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Revisit power system dispatch: Concepts, models, and solutions

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ABSTRACT

Power system dispatch is a general concept with a wide range of applications. It is a special category of optimization problems that determine the operation pattern of the power system, resulting in a huge influence on the power system security, efficiency, and economics. In this paper, the power system dispatch problem is revisited from the basis. This paper provides a categorization of the dispatch problem, especially with an emphasis on industrial applications. Then, this paper presents a detailed review of the dispatch models. The common formulations of the dispatch problem are provided. Finally, this paper discusses the solutions of the dispatch problem and lists the major challenges.

KEYWORDS

Power system dispatch, optimal power flow, unit commitment, energy storage.

Electric power is one of the most important energy sources for human. As shown in Figure 1, in China, the proportion of the energy that is consumed via electric power is continuously increasing recently and it is estimated that the proportion will reach 31.2% in 2025. Meanwhile, because of the lack of cost-efficient large-scale storage, electric power is a specific form of energy that requires the instant balance between production and consumption[1]. For a single user of electric power, the consumption behavior is highly uncertain. However, the aggregation of enormous users will exhibit a predictable consumption pattern, making it possible for the power production to trace the consumption[2]. To achieve this, every country in the world has built meshed power transmission network to connect a variety of power generations and consumers. Distribution network extends the power in the transmission network from a substation for the delivery to end users.

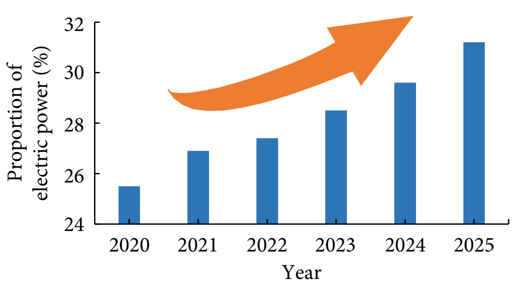

Fig. 1 Proportion trend of the energy that is consumed via electric power.

In a provincial power transmission network in China, the power consumptions range from 1.3×10^3 MW to 8.94×10^4 MW. It is a difficult job worldwide to provide a desired scheduling of power generations to instantly meet the power demand. By saying "desired", we refer to the target of power system operation, commonly including lower costs, lower carbon emission, lower network losses, higher security redundancy, and so on[3,4]. Meanwhile, the delivery of power generations to the consumers needs to consider various constraints, including the power balance constraints, transmission security constraints, generation operation constraints, and so on[5,6]. With the above essentials in mind, system operators can finally make the final decision of the scheduling for each power producer and consumer.

It can be observed that the power balance procedure described above is a classic decision-making problem: decision variables are the power generation, demand consumption, etc.; constraints are the requirements of power system secure operation; objective is the efficient and economic power delivery. Such a decision-making problem can be generally termed as power system dispatch. It is a very traditional problem in power system, which can be traced back to the 1960s for the first proposal of optimal power flow[7]. During the past decades, we have observed a great variety of sub-problems originating from the basic dispatch concept, including reactive dispatch problem[8,9], unit commitment problem[10,11], economic dispatch problem[12,13], security-constrained economic dispatch problem[14,15], market clearing problem[16,17], storage optimization problem[18,19], stochastic optimization problem[20–22], etc. (see Figure 2). Each of the sub-category emphasizes on a certain perspective, and results in different research focuses.

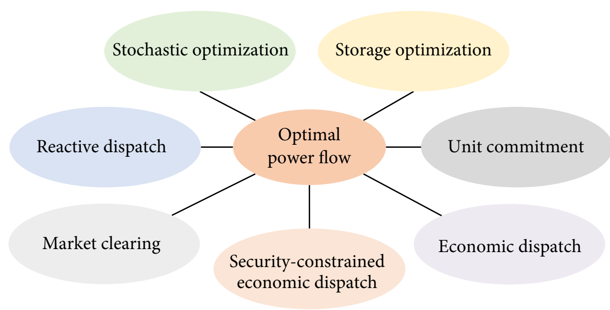

Fig. 2 Extension of optimal power flow problem.

Meanwhile, with the development of academic methodologies and computation tools, the power industries are also continuously

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engaging more advanced dispatch tools[23,24]. The basic trend is to replace the human-decision process in a various application scenarios of power system dispatch with optimization software. The power industries have witnessed a great cost-saving effect by doing so[25]. More powerful dispatch tools that can really solve the practical problem always attracts the attention from industries. However, we observe that there is still a clear gap between the ongoing academic research and the industrial requirements[26,27]. There are actually very few studies that exactly respond to the practical industrial requirement and provide a promising computational performance for practical applications.

The whole family of power system dispatch problem still remains one of the hottest topics in power system, but there lacks a full review of the dispatch problem, especially linking to the practical industrial requirements. To fill this gap, this paper provides a comprehensive revisit to the dispatch problem. We categorize the current dispatch studies and focus on those that are closely related to practical requirements. We present a map of the basic dispatch models and their properties. The future trends of power system dispatch development and its challenges are discussed. We are not aiming to provide a detailed review that covers every type of related research, which is nearly impossible. By contrary, we would like to grasp the key feature of the representative dispatch problems and provide our understandings.

1 General categorization of power system dispatch

Basically, power system dispatch determines the optimal operation pattern of power grid to meet the power demand, which is a rather broad concept. Take the situation in China as an example, the power system dispatch framework considering the market environment is shown in Figure 3, which is a common trend of power system dispatch. In general, the energy and demand-side resources need to submit their bids (including the prices and operation limits), based on which the power system dispatch model will be established. After that, the dispatch model will be solved to obtain the optimal operation pattern for energy and demand-side resources.

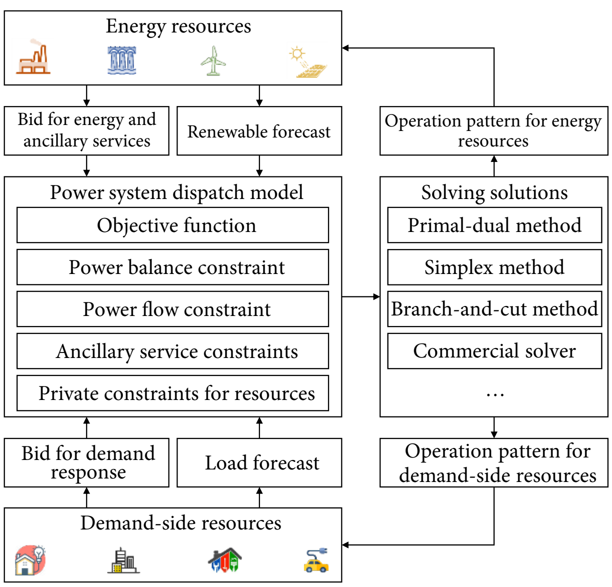

Fig. 3 Framework of power system dispatch.

Here, we provide a general categorization of power system dispatch problem from both the academic research and industrial application point of view. Specially, we focus on the short-term power system dispatch problem, namely the day-ahead[28,29] and real-time dispatch[30,31].

1.1 Categorization of dispatch problem in the field of academic research

Optimal power flow (OPF) problem

Power system dispatch is a special case of the operations research problem under the requirement of power system operation. The typical objective function is the minimization of operation costs or the maximization of social welfare. These two objectives are equivalent when the demand side response is not considered. The equality constraints that reflect the physical nature of the power system include the power balance constraint and power flow equations that describe the relationship between power injections, power flow, voltage angles, and voltage magnitudes. Inequality constraints include power flow limits, generation output limits, and voltage angle/magnitude limits. Power flow equations are derived based on the Kirchhoff's laws, which are nonlinear equations. Other constraints are basically linear. The above objective function together with the constraints forms a basic power system dispatch problem, namely the OPF problem. Apparently, the OPF problem is a nonlinear programming (NLP) problem. It can be traced back to the 1960s since Carpenter first proposed this concept[32].

Direct current optimal power flow (DC OPF) problem

The algorithm for the NLP problems cannot guarantee convergence and occasionally faces computational robustness failure in large-scale power systems. Hence, engineers propose to transform the nonlinear OPF model into a linear one. The key is the proper linearization of the nonlinear power flow equations[33,34]. Engineers have observed the quasi-linear relationship between the active power and voltage angle, especially in high-voltage power network. Also, the voltage magnitude is close to 1.0 p.u. and the reactive power flow on branches is much smaller than the active power flow. Hence, power engineers propose to use a linear power flow equation that describes the relationship between active power and voltage angle and ignores the reactive power and voltage magnitude. This equation is called the DC power flow equation[35]. By replacing the nonlinear power flow equation in OPF with the DC power flow equation, we can obtain a linear programming (LP) model called the DC OPF. Taking advantage of the LP formulation, it has desired computational performance and is widely accepted by power industries around the world.

Security-constraint economic dispatch (SCED) problem

The OPF problem is normally considered as a single-period dispatch problem, which means that it only considers a certain snapshot. Actually, the power balance is a time-continuous task. The power balance of different time steps is tightly coupled because the adjustment of generations between time steps is coupled by the ramping capability[36]. Hence, the SCED problem considers a multi-period OPF coupled by the ramping constraints of generators. Also, the SCED problem considers a special transmission constraint, namely the N-1 requirement[37]. It means that the power flow limits should still be satisfied when a branch is broken down. This is a common procedure in power system operation to provide redundancy. In this way, the number of power flow limits explodes because we have to consider the limits in each contingency scenario. This modeling complexity leads to a larger computational burden. Also, it should be noted that the SCED model also has two major modeling methods, mainly distinguished by the branch flow modeling in contingency. If the generator is allowed to adjust under contingency, it is called the corrective control modeling; otherwise, it is called the preventive control modeling[38].

Security constraint unit commitment (SCUC) problem

For either OPF problem or SCED problem, it usually only considers continuous decision variables, mainly include the generator outputs. In fact, the practical power system operation needs to make discrete decisions, such as the on/off status of generators[39]. For thermal generators, there is normally a minimum output level[40]. Hence, the operation range is discontinuous, i.e., either 0 or [minimum output, maximum output]. Hence, integer variables are required in the dispatch problem to describe this feature. Then, the optimization problem becomes a mixed integer optimization problem. In modern power systems, the SCUC problem is rather challenging to solve. For a common SCUC problem in a Chinese province, we can have over 100,000 integer variables and over 450, 000 constraints. The time limit is only less than an hour.

Stochastic dispatch problem

In power systems around the world, it is a general trend to integrate a high percentage of renewables. As a result, there are increasing fluctuations in power systems[41]. The above dispatch problems are decision making problems with certain operation boundaries. When considering uncertainties, the boundaries become stochastic. The dispatch decisions need to ensure the secure and economic operation of power systems not only under normal operation conditions, but also under uncertainties. The common techniques include the robust optimization[42], chance-constrained optimization[43], multi-scenario optimization[44], etc.

Above dispatch problems are among the mostly used basic forms. With the evolving of power system technology, there are a great deal of dispatch problems with new elements, such as those considering energy storage[45], frequency security[46], and so on. However, all of these varieties come from the basic form. We will give a basic modeling framework of the dispatch problem in Section 2, aiming to cover the key features of these problems.

1.2 Practical application examples of dispatch problem in power industry

In power industries, the dispatch problem has a wide range of applications. Here we make two examples in terms of the non-market environment and the market environment. Especially, the situations in China are provided as examples.

Dispatch in non-market environment

The power industry is naturally monopolistically and highly regulated. Before involving electricity market reform, the power system operation manner is determined by the system operators without involving the competition among generators or users. The generators need to strictly follow the dispatch decisions according to the regulation rules. In China, it experiences several stages. Traditionally, the power system has a similar operation pattern from day-to-day. Not many changes in the dispatch are required to keep the power balance. Hence, experienced system operators can provide the scheduling of the power system without the need for help from dispatch optimization[47]. As the power system becomes larger and environmental issues arise, it becomes more challenging to balance the power, and also, multiple operation objectives arise, such as the minimization of coal consumption. In this case, it becomes harder for system operators to manually determine the dispatch decision. Power industries turn to the help of decision software to automatically determine the most desired operation condition.

The short-term dispatch problem is normally divided into two stages: the day-ahead stage and the intra-day stage (also called the real-time stage). In the day-ahead stage, a SCUC problem is solved to determine the operation status of generators, including the commitment status and power outputs. There are a lot of practical operation constraints that need to consider, including but not limited to generator operation constraints, power plant operation constraints, hydro vibration constraints, power flow constraints on transmission lines and a certain groups of transmission lines that reflect the transient security requirements, and power flow security in contingencies. Noted that it is nearly impossible to find a feasible solution that meets all the requirements. Hence, it is a common practice to add relaxations for the constraints and set different levels of penalty factors as a punishment for the constraint violations[48,49]. Because of the large value of punishment, the coefficients matrices have a wide range of values, causing practically numerical issues and challenges[50]. Also, although the number of constraints is large, the percentage of those that active for the optimal solution is relatively small[51]. Hence, many provinces will first solve an unconstrained SCUC model and iteratively add violated constraints. This process will be limited by the total number of iteration times. For the power industries in China, we normally consider a 15-minute dispatch interval in the day-ahead SCUC dispatch.

Then, with the determined day-ahead dispatch, the intra-day dispatch adjusts the generator outputs for updated load forecast or other changes of operation conditions. The optimization problem becomes easier because the integer variables representing generator outputs are fixed and an LP optimization of SCED is solved. Normally, in additional to the constraints in day-ahead dispatch, the ideal point approaching constraints is added in the SCED model to find the solution nearest to the day-ahead solution. Depending on the operation requirements, provincial power systems in China commonly roll the dispatch window of one hour or two hours with a 15-miunate resolution in the intra-day dispatch.

The dispatch optimization releases the work load of system operators and helps to improve the operation efficiency of the power grid. However, manual adjustment is still required because of the following reasons. Firstly, the dispatch problem is built based on the simplified DC power flow equations[52]. Changes are required to fill the gap toward the practical operation systems. Secondly, the boundary of optimization sometimes cannot fully reflect the true operation limits of the power system. For example, the power system operation needs to consider transient security[53]. Such requirements are reflected in the proxy constraints of the transmission limits on a certain group of constraints, but sure has accuracy loss. Thirdly, the optimization may face computational challenge, including infeasibility, suboptimality, and so on[54]. Human interference is required on this circumstance.

Dispatch in market environment

With the electricity market reform, now the power systems in many countries are operating under a market environment. In electricity markets, the market participants, including generators and demands, need to submit their bids, including the production costs /consumption payment and operation limits. A dispatch model will be formulated based on the submitted information and be solved to determine the dispatch solution. Such a process is called market clearing.

The market clearing process can also be separated into the day-ahead stage and the intra-day stage. The basic procedure is very similar to that in the non-market environment. One major difference is that in the day-ahead stage, a SCED model will be solved with the fixed integer variables obtained from SCUC to determine the electricity prices[55,56]. Although the dispatch models are similar, the market environment poses a much higher requirement for the dispatch solutions. The first reason is that the market is organized following a strict rule of the time for market clearing. Hence, the dispatch model needs to be solved to the preset convergence gap within a certain time[57]. In modern power systems, this requirement still cannot be fully realized in all situations. The second reason is that under the market environment, the market clearing results, i.e., the dispatch solution, need to be strictly obeyed. If the system operators manually adjust the dispatch solution due to operational concerns, it will bring economic loss and affect the total social welfare[58].

From the above discussions on the example of power system dispatch in practical systems, it can be seen that the proper formulation and solving of the dispatch problem is important for the economic and secure operation of the power systems. The following content will further introduce the basic mathematical models of the dispatch problem and their solutions.

2 Model of power system dispatch

Although various types of power system dispatch models have been proposed with respective purposes and concerns, they have some general features. This section first presents the basic formulation of a power system dispatch problem in literature, concluding the common elements that are usually considered in a power system dispatch model. Then, this section discusses the varieties of power system dispatch models from several aspects. Finally, we give a multi-dimensional categorization of power system dispatch models.

2.1 Basic formulation of power system dispatch

The power system dispatch problem is usually formulated as optimization-based models, with respective variables, objective functions, and constraints. Generally, power system dispatch models can be abstracted as the following form:

$$\begin{aligned} &\min/\max\ c(\boldsymbol{x}) \\ &\text{s.t. } f(\boldsymbol{x}) \leqslant 0 \\ &g(\boldsymbol{x}) = 0 \\ &\boldsymbol{x} \in \Omega \end{aligned}$$

Here, $\boldsymbol{x}$ denotes the variables of the optimization problem. $f(\boldsymbol{x})$ and $g(\boldsymbol{x})$ are the public or system-wise constraints. Ω denotes the feasible operation region of $\boldsymbol{x}$, which is determined by the characteristics of dispatch objects. Ω can also be referred as private or object-wise constraints.

Therefore, a power system dispatch model is to minimize or maximize a given objective function with a set of public and private constraints. The following parts discuss the variables, objective functions and constraints and give examples.

2.1.1 Variable

In an optimization-based power system dispatch model, variables can be usually categorized as decision variables and state variables. Decision variables correspond to the actions of the power system dispatch, while state variables represent the states of dispatch objects or power systems. For example, for a conventional generator in power systems, the active power generation and reactive power generation are decision variables, while the on/off status are object-level state variables. At the system-level, state variable examples are nodal voltage amplitude, nodal phase angle, active/reactive power on transmission lines, etc.

Moreover, the variables can be either continuous or discrete. Again, taking a conventional generator in power systems as an example, the active power generation and reactive power generation are continuous variables, while the on/off status are usually expressed as binary variables. Once discrete variables are introduced into the studied optimization model, it would become a mixed integer programming (MIP), where solving difficulty rises significantly.

2.1.2 Objective function

The objective function of a power system dispatch model is designed towards a given dispatch target. In general, the dispatch targets of power system dispatch include minimizing the operation cost[59], maximizing the social profits[60], maximizing the generation company profits[61], minimizing the transmission loss[62], environmental concerns[63], etc. Moreover, the dispatch targets can also a combination of several single goals[64].

Taking the operation cost minimization as an example, which is usually applied to economic dispatch problems, the objective function represents the sum of operation cost of all generators of the given periods[65].

$$Obj = \sum_{t=1}^{T}\sum_{g=1}^{G} C_g(p_{g,t})$$

In the objective function, there are T decision periods and G generators. $P_{g,t}$ is the active power generated by generator g in period t.$C_g(p_{g,t})$ is the power generation cost of generator g in period t. Different types of generation cost functions have been studied. However, the most typical generation cost function for conventional thermal generators is quadratic[66].

$$C_g(p_{g,t}) = a_g + b_g \cdot p_{g,t} + c_g \cdot {p_{g,t}}^2$$

where a_g, b_g, and c_g are coefficients determined by the generator characteristics. This function means that when a conventional thermal generator is scheduled, the fuel consumption cost is quadratic to the active power it generates. Moreover, some researches use piece-wise linear method to approximate the cost function so that the model can be easier to be solved[67]. Based on this quadratic function, some literature considers the valve point loading effects[68–70]. As a result, the generation cost function becomes non-smooth.

$$C_g(p_{g,t}) = a_g + b_g \cdot p_{g,t} + c_g \cdot {p_{g,t}}^2 + |e_g \sin(f_g(p_{g,\min} - p_g))|$$

where e_g and f_g are coefficients determined by the generator charact–eristics.

Other types of generation cost functions such as linear ones[71] are also applied to the power system dispatch problem.

Further, for the operation cost minimization, some other factors can be considered besides the operation cost of generators. When the turn-on/turn-off operation of generators is considered, the corresponding cost should be incorporated[72]; if the load shedding is considered, then the loss of load cost ought to be added to the cost[73]; if the renewable energy curtailment is considered, then the curtailment penalty can be modeled[74]; if the carbon emission is considered, the corresponding emission cost can be added[3]; and so on.

2.1.3 Constraint

As discussed before, the constraints of power system dispatch models can be categorized into public and private constraints. Public constraints describe the physical laws and operation requirements of the power system; while private constraints describe the operation characteristics of the objects that are dispatched.

Public constraint

The most important public constraints are the power flow equations, which are the basis of power system steady-state analysis and optimization. Generally, the original power flow equations (known as alternating current (AC) power flow) are

$$P_i = \sum_{j=1}^{N} G_{ij} V_i V_j \cos\theta_{ij} + \sum_{j=1}^{N} B_{ij} V_i V_j \sin\theta_{ij}$$
$$Q_i = -\sum_{j=1}^{N} B_{ij} V_i V_j \cos\theta_{ij} + \sum_{j=1}^{N} G_{ij} V_i V_j \sin\theta_{ij}$$

where P_i and Q_i are the active and reactive power injection of node i, assuming that there are N nodes in the studied system; V_i is the voltage amplitude of node i; θ_{ij} is the voltage angle difference between node $i$and node j; G_{ij} and B_{ij} are components of the conductance matrix and the susceptance matrix, respectively. Moreover, in order to constraint the active and reactive power of transmission lines, the branch flows can be calculated as follows[75]:

$$P_{ij} = g_{ij}(V_i^2 - V_i V_j \cos\theta_{ij}) - b_{ij} V_i V_j \sin\theta_{ij}$$
$$Q_{ij} = -b_{ij}(V_i^2 - V_i V_j \cos\theta_{ij}) - g_{ij} V_i V_j \sin\theta_{ij}$$

where P_{ij} and Q_{ij} are the active power and reactive power with line ij (from node i's side); g_{ij} and b_{ij} are the conductance and the susceptance of line ij. Then, the nodal balance equations can be established according to the Kirchhoff's current law.

$$\sum_{g\in G_i} p_g - P_i^{\mathrm{d}} = \sum_{ij\in K_i} P_{ij} + g_{ii} v_i^2$$
$$\sum_{g\in G_i} q_g - Q_i^{\mathrm{d}} = \sum_{ij\in K_i} Q_{ij} + (-b_{ii}) v_i^2$$

where p_g and q_g are the active and reactive power generation of generator g; G_i is the generator set that connected to node i; K_i is the line set that connected to node i; P_i^{d} and Q_i^{d} are the load demand of node i. Moreover, some power system dispatch models allow energy not served and load shedding, so the corresponding terms are added to the nodal balance equations[74,76,77].

Then, the transmission power on every transmission line should not exceed the rated power.

$$(P_{ij})^2 + (Q_{ij})^2 \leqslant (f_{ij}^{\max})^2$$

However, the nonlinearity of power flow equations makes the dispatch model hard to solve. Various types of methods are proposed. The most well-known one is the DC power flow. By a sequence of assumptions and approximations, the active power and voltage angle difference of line ij is expressed as follows[66]:

$$P_{ij} = \frac{\theta_{ij}}{x_{ij}}$$

where x_{ij} is the reactance of line ij. In the DC power flow model, reactive power and transmission loss are ignored, and the voltage amplitude of each node is assumed to be 1. This approximated power flow model is reasonably accurate for power transmission systems[35], and has been widely used in power system dispatch models. Since the reactive power is ignored, the power transmission limits become

$$-P_{ij}^{\max} \leqslant P_{ij} \leqslant P_{ij}^{\max}$$

Although the DC power flow performs well in a lot of models, its drawbacks are obvious. When the reactive power, transmission loss, and voltage amplitude need to be considered, the DC power flow does not suit the requirement. Many researches focus on how to build power flow models considering the above issues while maintaining accuracy and solvability.

- Convex relaxation methods: semidefinite programming (SDP) relaxation[78,79], quadratic programming (QP) relaxation[80], second-order cone programming (SOCP) relaxation[81–83], etc.
- Linearization methods: some literature starts from the original power flow equation, using approximations, hypothesizes, variable substitutions, and other skills to obtain a linearized power flow model[33,34,84,85]. Some literature studies data-driven methods, using regression techniques to directly obtain the mappings between P, Q and V, θ[86–88].

Also, the power balance requirement should be considered. A typical way to constrain the active power balance in power system dispatch models is shown as follows[59]:

$$\sum_{g=1}^{G} p_g = \sum_{i=1}^{N} P_i^{\mathrm{d}} + P_{\mathrm{loss}}$$

where P_{loss} denotes the active power transmission loss within the power systems. The amount of loss can be estimated[66] and allocated to different nodes[89]. In some old power system dispatch models, the power flow equations are not included because of computational limitations[70,90,91]. However, with the development of computer hardware and optimization algorithms, modern power system dispatch models take the power flow equations into consideration to make sure the dispatch results do not violate the power transmission limits.

Besides the power flow, there are other public constraints that a power system dispatch model usually considers. Spinning reserve plays an important role in the power system dispatch decision making to deal with the future uncertainties in real-time operation. Generally, the spinning reserve constraints can be formulated as follows:

$$\sum_{g=1}^{G} r_{g,t} \geqslant R_t$$

where $r_{g,t}$ is the spinning reserve provided by generator g in period t, and R_t is the system reserve requirement in period t. The amount of spinning reserve the power system needed has also been studied[65,92,93], which is related to the load demand level, renewable energy outputs, capacity of the scheduled generators, etc. Also, some literature models the up and down spinning reserve separately in high-renewable-penetrated power systems[74].

$$\sum_{g=1}^{G} r_{g,t}^{\mathrm{up}} \geqslant R_t^{\mathrm{up}}$$
$$\sum_{g=1}^{G} r_{g,t}^{\mathrm{down}} \geqslant R_t^{\mathrm{down}}$$

where $r_{g,t}^{\mathrm{up}}$ and $r_{g,t}^{\mathrm{down}}$ are the up and down reserve provided by generator g in period t; R_t^{up} and R_t^{down} are the system up and down reserve requirement, respectively.

If the nodal voltage is considered in the power flow, then the corresponding limits are needed:

$$V_i^{\min} \leqslant V_{i,t} \leqslant V_i^{\max}$$
$$\theta_{ij}^{\min} \leqslant \theta_{ij,t} \leqslant \theta_{ij}^{\max}$$

where $V_{i,t}$ is the voltage amplitude of node i in period t; $\theta_{ij,t}$ is the voltage angle difference between node i and node j in period t.

Private constraint

Private constraints are used to model the operation characteristics and operation limits of dispatch objects. In power system dispatch, the basic dispatch objects are different types of generators. Here conventional thermal generators, renewable power plants, and energy storage are discussed.

For conventional thermal generators, the power outputs and on/off statuses are the main concerns. The turn-on and turn-off actions and the corresponding minimum up and minimum down duration requirements have several ways to express. Here the form used in Ref. [74] is given.

$$x_{g,t-1} - x_{g,t} + u_{g,t} \geqslant 0$$
$$x_{g,t} - x_{g,t-1} + v_{g,t} \geqslant 0$$

$$(x_{g,t} - x_{g,t-1}) \cdot t_g^{\mathrm{on}} + \sum_{\tau=t-t_g^{\mathrm{on}}-1}^{t-1} x_{g,\tau} \geqslant 0$$

$$(x_{g,t-1} - x_{g,t}) \cdot t_g^{\mathrm{off}} + \sum_{\tau=t-t_g^{\mathrm{off}}-1}^{t-1} (1 - x_{g,\tau}) \geqslant 0$$

where $x_{g,t}$ represents the status of generator g in period t; $u_{g,t}$ represents the turn-on action of generator g in period t; $v_{g,t}$ represents the turn-off action of generator g in period t; t_g^{on} and t_g^{off} are the minimum up and minimum down duration, respectively. Here, $x_{g,t}$, $u_{g,t}$, $v_{g,t}$ are all binary variables. When dispatching the active power of generators, the power limits are formed as follows:

$$p_{g,t} + r_{g,t} \leqslant p_g^{\max} \cdot x_{g,t}$$

$$p_{g,t} - r_{g,t} \geqslant p_g^{\min} \cdot x_{g,t}$$

$$0 \leqslant r_{g,t} \leqslant r_g^{\max}$$

where $p_g^{\max}$ and $p_g^{\min}$ are the maximum and minimum active power output of generator g; $r_g^{\max}$ is the maximum reserve of generator g. Moreover, in a multi-period dispatch, the ramp rate constraints should be considered between two adjacent periods.

$$p_{g,t} - p_{g,t-1} + x_{g,t} \cdot (p_g^{\max} - p_g^{\min}) + x_{g,t-1} \cdot (p_g^{\min} - \Delta p_g^{\mathrm{up}}) \leqslant p_g^{\max}$$

$$p_{g,t-1} - p_{g,t} + x_{g,t-1} \cdot (p_g^{\max} - p_g^{\min}) + x_{g,t} \cdot (p_g^{\min} - \Delta p_g^{\mathrm{down}}) \leqslant p_g^{\max}$$

where Δp_g^{up} and $\Delta p_g^{\mathrm{down}}$ are the ramp-up and ramp-down limits of generator g. Because the on/off statuses are considered, the constraints are complicated. If the on/off statuses are not considered in the dispatch, the power and ramp limits become intuitive.

$$p_{g,t} + r_{g,t} \leqslant p_g^{\max}$$

$$p_{g,t} - r_{g,t} \geqslant p_g^{\min}$$

$$-\Delta p_g^{\mathrm{down}} \leqslant p_{g,t} - p_{g,t-1} \leqslant \Delta p_g^{\mathrm{up}}$$

For renewable power plants, when dispatching their active power outputs, the constraints are usually set as follows:

$$0 \leqslant p_{r,t} \leqslant p_{r,t}^{\max}$$

where $p_{r,t}$ is the active power output of renewable power plant r in period t; $p_{r,t}^{\max}$ is the forecast output of renewable power plant r in period t, which are estimated at the dispatch decision making moment.

For energy storage, although there are different kinds of storage facilities deployed in power system, the power system dispatch model can consider energy storage in a unified manner[94]:

$$e_{s,t} = (1 - \alpha_s) e_{s,t-1} + \eta_s^{\mathrm{c}} \cdot p_{s,t}^{\mathrm{c}} - \frac{p_{s,t}^{\mathrm{d}}}{\eta_s^{\mathrm{d}}}$$

where $e_{s,t}$ denotes the energy stored in energy storage s in period t; α_s is the energy depreciation factor; $p_{s,t}^{\mathrm{c}}$ and $p_{s,t}^{\mathrm{d}}$ are the charge and discharge power; η_s^{c} and η_s^{d} are the charge and discharge efficiency. Then, the energy, charge power, and discharge power are constrained as follows:

$$e_s^{\min} \leqslant e_{s,t} \leqslant e_s^{\max}$$

$$0 \leqslant p_{s,t}^{\mathrm{c}} \leqslant p_s^{\mathrm{c,max}}$$

$$0 \leqslant p_{s,t}^{\mathrm{d}} \leqslant p_s^{\mathrm{d,max}}$$

$$p_{s,t}^{\mathrm{c}} \perp p_{s,t}^{\mathrm{d}}$$

This model can be called the "tank model" and it is the most representative one for energy storage. However, it is worth mentioning that although the tank model is commonly used and has wide applicability, it is still a rough model. A lot of literature has been studied to formulate refined models for different kinds of energy storage facilities. Regardless of their details, energy storage models should have state variables to represent the state of charge, action variables to represent the charge/discharge actions, and state transition equations to describe the energy conservation. Therefore, time coupling is inevitable for energy storage models.

2.1.4 Model example

We give two basic but quite typical power system dispatch models here, which are known as economic dispatch (ED) and unit commitment (UC). Here, the models only consider optimizing the active power and the dispatch objects are conventional thermal generators for simplicity.

The ED model is given as follows:

$$Obj = \sum_{t=1}^{T} \sum_{g=1}^{G} C_g(p_{g,t})$$

Subject to:

- System power balance:

$$\sum_{g=1}^{G} p_{g,t} = \sum_{i=1}^{N} P_{i,t}^{\mathrm{d}} + P_{\mathrm{loss},t}$$

- Power flow equations:

$$P_{f,t} = T_{f-i} \cdot \left(\sum_{g \in G_i} p_g - P_i^{\mathrm{d}} - D_i \cdot P_{\mathrm{loss},t} \right)$$

Here, D_i is the loss distribution factor and T_{f-i} is the power transfer distribution factor (PTDF). The PTDF can be deduced from the DC power flow equation[35].

- Power transmission limits:

$$-P_f^{\max} \leqslant P_{f,t} \leqslant P_f^{\max}$$

- System reserve requirement:

$$\sum_{g=1}^{G} r_{g,t} \geqslant R_t$$

- Generator operation limits:

$$p_{g,t} + r_{g,t} \leqslant p_g^{\max}$$

$$p_{g,t} - r_{g,t} \geqslant p_g^{\min}$$

$$-\Delta p_g^{\text{down}} \leqslant p_{g,t} - p_{g,t-1} \leqslant \Delta p_g^{\text{up}}$$

$$0 \leqslant r_{r,t} \leqslant r_{r,t}^{\max}$$

Compared with the ED model, the UC model takes the on/off actions of generators into consideration Therefore, a typical form of UC can be formulated as follows:

$$Obj = \sum_{t=1}^{T}\sum_{g=1}^{G}(C_g(p_{g,t}) + c_g^u \cdot u_{g,t} + c_g^v \cdot v_{g,t})$$

where c_g^u and c_g^v are the turn on/off cost of generator g, respectively.

Subject to:

- System power balance:

$$\sum_{g=1}^{G} p_{g,t} = \sum_{i=1}^{N} P_{i,t}^{\text{d}} + P_{\text{loss},t}$$

- Power flow equations:

$$P_{f,t} = T_{f-i} \cdot (\sum_{g \in G_i} p_g - P_i^{\text{d}} - D_i \cdot P_{\text{loss},t})$$

- Power transmission limits:

$$-P_f^{\max} \leqslant P_{f,t} \leqslant P_f^{\max}$$

- System reserve requirement:

$$\sum_{g=1}^{G} r_{g,t} \geqslant R_t$$

- Generator operation limits:

$$x_{g,t-1} - x_{g,t} + u_{g,t} \geqslant 0$$
$$x_{g,t} - x_{g,t-1} + v_{g,t} \geqslant 0$$

$$(x_{g,t} - x_{g,t-1}) \cdot t_g^{\text{on}} + \sum_{\tau=t-t_g^{\text{on}}-1}^{t-1} x_{g,\tau} \geqslant 0$$

$$(x_{g,t-1} - x_{g,t}) \cdot t_g^{\text{off}} + \sum_{\tau=t-t_g^{\text{off}}-1}^{t-1} (1 - x_{g,\tau}) \geqslant 0$$

$$p_{g,t} + r_{g,t} \leqslant p_g^{\max} \cdot x_{g,t}$$
$$p_{g,t} - r_{g,t} \geqslant p_g^{\min} \cdot x_{g,t}$$

$$0 \leqslant r_{g,t} \leqslant r_g^{\max}$$

$$p_{g,t} - p_{g,t-1} + x_{g,t} \cdot (p_g^{\max} - p_g^{\min}) + x_{g,t-1} \cdot (p_g^{\min} - \Delta p_g^{\text{up}}) \leqslant p_g^{\max}$$

$$p_{g,t-1} - p_{g,t} + x_{g,t-1} \cdot (p_g^{\max} - p_g^{\min}) + x_{g,t} \cdot (p_g^{\min} - \Delta p_g^{\text{down}}) \leqslant p_g^{\max}$$

The UC model is usually used to determine the on/off statuses of generators and schedule their outputs in a day-ahead or longer horizon decision making.

2.2 Varieties of power system dispatch

Based on the basic power system dispatch models, we discuss the varieties of power system dispatch from different perspectives, including the dispatch objects, dispatch scopes, security concerns, and uncertainties.

2.2.1 New dispatch object

Traditional power system operators dispatch conventional generators to meet the power demands within the power system with a specific target under a series of constraints. Over the decades, new technologies have developed, and environmental concerns have risen. Thus, the dispatch objects in modern power systems have greatly enriched. Besides wind power plants[95,96], photovoltaic (PV) plants[97,98], and pumped hydro energy storage[99,100], there are still several heated topics in recent years. The power system dispatch models should take these objects into consideration correspondingly, as shown in Figure 4.

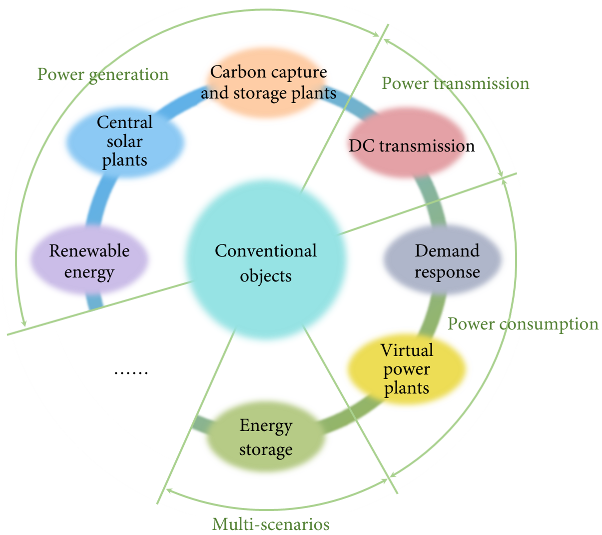

Fig. 4 Power system dispatch objects.

Battery energy storage station (BESS)

Energy storage does not generate electricity power, but it can provide flexibility to power systems and enhance power system dispatchability[101] Because of the technology improvement and cost reduction, BESSs are regarded as a promising type of energy storage for power system applications[102]. In the year of 2022, China has installed over 6 GW of battery energy storage, and much more projects are scheduled. Correspondingly, incorporating battery energy storage into power system dispatch models is necessary.

High voltage DC (HVDC) transmission

Compared with AC, DC systems have their own advantages in long-distance power transmission. For example, they could have fewer stability problems, greater power transmission efficiency, and could be easy to fulfill asynchronous connections. A lot of HVDC projects have been constructed worldwide[103]. Therefore, AC-DC hybrid power systems would be the future trend[104]. Literature has discussed the power system dispatch methods with the modeling of HVDC transmission lines[75,105,106].

Demand response (DR) and virtual power plant (VPP)

The demand-side resources are able to provide flexibility to power systems in smart grids. Therefore, the coordination of power generation, transmission, and consumption is realized. A famous method to aggregate the demand-side resources and utilize their flexibility to support power systems is DR programs [107–110]. Moreover, the concept of VPP is proposed to systematically organize the distributed energy resources (DER), distributed energy storage, and load resources to simulate the external characteristics of power plants[111–113]. In future power system dispatch, the demand-side resources would be no-longer treated as a fixed load demand, considering the impact of their behaviors in dispatch models is essential[114,115].

Central solar plant (CSP)

CSPs transform solar irradiation to heat power in the day-time, store the heat within the equipped thermal energy storage, and generate electricity using the heat power when needed. Compared with PVs, CSPs have more operational flexibility and can generate electricity even if there is no or little solar irradiation. Therefore, CSPs also have the potential to be widely deployed for the high-renewable-penetrated power systems[116]. The operation of CSPs in power system dispatch has been already studied[117,118].

Carbon capture and storage plant (CCSP)

Because of global warming, carbon emissions have attracted increasing attention from all over the world. By using carbon capture technology, most carbon dioxide emissions in the vented flue gas of thermal power plants are separated, transported, and stored in safe sites[119]. CCSPs have been regarded as one of the potential pathways toward a low-carbon society[120]. Hence, CCSPs are also potential new dispatch objects that the power system dispatch should consider[121].

2.2.2 Broaden dispatch scope

Traditional power system dispatch mainly focuses on the electricity sector itself. However, coupling with other energy sectors is the future trend. By building the energy Internet based on electrification, we can achieve an energy consumption roadmap with higher efficiency, more intelligence, and lower carbon emission. Correspondingly, the dispatch scopes are broadened.

Multi-energy system (MES)

MESs coordinate the generation, transmission, conversion, storage, and consumption of energy across different energy sectors[122]. Electricity, heat, cooling, gas, and other energy forms are coupled together under the concept of MESs. Compared with the separate energy sectors, there are four main advantages of MESs[123]: (1) increasing the ability to accommodate renewable energy through the flexibility of energy conversion and storage; (2) improving the efficiency of the entire energy system by utilizing energy in a cascading manner, including renewable energy; (3) promoting the system-wide optimal deployment of both centralized and decentralized energy resources by market interactions and (4) enhancing the energy supply reliability and resilience through the complementation of diverse energy infrastructures.

According to the scale of MESs, the study of MESs can be categorized into the district level energy network and the cross-region level energy network. The district level MESs mainly focus on the energy conversion and consumption, and are usually modeled as energy hubs (EHs)[124]. The modeling of EHs has been widely studied by literature[125–127]. Although the configuration of EHs varies, standardized modeling methods[128] have been proposed that apply to different types of EHs. The cross-region level MESs mainly focus on the long-distance energy transmission. For power transmission networks, power flow equations are used to describe the steady-state characteristics. For heat and gas networks, the time constants are much longer than that of electricity networks, so their dynamics cannot be ignored in dispatch. Inspired by the electric circuit analysis, the generalized electric circuit theories are proposed for heat networks[129] and gas networks[130], enabling to model different types of energy networks altogether.

Two typical multi-energy system operation situations are electricity-heat integrated dispatch[131] and electricity-gas integrated dispatch[132]. The coupling of different energy sectors provides significant benefits, but the power system dispatch models should be extended.

Electricity-transportation coordination

The transportation systems are now in a transition toward electrification[133]. In the future, the aggregated charging power of electric vehicles (EVs) will become a significant part of load demand in power systems. Moreover, the vehicle to grid (V2G) technology can provide extra operational flexibility for power systems to get a larger dispatch feasible region and integrate more renewable energy[134].

Thus, the power system dispatch will be extended to an electricity-transportation coordination framework. In related works, EV charging is usually treated as flexible loads and generalized energy storage[135]. The scheduling of EV charging and using EVs to provide ancillary services have been comprehensively studied[136–138]. In the highly electrified future, network models will be used to describe the dynamics of transportation systems[139]. In addition, electrified railways[140] and other transportation infrastructures provide more potential aspects of electricity-transportation coordination.

2.2.3 Security concern

Power system dispatch used to follow the decision-making and security-check procedure. In other words, the dispatch decisions are firstly obtained according to the optimization models, and then, the decisions are examined with some security analysis to verify that the dispatch operations are safe. If the security concerns are violated, modifications would be made and re-optimization is needed until the security analysis passes.

In high-renewable-penetrated power systems, the operation modes are diversified[141]. Moreover, with the increase of renewable energy and power electronic-based devices, the power system dynamic characteristics have profoundly changed[142,143]. Therefore, the traditional decision-making and security-check procedure is challenged. Considering security concerns in power system dispatch models are in fashion, as shown in Figure 5.

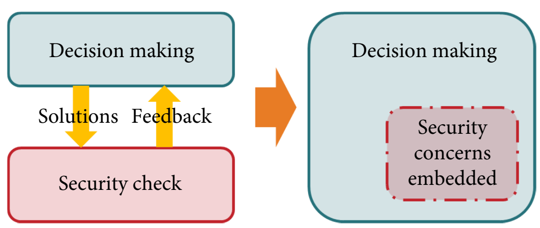

Fig. 5 Power system dispatch with security concerns.

Generally, security concerns are incorporated into power system dispatch by modeling the security regions or embedding security rules. The region-based methods first deduce the operation region of power systems where the system can operation safely and avoid violating security concerns[144,145]. The rule-based methods use explicit constraints or rules to describe the requirements of power system operation security. By adding these constraints or rules to power system dispatch models, the obtained solutions are guaranteed to be safe. The constraints or rules can be analytically deduced[146] or obtained by data-driven methods[147].

The following contents enumerate several critical security concerns that are considered in power system dispatch models.

N-1 security

N-1 security is one of the most common security concerns of power system dispatch models, and it is already applied to a lot of power grids in industry. The N-1 security requires that the power flows of all transmission lines in the studied system will not exceed their corresponding transmission limits even if a power transmission line is out of service. Therefore, the dispatch decisions should not only be subject to the power transmission constraints under normal scenarios, but also subject to the constraints under all N-1 scenarios.

As discussed in Section 1, dispatch models with N-1 security are called security-constrained dispatch models, such as SCED and SCUC. To ensure the N-1 requirement, the power flow equations under normal and N-1 constraints are all included in the studied dispatch model. If the model uses DC power flow and the PTDF is used to map active power injections to branch flows, then the PTDF matrices under normal and N-1 are considered. Consequently, the number of constraints of the power system dispatch model increases significantly. In large-scale power systems, considering N-1 security would make the solving more challenging.

Frequency security

The AC power system requires the frequency maintains within a small interval around the standard frequency (50 Hz or 60 Hz) in operation. However, the system frequency might drop below the tolerable range after some contingencies, such as the trip of a generator, which might cause serious accidents in power systems. Moreover, for the future high-renewable-penetrated power system, the system inertia will further decrease. As a result, the frequency security will be more urgent. Thus, studying the power system dispatch with the consideration of frequency security is necessary[148,149].

Rather than considering the whole frequency dynamics, power system frequency security mainly focuses on three indices, namely, frequency nadir, maximum rate of change of frequency (RoCoF), and quasi-steady frequency. Quantifying the accurate frequency nadir needs to solve the corresponding ordinary differential equations, which is not easy to incorporate into dispatch models. Hence, methods such as low-nonlinearity approximation[150,151], piece-wise linearization[148,152], and machine learning[153] are proposed to consider frequency nadir concerns in power system dispatch models.

Voltage stability

In power system analysis, voltage stability is roughly categorized into static voltage stability and transient voltage stability. Static voltage stability towards the small disturbance, which measures whether the power system stays in an unstable equilibrium point. Here, unstable equilibrium points refer to the status where a small disturbance will cause a collapse of the voltage on any bus in the system[154]. Traditionally, static voltage stability is guaranteed by constraints over the power flow and voltage drop of transmission lines. Transient voltage stability is used to represent the ability of a power system to restore stable voltage states after a fault. A classic metric is the transient voltage drop acceptability. However, with the increase of renewable energy power plants, power electronic devices bring new voltage stability mechanisms to power systems[155].

The voltage stability concerns have been considered in power system dispatch models. A typical two-step framework is used: first, build the voltage stability constraints; second, embed the constraints into dispatch models. In this way, the dispatch results are secure with respect to voltage concerns. Methods such as sensitivity analysis[156,157] and machine learning[158] tools are used to build embedding-friendly constraints. Moreover, because the power system voltage is highly coupled with reactive power, the typical DC power flow model is insufficient.

Angle stability

The angle stability refers to the ability of synchronous generators of an interconnected power system to remain synchronism after small or large disturbances[159]. Reference [160] points out that two kinds of angle instability situations are most likely to happen for a high-renewable-penetrated power system: non-oscillatory transient instability and small disturbance oscillatory instability. Here, the non-oscillatory transient instability refers to situations when some synchronous generators exhibit large rotor angle shifts after a large disturbance and lose synchronism in the transient dynamics. The small disturbance oscillatory instability occurs in power systems due to the lack of negative damping. The integration of inverter-interfaced renewable energy has made the analysis and prevention control of angle stability more challenging.

The transient power system angle dynamics is usually modeled as a large set of differential-algebraic equations, which are difficult to be incorporated into power system dispatch models. Thus, constructing constraints over decision variables to prevent angle stability problems is a practical way. Constraints can be established through decision trees[161] and trajectory-based sensitivity calculation[162].

Other security issues

Besides the above-mentioned security concerns, there are still other perspectives that are worth mentioning. Reference [159] provides a review of the definition and classification of power system stability, so stability issues beyond frequency, voltage, and angle are also important for power systems. Moreover, inverter-interfaced renewable energy resources would arise problems with the short circuit current of power systems. The short circuit current constraints have been established and incorporated into UC models [146]. The dynamic rating is another security concern for power systems. Unlike regarding the power transmission limits as fixed values, the concept of dynamic rating considers the power transmission abilities of lines as variable parameters associated with other factors[163], such as temperature. As a result, power system dispatch models with dynamic ratings make the dispatch results not violate transmission limits with environmental changes.

2.2.4 Considering uncertainty

The stochastic nature of renewable energy and demand-side resources brings uncertainties and intermittences to power systems. On the power system dispatch stage, it is impossible to predict the future renewable energy outputs and load demands. Although scheduling reserves is an effective way to handle future uncertainties, deterministic dispatch models have difficulties in balancing the conservativeness and efficiency. In high-renewable-penetrated power systems, the uncertainties increase significantly, so modeling uncertainties accurately in power system dispatch becomes essential.

Stochastic optimization

In stochastic optimization models, the uncertainties are usually modeled as scenarios[164]. Each scenario represents a possible realization of the future uncertainty sources. Then, the dispatch decisions are obtained based on the generated scenarios. In general, the stochastic power system dispatch models can be abstracted as follows:

$$\min_{x\in\chi} E_{\xi} f(x,\xi),$$

where x denotes the dispatch decision variables, χ is the feasible operation region, ξ is the uncertainty sources, $f(x,\xi)$ is the optimization target. Correspondingly, by deploying scenario-based methods, the dispatch models can be transferred to

$$\min_{x\in\chi} \sum_{\xi_i} \pi_i \cdot f(x,\xi_i),$$

where ξ_i is the i-th potential realization scenario of the uncertainty sources ξ, π_i is the probability of ξ_i. If the scenarios accurately capture the characteristics of the uncertainty sources, the dispatch results are optimal with respect to uncertainties. Scenario generation methods are widely discussed in literature[165–167]. Moreover, the number of scenarios would influence the solving efficiency of dispatch models, so corresponding representative scenario selection and scenario reduction approaches are also studied[168,169].

A typical stochastic optimization model in power systems is the stochastic UC (SUC). The decision-making procedure of a UC problem can be regarded as two stages. In the first stage, the on/off statuses of generators are decided considering the future uncertainties. This stage is usually referred to as here-and-now. In the second stage, when the uncertainties are realized, the power outputs of generators are determined. Because these decisions are made after the realization of uncertainties, they are referred to as wait-and-see decisions. Therefore, the two-stage UC models are abstracted as follows:

$$\min_{x\in\chi, y\in\gamma_x} c(x) + \mathbb{E}_{\xi}(f(x,y,\xi)),$$

where x is the here-and-now decision variables, χ is the feasible operation region of x; y is the wait-and-see decision variables, γ_x is the feasible operation region of y with given x; $c(x)$ and $f(x,y,\xi)$ are the cost functions of the first and the second stage, respectively.

Chance constraint

In addition, some dispatch models incorporate chance constraints. Chance constraints refer to the probabilistic constraints that should hold with a certain level of confidence or probability. A general formulation of chance constraints is

$$P(g(x) \leqslant 0) \geqslant 1-\varepsilon,$$

where $g(x) \leqslant 0$ denotes the original constraints, $P(\cdot)$ is the probability, $1-\varepsilon$ is the confidence level with a small ε. This kind of modeling allows the constraints to be violated with a tiny probability. For example, if $\varepsilon = 0.05$, then the probability of violating the constraints $g(x) \leqslant 0$ should be no more than 5%.

Based on the concept of chance constraints, models with value-at-risk (VaR)[170,171] and conditional value-at-risk (CVaR)[172,173] methods are studied in power system dispatch.

Robust optimization

Different from stochastic optimization which focuses on the expected values, robust models optimize the dispatch results in the worst case. Robust optimization models do not need the probability distributions of uncertainties; instead, they only need the range of uncertainties. In other words, the uncertainties are modeled as a set. Then, the robust model selects the worst-case scenario from the uncertainty set and optimizes the decision variables based on the worst-case scenario. A general form of a robust power system dispatch model can be expressed as follows:

$$\min_{x\in\chi} \max_{\xi\in\psi} f(x,\xi),$$

where x denotes the dispatch decision variables, χ is the feasible operation region, ξ is the uncertainty sources, ψ is the uncertainty set, and $f(x,\xi)$ is the optimization target. This min-max problem cannot be solved directly, and mathematical transformations are needed.

Similar to the SUC, the two-stage robust UC (RUC) can be formulated as follows:

$$\min_{x\in\chi} c(x) + \max_{\xi\in\psi} \min_{y\in\gamma_x} f(x,y,\xi))$$

In the first stage, the here-and-now decisions are made before the realization of uncertainties. Then, in the second stage, the worst-case scenario realizes, and the wait-and-see decisions are made to minimize the optimization target in the worst-case scenario.

The common used methods to build the uncertainty sets in the robust dispatch models include box intervals[174], polyhedral sets[175], ellipsoidal sets[176], and discrete sets[177].

Other uncertainties modeling

Besides the classical stochastic and robust models, some advanced methods are deployed to capture the uncertainties in power system dispatch in recent studies.

Note that the robust models could be over-conservative because the probability of the worst-case scenario is usually very small, adaptive robust models are proposed for power system dispatch[175,178,179]. In adaptive robust models, the robustness of dispatch results can be modified according to the risk preference of power system operators.

Distributionally robust is another hot spot that has been widely discussed. The key idea is to model the uncertainties in power system dispatch using ambiguous distributions[180–183]. The ambiguous distributions are constrained by probability statistics or distance to empirical distributions. Then, the dispatch decisions are optimized under the worst possible distribution.

Uncertainty sources in power systems vary, so dealing with different uncertainty sources with different modeling is applicable. Therefore, combined stochastic-robust models are proposed for power system dispatch[184–186].

2.3 Categorization of dispatch models

In this paper, we categorize the power system dispatch models from six dimensions, as shown in Figure 6.

- **Optimization targets:** as discussed in Section 2.1.2, most power system dispatch models are established to improve the power system efficiency and economy, so the corresponding optimization targets are to minimize the total operation cost or maximize the social welfare. Also, other optimization targets, such as minimizing power transmission loss, and reducing carbon emissions, are studied in some models.

- **Power Flow:** the basic form of power flow in dispatch models is AC flow. Because of the nonlinearity and the nonconvexity of the original AC flow, simplifications and approximations are made to obtain DC flow and other linearized models. Also, there are still some models that do not have power flow equations.
- **Dispatch Periods:** power system dispatch models without time-coupling characteristics are single-period models, such as the OPFs. On the contrary, multi-period models consider time-coupling, such as the EDs and the UCs.
- **Decision Stages:** in some power system dispatch models, the dispatch results are determined at one stage, regardless of the number of dispatch periods. Some models separate the decision into here-and-now and wait-and-see to get two-stage optimization, such as SUCs and RUCs. Others model the decision-making processes as multi-stages. The typical examples are dynamic programming (DP) models.
- **Model Types:** the mathematical formations of power system dispatch models are vital to determine the corresponding solving algorithms. Common types include LP, mixed-integer LP (MILP), NLP, mixed-integer NLP (MINLP), and DP.
- **Uncertainties Modeling:** some power system dispatch models do not consider uncertainties and use deterministic optimization; others incorporate uncertainties into decision-making through different kinds of models, such as probability distributions, scenarios, uncertainty sets, ambiguous distributions, quantiles, etc.

2.4 Data-driven dispatch modeling method

Data-driven approaches have been widely discussed in power system research. In recent years, a lot of literature has studied the application of data-driven methods in different topics and has proved that data-driven models outperform conventional models in some power system analysis scenarios. Power system dispatch is not an exception.

Plenty of research has studied to construct the optimization targets or constraints of the power system dispatch models in a data-driven manner. To deal with the nonlinearity of power flow constraints, some researchers study the statistical mapping between P, Q and V, θ using regression techniques[86–88]. Then, they replace the physical-based power flow equations with the data-based mappings in power system dispatch models. Another example is the stability constraints. The stability analysis usually needs to study the power system dynamics, while the power system dispatch models focus on the steady-state operation. To fill the gap between the dynamics analysis and steady-state models, data-driven methods, such as decision trees and support vector machines[160], are proposed to build stability constraints that can be embedded into dispatch models.

Moreover, other advanced digital techniques are potentially beneficial to power system dispatch. The digital twin is one of the future trends of power system analysis. It can help power systems to enhance perception, cognition, intelligence, and control[187]. Correspondingly, with the development of digital twin and power system simulation technologies, the power system dispatch model can obtain more accurate parameters and give more applicable dispatch decisions. Artificial intelligence (AI) assisted decision-making approaches are also a heated topic. These approaches usually establish the power system dispatch problem under the reinforcement learning framework[188]. A lot of reinforcement learning techniques have been studied within the scope of power system dispatch, and satisfying results have been reported in the literature. However, current reinforcement learning methods are mostly using black box models. Similar to other AI decision-making research fields, such as autonomous driving, the interpretability of models is the biggest challenge in practical applications.

2.5 Discussion of modeling challenges

Recently, the rapid development of renewables has posed great challenges for power system dispatch modeling. Traditional dispatch models with lots of simplifications cannot adapt to the new form of the power system. Specifically, the following modeling challenges of power system dispatch are discussed.

Power flow modeling

Currently, the linear DC power flow model that ignores the reactive power and voltage magnitude is widely applied in practical power industries to guarantee the computational efficiencies of power system dispatch. However, in high-renewable-penetrated power systems, the uncertainties and fluctuations of power systems greatly increase, which imposes the urgent requirement for flexible resources. Correspondingly, the requirement for the modeling accuracy of the active and reactive power is increasing. Meanwhile, renewables are integrated into power systems through power electronic devices, with which the coupling of the active and reactive power of power systems becomes stronger[189]. Hence, it is necessary to incorporate the reactive power and voltage magnitude into the linearized power flow model. Researchers have proposed different types of linearized power flow models to achieve the above target[33, 34, 190]. However, the power flow modeling accuracy in practical power systems with large-scale and complex constraints still needs to be improved[191].

Operating boundary modeling for uncertainties

In high-renewable-penetrated power systems, the power system dispatch model needs to be improved to handle the uncertainties caused by renewables. Despite that stochastic dispatch problems (e.g., robust optimization, chance-constrained optimization, and multi-scenario optimization) have been widely studied in academia, the deterministic dispatch model is still used in practical power industries due to the concern of the computational efficiency [192]. In current deterministic dispatch models, the propoer operating boundary (e.g., operating reserve, regulation reserve, etc.) is set to prepare enough redundancy to ensure that the power system can handle the uncertainties in real-time operation. The key issue lies in the accurate modeling of the operating boundary. In the power industry, the operating boundary is set mainly based on the operating experience and the statistics of the historical operating data. The impact of renewables cannot be fully reflected. To improve this, data-driven methods with the forecast information of renewables have been studied in academia[193–195]. However, the inevitable approximation error of data-driven methods restricts their application. How to handle the approximation error and improve the reliability of data-driven methods still needs to be studied.

Security constraint modeling

The integration of renewables and power electronic devices brings a great change in power system dynamic characteristics. The traditional decision-making and security-check procedure cannot efficiently handle the aforementioned change. To improve this, incorporating security constraints (e.g., frequency stability constraint, voltage stability constraint, and angle stability constraint) into the power system dispatch model, which aims to obtain the

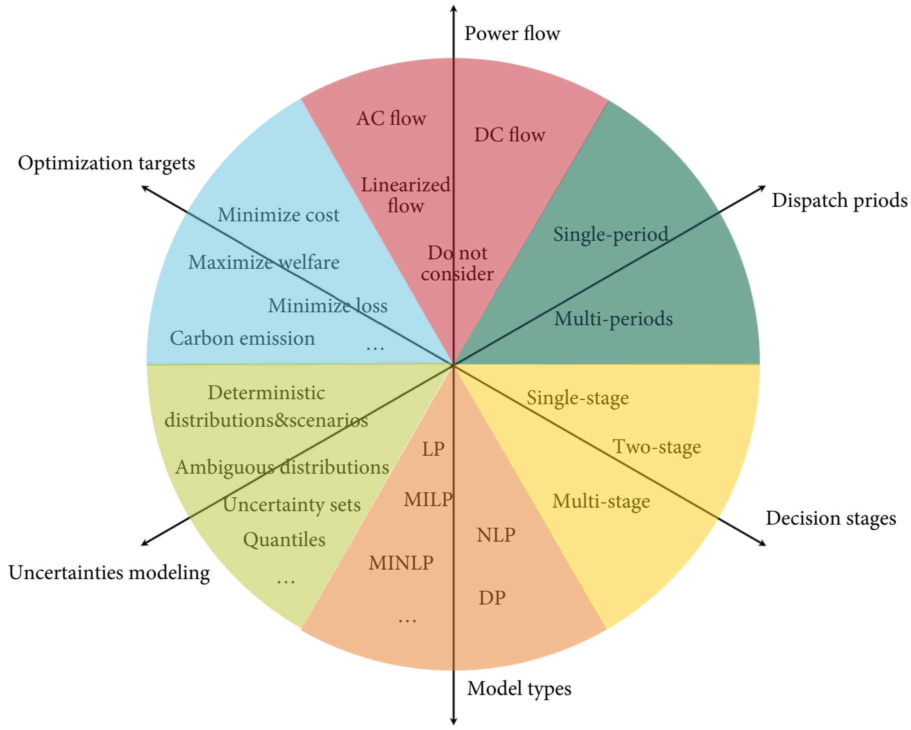

Fig. 6 Categorization of dispatch models.

operation pattern that can ensure the power system stability, has been widely studied. However, power system dynamic characteristics are extremely complex. The security constraint modeling that can be easily embedded into the power system dispatch model while accurately reflecting dynamic characteristics is a major challenge in this field. For instance, take the frequency stability constraint as an example, the frequency nadir constraint has drawn wide attention. However, the frequency nadir constraint is highly nonlinear[196] and unanalytical. Existing methods typically derive a nonlinear analytical expression for the frequency nadir under the assumption of a simplified governor model. This expression is further simplified using techniques such as piecewise linearization methods[148] or data-driven methods[197]. These simplified methods treat the primary frequency regulation of renewables as equivalent to a simple governor, their detailed frequency response behavior and control strategy are ignored. As a result, these simplified models may not accurately capture the system's frequency response behavior under high-renewable-penetrated power systems[198]. Moreover, detailed modeling of renewables is difficult to be solved analytically in the time domain, rendering existing methods inapplicable. Therefore, how to achieve the effective security constraint modeling still needs to be studied.

3 Solving solutions of power system dispatch

Given a variety of power system dispatch models, solution methods are required to provide a high-quality solution within the required time. This section will discuss the common solutions of power system dispatch. Note that there are numerous solving algorithms and methodologies, however, only a few are currently running in practical power industries. In this paper, we majorly provide our comments from the industrial application point of view.

3.1 Common solutions of power system dispatch

According to Section 2, the formulation of the power system dispatch model can be generally divided into forms including LP, NLP, MILP, MINLP, and DP. Rather complete reviews can be found in Refs. [199–201]. In power industries, the computational requirements for power system dispatch solutions are much higher than the academic research, which are discussed as follows.

Firstly, the solutions need to be computationally efficient. The power system dispatch needs to be timely solved. With the increasing need to execute the resource allocation in a wider range with higher time resolution, the scale of the dispatch problem is increasing. For example, China is preparing to execute the regional and even national electricity market. To achieve this, the scale of the market clearing model will greatly increase compared with the dispatch problem in a single province, causing higher challenges.

Secondly, the solutions need to be robust. In practical power system dispatch problems, there are many numerical problems that may not be faced in the standard test systems usually used in academic studies. For example, there may be unusual settings of the line parameters caused by the equivalent modeling of lower level systems or interconnection branches; the penalty factors to punish the constraint relaxations are several magnitudes higher than the common parameters, causing the numerical problems in matrix calculation. Such problems are seldom discussed in the research of the majority of algorithms, but are important in practice.

Thirdly, the solutions are preferred to have convergence guarantee. In practical applications, the dispatch solution is a must to proceed the followed operation procedure. For example, the market clearing results are needed to publish according to the given rule. If the solution cannot converge, human interference is required, which will harm the efficiency and economics of the power system operation.

Hence, in power industries, most of the dispatch problems will be simplified or transformed into the LP or MILP form because of the desired computational efficiency, robustness, and convergence properties of LP-based decision-making algorithms. Here, we mainly discuss the algorithms of LP and MILP dispatch problems.

For the LP problem, such as the typical ED and SCED problem, the algorithms are quite mature. The basic algorithms include the primal-dual method[202], interior point method[203], simplex method[204], dual simplex method[205], etc. The state-of-the-art algorithms have been proved to be polynomial-hard with convergence guarantee. Current solvers, including CPLEX, Gurobi, IPOPT, and so on, can efficiently provide the solutions of the LP problem. As a result, current power industries and academia normally pay attention to the modeling technique and leave the burden of LP solving to the solvers.

The power system dispatch problems formulated as the MILP form are the most computationally challenging ones in practice, which has attracted attentions for acceleration for a long time. The MILP optimization is theoretically non-deterministic npolynomial-time hardness (NP hard). In essence, it needs to strategically enumerate the combination of integer variables. Currently, the mainstream algorithm is called branch-and-cut method, which is a combination of branch-and-bound (B&B) method and cutting plane method. It will produce a search tree. Each node on the tree represents a certain combination of integer variables. The branches produced from this node represent the selection of 0 or 1 of the undetermined integer variables. On each node, several relaxation LP problems need to be solved. A common MILP problem in power systems can contain hundreds of thousands of nodes. Hence, the computational burden of MILP is much higher than the LP-based problems.

One of the most focused MILP dispatch problems is the UC problem, which is frequently solved on a daily base in modern power systems. To handle the difficulty caused by the large-scale of the optimization problem, power engineers propose to decompose the UC problem into several subproblems and iteratively coordinate the computational tasks of subproblems. Recently, commercial solvers, led by CPLEX and Gurobi, have been fast developing. It has been adopted by many power system operators to directly input the MILP model to the solver and obtain the results. The basic algorithm of these solvers is still the branch-and-cut method. However, it involves many other techniques like presolving, parallel computing, branching or nodding strategies, which distinguish the computational performance among the solvers. With the increasing scale of the MILP problem, some power engineers are proposing to combine the decomposition idea with the powerful MILP solver[27]. In China, there is an evolving trend to develop domestic solvers, like the COPT and mindOPT. The performance comparison in practical systems needs to be further demonstrated.

3.2 Discussion of computational challenges

Along the whole evolution of the power system, the efficient optimization of dispatch problem is always an important and difficult task. Constant efforts to improve the dispatch decision efficiency and accuracy are made by both power engineers and mathematicians. Specifically, we would like to discuss the following computational challenges in current power dispatch problems.

We first discuss the challenge brought by modeling complexity. The physical property of the power grid has been significantly different from the traditional dispatch problem. Hence, the dispatch model needs to be updated, along with the computational challenges.

From the generation side, the percentage of renewables is increasing, causing a need to model the uncertainties more accurately. Currently, the uncertainties are considered in the power industries by the capacity reserve. The level of capacity reserve is usually determined in an ad-hoc manner. In a power system with an extremely high percentage of renewables, such a manner either causes security issues or results in unnecessary redundancy. The dispatch modeling with uncertainties proposed in Section 2 becomes a solution, but also brings a significant increase in computational burden. Another thought is to keep the current dispatch model formulation, but express the operation boundary, like the capacity reserve, as an explicit function of the renewables. In this way, the reserve can be more accurate and timely change with the operation condition. Also, it provides the opportunity to trace the costs of renewable fluctuation by considering its influence on the operation boundary. Obviously, such a treatment also increases the scale of the dispatch model, calling for more powerful solving algorithms. Besides, the more accurate modeling of the generations, including the valve point effect of thermal generators, will also increase the modeling complexity. With more powerful computation tools, more detailed generation models can be considered, leading to economic and secure benefits.

From the grid side, many countries currently have a hybrid AC and DC power grid with a much higher percentage of electronic devices. These characteristics challenge the applicability of the DC power flow model, which is the foundation of most of the LP and MILP-based dispatch problems. The detailed modeling of the power flow features will increase the modeling scale and introduce nonlinearity, all leading to computational challenges.

From the demand side, modern power systems need the flexibility of the power demand to handle the fluctuations, which is usually assumed as a constant in the traditional dispatch. For the resources on the demand side, the adjustability of a single resource is normally not comparable with the generators, while the total amount of resources, like a building or a house, is much larger than the generation side. Hence, the modeling scale will be exploded if all the resources are modeled in detail as the generators. A popular way is to aggregate the demand side and form a resource with the flexibility visible to the system operator, such as the virtual plant. Nevertheless, the dispatch problem is much larger when considering the demand side, causing computational challenges.

Last but not the least, the inclusion of storage also increases the modeling complexity, resulting in significant computational challenges. The modeling of storage normally includes nonlinear elements, which can be partly handled by involving integer variables. If the degradation of the storage is considered, the model will be more complex, bringing computational challenges.

Except for the modeling perspective, the scale of the dispatch model also brings great computational challenges. Traditionally, the regional power balance, such as the provincial power system in China, can be made with a rather fixed power exchange with other regions. However, modern power systems face tighter operation space, resulting in an urgent need of the dispatch optimization across the regions. More resources are included, and naturally, the scale of the dispatch model increases. In China, two main regional power networks are proposing to construct a dispatch optimization model across the region, but are currently facing distinct computational challenges.

In essence, the current technologies cannot solve the enormously large dispatch model that considers all the details in power systems. The development of advanced dispatch solutions is always of interests and can potentially bring huge benefits to the power system.

3.3 Future trends of solving solutions

To solve the large-scale and complex dispatch problems, many efforts have been made from the academia and industries. Firstly, if we treat the dispatch problem as a special kind of optimization problem, the advancement in general-purpose solving algorithms will always bring benefits to the dispatch problem. For example, Gurobi has witnessed over 75 times acceleration for the same problem from the initial version to the latest version over the decades[206]. These improvements in efficiency also motivate the power industries to use the MILP solvers for the large-scale UC problem. Hence, a major improvement of solution methodologies for power system dispatch problems comes from the mathematicians.

On the other hand, the power system dispatch is gradually becoming one of the most challenging decision-making problems because of the issues mentioned above. Treating the dispatch problem as a common mathematical problem may not meet the solving requirement, even with the fast development of solving tools. One promising way is deeply combining the domain knowledge of power system dispatch and advances in mathematics. The basic idea is to utilize the special structure and numerical properties of the power system dispatch problem to accelerate the solving process. There are majorly two categories of methods to achieve this, which will be introduced as follows.

One approach is decomposition. The basic idea is to decompose the solving problem into several solving tasks to reduce the computational burden. Classic decomposition method includes the Lagrangian decomposition[207] and Benders decomposition[208]. The decomposition should be executed based on the structure of the problem. The power system dispatch problem has distinct numerical properties. For example, the dispatch constraints in each time step are coupled only by the ramp capabilities, and hence, many methods are proposed to decompose the dispatch model according to different time horizons[209]. Also, for a regional power network, the dispatch problem of different regions is coupled by the power transfer on the tie lines. There are methods proposed to decompose the dispatch problem of the whole region to several subregions and coordinate the dispatch of subregions by tie-line power optimization[210].

Another approach is to improve the decision-making algorithm of the dispatch problems using the power-domain knowledge. As discussed above, the power system dispatch problem is challenging in the MILP form. Current dispatch solutions normally formulate the dispatch problems and then solve them using general-purpose solvers. However, the power domain knowledge may help to improve the efficiency. For example, Refs. [211, 212] have shown that the power-domain knowledge can help to accelerate the solving process of the MILP solver at a considerable scale. However, current research on this field still needs further investigations. The collaboration between the mathematicians and power engineers will be highly appreciated. The U.S. is funding a project called High-Performance Power Grid Optimization (HIPPO) to achieve this task[213]. China also organized National Key R&D Program Projects with similar purposes. Still, there is a long way to go to improve the efficiency of the power system dispatch problem.

4 Conclusion

In this paper, the common concept of power system dispatch is revisited. The categorization of the power system dispatch problem is provided, especially with the emphasis on the industrial applications. Then, the common dispatch models are given and categorized, providing guidance for the models of specific problems. Finally, this paper discusses the solution of the dispatch problem and provides the challenges faced by the current industries. Hope this paper can help the researchers and engineers in this field to get the basic concept of the power system dispatch and learn the current challenges.

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Additional information

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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