A Comprehensive Review of Security-constrained Unit Commitment

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***Abstract*—Security-constrained unit commitment (SCUC) has been extensively studied as a key decision-making tool to determine optimal power generation schedules in the operation of electricity market. With the development of emerging power grids, fruitful research results on SCUC have been obtained. Therefore, it is essential to review current work and propose future directions for SCUC to meet the needs of developing power systems. In this paper, the basic mathematical model of the standard SCUC is summarized, and the characteristics and application scopes of common solution algorithms are presented. Customized models focusing on diverse mathematical properties are then categorized and the corresponding solving methodologies are discussed. Finally, research trends in the field are prospected based on a summary of the state-of-the-art and latest studies. It is hoped that this paper can be a useful reference to support theoretical research and practical applications of SCUC in the future.**

***Index Terms*—Security-constrained unit commitment, electricity market, accurate model, AC power flow, data-driven.**

I. Introduction

As a critical decision-making tool for power system operations and as a theoretical basis for day-ahead electricity markets, independent system operators (ISOs) execute unit commitment (UC) to determine the optimal commitment and dispatch of thermal generation units at minimal operation cost, subject to prevailing unit and system constraints [1]. Therefore, different UC models and solutions have attracted considerable attention in academia and industry for their research and practical benefits [2]. Nevertheless, network security constraints such as transmission capacity and nodal voltage limits are not widely considered or utilized in UC models. With the continual growth of power demands, transmission networks may be operated close to their physical limits in market-oriented power systems [3]. Consequently, generation scheduling based only on UC models may lead to transmission congestion and increased operation costs due to potential network violations. Accordingly, ISOs must consider network security constraints when dispatching generation units [4], [5]. In this context, traditional UC problems are gradually developed into security-constrained unit commitment (SCUC) models [6], [7].

Several review papers related to SCUC have been published. Reference [7] analyzed network models under normal and contingency cases and introduced two-level optimization methods for SCUC. However, [7] mainly summarized the SCUC models and solutions introduced prior to 2006, which is effectively outdated. In [8], solutions for deterministic and uncertain UC were reviewed, but the corresponding mathematical models were hardly introduced. Two- and multi-stage stochastic SCUC models and current solution algorithms were investigated in [9]. However, the study mainly focused on the effects of uncertainties on SCUC while failing to cover other aspects of the existing research. The study in [10] detailed the characteristics and application status of intelligent optimization algorithms for solving SCUC but did not consider mathematical optimization methods or the potential integration of the two types of methods. In [11], the models, methods, and challenges of profit-based UC in restructured power systems were discussed, but the surveys on SCUC were relatively limited. Recently, an increasing number of novel theories of and methods for SCUC have been presented in response to the considerable changes in energy structures and the rapid development of power systems. However, comprehensive surveys of the latest research achievements of SCUC and prospects for future research trends have rarely been reported.

Based on the state of the art of SCUC, this paper conducts a comprehensive summary of the modeling approaches and solution algorithms according to practical needs and then prospects future research trends. This paper can act as a reference for researchers and engineers interested in theoreti-

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cal research and practical application of SCUC.

The remainder of this paper is organized as follows. Section II presents the mathematical model of the standard SCUC and summarizes the characteristics and application scopes of common solution algorithms. The modeling and solution methodologies of SCUC with diverse mathematical properties are reviewed in Section III. Section IV prospects the research trends of SCUC based on the latest achievements. Finally, conclusions are drawn in Section V.

II. Mathematical Model of Standard SCUC and Solution Algorithms

A. Mathematical Model of Standard SCUC

1) Objective Function

The objective of the standard SCUC model is to minimize the total cost during a particular scheduling cycle subject to various physical constraints [9], [11]. The objective function covering operation costs of conventional thermal power units is given as:

$$\min F_{\mathrm{G}}(U_{\mathrm{G}i,t},P_{\mathrm{G}i,t})=\min\sum_{t=1}^{T}\sum_{i=1}^{N_{\mathrm{G}}}\Big[U_{\mathrm{G}i,t}(1-U_{\mathrm{G}i,t-1})\cdot SU_{\mathrm{G}i,t}+ U_{\mathrm{G}i,t-1}(1-U_{\mathrm{G}i,t})\cdot SD_{\mathrm{G}i,t}+U_{\mathrm{G}i,t}R_{\mathrm{G}i,t}(P_{\mathrm{G}i,t})\Big] \tag{1}$$

where $F_{\mathrm{G}}(U_{\mathrm{G}i,t},P_{\mathrm{G}i,t})$ is the overall operation cost; T is the number of time periods; N_{G} is the number of thermal units; $U_{\mathrm{G}i,t}$ is the on/off status of unit i at time t, which equals 0 when unit i is off, and 1 otherwise; $P_{\mathrm{G}i,t}$ is the active power output of unit i at time t; and $R_{\mathrm{G}i,t}(P_{\mathrm{G}i,t})$, $SU_{\mathrm{G}i,t}$, and $SD_{\mathrm{G}i,t}$ are the generation cost, start-up cost, and shut-down cost of unit i at time t, respectively.

2) Unit Constraints

1) Generation power limits. The unit output is limited by the minimum technical output. In addition, the sum of the output and spinning reserve is also restricted by its capacity [12].

$$\begin{cases}P_{\mathrm{G}i,t}+SR_{\mathrm{G}i,t}\le U_{\mathrm{G}i,t}P_{\mathrm{G}i}^{\max}\\ U_{\mathrm{G}i,t}P_{\mathrm{G}i}^{\min}\le P_{\mathrm{G}i,t}\end{cases} \tag{2}$$

where $P_{\mathrm{G}i}^{\min}$ and $P_{\mathrm{G}i}^{\max}$ are the minimum and maximum power limits of unit i, respectively; and $SR_{\mathrm{G}i,t}$ is the spinning reserve of unit i at time t.

2) The minimum on/off time constraints. The frequent start-up/shut-down of a generator over a short period can induce excessive tear and wear, which should be avoided [2]. Thus, generators are required to stay in the on/off status for an extended period before they can be switched off/on.

$$\begin{cases}(X_{\mathrm{G}i,t-1}^{\mathrm{on}}-T_{\mathrm{G}i}^{\mathrm{on}})(U_{\mathrm{G}i,t-1}-U_{\mathrm{G}i,t})\ge 0\\ (X_{\mathrm{G}i,t-1}^{\mathrm{off}}-T_{\mathrm{G}i}^{\mathrm{off}})(U_{\mathrm{G}i,t}-U_{\mathrm{G}i,t-1})\ge 0\end{cases} \tag{3}$$

where $X_{\mathrm{G}i,t}^{\mathrm{on}}$ and $X_{\mathrm{G}i,t}^{\mathrm{off}}$ are the on and off time counters of unit i at time t, respectively; and $T_{\mathrm{G}i}^{\mathrm{on}}$ and $T_{\mathrm{G}i}^{\mathrm{off}}$ are the minimum on and off time requirements of unit i, respectively.

3) Ramping rate constraints. The power adjustment ranges of generators per unit time are constrained by the maximum ramping up/down capability [13].

$$\begin{cases}P_{\mathrm{G}i,t}-P_{\mathrm{G}i,t-1}\le RU_i\\ P_{\mathrm{G}i,t-1}-P_{\mathrm{G}i,t}\le RD_i\end{cases} \tag{4}$$

where RU_i and RD_i are the ramping up and down limits of unit i, respectively.

In particular, for units that can provide ancillary services, the spinning and operation reserve capabilities should be constrained [12]:

$$\begin{cases}SR_{\mathrm{G}i,t}\le 10\cdot MSR_i\cdot U_{\mathrm{G}i,t}\\ OR_{\mathrm{G}i,t}=(1-U_{\mathrm{G}i,t})\cdot QSC_i\end{cases} \tag{5}$$

where MSR_i is the maximum sustained ramping rate of unit i; $OR_{\mathrm{G}i,t}$ is the operation reserve of unit i at time t; and QSC_i is the quick-start capacity of unit i.

3) System Constraints

1) System power balance constraint. The total output of operating units must meet the system load demand and is expressed as:

$$\sum_{i=1}^{N_{\mathrm{G}}}U_{\mathrm{G}i,t}P_{\mathrm{G}i,t}=P_{\mathrm{L}t}+P_{\mathrm{loss}} \tag{6}$$

where $P_{\mathrm{L}t}$ is the system load forecasting value; and P_{loss} is the total losses.

2) Reserve requirements. To cope with unforeseen conditions such as generator outages and/or load fluctuations, sufficient spinning and operation reserves should be considered [14], [15]. These can be expressed as:

$$\begin{cases}\sum_{i=1}^{N_{\mathrm{G}}}SR_{\mathrm{G}i,t}\ge SR_t\\ \sum_{i=1}^{N_{\mathrm{G}}}OR_{\mathrm{G}i,t}\ge OR_t\end{cases} \tag{7}$$

where SR_t and OR_t are the system spinning and operation reserve requirements at time t, respectively.

3) Network security constraints. To maintain secure operation, power flows of transmission lines cannot exceed their limits [16], [17]. For network contingencies, $N-1$ transmission security checking is applied to ensure system operational security against any single line failure:

$$-P_{l,c}^{\max}\le\sum_{i=1}^{N}\Big(G_{l,i}+d_{l,c}G_{c,i}\Big)P_{\mathrm{G}i,t}-\sum_{d=1}^{D}\Big(G_{l,d}+d_{l,c}G_{c,d}\Big)P_{\mathrm{L}d,t}\le P_{l,c}^{\max}\quad c\in C \tag{8}$$

where $P_{l,c}^{\max}$ is the capacity limit of line l under line outage contingency c; $d_{l,c}$ is the line outage distribution factor; $G_{l,i}$, $G_{c,i}$, $G_{l,d}$, and $G_{c,d}$ are the power transfer distribution factors; D is the number of load nodes; $P_{\mathrm{L}d,t}$ is the load of node d at time t; and C is the set of N−1 contingencies.

B. Solving Algorithms of Standard SCUC Model

The standard SCUC model can be formulated as a mixed-integer non-linear programming (MINLP) problem. The common solving algorithms include heuristic, mathematical optimization (DP, BBA, LR, BD, OA, OO, C&CG), and intelligent optimization algorithms. The advantages and disadvantages of these algorithms are summarized in Table I.

TABLE I
ADVANTAGES AND DISADVANTAGES OF SOLVING ALGORITHMS FOR STANDARD SCUC MODEL

Algorithm	Advantage	Disadvantage
Heuristic	Solving process is relatively easy	Global optimum cannot be guaranteed
DP	Solving space is compressed	Curse of dimensionality issue may incur
BBA	High searching efficiency	Inapplicability for large-scale problems
LR	Dealing with constraints effectively	Oscillation along iterations
BD	Original large-scale problem can be decoupled	Slow convergence
OA	Optimal solution can be obtained	Time-consuming calculation
OO	Fast convergence	Only suboptimal solution is guaranteed
C&CG	Effective for two-stage optimization	Solving speed is relatively limited
Intelligent optimization	Rapid convergence	Uncertainty and instability in solving process

1) Heuristic Algorithm

The heuristic algorithm is one of the earliest algorithms employed to solve the SCUC. The most common heuristic algorithms are the local search method [18] and priority list algorithm [19]. These types of algorithms are simple in principle and efficient in calculation. However, the global optimality cannot be theoretically guaranteed, so these algorithms are usually applied to UC in combination with other algorithms [20].

2) Mathematical Optimization Algorithm

The mathematical optimization algorithm solves SCUC problems by leveraging analytical methods and the properties of the model. As the physical meaning of this process is clear, mathematical optimization algorithms have been widely applied to SCUC problems including the dynamic programming (DP) [21], branch-and-bound algorithm (BBA) [22], Lagrangian relaxation (LR) [23], Benders decomposition (BD) [24], outer approximation (OA) [25], ordinal optimization (OO) [26], [27], and column-and-constraint generation (C&CG) [28].

DP is used to solve multi-stage optimization problems. The main idea is to phase solution seeking to compress the feasible space. However, this requires that the problem satisfy the basic premise of the optimality theorem; otherwise, the global optimality cannot be guaranteed. In addition, the "curse of dimensionality" may incur with the increasing number of generation units. In practice, DP is typically utilized in combination with the priority list algorithm [29].

The main idea of BBA is to solve a series of relaxation problems of the original problem along the branch-and-bound tree and to update the upper and lower bounds of the objective function iteratively. In essence, BBA uses different searching strategies to find the optimal solution and improves the searching efficiency through reasonable branch-and-bound actions. The number of subproblems, however, increases sharply, leading to a considerable reduction in computational efficiency with the expansion of power systems [22].

LR is widely used in solving SCUC problems. Its main strategy is to convert the inequality constraints as penalty terms into the objective function. Then, based on the duality principle, it decouples the UC problem into a series of subproblems. LR is flexible in application and overcomes the obstacle of dimensionality but is easily affected by the initial value and Lagrangian multiplier update strategies, which may cause oscillations in the iterative process [23].

To reduce the solving complexity, the BD decouples the SCUC model into a master problem and several subproblems, which coordinate through Benders cuts iteratively. Currently, the BD, which has been employed in SCUC problems extensively, is one of the most effective algorithms to address the complicated constraints in SCUC [30].

As a decomposition strategy to solve MINLP, the OA involves solving an alternating sequence of primal and relaxed mixed-integer linear programming (MILP) problems. A sequence of valid lower and upper bounds on the global optimum are generated, which offers a theoretical guarantee of convergence to the global optimum in a finite number of iterations. Different from the BD, the OA and its variants are based on the use of optimal primal information [25].

In the solving process of OO, a rough model with a relatively simple structure is used to screen the feasible space rapidly, obtaining the selected set. Then, the suboptimal solution that satisfies the practical needs is identified through the accurate model through complicated calculation that renders higher accuracy [26]. This algorithm focuses on seeking the suboptimal solutions that satisfy practical needs rather than the global optimality. In addition, the calculation space of the accurate model can be significantly reduced by the rough model for preliminary screening. Thus, OO presents great advantages in improving calculation efficiency.

C&CG has been widely applied to solve two-stage optimization problems, where the column generation step adds new decision variables of the second stage to the master problem, and the constraint generation step adds the cutting planes. As new variables are introduced in each iteration, the dimensionality of the solution space increases significantly [28].

3) Intelligent Optimization Algorithm

Unlike mathematical optimization algorithms based on model analysis, intelligent optimization algorithms seek the optimal solution directly through a multi-point random migration strategy. They include two core steps: an evaluation method and a migration strategy. The first evaluates the performance of the results generated in the current stage and determines the direction of the next stage. The second uses a fixed strategy to promote the algorithm convergence with an optimal direction. As the lesser requirement on model information and multi-point optimization, intelligent optimization algorithms offer better application and faster calculation.

Therefore, they are widely applied in solving SCUC. Researchers usually seek inspiration for migration strategies from nature or human social behavior. Depending on the different migration strategies, intelligent optimization algorithms include the genetic algorithm [31], particle swarm optimization [32], immune algorithm [33], and simulated annealing algorithm [34].

In general, uncertainty and instability exist in the solving process of intelligent optimization algorithms. The algorithms may also rapidly converge to suboptimal solutions restricted by migration strategies. To enhance calculation efficiency, some intelligent optimization algorithms have been used in a hybrid manner. These include the chaotic particle swarm optimization [35] and chaotic immune genetic [36] algorithms.

III. Modeling and Solving Methodologies of SCUC with Diverse Mathematical Properties

With the increasing complexity of power systems, standard SCUC model usually cannot satisfy practical engineering needs. Accordingly, many researchers have made efforts to improve the mathematical models in terms of the objective function, complicated constraints, or a combination of the two. Based on the mathematical models from particular applications, we categorize them into SCUC models with multiple objectives, with uncertainties, with additional variables, with complicated constraints, as well as with multiple areas and timescales.

A. SCUC Model with Multiple Objectives

With the transformation of energy infrastructures and increasing environmental concerns, the standard SCUC model with minimal economic cost as the optimization objective may not be sufficient. To this end, many efforts have been made to study SCUC with multiple objectives [37], [38].

1) Mathematical Formulation

The SCUC with multiple objectives can be commonly expressed as:

$$\begin{cases} \min\left(F_1(U_{\mathrm{G}i,t},P_{\mathrm{G}i,t}),\dots,F_m(U_{\mathrm{G}i,t},P_{\mathrm{G}i,t})\right) \\ \text{s.t.}\ \ g_a(U_{\mathrm{G}i,t},P_{\mathrm{G}i,t})\le 0 \quad a=1,2,\dots,A \\ \qquad h_b(U_{\mathrm{G}i,t},P_{\mathrm{G}i,t})=0 \quad b=1,2,\dots,B \end{cases} \tag{9}$$

where $F_m(U_{\mathrm{G}i,t},P_{\mathrm{G}i,t})$ is the m^{th} subobjective function; $g_a(U_{\mathrm{G}i,t},P_{\mathrm{G}i,t})\le 0$ is the a^{th} inequality constraint; $h_b(U_{\mathrm{G}i,t},P_{\mathrm{G}i,t})=0$ is the b^{th} equality constraint; and A and B are the numbers of inequality and equality constraints, respectively.

In addition to the economic cost, the SCUC with multi-objectives usually includes pollutant emission and social welfare. Specifically, the objective function for minimizing pollutant emission can be expressed as [38]:

$$\min F_{\mathrm{PE}}(U_{\mathrm{G}i,t},P_{\mathrm{G}i,t})=\min\sum_{v=1}^{N_v}\sum_{t=1}^{T}\sum_{i=1}^{N_{\mathrm{G}}}U_{\mathrm{G}i,t}(\alpha_{iv}+\beta_{iv}P_{\mathrm{G}i,t}+\gamma_{iv}P_{\mathrm{G}i,t}^2) \tag{10}$$

where $F_{\mathrm{PE}}(U_{\mathrm{G}i,t},P_{\mathrm{G}i,t})$ is the overall pollutant emission; N_v is the number of pollutant types, including CO_2, SO_2, and NO_2; and α_{iv}, β_{iv}, and γ_{iv} are the coefficients of pollutants.

The objective function of social welfare is [39]:

$$\max F_{\mathrm{S}}(U_{\mathrm{G}i,t},P_{\mathrm{G}i,t})=\max\sum_{t=1}^{T}\sum_{n=1}^{N_{\mathrm{b}}}\sum_{i=1}^{N_{\mathrm{G}}}\left(F_{\mathrm{U}}-F_{\mathrm{G}}(U_{\mathrm{G}i,t},P_{\mathrm{G}i,t})\right) \tag{11}$$

where $F_{\mathrm{S}}(U_{\mathrm{G}i,t},P_{\mathrm{G}i,t})$ is the social welfare function; F_{U} is the gross earnings of utility with the implemented electricity price; and N_{b} is the number of buses.

2) Solving Methodology

For SCUC with multiple objectives, the solution is to transform the multi-objective problem into a single-objective one. The corresponding methodologies include the weighted sum method, fuzzy optimization algorithm, and Pareto optimization.

The main idea of the weighted sum method is to endow individual objectives with weights, converting the multi-objective problem into a single-objective one. A primary issue is to determine the weights of individual objectives. According to the setting strategies, weighted sum method can be categorized into subjective [40], objective [41], and comprehensive [42] weighting methods.

The fuzzy optimization algorithm commonly normalizes each subobjective first and then establishes the corresponding membership function by using a real number between 0 and 1 to indicate the membership degree. It then sums the membership functions of individual subobjectives to convert the multi-objective problem to a single-objective one [43].

The common idea of the Pareto optimization is to guarantee the optimality for at least one objective without exacerbating others [37]. Specifically, it first seeks a Pareto optimal front that satisfies the dominating conditions and then obtains the optimal solution by sorting the non-dominating solution. Compared with other methods, it seeks to identify a set of optimal solutions rather than just one.

B. SCUC Model with Uncertainties

The large-scale penetration of intermittent renewable energy such as wind power and photovoltaic power produces numerous uncertainties in power systems [44]-[46]. Accordingly, SCUC with generation or load uncertainty has attracted widespread attention [8], [47]. These studies have investigated how to formulate the uncertainties precisely and improve the solving accuracy and robustness of SCUC.

1) Mathematical Formulation

When a single type of uncertainty is considered in an SCUC problem, the general model mainly includes stochastic and robust SCUC according to whether the probabilistic distribution of uncertain parameters is known.

If the probability distribution of uncertainty has been assumed, the SCUC with uncertainty can be formulated as a stochastic SCUC:

$$\begin{cases} \min E_{\Omega}\left(F_{\mathrm{G}}(U_{\mathrm{G}i,t},P_{\mathrm{G}i,t})\right) \\ \text{s.t.}\ \ g_l(U_{\mathrm{G}i,t},P_{\mathrm{G}i,t},\omega)\le 0 \quad l=1,2,\dots,L \\ \qquad h_m(U_{\mathrm{G}i,t},P_{\mathrm{G}i,t},\omega)=0 \quad m=1,2,\dots,M \end{cases} \tag{12}$$

where $E_{\Omega}(F_{\mathrm{G}}(U_{\mathrm{G}i,t},P_{\mathrm{G}i,t}))$ is the expected total operation cost of generation units under the assumed distribution Ω; ω is a random variable that obeys the distribution Ω;

$g_l(U_{\mathrm{G}i,t}, P_{\mathrm{G}i,t}, \omega) \leq 0$ is the l^{th} inequality constraint; $h_m(U_{\mathrm{G}i,t}, P_{\mathrm{G}i,t}, \omega) = 0$ is the m^{th} equality constraint; and L and M are the numbers of inequality and equality constraints, respectively.

If the probability distribution of uncertainty is not given, the SCUC model with uncertainties can be formulated as a robust SCUC model:

$$\begin{cases} \min \max\limits_{\mu \in [\mu^-, \mu^+]} F_{\mathrm{G}}(U_{\mathrm{G}i,t}, P_{\mathrm{G}i,t}) \\ \text{s.t. } g_x(U_{\mathrm{G}i,t}, P_{\mathrm{G}i,t}, \mu) \leq 0 \quad x = 1, 2, \ldots, X \\ \qquad h_y(U_{\mathrm{G}i,t}, P_{\mathrm{G}i,t}, \mu) = 0 \quad y = 1, 2, \ldots, Y \end{cases} \tag{13}$$

where $[\mu^-, \mu^+]$ is the uncertainty interval of parameter μ; $g_x(U_{\mathrm{G}i,t}, P_{\mathrm{G}i,t}, \mu) \leq 0$ is the x^{th} inequality constraint; $h_y(U_{\mathrm{G}i,t}, P_{\mathrm{G}i,t}, \mu) = 0$ is the y^{th} equality constraint; and X and Y are the numbers of inequality and equality constraints, respectively.

In general, these stochastic and robust SCUC models are regarded as two-stage optimization problems. In other words, the commitment solution is solved in the first stage with the aim of minimizing the operation cost of traditional units. In the second stage, the initial decisions are checked and generation dispatches are further determined to satisfy the uncertainty realizations in real time [15], [37].

Overall, these two-stage SCUC models cannot rigorously consider the situations in which uncertainty realizations are reviewed gradually and decisions are made at each time step along the scheduling horizon with all uncertainty realization information available up to the current time point. Accordingly, some researchers have proposed multi-stage optimization models that can make decisions dynamically by leveraging uncertainty information over time. The operation costs can be reduced by the more accurate interaction between decision-making and uncertainty in the multi-stage stochastic model. However, as the numbers of stages and decisions within each stage increase dramatically, the multi-stage models are harder to solve. The multi-stage model can be transformed into a two-stage problem to obtain the solution. Advanced decomposition algorithms have also been developed to accelerate the solving process [48], [49].

In addition, there are various uncertainty factors in practical power systems [37], [50]. Conventional stochastic SCUC models regard all types of uncertainties as independent factors, and they determine the worst-case scenarios using a simple linear weighted sum. However, because of the installation location of intermittent energy units, time sequence of unit dispatching, and other factors, certain correlations exist between different uncertainty factors. The worst-case scenarios of these uncertainty factors with probability correlations may not appear simultaneously [51]. Therefore, the conventional stochastic SCUC that ignores these correlations may obtain an overly conservative decision. To improve decision accuracy, the probability correlations of multiple uncertainties in SCUC should be considered. In [51], intervals were used to describe the uncertainties of wind power and photovoltaic power, and a function was then constructed to reflect the correlation between these two intervals. This method is simple and efficient but can only deal with correlations between two uncertainty factors. Thus, its applicability is limited. Reference [52] introduced Cholesky decomposition to transform uncertainties with probability correlations into independent ones and then employed robust optimization (RO) to seek the worst-case scenario and make SCUC decisions. By comparison, the number of uncertainties that can be handled by this method is not limited. It can also be combined with existing stochastic methods despite the increase in computational complexity.

2) Solving Methodology

Currently, the common solution methodologies to solve SCUC models with uncertainties include the scenario-based approach (SBA), chance-constrained optimization (CCO), RO, and information-gap decision theory (IGDT).

The main idea of the SBA is to generate a set of scenarios for simulating the possible conditions of uncertain factors. With the two-stage model, the sampling method is used to generate multiple independent scenarios based on the presumed probabilistic distribution functions. With the multi-stage model, a scenario tree with random paths is generated based on the dynamic stochastic process. However, many scenarios are needed to formulate the uncertainties (up to a point precisely), which complicates the solving process [8]. Therefore, scenario reduction and scenario aggregation techniques are employed to reduce the computational burden without significantly compromising the solution accuracy [53].

CCO is another technique for handling stochastic problems, where constraints can be violated by a specified small level of probability [54]. CCO converts certain stochastic equivalents into chance constraints that are satisfied at a certain probability. For instance, the overloaded probability of transmission line can be specified to be no larger than a assigned value. Then, the chance-constrained stochastic SCUC is converted into a deterministic SCUC that can be solved by the standard techniques [16].

RO seeks the optimal solution in a worst-case scenario in which the uncertain factors have the greatest impact on system economics and/or reliability and then seeks the corresponding optimal solution [28]. For SCUC problems with intermittent energy, this method minimizes the worst-case total cost over all possible realizations and converts the min-max model to an equivalent single-level model with the same optimal decisions. RO requires only fluctuation intervals of intermittent energy rather than an exact distribution of random parameters.

IGDT constructs the robust model hedging risk and the chance model pursuing risk benefits by estimating the impact of uncertainties on the specified goals. The obtained robust and chance results can provide decision guidance for system operators. It does not require probability distribution functions of uncertainties and is suitable for the cases with numerous uncertainties or lacking uncertainty information [55].

The aforementioned solution methodologies for SCUC models with uncertainties are compared in Table II. Considering the diverse limitations of the aforementioned solving methodologies, some researchers have addressed stochastic

SCUC problems by improving the existing uncertainty processing methods. The most effectively applied methods include distributionally robust optimization (DRO) [56] and stochastic RO [57]. DRO can incorporate some distribution information into the ambiguity sets for describing probability distributions of uncertainties. As the worst-case distribution becomes less conservative when more distributed information is included into the ambiguity set, it results in a lower expected cost than RO. Reference [58] proposed an extreme distribution generation method based on DRO to solve the SCUC problem much more efficiently. Stochastic RO takes advantage of both stochastic and RO approaches by achieving a low expected cost while ensuring system robustness. By introducing weights for the stochastic and robust parts in the objective function, system operators can adjust the weights based on their preferences [57].

TABLE II
COMPARISON OF SOLVING METHODOLOGIES FOR SCUC MODELS WITH UNCERTAINTIES

Methodology	Advantage	Disadvantage
SBA	Easy to solve for simple principle	May come with higher computational burden
CCO	Rigid constraints can be relaxed	Solutions only provide probabilistic guarantees
RO	Only fluctuation intervals of uncertainties are required	Could result in over-conservative solutions
IGDT	Requirement of uncertain information is not strict	Computational burden is relatively heavy

C. SCUC Model with Additional Variables

With the rapid development of smart grids, system operators can leverage flexible demand-side resources along with supply-side dispatching. In this regard, some researchers have attempted to plug demand response (DR) resources into the SCUC model as additional variables [59]. In this paper, the additional variables in the SCUC model include interruptible load (IL) and energy storage system (ESS).

1) SCUC Model with IL

As a potential demand-side response resource, ILs may reduce the system operation cost effectively by load shedding during peak or system fault periods. In addition, regarding the output fluctuation of intermittent resources, they could also be applied to balance system loads and to optimize the configuration of system resources. Therefore, the general objective function of SCUC model with IL is [59]:

$$\min\left(\sum_{t=1}^{T}\sum_{i=1}^{N_{\mathrm{G}}}F_{\mathrm{G}}(P_{\mathrm{G}i,t},U_{\mathrm{G}i,t})+\sum_{t=1}^{T}\sum_{j=1}^{N_{\mathrm{IL}}}F_{\mathrm{IL}j}(P_{\mathrm{IL}j,t},U_{\mathrm{IL}j,t})\right) \tag{14}$$

where $F_{\mathrm{IL}j}(P_{\mathrm{IL}j,t},U_{\mathrm{IL}j,t})$ is the compensation expense of IL j at time t; N_{IL} is the number of ILs; $P_{\mathrm{IL}j,t}$ is the demand level of ILs; and $U_{\mathrm{IL}j,t}$ is the state of IL j at time t, which equals 1 when the IL participates in scheduling, and 0 otherwise.

In addition to the prevailing constraints, the constraints such as the minimum interrupted time and maximum continuous invocation time [60] for IL should be considered.

2) SCUC Model with ESS

As an efficient resource to mitigate the fluctuation and uncertainty of intermittent energy, ESSs can be embedded into SCUC models. The operation cost of ESSs should be considered in the SCUC model, and the specific function is [61]:

$$\min\left[\sum_{t=1}^{T}\sum_{i=1}^{N_{\mathrm{G}}}F_{\mathrm{G}}(P_{\mathrm{G}i,t},U_{\mathrm{G}i,t})+\sum_{t=1}^{T}\sum_{n=1}^{N_{\mathrm{ESS}}}(C_{\mathrm{c}}P_{\mathrm{ESS}n,t}^{\mathrm{c}}-C_{\mathrm{d}}P_{\mathrm{ESS}n,t}^{\mathrm{d}})\right] \tag{15}$$

where N_{ESS} is the number of dispatchable ESSs; C_{c} and C_{d} are the coefficients of charging and discharging expenses, respectively; and $P_{\mathrm{ESS}n,t}^{\mathrm{c}}$ and $P_{\mathrm{ESS}n,t}^{\mathrm{d}}$ are the charging power and discharging power of ESS n at time t, respectively.

Similar to the ESS, an electric vehicle (EV) can operate as load under charging state and inject power to the system by vehicle-to-grid (V2G). As a result, some studies have embedded EVs into the SCUC model [62]. Correspondingly, the charging/discharging power limits, and charging/discharging time constraints of the ESS and EV should also be satisfied [63].

D. SCUC Model with Complicated Constraints

Researchers have also proposed SCUC models with complicated constraints. These mainly include SCUC models with transmission switching, with AC constraints, and with frequency constraints.

1) SCUC Model with Transmission Switching

The high penetration of wind power and EVs in day-ahead electricity markets usually causes disturbances to power systems. In addition, abnormal changes of power flows and line losses under extreme conditions may increase the system operation costs. Accordingly, transmission switching is typically adopted to maintain secure operations. Therefore, the constraints of transmission switching have been introduced into SCUC models [64], [65]. With this, the SCUC model can reconfigure the transmission network to control line power and optimize the system operation cost with reduced line losses.

The objective function of the SCUC model with transmission switching remains the same as that of the standard SCUC model. The additional constraints are formulated as [64]:

$$-z_{k,t}P_{k,\max}\leq P_{k,t}\leq z_{k,t}P_{k,\max} \tag{16}$$

where $P_{k,\max}$ is the active power limit of line k; $z_{k,t}$ is the state of line k at time t, which equals 0 when line k is switched off without active power; and $P_{k,t}$ is the active power of line k at time t.

To maintain system voltage stability, the voltage phase angle constraint before closing lines should also be considered as [65]:

$$-\Delta\delta_k^{\max}-J(z_{k,t-1}-z_{k,t}+1)\leq\delta_{k,t}\leq\Delta\delta_k^{\max}+J(z_{k,t-1}-z_{k,t}+1) \tag{17}$$

where $\delta_{k,t}$ is the phase angle of line k at time t; $\Delta\delta_k^{\max}$ is the maximum stable phase angle difference of line k; and J is a large positive constant.

2) SCUC Model with AC Constraints

As the DC power flow model can be solved directly without iterative calculation, it is always adopted to formulate the network security constraints in SCUC models [66]. This can effectively mitigate to a certain extent the solving difficulties while satisfying network security. However, the DC power flow model is based on the assumption that conventional generators have good regulation performance and hardly absorb reactive power from the grid. Moreover, some wind turbines may absorb reactive power from the grid when started up. Therefore, large-scale penetration of wind power will result in severe reactive power issues and invalidate the application premise of the DC power flow model. In this case, the DC power flow based SCUC model may result in the shortage of reactive power, the drop in grid voltage, and the over-limit of transmission power. In this regard, the AC power flow model is used to accurately describe the security constraints in the SCUC [67].

Because of strong non-linearity, the AC power flow model must be solved using an iterative calculation. The computational complexity also increases sharply with the increase in grid scale. The SCUC model itself is a non-convex problem, and the introduction of AC constraints in the SCUC model will considerably complicate the solution and may result in non-convergence [68]. Therefore, solving efficiency is the main bottleneck of this model. Existing studies can be divided into the following categories.

1) Introduce network loss factor or voltage index into the DC power flow model [69], [70]. In essence, this approach still utilizes a DC power flow based SCUC model and can consider fluctuations in system reactive power and voltage to a certain extent. Overall, it effectively balances the solving difficulty and decision accuracy, but its decision accuracy remains limited.

2) Introduce an AC power flow model but linearize it in the solving process [71], [72]. Compared with [69], the accuracy of this approach is further enhanced. Although the linearization method can simplify the solving process to some extent, this method requires many iterations and may therefore be challenging when applied to large-scale power systems.

3) Directly introduce AC power flow constraints into the SCUC model without simplifications [73], [74]. Reference [74] facilitated solving efficiency by utilizing an OO algorithm to ensure decision accuracy and realize a stable solution.

3) SCUC Model with Frequency Constraints

For power systems with high penetration of renewable energy sources, because of the low inertia and limited reserve capacity of renewable energy sources, the frequency is likely to exceed the limit when disturbances occur, leading to a frequency collapse of the entire system [75]. Accordingly, to improve the frequency stability of the power grid with large-scale renewable energy sources, some researchers have introduced system frequency constraints into SCUC decision-making.

The existing SCUC models that consider frequency constraints mainly focus on steady-state [76], [77] and dynamic frequency constraints [78], [79]. For the former, in terms of the maximum adjustable reserve capacity, the primary and secondary frequency control schemes were implemented to satisfy the steady-state frequency constraints [77]. For the latter, [79] analyzed the dynamic frequency response of renewable energy sources and took the frequency nadir against system disturbance as the evaluation index. The SCUC model with dynamic frequency constraints was then decomposed into the UC master problem and frequency over-limit detection subproblem for calculation.

E. SCUC Models with Multiple Areas and Timescales

Based on the dispersed locations of generation resources and the solving timescale, some researchers have also concentrated on the modeling and solutions of SCUC models with multiple areas and timescales.

1) SCUC Model with Multiple Areas

To tackle the problems of uneven energy distribution and power-supply/demand balance, inter-regional electricity interconnection has become a major choice for system operators [80]. However, it also poses new challenges to SCUC problems. Currently, the solution strategy for SCUC models with multiple areas can be categorized into centralized and distributed decision-making strategies.

1) Centralized decision-making strategy

With superior dispatching centers as participants, the centralized decision-making strategy is a vertical decision-making, multi-level coordination, and level-by-level refinement process. This strategy is implemented to break information blocking between multiple areas and to further realize optimal allocation of resources in a larger scope. Based on different operation modes of power systems, we categorize the centralized decision-making strategy into two types: regional-provincial grid coordination and transmission-distribution system coordination.

For the regional-provincial grid coordination, we take the coordinated dispatching of regional-provincial grid as an example, which can be described as a bi-level optimization problem. Its decision framework can be illustrated by Fig. 1.

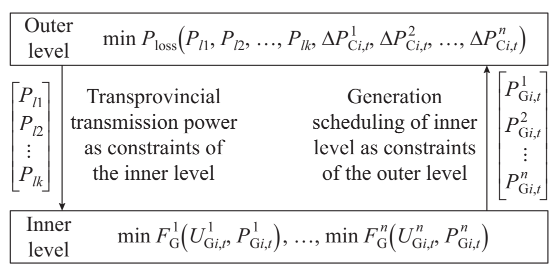

Fig. 1. Framework of regional-provincial grid coordination.

In Fig. 1, the inner level uses $U^n_{\text{G}i,t}$ and $P^n_{\text{G}i,t}$ as decision variables, where $U^n_{\text{G}i,t}$ and $P^n_{\text{G}i,t}$ are the on/off status and power of unit i at time t in the province n, respectively. Based on the power of transprovincial transmission line k P_{lk} determined at the outer level, each province takes its total generation cost $F^n_{\text{G}}(U^n_{\text{G}i,t}, P^n_{\text{G}i,t})$ as the optimal objective at the inner level. Based on the obtained generation schemes of units in all provinces, the outer level takes the power adjustment of coordinating unit i at time t in province n $\Delta P^n_{\text{C}i,t}$ and P_{lk} as the variables with the goal of reducing the losses of transprovincial transmission lines [81]. In addition, P_{loss} is the power loss of transprovincial transmission lines.

For the transmission-distribution system coordination, in market-oriented power systems, ISOs derive the day-ahead generation scheme through market clearing, where the distribution systems are usually directly simplified as loads. With the rapid deployment of distributed generators (DGs), the distribution network has changed from the fixed load form with unidirectional power flow to a new network pattern with bidirectional power flows between power supply and demand. In this context, as simplifying distribution systems as fixed load fails to reflect the internal operation features of distribution systems, the corresponding SCUC model may lead to problems such as over-voltage and transmission line congestion. Therefore, some researchers have embedded distribution systems with DGs into the SCUC problem, where a bi-level optimization-based transmission-distribution system coordination was established in [82]. In other words, generation units are taken as decision subjects by the ISO at the upper model, whereas the outputs of DGs are determined by distribution system operators (DSOs) at the lower model. This strategy does not require the ISO to directly observe the configuration details of distribution systems. However, it must be solved repeatedly and iteratively, significantly increasing the computational burden.

To cope with the issue of computational efficiency, in [82], the distribution system was modeled through a linear function to describe the relationship between the operation cost and injected power of the transmission network (where the day-ahead decision is then made by the ISO). However, this method assumes that the transmission system is connected with the distribution system through a single line. Accordingly, a transmission-distribution system model with multiple connections was established in [83], and the feasible region of bus voltages and line power flows of the distribution system was formulated based on the operation data. In turn, the generation schedule was determined based on the feasible region of the distribution system operation. Overall, the models in [83], [84] could reflect the internal operation information of the distribution systems and improve the calculation efficiency compared with previous bi-level models.

2) Decentralized decision-making strategy

With the expansion of the scale of interconnected power systems, for the centralized decision-making strategy, it is difficult to obtain global information of large-scale power systems without compromising the information privacy among interconnected areas. As a result, the generation resources of interconnected regional power grids cannot be optimally scheduled. Accordingly, studies have been conducted that utilized decentralized decision-making strategies to calculate SCUC decisions [85], [86].

Without the participation of superior dispatching centers, the decentralized decision-making strategy could maximize the overall economic benefit of interconnected power systems by adjusting the tie-line power flows through neighbors' information. The general framework of decentralized decision-making strategy is shown in Fig. 2.

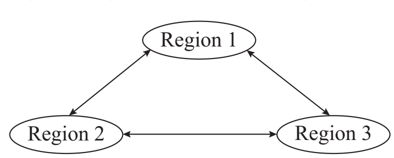

Fig. 2. Framework of decentralized decision-making strategy.

The common solutions of decentralized decision-making strategies include the alternating direction method of multipliers (ADMM) and synchronous alternating direction method of multipliers (SADMM). ADMM solves a convex optimization problem by decomposing it into several smaller subproblems that can be easily handled. It can guarantee the independent autonomy of each subsystem and information privacy simultaneously [87]. SADMM requires only the necessary information exchange among the areas during the iterative procedure without the participation of superior coordinators [88]. This can accelerate the iterative process and achieve distributed autonomy.

2) SCUC Model with Multiple Timescales

SCUC models use 1 hour as a basic time step size to calculate day-ahead schedules. However, with the increasing deployment of intermittent energy and flexible loads, some researchers have strategically adopted different time resolutions for the SCUC calculation. The main types include adaptive timescale, intraday multi-timescale, and long-term multi-timescale SCUC models.

1) Adaptive timescale SCUC model

The decision step size is generally fixed at 1 hour or 30 min in most day-ahead SCUC models. Therefore, these models may fail to accurately capture the random fluctuations of load or intermittent power at a finer time resolution. Therefore, shortening the time step size is a possible means of improving decision accuracy. However, this would increase the computational burden considerably. To this end, [89] proposed a UC model that adopted a finer time resolution in the first few hours of the scheduling horizon and a coarser time resolution for the rest. In addition, [90] adopted a hierarchical clustering algorithm to determine different time resolutions according to the fluctuation amplitude of load, and an adaptive-timescale model was established accordingly. In this model, the generation decision is made intensively when the load fluctuates sharply and less frequently when the load fluctuation is slight. However, the time resolution must be calculated prior to modeling. Furthermore, the modifications of temporal constraints are rather complicated, and certain constraints may have to be approximated or even excluded if they cannot be properly modified.

2) Intraday multi-timescale SCUC model

Currently, the forecasting accuracy of intermittent energy increases gradually with a finer time resolution. In addition, the response characteristics of loads vary under different timescales [91]. Consequently, some studies have investigated the intraday multi-timescale SCUC model [92], as shown in Fig. 3.

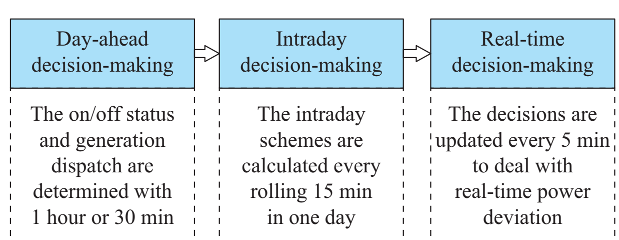

Fig. 3. Intraday multi-timescale SCUC model.

The intraday multi-timescale SCUC model first must make day-ahead decisions based on day-ahead load forecasting. Then, based on continual updated forecasting, it derives intraday and real-time schemes to allocate flexible load resources and intermittent energy reasonably.

3) Long-term multi-timescale SCUC model

Start-up processes of thermal generators, particularly those with large capacities, may require considerable time with multiple steps, thereby limiting the economics and operability of the day-ahead SCUC [93]. To guarantee that the units are operated at the best working point, it is necessary to optimize the UC scheme on a weekly or even monthly time span. In addition, when the load notably fluctuates over consecutive days such as holidays, in extreme weather, or according to other factors, day-ahead SCUC methods cannot allocate generation resources reasonably and economically on a long-term timescale. Accordingly, researchers have attempted to study long-term multi-timescale SCUC models [94], as shown in Fig. 4.

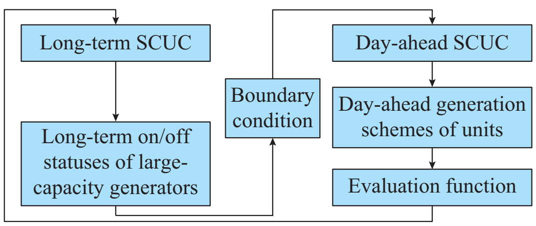

Fig. 4. Long-term multi-timescale SCUC model.

Compared with standard SCUC models, the optimization periods as well as the decision variables and constraints of long-term multi-timescale SCUC models are multiplied. In addition, the critical factors affecting the calculation efficiency are the coupling relationships among constraints such as the minimum start-up/shut-down time constraints. Regarding the processing of time coupled constraints, existing studies have utilized cutting plane methods to adjust the constraint-variable relationship of valid inequalities [95]. Then, the SCUC model can be constructed and solved.

IV. Research Trends of SCUC

A. *SCUC for Multi-energy Systems*

To handle the problems of environmental pollution and to promote the sustainable development of clean energy, integrated operations of multiple energy systems such as power, natural gas, and heating are currently being considered. Indeed, integrated energy systems (IESs) with multiple supplying resources, loads, and coupled energy forms have been established to improve energy efficiency [96]. In this context, it is critical to study the methods for optimizing the multi-energy generation schedule in an IES. Existing studies have mainly concentrated on SCUC for power-gas and heat-power systems.

1) SCUC for Power-gas Systems

Due to their fast response, low pollution, and high energy efficiency, gas turbines have had rapid growth in recent years as connecting hubs between power and natural gas systems. In addition, with the extensive application of power-to-gas (P2G) technology, energy begins to flow bidirectionally between power and natural gas systems. Taking gas turbines and P2G devices as coupling nodes, power and natural gas systems are tightly coupled into a highly dependent IES at both the physical and information levels. For this type of system, in addition to the standard SCUC model for power systems, the constraints of natural gas pipeline networks and related characteristics should be considered. Therefore, a new SCUC framework has been developed [97].

Some similarities exist between models of natural gas and power systems. The energy sources are limited by upper/lower boundaries, and the energy transmission is limited by the physical characteristics of lines or pipelines. However, the operation characteristics and energy transmission speeds of these models are different, which present new and significant challenges.

Existing studies have presented two main strategies in the SCUC modeling of power-gas systems: sequential optimization [98] and co-optimization [99], [100]. The main idea of sequential optimization is first to calculate the optimal generation schemes of units, including gas-fired units in the power systems. Then, the natural gas supplying scheme can be solved according to the fixed gas demands of gas-fired units. However, this strategy cannot guarantee global optimality. By contrast, power and natural gas systems are taken as a single unit into the co-optimization model, where the constraints of the natural gas system are embedded into the model with the aim of minimizing the total cost of the two energy systems. As the extreme operation conditions of two energy systems are considered, the operational security of the entire energy infrastructure can be ensured.

In terms of solution approaches, the main challenge is the non-linearity of the natural gas pipeline constraints. In this regard, the latest studies have mostly focused on refining the static models, despite their required simplification in the solving process. Specifically, non-linear constraints such as the flow equations of natural gas are usually linearized or relaxed. Under the assumption that pipeline gas flow direction is known, [101] tackled the complex constraints of natural gas networks using the second-order cone relaxation method. In [102], the pipeline gas flow direction was expressed by integer variables, the pipeline formula was relaxed to a mixed-integer second-order cone constraint, and the non-convex problem was solved by transforming it into a convex one.

However, several challenging issues remain that must be further studied. First, influenced by the price fluctuation and supply shortage of natural gas, natural gas systems face certain uncertainties. In addition, because of the different response speeds of power and natural gas systems, the influence mechanisms and response characteristics of their uncertainty factors are also different. How to construct an SCUC model that can comprehensively consider the uncertainties of these two systems must be resolved [103]. Second, in recent years, DR technology has been rapidly developed in power systems. In fact, with the large-scale installation of natural gas generating units, they represent a type of DR resource that can be dispatched in natural gas networks. Consequently, how to consider the DR resources from both electricity and natural gas sides simultaneously and how to formulate precisely their interactions deserve further exploration [104], [105].

2) SCUC for Heat-power Systems

The heat loss of conventional thermal power units in the generation process usually leads to lower energy utilization [106]. Accordingly, considering heating in the SCUC model can partly improve the overall energy efficiency.

Regarding the SCUC for heat-power systems, because of the slow dynamics of the heating, the heterogeneous time step in the SCUC modeling is a major issue that deserves attention. In this regard, the studies employing a variable timescale to establish the model have been conducted [107]. In addition, the heat flow model that considers temperature dynamics and coupling constraints is complicated. Accordingly, existing studies have usually converted non-convex quadratic equality constraints and coupling constraints into convex ones for the solution [108], [109]. Then, the solving methodology can be generally partitioned into two algorithms based on an iterative strategy and model hypothesis, respectively. The former commonly uses a fixed time delay of heat transfer in each iteration but is often limited by application scenarios [110], [111]. The latter assumes that the heat flow model is linear. This can improve the solving efficiency but derives only suboptimal solutions [112].

Limited by the "heat-led" mode, the outputs of combined heating and power units must be adjusted based on the dynamic changes of heating loads [113]. In addition, the heating inertia varies among different devices. To identify decision schemes for improving system flexibility and reducing operation costs, it is essential to explore the methods for relaxing the stringent constraints of the "heat-led" mode and co-optimizing heat-power systems under multiple heating inertia [114]. Furthermore, because of the non-uniform spatial distribution of heat pipe temperatures, it is necessary to precisely formulate heating balance constraints to ensure the reliability and comfort of energy consumers. In this regard, based on existing quasi-steady-state models, the partial differential dynamic model should be considered to formulate the spatial dynamics of heat transfer [115], [116]. In addition, to realize the cascade utilization of various forms of energy, regional IESs based on combined cooling, heating, and power have been deployed. Accordingly, a potential research direction is to describe the heat-to-electric ratio change in different operation modes in SCUC [117], [118]. Related studies have provided some guidance for system operators to make generation schemes based on the costs of various energy forms.

B. Trade-offs Between Decision Accuracy and Computational Efficiency of SCUC

As an optimization problem, the studies on SCUC have consistently encountered the trade-offs between decision accuracy and computational efficiency. The pursuit of more accurate SCUC decisions requires a more refined model [119]. However, model refinements often aggravate computational difficulties. Therefore, studying effective methods for refined SCUC models are achieved.

1) Model-tightening Technology

Compact modeling is recognized as an effective means of improving the solving efficiencies of SCUC [120]. Currently, inactive security constraint identification and decision variable reduction are two typical strategies.

By the Buckets effect, optimal SCUC decisions are commonly described by a small portion of constraints [121], [122]. In other words, many existing security constraints do not actually bind at the optimal solution; these are referred to as inactive security constraints. Therefore, if these constraints can be identified and eliminated before the solving process, the model can be tightened and the computational complexity can be greatly reduced. Reference [121] developed an analytical sufficient condition to identify inactive security constraints quickly without affecting the calculation accuracy. To prevent over-relaxation and to identify proper redundant constraints, [123] proposed an efficient feasibility-based bound tightening strategy. Overall, although many researchers have worked on this problem, the approaches for using as little system information as possible to identify redundant security constraints can be further studied.

The on/off statuses of certain units remain unchanged throughout a scheduling day. Thus, eliminating these integer variables can effectively compress the solution space and facilitate calculation efficiency [124]. In [27], deep learning was used to identify those units with fixed on/off statuses, and high solving efficiency was achieved. However, in the long term, the statuses of these units in actual systems could change dynamically, and the power generation configuration of various systems could be considerably different. Thus, the applicability of this method is limited. Accordingly, it is recommended to study efficient and universally applicable identification methods for the units with fixed on/off statuses.

2) Efficient Algorithms for SCUC

The efficient algorithm is an important theoretical guarantee for refining SCUC models. With the development of parallel computing technology, [125] attempted to solve sparse linear equations in an AC power flow model based on a heterogeneous computing framework. Distributed optimization has also been widely used as a computational framework, where the basic idea is to reduce the size of the optimization problem by decomposing the system into several zones. A set of auxiliary variables is introduced between a master problem and subproblems to coordinate the coupling variables and/or constraints. As no direct link exists between the subproblems, they must be solved in parallel using an improved solving methodology [126], [127].

Reference [128] decoupled the time coupling constraints of SCUC problems to realize parallel computing. However, because of the strong coupling in time and space, how to decouple the SCUC effectively while making it suitable for parallel computing without compromising solving accuracy remains an open question for further study. In addition, the rapid development of artificial intelligence offers a new opportunity to break through the computational bottleneck of SCUC. Based on existing artificial intelligence and big data technologies, proposing an efficient solution method for

SCUC is another research direction [129].

C. Application of Intellectual Technology in SCUC

Conventionally, the main idea behind an SCUC is first to establish the corresponding models according to engineering needs, introduce various mathematical methods to process or simplify them, and finally study the applicable solving algorithms. The entire modeling and solving processes are based on rigorous logical deductions and supported by mathematical theories. These are referred to as physical-model-driven SCUC (PMD-SCUC) [130]. However, PMD-SCUC has the following two drawbacks. ① PMD-SCUC decision-making may be less accurate for practical systems, where manual intervention to finalize its decisions is required. A PMD-SCUC is typically formulated as a mixed-integer linear or nonlinear programming problem. As a typical NP-hard problem, its complex sample data could lead to high computational burden [131]. To facilitate the calculation, many factors such as weather conditions and maintenance schedules [132] are often ignored in the modeling. This could compromise solving accuracy and require manual intervention to refine decision results in practice. ② PMD-SCUC decision-making methods lack generalizability. In general, a PMD-SCUC is constructed based on a particular situation. The modeling and computation of PMD-SCUC are complicated. Therefore, for new operation problems, the previous models and algorithms must be modified, leading to a long research cycle and the loss of generalizability.

In recent years, with the rapid development of artificial intelligence technologies and their wide applications in various fields of power systems [133], [134], data-driven SCUC (DD-SCUC) based on artificial intelligence have been studied. In practice, SCUC problems can be solved repeatedly over similar typical days. Indeed, over a relatively long period, power system conditions on different days can be regarded as unchanged [135]-[137]. In this regard, historical data could be of great value in guiding optimal SCUC decision-making in the subsequent days [135]. In addition, in practical operations, the ISO would amend the decision results of the PMD-SCUC by considering all factors and constraints not included in the original SCUC. Accordingly, the historical data of the ISO would include PMD-SCUC results and expert guidances. Given these insights, it would be helpful to explore a DD-SCUC based on historical data.

Some studies have conducted the applications of artificial intelligence in SCUC problems. Long short-term memory was previously introduced in [130], and a data-driven intelligent decision-making method for SCUC was proposed for the first time. A single mapping model between system loads and thermal power unit outputs was established by training massive historical data. The simulation results showed that the proposed data-driven method not only possessed superior applicability and computational efficiency, but also had the characteristics of self-learning and self-evolution. References [130] and [138] introduced an expanded sequence-to-sequence technology with multiple encoder-decoder configurations and full-connection expansion layers. They then constructed decision-making models that could tackle multiple input-output factors.

As one of the latest research directions in this field, the following problems remain in DD-SCUC that must be solved. ① Neural network training generally requires data with a fixed structure. By contrast, in the long-term development of power systems, the dynamic changes of generation resources and grid structures lead to non-stationary data samples. To solve this issue, [138] constructed a larger neural network architecture to withhold a margin for system development. However, this leads to a considerable waste of computing resources. Therefore, developing an adaptive deep learning model that can deal with the dynamic changes of a sample configuration represents a valuable research direction. ② In supervised learning methods, the solving accuracy of existing deep learning models is highly dependent on the quality of training samples. Although the actual scheduling data are manually adjusted based on PMD-SCUC results, as an optimization problem, global optimization is not easily guaranteed. Therefore, it is still required to finalize the results of DD-SCUC by mathematical methods [130]. Accordingly, unsupervised learning technologies could be introduced to mitigate the limitations of existing supervised learning in terms of sample accuracy [139]-[142].

V. Conclusion

With the continual changes in energy structures and the rapid development of emerging technologies, SCUC problems present new challenges and opportunities. This study reviewed the major research findings of the studies on SCUC and discussed future research trends. The basic mathematical model of the standard SCUC was first summarized, and the characteristics and application scopes of common solutions were then presented. SCUC models from different research focuses were next classified in terms of their mathematical properties. These SCUC models included those with multi-objectives, uncertainties, additional variables, complicated constraints, and those designed for multiple areas and multiple timescales. The corresponding solution ideas were then generalized. Finally, the research trends of SCUC were prospected based on a survey of the state-of-the-art and latest research achievements. The trends mainly include the challenges posed to SCUC by the interconnection of power and other energy systems, the new contributions toward trade-off between decision accuracy and computational efficiency throughout SCUC research, and the potential opportunities for SCUC presented by the rapid development of artificial intelligence.

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