generators (Real Size)	Xpress-MP 7.0 under MOSEL
[60]	•	•			•								Outages of Generation Units Demand Wind Power	Generation System of a medium-size Greek Island (6 h)	NS
[61]	•		•		•	•					•		Electricity Price	3 Bus System	NS
[64]	•	•	•		•	•		•	•				Wind Power Demand	10—Unit System (24 h)	GAMS with CPLEX 11
[65]	•				•						•		Wind Power	IEEE 30 Bus System (24 h)	YALMIP toolbox in MATLAB and CPLEX
[66]	•		•		•		•	•	•		•		Wind Power Demand Outages of Generation Units	IEEE Reliability Test System (24 h)	MATLAB with CPLEX 12.2
[67]	•		•		•	•	•	•	•				Outages of Generation Units Wind Power PV Power Demand	Test System	MATLAB 2016a
[69]	•		•		•		•	•	•				Outages of Generation Units	IEEE RTS (24 h)	GAMS with CPLEX 12.7
[70]	•				•		•	•	•		•		PEV Wind Power	6 Bus System IEEE RTS 24 Bus System IEEE 118 Bus System	GAMS with CPLEX

														(24 h)	
[71]	•		•		•	•	•						Wind Power	Typical MG Network (24 h)	MATLAB
[72]	•	•	•	•	•	•	•	•	•				PEV Demand Wind Power	6 Bus System 118 Bus System (24 h)	CPLEX 12.1
[73]	•				•		•	•	•				Wind Power	IEEE RTS (24 h)	GAMS 22.5 with CPLEX 10.2
[75]	•	•											Demand PEV PV	Residential PV-Battery System with EV (24 h)	MATLAB
[76]	•				•		•	•	•		•		Demand Wind Power	IEEE 30 Bus System (24 h)	CPLEX 12.1
[77]	•		•			•							Demand	IEEE 57 Bus System (24 h)	NS
[79]	•	•	•		•	•	•	•	•		•		Wind Power Demand	IEEE 118 Bus System (24 h)	GAMS with CPLEX 12.5
[80]	•	•	•		•	•	•	•	•	•	•		Demand	6 Bus System IEEE 24 Bus System IEEE 118 Bus System (24 h)	GAMS with CPLEX
[82]	•		•		•	•	•	•	•				Wind Power Demand	12 Generators and a windfarm serving a load of 8 GW (24 h)	NS
[83]	•	•	•		•	•	•	•	•		•		Load Growth Electricity Price	European Power System (8760 h)	GAMS with CPLEX 12.6.1
[85]	•	•			•				•	•	•		Electricity Price	PJM 5 Bus System IEEE 118 Bus System (8760 h)	GAMS with MINOS
[86]	•	•	•	•	•	•	•	•	•	•	•	•	PEV	IEEE 69 Bus System (24 h)	NS
[88]	•	•	•		•	•		•	•		•		Wind Power	8 Bus System Province level Power Grid in China (24 h)	CPLEX 12.4
[89]	•		•		•	•	•	•	•	•	•	•	Wind Power	6 Bus System 118 IEEE Bus System (24 h)	NS
[91]	•	•			•		•	•					Wind Power	NS	AMPL

														CBC Solver from the COIN-OR repository
[92]	•		•		•	•	•	•	•	•	•	Wind Power	6 Bus System IEEE 118 Bus System (24 h)	CPLEX 12.1
[93]	•				•		•	•	•			Wind Power	IEEE 118 Bus System (24 h)	CPLEX 12.1
[94]	•	•			•		•	•	•	•	•	Wind Power	IEEE-118 Bus System (24 h)	CPLEX 12.1
[96]	•	•	•	•	•	•	•	•	•			Wind Power	Denmark, Finland, Germany, Norway, and Sweden (168 h)	NS
[97]	•				•		•	•	•	•		Wind Power	IEEE 118 Bus System (24 h)	MATLAB
[98]	•				•		•	•	•		•	Wind Power	Modified IEEE RTS Modified IEEE 118 Bus System	CPLEX 12.6.2
[99]	•	•	•		•	•	•	•	•			Wind Power	Single Bus Test System (12 h)	NS
[100]	•	•					•					Disaster	Wind-Solar-Hydro Hybrid System (24 h)	NS
[101]	•		•		•	•	•	•	•		•	Wind Power	26—Generator System 100—Generator System	NS
[102]	•				•			•				Wind Power	Hubei Power Grid (24 h)	NS
[103]	•	•			•		•	•	•	•	•	Wind Power	IEEE RTS (24 h)	GAMS with CPLEX 12.3
[105]	•				•		•	•	•			Electricity Price Wind Power	NS	GAMS with CPLEX 12
[106]	•		•		•	•	•		•			PEV Wind Power Demand	10 Unit System (24 h)	MATLAB 7.8
[107]	•				•							Renewable Energy Demand	Fort Sill Microgrid (24 h)	NS
[109]	•	•	•		•	•	•	•	•	•	•	Wind Power	6 Bus System IEEE RTS (24 h)	CPLEX 12.1
[111]	•				•							Renewable Energy Demand	East China Power Grid (24 h)	NS

[113]	•	•	•	•	•	•	•	•			Electricity Price Renewable Energy	Standard System (8760 h)	MATLAB GAMS
[115]				•		•	•	•			Electricity Price	Iberian Peninsula (24 h)	GAMS with CPLEX 11.2.1
[116]	•	•		•		•	•	•	•	•	Random Disaster	IEEE 118 Bus System	NS
[119]	•		•	•	•		•	•			PV Power Wind Power	Study System (24 h)	MATLAB
[135]	•	•	•	•	•	•					PV Power Wind Power	10 unit Benchmark System (24 h)	NS

A variety of constraints are identified in the studies and the demand balance and constraints on thermal units are mentioned in most of them.

The studied systems range from simple systems to IEEE bus systems and sometimes real-life grids with periods of 4, 24, 168, and 8760 h. Most of the studies involve the IEEE test system for 24 h.

CPLEX and GUROBI have been the most used solvers to be implemented using C, C++, Python, MATLAB, and GAMS. In most of the studies, MATLAB and GAMS have been used for simulation owing to their availability and ease of use.

6. General Notes on Reviewed Methods

Section 6 discusses some important issues regarding the reviewed methods. Table 18 summarizes all the reviewed studies in this paper in terms of method, solver, hardware specification, run – time, and simulation results. Based on Table 18, the following information can be summarized:

1. As the system size increases, the corresponding run – time also increases.
2. As more constraints are included in the UCP, the solution steps require a longer run time.
3. The modeling of uncertainty parameters affects the UCP result.
4. The CPLEX solver can be applied to any method.
5. The Gurobi solver is used on some methods where uncertainty can be adjusted; they include CCP, risk-based optimization and RO.
6. Advanced computing tools result in short run time regardless of methods applied.
7. SP has been used in the majority of the studies due to the short run – time. The drawback is it may result in a sub-optimal result or infeasible solution due to its limitation. SP combined with other methods will optimize the solution but increase the run time. This has been the commonly used strategy due to the advancement of computing tools.
8. RO has become of interest to a lot of researchers since it can handle more constraints compared to other methods. The only drawback to this method is its run – time, but this has already been solved due to more advanced computing tools.

Table 18. Summaries Regarding Methods, Hardware Specification, Run – time And Simulation Results.

Method	Solver	Ref.	Hardware Specification	Run – time, or Simulation Results
SP	CPLEX	[12]	Intel Core Duo (1.83 MHz), 1 GB RAM	NS
SP	CPLEX	[30]	Intel core i7-7700 (4.2 GHz), 32 GB RAM	21.25 s
SP	CPLEX	[44]	NS	28.3 min. in 153 iterations
SP	CPLEX	[58]	Intel Xeon-W3520 (2.67 GHz), 12 GB RAM	24 h
SP	CPLEX	[72]	NS	NS
SP	CPLEX	[73]	64-bit Dual Core (2.39 GHz) AMD Opteron	NS
SP	CPLEX	[83]	Server using Linux with four 3.0 GHz processors, 250 GB RAM	NS
SP	CPLEX	[103]	i5 with 4 cores (3.2 GHz), 4 GB RAM	1.155 s
SP	OSL	[19]	NS	553.1 s at 729 scenarios
SP	CBC	[91]	350 compute nodes (each with a 2.4-GHz Pentium Xeon and 1.5 GB RAM)	32 CPUs for 10 h
CCP	CPLEX	[9]	Computer workstation with 4 Intel Cores, 8 GB RAM	1364 s
CCP	CPLEX	[13]	Workstation with 4 Intel Cores, 8 GB RAM	1334.5 s
CCP	CPLEX	[14]	Intel Quad Core (2.40 GHz), 8 GB RAM	6 Bus System—0.02 s 118 Bus System—64.5 s
CCP	CPLEX	[40]	NS	18.142 s
CCP	CPLEX	[64]	Intel Core Duo-E7500 (2.93 GHz), 4 GB RAM	Independent Constrained—11.8 s Jointly Constrained—149 s
CCP	CPLEX	[65]	NS	NS
CCP	CPLEX	[79]	3.10 GHz, 8 GB RAM	6 Bus System—42.40 s 118 Bus System—1092 s
CCP	Gurobi	[38]	Intel Core i7-6700 (3.40 GHz), 8 GB RAM	NS
CCP	Gurobi	[52]	Intel Core i7-4790 (3.60 GHz), 16 GB RAM	397,696 constraints—889.24 s 389,952 constraints—160.69 s
RO	CPLEX	[15]	Intel Quad Core (2.40 GHz), 8 GB RAM	No Uncertainty—1876 s 50% Uncertainty—3594 s
RO	CPLEX	[16]	Intel Quad Core (2.40 GHz), 8 GB RAM	1126 s
RO	CPLEX	[18]	Intel Core 2 Duo (2.50 GHz), 3 GB RAM	NS
RO	CPLEX	[22]	Intel Core i7- 7500U Two Core (2.70 GHz), 16 GB RAM	500 s/iteration
RO	CPLEX	[24]	Intel i5 (1.80 GHz), 8 GB RAM	680 s for 3 iterations
RO	CPLEX	[26]	Intel Core (3.2 GHz), 8 GB RAM	2 Uncertainty Sets—0.36 s 20 Uncertainty Sets—2.18 s
RO	CPLEX	[27]	Intel Core i3, 8 GB RAM	UC—3.50 s ($ 485,195.9) FRRUC—38.23 s ($ 484,970.2)
RO	CPLEX	[32]	PC with a 2.2 GHz, 4 GB RAM	NS
RO	CPLEX	[36]	NS	NS
RO	CPLEX	[37]	Core i7 (3.0 GHz), 8 GB RAM	NS
RO	CPLEX	[93]	Dell OPTIPLEX 760 (3.00 GHz), 3 GB RAM	1 Uncertainty Budget Constraint—85 s ($ 587,606) 5 Uncertainty Budget Constraint—622 s ($ 580,419)
RO	CPLEX	[94]	Intel Quad Core (2.40 GHz), 8 GB RAM	3468.16 s

RO	CPLEX	[115]	Server using Linux with four 2.6 GHz processors, 32 GB RAM	NS
RO	Gurobi	[25]	3.2 GHz CPU, 32 GB RAM	NS
RO	Gurobi	[29]	Xeon E5-2680 (2.5 GHz), 128 GB RAM	6 Bus System—20 s 118 Bus System—774 s
RO	Gurobi	[35]	Intel i5 CPU (1.80 GHz), 8 GB RAM	UC—0.25 s RUC—0.94 s DRUC—271.57 s
RO	MOSEL	[59]	Intel Core i7 (3.2-GHz), 16 GB RAM	10 Unit System—0.8 s 100 Unit System—33.6 s
Risk-based Optimization	CPLEX	[10]	Windows-based PC with four threads (2.5 GHz), 4 GB RAM	DUC (5924 constraints)—5.52 s RUC (15524 constraints)—10.4 s SUC1 (70924 constraints)—286.39 s SUC2 (77164 constraints)—518.75 s
Risk-based Optimization	CPLEX	[39]	Intel Core i7-8700k, 16 GB RAM	6 Bus System—0.172 s 118 Bus System—8.417 s
Risk-based Optimization	CPLEX	[98]	Intel Core-i7 (4.2 GHz), 32 GB RAM	35 min.
Risk-based Optimization	Gurobi	[50]	Intel Xeon (3.50 GHz), 32 GB RAM	325 s
Hierarchical Scheduling Strategy	CPLEX	[88]	Intel dual core (3.2 GHz), 4 GB RAM	With Constraints Simplification—40.33 s ($ 1,612,972) Without Constraints Simplification—398.31 s ($ 1,612,436)
IGDT	CPLEX	[80]	Core i5, 4 GB RAM	NS
SP and RO	CPLEX	[17]	4 Intel Cores, 8 GB RAM	SP—62 s ($ 49,500) SP and RO—50 s ($ 49,500) RO—375 s ($ 49, 500)
CCP and RO	Gurobi	[38]	Core i7-6700 (3.40 GHz), 8 GB RAM	50 Data Size—$ 1,150,931.70 5000 Data Size—$ 1,144,773.40
CCP and RO	CPLEX	[45]	NS	NS
RO and IGDT	CPLEX	[70]	Core i7 CPU, 16 GB RAM	NS
CCP and RO	Minos	[85]	NS	Gaussian Distribution—$ 54,165.50 Symmetrical Robustness—$ 57,524.10 Distributional Robustness—$ 59,636.10

7. Conclusions

Uncertainty management in a UCP is crucial in the operations, control, and monitoring of power systems. It has attracted considerable attention since it influences the cost of the operation and maintenance of power grids. Considering the significance of this topic, this paper reviews a significant number of studies in this area.

The review identifies various types of uncertainty parameters and identifies how each is modeled. These types are technical, economic, and "epidemics, pandemics, and disasters". The latter category is found to be of great importance because this type cannot be modeled as simply as the first two types because it affects not only the techno-economic aspect of the energy sector but also the social aspect and thus, may lead to future studies.

This review examines various methods for uncertainty management and describes key concepts and innovations. The management of uncertainties related to renewable energy has seen an increase in studies conducted in recent years. These uncertainties arise from sustainable grid reconstruction and evolving environmental policies. In addition, the management of uncertainties related to electricity prices and demand continue to be of great importance today. These uncertainties arise from market liberalization and the increase in world population.

Computing tools such as GAMS and MATLAB are identified as the most used software tools, along with CPLEX or GUROBI solvers. For the studied system, IEEE test systems using 24-h intervals are easily implemented owing to data availability and their ease of use. A realistic test system (real power grid) should also be considered in conducting the uncertainty management of a UCP. Robust optimization has recently become a method of interest due to the availability of highly advanced computing tools. Lastly, this review shows how different studies propose policies or strategies in improving the control and operation for power systems. These strategies include the hierarchical scheduling of reserve, penalty cost for RE spillage and load shedding, and proper management of thermal units and ESS.

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Nomenclature

Abbreviations

ACPF	AC Power Flow
ADP	Adaptive Dynamic Programming
ATC	Analytical Target Cascading
BB	Branch/Bound
BCD	Block Coordinate Descent
BESS	Battery Energy Storage System
BPECI	Bulk Power Energy Curtailment Index
BPII	Bulk Power Interruption Index
BVC	Bus Voltage Constraint
CCP	Chance Constrained Programming
CCTS	Chance – Constrained Two – Stage
CHP	Combined Heat and Power
CFSDP	Clustering by Fast Search and the finding of Density Peaks
CVaR	Conditional Value-at-Risk
DDRC	Data-driven Distributionally Robust Chance – Constrained
DG	Distributed Generation
DHN	District Heating Network
DLOL	Duration of Loss of Load
DR	Demand Response
DR&RO	Distributionally Robust and Robust Optimization
DRUC	Distributionally Robust UC
EB	Energy Balance
EC	Energy Constraint
ED	Economic Dispatch
EENS	Expected Energy Not Supplied
EOB	Expected Overflow of Branch
EWPC	Expected Wind Power Curtailed
ESS	Electricity Storage System
ESU	Energy Storage Unit

EUE	Expected Unserved Energy
EV	Electric Vehicle
FDCUCP	Frequency Dynamics – Constrained UCP
FLOL	Frequency of Loss Of Load
GAMS	General Algebraic Modeling Language
GENCO	Generation Company
GP	Gaussian Process
GRCC-RTD	Generalized Robust Chance Constrained Real-Time Dispatch
HLOLE	Hourly Loss of Load Expectation
HUC	Hierarchical Unit Commitment
IEEE	Institute of Electrical and Electronics Engineers
IEEE RTS	IEEE Reliability Test System
IGDT	Information Gap Decision Theory
IMS	Interconnected Microgrid System
IP	Interior – Point
LMP	Locational Marginal Price
LOLE	Loss of Load Expectation
LOLP	Loss of Load Probability
LS	Line Search
MBA	Modified Bat Algorithm
MCMCS	Markov Chain MCS
MCS	Monte Carlo Simulation
MI-SDP	Mixed – Integer Semi – Definite Programming
MDT	Minimum Down Time
MILP	Mixed – Integer Linear Programming
MIP	Mixed – Integer Programming
MUT	Minimum Up Time
NCUC	Network – Constrained Unit Commitment
NS	Not Stated
NWP	Numerical Weather Predictions
PDF	Probability Density Function
PDN	Power Distribution Network
PEM	Point Estimate Method
PEV	Plug-in Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
PLOL	Probability of Loss of Load
POPM	Probability of Positive Margin
PPD	Payment for Power Delivered
PPRP	Price Process for Reserve Price Payment
PRA	Payment for Reserve Allocation
PRCBUC	Probabilistic Risk/Cost-Based UC
PSO	Particle Swarm Optimization
PUL	Power Unit Limit
PV	Photovoltaics
Q	Quality index
RBDAUC	Risk – Based Day – Ahead UC
RE	Renewable Energy
RES	Renewable Energy Source
RLD	Risk – Limiting Dispatch
RR	Reserve Requirement
RRL	Ramp Rate Limit
RTED	Real – Time Economic Dispatch
RTD	Real – Time Dispatch
RUC	Robust UC

RUL	Reserve Unit Limit
SAA	Sample Average Approximation
SCED	Security – Constrained Economic Dispatch
SCUC	Security – Constrained UC
SCUCP	Security – Constrained UCP
SO	System Operator
SOC	State of Charge
SP	Stochastic Programming
STT	Scenario Tree Tool
TL	Transmission Loss
TLF	Transmission Line MVA Flow Limits
U-LMP	Uncertainty – contained – Locational Marginal Price
$UBFUCC^{DRRs}$	Uncertainty – Based Flexible UC and Construction in Combination with Demand Response Resources
UC	Unit Commitment
UCP	Unit Commitment Problem
USL	Unit Status Limit
UT	Unscented Transformation
VOLL	Value Of Lost Load
V2G	Vehicle – to – Grid
WECS	Wind Energy Conversion System
XLNS	Conditional Expectation of Load Not Supplied
XLOL	Expected Loss of Load

Index

i and j	Generator Unit
p and q	Bus
t	Period (hour)

Parameters

A	Area swept by the rotor
A_{PV}	Area of the PV power plant
A_i	Confidence interval (p.u.)
a_i, b_i and c_i	Cost coefficients for thermal generator i
B_i	Target value
$B_{i,j}$, B_0 and B_{00}	Coefficients of power losses in the B matrix
B_{pq}	Mutual susceptance of the connected lines between buses p and q
c	PV module constant
C_p	Power coefficient
CC_i	Cooling constant of thermal generator i
$CSSMC_i$	Total cold start maintenance and staff cost of thermal generator i ($/h)
$CSUC_i$	Cold start-up costs for thermal generator i ($/h)
DR_i	Allowable rate of decrease of generator i
E_i^{MAX}	Maximum energy deliveries of generator i
E_i^{min}	Minimum energy deliveries of generator i
EP	Electricity price
FF	Fill factor of the PV module
G_{pq}	Conductance of the connected lines between buses p and q
G_{std}	Solar radiation in the standard environment (1000 W/m^2)
$HSUC_i$	Hot start-up costs for thermal generator i ($/h)
I_{mpp}	Current at the maximum power point

I_{NSC}	Nominal short – circuit current
I_{SC}	Short – circuit current of the PV module
k	Boltzmann constant
K_i	Current temperature coefficient
K_v	Voltage temperature coefficient
$MVAflow_{pq}^{MAX}$	Maximum MVA flow of transmission line p-q
n	Density factor (n = 1.5)
N_B	Set number of network buses
N_g	Total generator units
N_S	Number of PV modules in series
N_P	Number of PV modules in parallel
N_{PQ}	Set number of PQ buses
NOCT	Normal operational cell temperature
P_d^t	Demand in period t
P_{gi}^{MAX}	Maximum generations of generator i
P_{gi}^{min}	Minimum generations of generator i
P_{loss}^t	Transmission power loss in period t
P_{sr}	Rated power output of PV
P_r	Rated wind power
q	Charge of an electron
SDC_i	Shutdown cost of generator i
SI	Forecasted solar irradiance
SR^t	Forecasted reserve in period t
SUC_i	Start-up cost of generator i
T	Time horizon (24, 48, 96, 168, 8760 h)
T_i^{down}	Minimum downtime duration of generator i
T_i^{up}	Minimum uptime duration of generator i
UR_i	Allowable rate of increase of generator i
V_{mpp}	Voltage at the maximum power point
V_{NOC}	Nominal open – circuit voltage
V_{OC}	Open – circuit voltage of the PV module
V_q^{MAX}	Allowable maximum voltage at bus q
V_q^{min}	Allowable minimum voltage at bus q
X_c	Certain radiation point (150 W/m^2)
α_i, β_i, γ_i, ξ_i and λ_i	Emission coefficients for generator i
θ_{pq}	Voltage angle difference between buses p and q
α	Scale parameter for the PDF of the Weibull function
β	Shape parameter for the PDF of the Weibull function
β_T	PV temperature coefficient
ξ	Error of the function $f_i(x)$
ζ_{PV}	Efficiency of the PV power plant
μ_D	Mean value of the load demand
μ_{EP}	Mean value of electricity price
μ_S	Mean deviation of solar irradiance
$\mu_{\Delta P_L}$	Mean value of load growth
η_{PV}	Power reduction factor of photo-voltaic panels (%)
σ_D	Standard deviation of the load demand
σ_{EP}	Standard deviation of electricity price
σ_S	Standard deviation of solar irradiance
$\sigma_{\Delta P_L}$	Standard deviation of load growth
ω	Wind speed (m/s)
ω_i	Cut – in wind speed (m/s)
ω_o	Cut – off wind speed (m/s)

ω_r	Rated wind speed (m/s)
τ	Temperature
τ_a	Actual module temperature
τ_C	Cell temperature
τ_N	Nominal module temperature
ρ	Air density
Variables	
$E_i\left(P_{gi}^t+R_{gi}^t\right)$	Emission function of generator i in period t
$F_i\left(P_{gi}^t+R_{gi}^t\right)$	Fuel cost of generator i in period t
f_{EP}	PDF of the electricity price
f_L	PDF of the load demand
f_S	PDF of the solar irradiance
f_ω	PDF of the wind speed
$f(G_S)$	PDF of G_s
$f_{\Delta P_L}$	PDF of the incremental load growth
$MVAflow_{pq}^t$	MVA flow of the power transmission line p-q in period t
P_{gi}^t	Real power that is delivered by generator i in period t
P_{gj}^t	Real power that is delivered by generator j in period t
P_{Bdp}^t	Absorbed active power at bus p in period t
P_{Bgp}^t	Generated active power at bus p in period t
$P_W(\omega)$	Output wind power (kW or MW) at wind speed (m/s)
$P_{PV,out}$	Output power of PV
$P_a(G_s)$	Average power output from a PV module for a given G_S
Q_{Bdp}^t	Absorbed reactive power at bus p in period t
Q_{Bgp}^t	Generated reactive power at bus p in period t
R_{gi}^t	Reserve of generator i in period t
$SX_{i(OFF)}^t$	Cumulative downtime of thermal generator i in period t
$T_{i(cold)}^t$	Time taken to cool thermal generator i in period t
$T_{i(down)}^t$	Time of downstate for thermal generator i in period t
$T_{i(ON)}^t$	Time of the ON state for thermal generator i in period t
$T_{i(OFF)}^t$	Time of the OFF state for thermal generator i in period t
TC_i^t	Total cost ($) of generator i at period t
TR_i^t	Total revenue ($) of generator i at period t
U_i^t	Status of generator i in period t
V_q^t	Voltage of bus q in period t
X_i^t	ON/OFF status of generator i in period t

References

1. Ebeed, M.; Aleem, S.H.E.A. *Overview of Uncertainties in Modern Power Systems: Uncertainty Models and Methods*; Elsevier Inc.: Amsterdam, The Netherlands, 2021. https://doi.org/10.1016/b978-0-12-820491-7.00001-3.
2. OECD. The Impact of the Coronavirus (COVID-19) Crisis on Development Finance, Tackling Coronavirus Contribution to a Global Effort. 2020. Volume 100, pp. 468–470. Available online: http://www.oecd.org/termsandconditions (accessed August 4, 2021).
3. Emovon, I. A Fuzzy Multi-Criteria Decision-Making Approach for Power Generation Problem Analysis. *J. Eng. Sci.* **2020**, *7*, E26–E31. https://doi.org/10.21272/jes.2020.7(2).e5.
4. Kanagasabai, L. Heat Transfer and Simulated Coronary Circulation System Optimization Algorithms for Real Power Loss Reduction. *J. Eng. Sci.* **2021**, *8*, E1–E8. https://doi.org/10.21272/jes.2021.8(1).e1.
5. Abujarad, S.Y.; Mustafa, M.W.; Jamian, J.J. Recent approaches of unit commitment in the presence of intermittent renewable energy resources: A review. *Renew. Sustain. Energy Rev.* **2017**, *70*, 215–223. https://doi.org/10.1016/j.rser.2016.11.246.
6. Dai, H.; Zhang, N.; Su, W. A Literature Review of Stochastic Programming and Unit Commitment. *J. Power Energy Eng.* **2015**, *3*, 206–214. https://doi.org/10.4236/jpee.2015.34029.

7. Jurković, K.; Pandžić, H.; Kuzle, I. Review on unit commitment under uncertainty approaches. In Proceedings of the 2015 38th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), Opatija, Croatia, 25–29 May 2015; pp. 1093–1097. https://doi.org/10.1109/MIPRO.2015.7160438.
8. Reddy, S.; Panwar, L.; Panigrahi, B.K.; Kumar, R.; Goel, L.; Al-Sumaiti, A.S. A profit-based self-scheduling framework for generation company energy and ancillary service participation in multi-constrained environment with renewable energy penetration. *Energy Environ.* **2020**, *31*, 549–569. https://doi.org/10.1177/0958305X19878426.
9. Zhao, C.; Wang, Q.; Wang, J.; Guan, Y. Expected value and chance constrained stochastic unit commitment ensuring wind power utilization. *IEEE Trans. Power Syst.* **2014**, *29*, 2696–2705. https://doi.org/10.1109/TPWRS.2014.2319260.
10. Zhang, N.; Kang, C.; Xia, Q.; Ding, Y.; Huang, Y.; Sun, R.; Huang, J.; Bai, J. A Convex Model of Risk-Based Unit Commitment for Day-Ahead Market Clearing Considering Wind Power Uncertainty. *IEEE Trans. Power Syst.* **2015**, *30*, 1582–1592. https://doi.org/10.1109/TPWRS.2014.2357816.
11. Wang, Q.; Wang, J.; Guan, Y. Stochastic unit commitment with uncertain demand response. *IEEE Trans. Power Syst.* **2013**, *28*, 562–563. https://doi.org/10.1109/TPWRS.2012.2202201.
12. Tuohy, A.; Meibom, P.; Denny, E.; O'Malley, M. Unit Commitment for Systems with Significant Wind Penetration. *IEEE Trans. Power Syst.* **2009**, *24*, 592–601. https://doi.org/10.1109/TPWRS.2009.2016470.
13. Wang, Q.; Wang, J.; Guan, Y. Price-based unit commitment with wind power utilization constraints. *IEEE Trans. Power Syst.* **2013**, *28*, 2718–2726. https://doi.org/10.1109/TPWRS.2012.2231968.
14. Wang, Q.; Guan, Y.; Wang, J. A chance-constrained two-stage stochastic program for unit commitment with uncertain wind power output. *IEEE Trans. Power Syst.* **2012**, *27*, 206–215. https://doi.org/10.1109/TPWRS.2011.2159522.
15. Jiang, R.; Wang, J.; Guan, Y. Robust Unit Commitment with Wind Power and Pumped Storage Hydro. *IEEE Trans. Power Syst.* **2012**, *27*, 800–810. https://doi.org/10.1109/TPWRS.2011.2169817.
16. Zhao, C.; Wang, J.; Watson, J.P.; Guan, Y. Multi-stage robust unit commitment considering wind and demand response uncertainties. *IEEE Trans. Power Syst.* **2013**, *28*, 2708–2717. https://doi.org/10.1109/TPWRS.2013.2244231.
17. Zhao, C.; Guan, Y. Unified stochastic and robust unit commitment. *IEEE Trans. Power Syst.* **2013**, *28*, 3353–3361. https://doi.org/10.1109/TPWRS.2013.2251916.
18. Lorca, Á.; Sun, X.A.; Litvinov, E.; Zheng, T. Multistage adaptive robust optimization for the unit commitment problem. *Oper. Res.* **2016**, *64*, 32–51. https://doi.org/10.1287/opre.2015.1456.
19. Takriti, S.; Krasenbrink, B.; Wu, L.S.Y. Incorporating fuel constraints and electricity spot prices into the stochastic unit commitment problem. *Oper. Res.* **2000**, *48*, 268–280. https://doi.org/10.1287/opre.48.2.268.12379.
20. Carpentier, P.; Cohen, G.; Culioli, J.C. Stochastic Optimization of Unit Commitment: A New Decomposition Framework. *IEEE Trans. Power Syst.* **1996**, *11*, 1067–1073. https://doi.org/10.1109/59.496196.
21. Takriti, S.; Birge, J.R.; Long, E. A stochastic model for the unit commitment problem. *IEEE Trans. Power Syst.* **1996**, *11*, 1497–1508. https://doi.org/10.1109/59.535691.
22. Isuru, M.; Hotz, M.; Gooi, H.B.; Utschick, W. Network-constrained thermal unit commitment fortexhybrid AC/DC transmission grids under wind power uncertainty. *Appl. Energy* **2020**, *258*, 114031. https://doi.org/10.1016/j.apenergy.2019.114031.
23. Kong, X.; Liu, D.; Wang, C.; Sun, F.; Li, S. Optimal operation strategy for interconnected microgrids in market environment considering uncertainty. *Appl. Energy* **2020**, *275*, 115336. https://doi.org/10.1016/j.apenergy.2020.115336.
24. Zheng, X.; Chen, H.; Xu, Y.; Liang, Z.; Chen, Y. A Hierarchical Method for Robust SCUC of Multi-Area Power Systems with Novel Uncertainty Sets. *IEEE Trans. Power Syst.* **2020**, *35*, 1364–1375. https://doi.org/10.1109/TPWRS.2019.2939395.
25. Du, Y.; Li, Y.; Duan, C.; Gooi, H.B.; Jiang, L. Adjustable Uncertainty Set Constrained Unit Commitment with Operation Risk Reduced through Demand Response. *IEEE Trans. Ind. Inform.* **2021**, *17*, 1154–1165. https://doi.org/10.1109/TII.2020.2979215.
26. Zhou, Y.; Shahidehpour, M.; Wei, Z.; Sun, G.; Chen, S. Multistage robust look-ahead unit commitment with probabilistic forecasting in multi-carrier energy systems. *IEEE Trans. Sustain. Energy* **2021**, *12*, 70–82. https://doi.org/10.1109/TSTE.2020.2979925.
27. Zhang, G.; Li, F.; Xie, C. Flexible Robust Risk-Constrained Unit Commitment of Power System Incorporating Large Scale Wind Generation and Energy Storage. *IEEE Access* **2020**, *8*, 209232–209241. https://doi.org/10.1109/ACCESS.2020.3038685.
28. Bavafa, F.; Niknam, T.; Azizipanah-Abarghooee, R.; Terzija, V. A New Biobjective Probabilistic Risk-Based Wind-Thermal Unit Commitment Using Heuristic Techniques. *IEEE Trans. Ind. Inform*. **2017**, *13*, 115–124. https://doi.org/10.1109/TII.2016.2616109.
29. Velloso, A.; Street, A.; Pozo, D.; Arroyo, J.M.; Cobos, N.G. Two-stage robust unit commitment for co-optimized electricity markets: An adaptive data-driven approach for scenario-based uncertainty sets. *IEEE Trans. Sustain. Energy* **2020**, *11*, 958–969. https://doi.org/10.1109/TSTE.2019.2915049.
30. Naghdalian, S.; Amraee, T.; Kamali, S.; Capitanescu, F. Stochastic Network-Constrained Unit Commitment to Determine Flexible Ramp Reserve for Handling Wind Power and Demand Uncertainties. *IEEE Trans. Ind. Inform.* **2020**, *16*, 4580–4591. https://doi.org/10.1109/TII.2019.2944234.
31. Zhang, M.; Fang, J.; Ai, X.; Zhou, B.; Yao, W.; Wu, Q.; Wen, J. Partition-Combine Uncertainty Set for Robust Unit Commitment. *IEEE Trans. Power Syst.* **2020**, *35*, 3266–3269. https://doi.org/10.1109/TPWRS.2020.2967887.
32. Wang, Y.; Dong, K.; Zeng, K.; Lan, X.; Zhou, W.; Yang, M.; Hao, W. Robust unit commitment model based on optimal uncertainty set. *IEEE Access* **2020**, *8*, 192787–192796. https://doi.org/10.1109/ACCESS.2020.3023765.
33. Morales, J.M.; Conejo, A.J.; Pérez-Ruiz, J. Economic valuation of reserves in power systems with high penetration of wind power. *IEEE Trans. Power Syst.* **2009**, *24*, 900–910. https://doi.org/10.1109/PES.2009.5260229.

34. Liu, K.; Zhong, J. Generation dispatch considering wind energy and system reliability. In Proceedings of the IEEE PES General Meeting, Minneapolis, MN, USA, 25–29 July 2010; pp. 1–7. https://doi.org/10.1109/PES.2010.5590047.
35. Zheng, X.; Chen, H.; Xu, Y.; Li, Z.; Lin, Z.; Liang, Z. A mixed-integer SDP solution to distributionally robust unit commitment with second order moment constraints. *CSEE J. Power Energy Syst.* **2020**, *6*, 374–383. https://doi.org/10.17775/CSEEJPES.2019.00930.
36. Zhao, T.; Zhang, H.; Liu, X.; Yao, S.; Wang, P. Resilient Unit Commitment for Day-Ahead Market Considering Probabilistic Impacts of Hurricanes. *IEEE Trans. Power Syst.* **2021**, *36*, 1082–1094. https://doi.org/10.1109/TPWRS.2020.3025185.
37. Esfahani, M.; Amjady, N.; Bagheri, B.; Hatziargyriou, N.D. Robust Resiliency-Oriented Operation of Active Distribution Networks Considering Windstorms. *IEEE Trans. Power Syst.* **2020**, *35*, 3481–3493. https://doi.org/10.1109/TPWRS.2020.2977405.
38. Shi, Z.; Liang, H.; Dinavahi, V. Data-Driven Distributionally Robust Chance-Constrained Unit Commitment with Uncertain Wind Power. *IEEE Access* **2019**, *7*, 135087–135098. https://doi.org/10.1109/ACCESS.2019.2942178.
39. Zhang, Y.; Han, X.; Xu, B.; Wang, M.; Ye, P.; Pei, Y. Risk-Based Admissibility Analysis of Wind Power Integration into Power System with Energy Storage System. *IEEE Access* **2018**, *6*, 57400–57413. https://doi.org/10.1109/ACCESS.2018.2870736.
40. Wang, Y.; Zhao, S.; Zhou, Z.; Botterud, A.; Xu, Y.; Chen, R. Risk Adjustable Day-Ahead Unit Commitment with Wind Power Based on Chance Constrained Goal Programming. *IEEE Trans. Sustain. Energy* **2017**, *8*, 530–541. https://doi.org/10.1109/TSTE.2016.2608841.
41. Poncelet, K.; Delarue, E.; D'haeseleer, W. Unit commitment constraints in long-term planning models: Relevance, pitfalls and the role of assumptions on flexibility. *Appl. Energy* **2020**, *258*, 113843. https://doi.org/10.1016/j.apenergy.2019.113843.
42. Hetzer, J.; Yu, D.C.; Bhattarai, K. An Economic Dispatch Model Incorporating Wind Power. *IEEE Trans. Energy Convers.* **2008**, *23*, 603–611. https://doi.org/10.1109/TEC.2007.914171.
43. de Jonghe, C.; Hobbs, B.F.; Belmans, R. Value of price responsive load for wind integration in unit commitment. *IEEE Trans. Power Syst.* **2014**, *29*, 675–685. https://doi.org/10.1109/TPWRS.2013.2283516.
44. Xu, Y.; Ding, T.; Qu, M.; Du, P. Adaptive Dynamic Programming for Gas-Power Network Constrained Unit Commitment to Accommodate Renewable Energy with Combined-Cycle Units. *IEEE Trans. Sustain. Energy* **2020**, *11*, 2028–2039. https://doi.org/10.1109/TSTE.2019.2951616.
45. Upadhyay, A.; Hu, B.; Li, J.; Wu, L. A chance-constrained wind range quantification approach to robust scuc by determining dynamic uncertainty intervals. *CSEE J. Power Energy Syst.* **2016**, *2*, 54–64. https://doi.org/10.17775/cseejpes.2016.00009.
46. Wen, T.; Zhang, Z.; Lin, X.; Li, Z.; Chen, C.; Wang, Z. Research on Modeling and the Operation Strategy of a Hydrogen-Battery Hybrid Energy Storage System for Flexible Wind Farm Grid-Connection. *IEEE Access.* **2020**, *8*, 79347–79356. https://doi.org/10.1109/ACCESS.2020.2990581.
47. Pérez-Díaz, J.I.; Jiménez, J. Contribution of a pumped-storage hydropower plant to reduce the scheduling costs of an isolated power system with high wind power penetration. *Energy* **2016**, *109*, 92–104. https://doi.org/10.1016/j.energy.2016.04.014.
48. Wu, L.; Shahidehpour, M.; Li, T. Stochastic Security-Constrained Unit Commitment. *IEEE Trans. Power Syst.* **2007**, *22*, 800–811. https://doi.org/10.1109/TPWRS.2007.894843.
49. Zhou, W.; Sun, H.; Peng, Y. Risk reserve constrained economic dispatch model with wind power penetration. *Energies* **2010**, *3*, 1880–1894. https://doi.org/10.3390/en3121880.
50. Ghorani, R.; Pourahmadi, F.; Moeini-Aghtaie, M.; Fotuhi-Firuzabad, M.; Shahidehpour, M. Risk-Based Networked-Constrained Unit Commitment Considering Correlated Power System Uncertainties. *IEEE Trans. Smart Grid.* **2020**, *11*, 1781–1791. https://doi.org/10.1109/TSG.2019.2943311.
51. Li, N.; Uckun, C.; Constantinescu, E.M.; Birge, J.R.; Hedman, K.W.; Botterud, A. Flexible Operation of Batteries in Power System Scheduling with Renewable Energy. *IEEE Trans. Sustain. Energy* **2016**, *7*, 685–696. https://doi.org/10.1109/TSTE.2015.2497470.
52. Marino, C.; Quddus, M.A.; Marufuzzaman, M.; Cowan, M.; Bednar, A.E. A chance-constrained two-stage stochastic programming model for reliable microgrid operations under power demand uncertainty. *Sustain. Energy Grids Netw.* **2018**, *13*, 66–77. https://doi.org/10.1016/j.segan.2017.12.007.
53. Zhou, Z.; Botterud, A. Dynamic scheduling of operating reserves in co-optimized electricity markets with wind power. *IEEE Trans. Power Syst.* **2014**, *29*, 160–171. https://doi.org/10.1109/TPWRS.2013.2281504.
54. Abdi, H. Profit-based unit commitment problem: A review of models, methods, challenges, and future directions. *Renew. Sustain. Energy Rev.* **2021**, *138*, 110504. https://doi.org/10.1016/j.rser.2020.110504.
55. Wu, C.X.; Chung, C.Y.; Wen, F.S.; Du, D.Y. Reliability/cost evaluation with pev and wind generation system. *IEEE Trans. Sustain. Energy* **2014**, *5*, 273–281. https://doi.org/10.1109/TSTE.2013.2281515.
56. Ruiz, P.A.; Philbrick, C.R.; Zak, E.; Cheung, K.W.; Sauer, P.W. Uncertainty management in the unit commitment problem. *IEEE Trans. Power Syst.* **2009**, *24*, 642–651. https://doi.org/10.1109/TPWRS.2008.2012180.
57. Bouffard, F.; Galiana, F.D. Stochastic security for operations planning with significant wind power generation. In Proceedings of the 2008 IEEE Power and Energy Society General Meeting—Conversion and Delivery of Electrical Energy in the 21st Century, Pittsburgh, PA, USA, 20–24 July 2008; Volume 23, pp. 306–316. https://doi.org/10.1109/PES.2008.4596307.
58. Lowery, C.; O'Malley, M. Impact of Wind Forecast Error Statistics Upon Unit Commitment. *IEEE Trans. Sustain. Energy* **2012**, *3*, 760–768. https://doi.org/10.1109/TSTE.2012.2210150.
59. Jeong, J.; Park, S. A robust contingency-constrained unit commitment with an N-αk security criterion. *Int. J. Electr. Power Energy Syst.* **2020**, *123*, 1581–1590. https://doi.org/10.1016/j.ijepes.2020.106148.

60. Contaxis, G.C.; Kabouris, J. Short term scheduling in a wind/diesel autonomous energy system. *IEEE Trans. Power Syst.* **1991**, *6*, 1161–1167. https://doi.org/10.1109/59.119261.
61. Galiana, F.D.; Bouffard, F.; Arroyo, J.M.; Restrepo, J.F. Scheduling and pricing of coupled energy and primary, secondary, and tertiary reserves. *Proc. IEEE* **2005**, *93*, 1970–1982. https://doi.org/10.1109/JPROC.2005.857492.
62. Bouffard, F.; Galiana, F.D.; Conejo, A.J. Market-clearing with stochastic security—Part I: Formulation. *IEEE Trans. Power Syst.* **2005**, *20*, 1818–1826. https://doi.org/10.1109/TPWRS.2005.857016.
63. Bouffard, F.; Galiana, F.D.; Conejo, A.J. Market-clearing with stochastic security—Part II: Case studies. *IEEE Trans. Power Syst.* **2006**, *20*, 1827–1835. https://doi.org/10.1109/pes.2006.1708880.
64. Pozo, D.; Contreras, J. A chance-constrained unit commitment with an n-k security criterion and significant wind generation. *IEEE Trans. Power Syst.* **2013**, *28*, 2842–2851. https://doi.org/10.1109/TPWRS.2012.2227841.
65. Vrakopoulou, M.; Margellos, K.; Lygeros, J.; Andersson, G. A Probabilistic Framework for Reserve Scheduling and N−1 Security Assessment of Systems with High Wind Power Penetration. *IEEE Trans. Power Syst.* **2013**, *28*, 3885–3896. https://doi.org/10.1109/TPWRS.2013.2272546.
66. Liu, G.; Tomsovic, K. Quantifying Spinning Reserve in Systems With Significant Wind Power Penetration, IEEE Trans. Power Syst. 27 (2012) 2385–2393. https://doi.org/10.1109/TPWRS.2012.2207465.
67. Salkuti, S.R. Day-ahead thermal and renewable power generation scheduling considering uncertainty. *Renew. Energy* **2019**, *131*, 956–965. https://doi.org/10.1016/j.renene.2018.07.106.
68. Osório, G.J.; Lujano-Rojas, J.M.; Matias, J.C.O.; Catalão, J.P.S. A probabilistic approach to solve the economic dispatch problem with intermittent renewable energy sources. *Energy* **2015**, *82*, 949–959. https://doi.org/10.1016/j.energy.2015.01.104.
69. Wang, M.Q.; Yang, M.; Liu, Y.; Han, X.S.; Wu, Q. Optimizing probabilistic spinning reserve by an umbrella contingencies constrained unit commitment. *Int. J. Electr. Power Energy Syst.* **2019**, *109*, 187–197. https://doi.org/10.1016/j.ijepes.2019.01.034.
70. Ahmadi, A.; Nezhad, A.E.; Siano, P.; Hredzak, B.; Saha, S. Information-Gap Decision Theory for Robust Security-Constrained Unit Commitment of Joint Renewable Energy and Gridable Vehicles. *IEEE Trans. Ind. Inform.* **2020**, *16*, 3064–3075. https://doi.org/10.1109/TII.2019.2908834.
71. Khorramdel, H.; Aghaei, J.; Khorramdel, B.; Siano, P. Optimal Battery Sizing in Microgrids Using Probabilistic Unit Commitment. *IEEE Trans. Ind. Inform.* **2016**, *12*, 834–843. https://doi.org/10.1109/TII.2015.2509424.
72. Khodayar, M.E.; Wu, L.; Shahidehpour, M. Hourly coordination of electric vehicle operation and volatile wind power generation in SCUC. *IEEE Trans. Smart Grid.* **2012**, *3*, 1271–1279. https://doi.org/10.1109/TSG.2012.2186642.
73. Restrepo, J.F.; Galiana, F.D. Assessing the yearly impact of wind power through a new hybrid deterministic/stochastic unit commitment. *IEEE Trans. Power Syst.* **2011**, *26*, 401–410. https://doi.org/10.1109/TPWRS.2010.2048345.
74. Ruiz-Rodriguez, F.J.; Hernández, J.C.; Jurado, F. Probabilistic load flow for photovoltaic distributed generation using the Cornish-Fisher expansion. *Electr. Power Syst. Res.* **2012**, *89*, 129–138. https://doi.org/10.1016/j.epsr.2012.03.009.
75. Langenmayr, U.; Wang, W.; Jochem, P. Unit commitment of photovoltaic-battery systems: An advanced approach considering uncertainties from load, electric vehicles, and photovoltaic. *Appl. Energy* **2020**, *280*, 115972. https://doi.org/10.1016/j.apenergy.2020.115972.
76. Wang, Y.; Xia, Q.; Kang, C. Unit Commitment with Volatile Node Injections by Using Interval Optimization. *IEEE Trans. Power Syst.* **2011**, *26*, 1705–1713. https://doi.org/10.1109/TPWRS.2010.2100050.
77. Shayesteh, E.; Yousefi, A.; Moghaddam, M.P. A probabilistic risk-based approach for spinning reserve provision using day-ahead demand response program. *Energy* **2010**, *35*, 1908–1915. https://doi.org/10.1016/j.energy.2010.01.001.
78. Hou, Q.; Zhang, N.; Du, E.; Miao, M.; Peng, F.; Kang, C. Probabilistic duck curve in high PV penetration power system: Concept, modeling, and empirical analysis in China. *Appl. Energy* **2019**, *242*, 205–215. https://doi.org/10.1016/j.apenergy.2019.03.067.
79. Zhang, Y.; Wang, J.; Zeng, B.; Hu, Z. Chance-Constrained Two-Stage Unit Commitment under Uncertain Load and Wind Power Output Using Bilinear Benders Decomposition. *IEEE Trans. Power Syst.* **2017**, *32*, 3637–3647. https://doi.org/10.1109/TPWRS.2017.2655078.
80. Ahmadi, A.; Nezhad, A.E.; Hredzak, B. Security-Constrained Unit Commitment in Presence of Lithium-Ion Battery Storage Units Using Information-Gap Decision Theory. *IEEE Trans. Ind. Inform.* **2019**, *15*, 148–157. https://doi.org/10.1109/TII.2018.2812765.
81. Luo, L.; Abdulkareem, S.S.; Rezvani, A.; Miveh, M.R.; Samad, S.; Aljojo, N.; Pazhoohesh, M. Optimal scheduling of a renewable based microgrid considering photovoltaic system and battery energy storage under uncertainty. *J. Energy Storage* **2020**, *28*, 101306. https://doi.org/10.1016/j.est.2020.101306.
82. Swaroop, P.V.; Erlich, I.; Rohrig, K.; Dobschinski, J. A stochastic model for the optimal operation of a wind-thermal power system. *IEEE Trans. Power Syst.* **2009**, *24*, 940–950. https://doi.org/10.1109/TPWRS.2009.2016504.
83. Domínguez, R.; Carrión, M.; Oggioni, G. Planning and operating a renewable-dominated European power system under uncertainty. *Appl. Energy* **2020**, *258*, 113989. https://doi.org/10.1016/j.apenergy.2019.113989.
84. Entriken, R.; Varaiya, P.; Wu, F.; Bialek, J.; Dent, C.; Tuohy, A.; Rajagopal, R. Risk limiting dispatch. In Proceedings of the 2012 IEEE Power and Energy Society General Meeting, San Diego, CA, USA, 22–26 July 2012; pp. 1–5. https://doi.org/10.1109/PESGM.2012.6344589.
85. Fang, X.; Hodge, B.M.; Du, E.; Kang, C.; Li, F. Introducing uncertainty components in locational marginal prices for pricing wind power and load uncertainties. *IEEE Trans. Power Syst.* **2019**, *34*, 2013–2024. https://doi.org/10.1109/TPWRS.2018.2881131.

86. Kavousi-Fard, A.; Niknam, T.; Fotuhi-Firuzabad, M. Stochastic Reconfiguration and Optimal Coordination of V2G Plug-in Electric Vehicles Considering Correlated Wind Power Generation. *IEEE Trans. Sustain. Energy* **2015**, *6*, 822–830. https://doi.org/10.1109/TSTE.2015.2409814.
87. Wu, T.; Yang, Q.; Bao, Z.; Yan, W. Coordinated energy dispatching in microgrid with wind power generation and plug-in electric vehicles. *IEEE Trans. Smart Grid.* **2013**, *4*, 1453–1463. https://doi.org/10.1109/TSG.2013.2268870.
88. Zhou, B.; Geng, G.; Jiang, Q. Hierarchical unit commitment with uncertain wind power generation. *IEEE Trans. Power Syst.* **2016**, *31*, 94–104. https://doi.org/10.1109/TPWRS.2014.2387118.
89. Wang, J.; Shahidehpour, M.; Li, Z. Security-constrained unit commitment with volatile wind power generation. *IEEE Trans. Power Syst.* **2008**, *23*, 1319–1327. https://doi.org/10.1109/TPWRS.2008.926719.
90. Khorramdel, B.; Raoofat, M. Optimal stochastic reactive power scheduling in a microgrid considering voltage droop scheme of DGs and uncertainty of wind farms. *Energy* **2012**, *45*, 994–1006. https://doi.org/10.1016/j.energy.2012.05.055.
91. Constantinescu, E.M.; Zavala, V.M.; Rocklin, M.; Lee, S.; Anitescu, M. A computational framework for uncertainty quantification and stochastic optimization in unit commitment with wind power generation. *IEEE Trans. Power Syst.* **2011**, *26*, 431–441. https://doi.org/10.1109/TPWRS.2010.2048133.
92. Wu, L.; Shahidehpour, M.; Li, Z. Comparison of scenario-based and interval optimization approaches to stochastic SCUC. *IEEE Trans. Power Syst.* **2012**, *27*, 913–921. https://doi.org/10.1109/TPWRS.2011.2164947.
93. Zhao, L.; Zeng, B. Robust unit commitment problem with demand response and wind energy. In Proceedings of the 2012 IEEE Power and Energy Society General Meeting, San Diego, CA, USA, 22–26 July 2012; pp. 1–8. https://doi.org/10.1109/PESGM.2012.6344860.
94. Jiang, R.; Wang, J.; Zhang, M.; Guan, Y. Two-stage minimax regret robust unit commitment. *IEEE Trans. Power Syst.* **2013**, *28*, 2271–2282. https://doi.org/10.1109/TPWRS.2013.2250530.
95. Methaprayoon, K.; Yingvivatanapong, C.; Lee, W.J.; Liao, J.R. An integration of ANN wind power estimation into unit commitment considering the forecasting uncertainty. *IEEE Trans. Ind. Appl.* **2007**, *43*, 1441–1448. https://doi.org/10.1109/TIA.2007.908203.
96. Barth, R.; Brand, H.; Meibom, P.; Weber, C. A stochastic unit-commitment model for the evaluation of the impacts of integration of large amounts of intermittent wind power. In Proceedings of the 2006 International Conference on Probabilistic Methods Applied to Power Systems, Stockholm, Sweden, 11–15 June 2006. https://doi.org/10.1109/PMAPS.2006.360195.
97. Zhu, X.; Yu, Z.; Liu, X. Security Constrained Unit Commitment with Extreme Wind Scenarios. *J. Mod. Power Syst. Clean Energy* **2020**, *8*, 464–472. https://doi.org/10.35833/MPCE.2018.000797.
98. Nikoobakht, A.; Aghaei, J.; Shafie-Khah, M.; Catalao, J.P.S. Minimizing Wind Power Curtailment Using a Continuous-Time Risk-Based Model of Generating Units and Bulk Energy Storage. *IEEE Trans. Smart Grid.* **2020**, *11*, 4833–4846. https://doi.org/10.1109/TSG.2020.3004488.
99. He, D.; Tan, Z.; Harley, R.G. Chance constrained unit commitment with wind generation and superconducting magnetic energy storages. In Proceedings of the 2012 IEEE Power and Energy Society General Meeting, San Diego, CA, USA, 22–26 July 2012; pp. 1–6. https://doi.org/10.1109/PESGM.2012.6345719.
100. Huang, K.; Liu, P.; Ming, B.; Kim, J.S.; Gong, Y. Economic operation of a wind-solar-hydro complementary system considering risks of output shortage, power curtailment and spilled water. *Appl. Energy* **2021**, *290*, 116805. https://doi.org/10.1016/j.apenergy.2021.116805.
101. Venkatesh, B.; Yu, P.; Gooi, H.B.; Choling, D. Fuzzy MILP Unit Commitment Incorporating Wind Generators. *IEEE Trans. Power Syst.* **2008**, *23*, 1738–1746. https://doi.org/10.1109/TPWRS.2008.2004724.
102. Yang, Y.; Zhou, J.; Liu, G.; Mo, L.; Wang, Y.; Jia, B.; He, F. Multi-plan formulation of hydropower generation considering uncertainty of wind power. *Appl. Energy* **2020**, *260*, 114239. https://doi.org/10.1016/j.apenergy.2019.114239.
103. Kalantari, A.; Restrepo, J.F.; Galiana, F.D. Security-constrained unit commitment with uncertain wind generation: The loadability set approach. *IEEE Trans. Power Syst.* **2013**, *28*, 1787–1796. https://doi.org/10.1109/TPWRS.2012.2230029.
104. Williams, T.; Crawford, C. Probabilistic load flow modeling comparing maximum entropy and gram-charlier probability density function reconstructions. *IEEE Trans. Power Syst.* **2013**, *28*, 272–280. https://doi.org/10.1109/TPWRS.2012.2205714.
105. Khaloie, H.; Abdollahi, A.; Shafiekhah, M.; Anvari-Moghaddam, A.; Nojavan, S.; Siano, P.; Catalão, J.P.S. Coordinated wind-thermal-energy storage offering strategy in energy and spinning reserve markets using a multi-stage model. *Appl. Energy* **2020**, *259*, 114168. https://doi.org/10.1016/j.apenergy.2019.114168.
106. Zhang, N.; Hu, Z.; Han, X.; Zhang, J.; Zhou, Y. A fuzzy chance-constrained program for unit commitment problem considering demand response, electric vehicle and wind power. *Int. J. Electr. Power Energy Syst.* **2015**, *65*, 201–209. https://doi.org/10.1016/j.ijepes.2014.10.005.
107. Soltani, N.Y.; Nasiri, A. Chance-Constrained Optimization of Energy Storage Capacity for Microgrids. *IEEE Trans. Smart Grid.* **2020**, *11*, 2760–2770. https://doi.org/10.1109/TSG.2020.2966620.
108. Zhou, A.; Yang, M.; Wang, Z.; Li, P. A linear solution method of generalized robust chance constrained real-time dispatch. *IEEE Trans. Power Syst.* **2018**, *33*, 7313–7316. https://doi.org/10.1109/TPWRS.2018.2865184.
109. Wen, Y.; Li, W.; Huang, G.; Liu, X. Frequency Dynamics Constrained Unit Commitment with Battery Energy Storage. *IEEE Trans. Power Syst.* **2016**, *31*, 5115–5125. https://doi.org/10.1109/TPWRS.2016.2521882.
110. Kamjoo, A.; Maheri, A.; Putrus, G.A. Chance constrained programming using non-Gaussian joint distribution function in design of standalone hybrid renewable energy systems. *Energy* **2014**, *66*, 677–688. https://doi.org/10.1016/j.energy.2014.01.027.

111. Zhu, F.; Zhong, P.; Xu, B.; Liu, W.; Wang, W.; Sun, Y.; Chen, J.; Li, J. Short-term stochastic optimization of a hydro-wind-photovoltaic hybrid system under multiple uncertainties. *Energy Convers. Manag.* **2020**, *214*, 112902. https://doi.org/10.1016/j.enconman.2020.112902.
112. Soleimanpour, N.; Mohammadi, M. Probabilistic load flow by using nonparametric density estimators. *IEEE Trans. Power Syst.* **2013**, *28*, 3747–3755. https://doi.org/10.1109/TPWRS.2013.2258409.
113. Roukerd, S.P.; Abdollahi, A.; Rashidinejad, M. Uncertainty-based unit commitment and construction in the presence of fast ramp units and energy storages as flexible resources considering enigmatic demand elasticity. *J. Energy Storage* **2020**, *29*, 101290. https://doi.org/10.1016/j.est.2020.101290.
114. Hajimiragha, A.H.; Cañizares, C.A.; Fowler, M.W.; Moazeni, S.; Elkamel, A. A robust optimization approach for planning the transition to plug-in hybrid electric vehicles. *IEEE Trans. Power Syst.* **2011**, *26*, 2264–2274. https://doi.org/10.1109/TPWRS.2011.2108322.
115. Baringo, L.; Conejo, A.J. Offering strategy via robust optimization. *IEEE Trans. Power Syst.* **2011**, *26*, 1418–1425. https://doi.org/10.1109/TPWRS.2010.2092793.
116. Arab, A.; Khodaei, A.; Khator, S.K.; Han, Z. Electric Power Grid Restoration Considering Disaster Economics. *IEEE Access* **2016**, *4*, 639–649. https://doi.org/10.1109/ACCESS.2016.2523545.
117. Albrecht, P.F.; Garver, L.L.; Jordan, G.A.; Patton, A.D.; van Horne, P.R. *Reliability Indexes for Power Systems. Final report, March 1981*; U.S. Department of Energy: Washington, DC, USA, 1981. https://doi.org/10.2172/6547533.
118. Kayal, P.; Chanda, C.K. Placement of wind and solar based DGs in distribution system for power loss minimization and voltage stability improvement. *Int. J. Electr. Power Energy Syst.* **2013**, *53*, 795–809. https://doi.org/10.1016/j.ijepes.2013.05.047.
119. Liang, R.H.; Liao, J.H. A fuzzy-optimization approach for generation scheduling with wind and solar energy systems. *IEEE Trans. Power Syst.* **2007**, *22*, 1665–1674. https://doi.org/10.1109/TPWRS.2007.907527.
120. Shojaabadi, S.; Abapour, S.; Abapour, M.; Nahavandi, A. Simultaneous planning of plug-in hybrid electric vehicle charging stations and wind power generation in distribution networks considering uncertainties. *Renew. Energy* **2016**, *99*, 237–252. https://doi.org/10.1016/j.renene.2016.06.032.
121. Ali, E.S.; Elazim, S.M.A.; Abdelaziz, A.Y. Ant Lion Optimization Algorithm for optimal location and sizing of renewable distributed generations. *Renew. Energy* **2017**, *101*, 1311–1324. https://doi.org/10.1016/j.renene.2016.09.023.
122. Gong, Q.; Lei, J.; Ye, J. Optimal siting and sizing of distributed generators in distribution systems considering cost of operation risk. *Energies* **2016**, *9*, 2541–2551. https://doi.org/10.3390/en9010061.
123. Reddy, S.S.; Bijwe, P.R.; Abhyankar, A.R. Real-Time Economic Dispatch Considering Renewable Power Generation Variability and Uncertainty over Scheduling Period. *IEEE Syst. J.* **2015**, *9*, 1440–1451. https://doi.org/10.1109/JSYST.2014.2325967.
124. Suganthi, S.T.; Devaraj, D.; Ramar, K.; Thilagar, S.H. An Improved Differential Evolution algorithm for congestion management in the presence of wind turbine generators. *Renew. Sustain. Energy Rev.* **2018**, *81*, 635–642. https://doi.org/10.1016/j.rser.2017.08.014.
125. Amrollahi, M.H.; Bathaee, S.M.T. Techno-economic optimization of hybrid photovoltaic/wind generation together with energy storage system in a stand-alone micro-grid subjected to demand response. *Appl. Energy* **2017**, *202*, 66–77. https://doi.org/10.1016/j.apenergy.2017.05.116.
126. Pallabazzer, R. Evaluation of wind-generator potentiality. *Sol. Energy* **1995**, *55*, 49–59. https://doi.org/10.1016/0038-092X(95)00040-X.
127. Ali, A.; Raisz, D.; Mahmoud, K.; Lehtonen, M. Optimal Placement and Sizing of Uncertain PVs Considering Stochastic Nature of PEVs. *IEEE Trans. Sustain. Energy* **2020**, *11*, 1647–1656. https://doi.org/10.1109/TSTE.2019.2935349.
128. Rawat, M.S.; Vadhera, S. Impact of Photovoltaic Penetration on Static Voltage Stability of Distribution Networks: A Probabilistic Approach. *Asian J. Water Environ. Pollut.* **2018**, *15*, 51–62. https://doi.org/10.3233/AJW-180043.
129. Salameh, Z.M.; Borowy, B.S.; Amin, A.R.A. Photovoltaic Module-Site Matching Based on the Capacity Factors. *IEEE Trans. Energy Convers.* **1995**, *10*, 326–332. https://doi.org/10.1109/60.391899.
130. Ruiz-Rodriguez, F.J.; Gomez-Gonzalez, M.; Jurado, F. Binary particle swarm optimization for optimization of photovoltaic generators in radial distribution systems using probabilistic load flow. *Electr. Power Compon. Syst.* **2011**, *39*, 1667–1684. https://doi.org/10.1080/15325008.2011.608771.
131. Qian, K.; Zhou, C.; Allan, M.; Yuan, Y. Modeling of load demand due to EV battery charging in distribution systems. *IEEE Trans. Power Syst.* **2011**, *26*, 802–810. https://doi.org/10.1109/TPWRS.2010.2057456.
132. Zangeneh, A.; Jadid, S.; Rahimi-Kian, A. Uncertainty based distributed generation expansion planning in electricity markets. *Electr. Eng.* **2010**, *91*, 369–382. https://doi.org/10.1007/s00202-010-0146-6.
133. Majidi, B. Mohammadi-Ivatloo, A. Soroudi, Application of information gap decision theory in practical energy problems: A comprehensive review, Appl. Energy. 249 (2019) 157–165. https://doi.org/10.1016/j.apenergy.2019.04.144.
134. Li, C.; Grossmann, I.E. A Review of Stochastic Programming Methods for Optimization of Process Systems Under Uncertainty. *Front. Chem. Eng.* **2021**, *2*, 1–20. https://doi.org/10.3389/fceng.2020.622241.
135. Yang, Z.; Li, K.; Niu, Q.; Xue, Y. A comprehensive study of economic unit commitment of power systems integrating various renewable generations and plug-in electric vehicles. *Energy Convers. Manag.* **2017**, *132*, 460–481. https://doi.org/10.1016/j.enconman.2016.11.050.