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Research Review on the Scheduling Optimization of Production and Energy Systems under Uncertain Environments

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Abstract

The uncertainties in actual production and energy systems pose severe challenges to the stable, efficient, and low-carbon operation of the systems. Centering around the core of "uncertainty handling," this paper systematically reviews the mainstream modeling and solution methods for dealing with uncertainties in the current scheduling optimization field. At the measurement level, uncertainties can be characterized from two dimensions: parameter fluctuations and event perturbations, and there are essential differences in the impact mechanisms of the two on the scheduling scheme. From the perspective of uncertainty modeling, the theoretical foundations and applicable scenarios of methods such as fuzzy programming, stochastic programming, robust optimization, and distributionally robust optimization are reviewed; from the perspective of solution strategies, the evolution of methods from exact algorithms to heuristic, meta-heuristic, and then to intelligent decision-making methods based on learning and simulation is analyzed. At the effect level, uncertainties will significantly weaken the economic benefits and environmental performance of the scheduling scheme, but there are significant scenario heterogeneities in the degree of their impact. Research shows that distributionally robust optimization has attracted much attention due to its good balance between conservatism and economy, and the hybrid-driven method that combines simulation and learning is becoming an important trend to improve the adaptability of the scheduling system. Future research needs to further focus on the decision-making requirements in complex scenarios such as the coupling of multiple uncertainties, multi-agent games, and real-time dynamic responses.

Keywords

Uncertainty; Scheduling Optimization; Robust Optimization; Distributionally Robust Optimization; Deep Reinforcement Learning

1. Introduction

In modern manufacturing and energy systems, scheduling serves as the critical link

between decision-making and execution. Its effectiveness directly impacts production efficiency, operational costs, energy consumption, and even environmental emissions. Scheduling problems are ubiquitous, spanning from flexible job shops to multi-microgrid systems, from multimodal transportation to repetitive construction projects. However, these systems do not operate in ideal environments; they are universally subject to various uncertain disturbances. In manufacturing workshops, factors such as differences in worker skills and learning effects make processing times difficult to estimate precisely; urgent order insertions and machine breakdowns can disrupt planned schedules. In power systems, the intermittency and volatility of wind and photovoltaic outputs are major obstacles to safe and economical system operation. In logistics and transportation, freight demand and transit times are equally fraught with uncertainty.

Traditional deterministic scheduling methods ignore these uncertainties, and the plans they generate often perform poorly in practice—or even prove infeasible. Therefore, how to effectively characterize, model, and respond to uncertainties in scheduling decisions has become a core issue of continuous concern in the fields of operations research, management science, and engineering. This paper aims to review the mainstream methods for handling uncertainty in scheduling optimization problems, with a focus on their modeling philosophies, solution techniques, performance in different application scenarios, and future research directions.

The remainder of this paper is organized as follows. Section II discusses the measurement and classification of uncertainties in scheduling problems. Section III reviews the major uncertainty modeling and optimization methods, including fuzzy programming, stochastic programming, robust optimization, and distributionally robust optimization. Section IV examines the multidimensional impacts of uncertainty on scheduling performance, covering economic losses, environmental effects, and heterogeneity. Section V concludes the paper with a summary and an outlook on future research directions.

2. Measurement and Classification of Uncertainty Scheduling Problems

2.1. Parameter Uncertainty

Parameter uncertainty focuses on the fluctuation range and distribution characteristics of key parameters in the scheduling model. In actual production scheduling, the most commonly processed uncertain parameters include processing time, demand, equipment availability, and renewable energy output. Regarding the uncertainty of processing time, researchers have developed various modeling tools. Jin Yihui and Dong Baoli (2026) used triangular fuzzy numbers to model the uncertain processing time, representing the processing time as a triple of the most optimistic time, the most likely time, and the most pessimistic time, and combined

the interval grey number processing method with an improved whitening weight function to whiten the fuzzy processing time into a computable exact value. Wang et al. (2024) further considered the evolution of the fuzzy characteristics of processing time in dynamic scheduling, pointing out that as production progresses, some fuzzy processing times will be converted into definite values, resulting in changes in the evaluation indicators of the original scheduling plan (such as the maximum fuzzy completion time and the expected customer satisfaction), thus causing the fuzzy scheduling plan to deviate from the actual situation. Li Wenqiang et al. (2025) in the distributed flexible job shop scheduling considering carbon emissions integrated energy consumption from multiple carbon emission boundaries, such as machine load, transportation, coolant, and lubricant consumption, and constructed a carbon emission calculation model, in which the uncertainty of processing time directly affects the calculation accuracy of carbon emissions.

Regarding the uncertainty on the demand side, Ma et al. (2024) used the scenario tree method to characterize the stochastic fluctuations of medical material demand under the framework of multi-stage stochastic programming and approximated it through the sample average approximation method. Guo Junhua and Miao Wanying (2026) used the robust optimization method, set the uncertain demand as a bounded interval, and controlled the conservatism of the model through the robust level control parameter. The larger the Γ value, the deeper the decision maker's aversion to risk, and the more conservative the scheduling plan. In the energy system, Yuan et al. (2021) and Cheng Shan et al. (2026) both focused on the prediction errors of wind and solar power outputs. The former used the fuzzy set based on the Wasserstein distance to describe, took the historical prediction error data as the empirical distribution, and constructed a Wasserstein ball around it; the latter used the first/second moment information of the random parameters to construct a fuzzy set, and characterized the statistical characteristics of uncertainty through the expectation and covariance matrix.

2.2. Event perturbation

Event disruptions refer to discrete, unexpected disturbance events. This type of uncertainty cannot be characterized through continuous distributions and thus requires discrete event modeling approaches. Wang et al. (2024) classified disturbances into two categories: one originates from the "time delay" inherent to fuzzy features—where processing times are initially represented as fuzzy numbers in the preliminary schedule, but as production progresses, some operations' processing times become definite values, causing changes in schedule evaluation indicators; the other stems from external emergencies such as new job insertions. For these two types of disturbances, they designed differentiated rescheduling strategies: for time delays, a satisfaction-driven rescheduling policy is adopted, triggering complete rescheduling when customer satisfaction falls below a threshold;

for new job insertions, an event-driven policy is employed, prioritizing insertion rescheduling and executing complete rescheduling only if satisfaction fails to meet the standard. Li et al. (2025) considered quality inspection disturbances as a specific event type in distributed flexible job shop scheduling, where, upon receiving a defective quality inspection result, all subsequent iterations are halted, and a partial rescheduling strategy combining right-shift rescheduling and complete rescheduling is adopted to re-optimize the population in response to real-time disturbances. Yao et al. (2026) focused on the impact of emergencies such as extreme weather, site constraints, and resource shortages on project duration in repetitive project scheduling, modeling these events as maximum deviation scenarios for sub-activity durations.

A critical distinction between the two types of uncertainty measures lies in the fact that parameter uncertainty can be absorbed and mitigated ex ante through optimization models, whereas event disruptions typically require ex post rescheduling mechanisms. This distinction directly influences the selection of scheduling strategies and the design of optimization frameworks. In the context of Industry 4.0 and IoT-enabled manufacturing environments, the frequency and complexity of event perturbations have increased significantly. Tan et al. (2023) conducted a scientometric analysis of 5,052 papers on scheduling and control in IoT environments for Industry 4.0 and found that dynamic scheduling, real-time control, and intelligent decision-making have become major research hotspots since 2016. Their analysis of keyword bursts reveals that "dynamic scheduling" (strength 9.17, 2007–2009) and "stochastic system" (strength 20.20, 2014–2022) are among the most prominent research fronts, indicating that both event-driven dynamics and parameter uncertainties have received sustained attention from the academic community.

2.3. Coupling of Dual Uncertainties

In real-world scenarios, parameter uncertainty and event disruptions often coexist, forming a complex landscape of dual or even multiple coupled uncertainties. Guo and Miao (2026), in their study on multimodal transportation, simultaneously considered the stochastic fluctuation of transportation demand and the random disturbance of transportation time, employing robust optimization for the former and Monte Carlo simulation for the latter. Yang et al. (2026) in the integrated energy system of high-altitude construction parks addressed both the probabilistic uncertainty of wind and solar output and the interval uncertainty of oxygen load, modeling the former based on probability cumulative distribution functions and characterizing the latter through the introduction of an uncertainty parameter Γ. Cheng et al. (2026) in multi-microgrid systems faced both the stochastic fluctuation of renewable energy output and the default risk in multi-agent transactions, handling the former through distributionally robust chance constraints and the

latter through a credit evaluation mechanism. This coupling of multiple uncertainties imposes higher demands on both modeling methodologies and solution algorithms.

3. Uncertainty Modeling and Optimization Methods

3.1. Fuzzy Programming

When decision-makers have qualitative knowledge of uncertainty but lack sufficient historical data to construct precise probability distributions, fuzzy programming provides an effective tool. This approach uses fuzzy numbers (such as triangular fuzzy numbers) to describe uncertain parameters and employs membership functions and fuzzy logic for reasoning and decision-making.

For instance, in dealing with flexible job shop scheduling problems with uncertain processing times, researchers often use triangular fuzzy numbers to represent time intervals and design defuzzification strategies to generate deterministic scheduling schemes (Jin and Dong, 2026; Wang et al., 2024). Jin and Dong (2026) further combined fuzzy Petri nets with deep reinforcement learning, dynamically adjusting strategies through fuzzy logic to cope with processing time uncertainty. The advantage of fuzzy programming lies in its flexibility and its capacity to incorporate subjective knowledge; however, its results are, to some extent, dependent on the choice of membership functions.

3.2. Stochastic Programming

When there is sufficient historical data on uncertain parameters to fit their probability distribution, stochastic programming is a natural choice. It describes multiple possible realizations of random variables through scenario trees or sampling methods and optimizes expected objectives or chance constraints on this basis. Ma et al. (2024) used the scenario tree method to characterize the joint uncertainty distribution of medical material demand and distribution capacity in the framework of multi-stage stochastic programming. Since the number of scenarios grows exponentially with the number of stages, they designed improved sample average approximation methods and progressive hedging algorithms, which significantly reduced the computational burden while ensuring the solution quality. Numerical experiments show that the gaps between the two algorithms and the optimal results are on average less than 0.7% and 0.9%, and the computational efficiency is far superior to commercial solvers in large-scale experiments. Guo Junhua and Miao Wanying (2026) used Monte Carlo simulation to handle the uncertainty of transportation time, generated random in-transit time and transfer time through truncated normal distribution, and used the mean value of 200 simulations as an unbiased estimator to achieve the integration of time uncertainty and the model optimization framework. Yuan et al. (2021) assumed that the wind power and photovoltaic prediction errors in the day-ahead scheduling of microgrids

follow a normal distribution, thus transforming the chance constraint into a deterministic equivalent form. However, the limitations of stochastic programming are that the true distribution is often difficult to accurately obtain, and the computational burden of solving large-scale stochastic programming problems is extremely heavy.

3.3. Robust Optimization

Robust optimization does not rely on the probability distribution of uncertain parameters. Instead, it constructs a deterministic "uncertainty set" to encompass all possible parameter fluctuations. Its core idea is to find a decision that is feasible and optimal in the worst case. Yao Zongyu et al. (2026) constructed a robust optimization model for repetitive project scheduling based on the Budget uncertainty set and adjusted the robustness level by controlling the upper bound of the sum of deviation variables. The larger the value of , the more sub-process durations are allowed to reach the maximum deviation simultaneously, and the more conservative the model is. The advantage of this method is that it can handle the situation where distribution information is unknown, and the trade-off between robustness and economy can be achieved by adjusting the conservatism parameter. However, this method faces a high "robustness cost" in application. An overly conservative scheduling plan may lead to resource idleness and cost overruns. To reduce this cost, they further proposed a finite-domain robust optimization strategy based on control routes, which only incorporates the duration deviation of control sub-processes into the uncertainty set, and the deviation of non-control sub-processes is ignored, thus reducing unnecessary buffer time while ensuring robustness. Experiments show that the finite-domain robust optimization strategy can further shorten the project duration by 2.5 days compared with the standard robust optimization strategy, and the robustness cost is significantly reduced. Guo Junhua and Miao Wanying (2026) used a similar budget uncertainty set to handle transportation demand fluctuations and reflected the decision maker's risk preference through the value of . Cheng Shan et al. (2026) pointed out the defect of traditional robust optimization being too conservative, so they adopted distributionally robust optimization as an alternative.

3.4. Distributionally Robust Optimization

To overcome the reliance of stochastic programming on precise distributions and the over-conservatism of robust optimization, distributionally robust optimization has emerged and become a research hotspot. This approach assumes that the true distribution is unknown but belongs to an "ambiguity set" constructed from historical data. Decision-makers optimize the objective under the worst-case distribution within this ambiguity set. Common approaches for constructing ambiguity sets include moment-based information and the Wasserstein distance.

Yuan et al. (2021), in day-ahead microgrid scheduling, employed an ambiguity set based on the Wasserstein distance to characterize the uncertainty of wind and solar forecast errors. This ambiguity set is a Wasserstein ball centered at the historical empirical distribution with radius $\rho(N)$, where the radius decreases as the sample size N increases. As historical data accumulate, the Wasserstein ball shrinks toward the true distribution, thereby reducing the conservatism of the model. Numerical results demonstrate that when the sample size increases from 50 to 1,000, the system operating cost decreases from 985.6 yuan to 873.5 yuan. Meanwhile, by adjusting the confidence level $1-\varepsilon$ of the chance constraints, a trade-off between economy and robustness can be achieved within the range of 95% to 99%. Cheng et al. (2026) in a multi-microgrid shared energy storage system, adopted a moment-based ambiguity set construction method, utilizing the first and second moments of random parameters to approximate the uncertainty space. This approach is computationally simpler than the Wasserstein method while still adequately capturing the statistical characteristics of uncertain variables. They further employed affine decision rules to transform stochastic constraints into deterministic ones and combined them with Chebyshev's inequality to convert the distributionally robust chance constraints into a mixed-integer second-order cone programming problem for solution. Esfahani and Kuhn (2018) theoretically proved that, under mild conditions such as the loss function being the pointwise maximum of a finite number of concave functions, the worst-case expectation problem over a Wasserstein ambiguity set can be equivalently reformulated as a finite-dimensional convex program, which laid the theoretical foundation for the widespread application of distributionally robust optimization in scheduling problems.

From a historical perspective, the evolution of production scheduling methods is closely tied to shifts in manufacturing paradigms and technological capabilities. Jiang et al. (2021) reviewed the development of production scheduling from Industry 3.0 to Industry 4.0, and identified three major paradigm shifts: from centralised scheduling to distributed scheduling, then to decentralised scheduling, and more recently to cloud manufacturing scheduling. They further pointed out that emerging technologies such as digital twins, edge computing, and big data analytics are enabling new scheduling modes that can better handle uncertainties in real time. This technological evolution has not only expanded the solution toolkit for uncertainty handling—from exact algorithms to metaheuristics and AI methods—but has also redefined the nature of uncertainty itself, shifting the focus from static parameter uncertainty to dynamic, event-driven, and even human-in-the-loop uncertainties.

4. Multidimensional Impacts of Uncertainty on Scheduling Performance

4.1. Economic Performance Loss

Ignoring uncertainty can lead to significant performance losses in the actual implementation of scheduling plans. Yao Zongyu et al. (2026) conducted Monte Carlo simulations in repetitive project scheduling and found that in the worst-case scenario, the project delay of the deterministic strategy was as high as 11%, while that of the robust optimization strategy was only 4.2%. More importantly, the actual cost of the robust optimization strategy is lower than that of the deterministic strategy in the worst-case scenario—because the latter needs to bear higher delay costs, while the former effectively reduces delay losses by paying additional robust costs. The finite domain robust optimization strategy further shortens the construction period to 121.1 days, which is 2.5 days shorter than the standard robust optimization. Wang et al. (2024) found in the fuzzy flexible job shop scheduling that without considering time delay, the average customer satisfaction decreased from 100% to 84% and 80% in two test scenarios, and it could recover to over 95% after triggering rescheduling. However, rescheduling is usually accompanied by an increase in energy consumption because when improving customer satisfaction, some operations need to be arranged on machines with higher processing power to shorten the processing time. Ma et al. (2024) found in the pharmaceutical supply chain scheduling that when the supply and distribution capabilities are tight, the proportion of external emergency procurement costs in the total cost exceeds 15%. If community demand can be predicted more accurately, the external procurement ratio can be significantly reduced. The study also found that, compared with the distribution capacity, the supply capacity has a greater impact on the total cost—under the same distribution capacity, the cost gap between different supply capacities exceeds 10%, while the cost gap between different distribution capacities is less than 5%.

4.2. Environmental performance impact

Under the background of low-carbon transformation, the impact of uncertainty on environmental performance has attracted increasing attention. The research by Li Wenqiang et al. (2025) shows that in a distributed flexible workshop, quality inspection disturbances will trigger rescheduling, and different rescheduling strategies have significant differences in the impact on carbon emissions. The carbon emissions calculation covers four dimensions: machine load energy consumption, transportation equipment energy consumption, coolant consumption, and lubricant consumption. After optimization by the hybrid memetic algorithm, the carbon emissions can be significantly reduced on the premise of meeting production constraints. Guo Junhua and Miao Wanying (2026) found in the multimodal transport research that as the robust level parameter rises from 0 to 1.0, the total transportation cost increases by about 23.5%, and the coefficient of variation of carbon emissions is generally above 65%, indicating that carbon emissions are most significantly affected by external disturbances, higher than the cost and time

dimensions. Yang Xudong et al. (2026) found in the integrated energy system of a high-altitude construction park that through the transformation of waste oxygen-rich combustion cogeneration units, the system carbon emissions can be reduced by 35.2%; through the transformation of hydrogen-blended gas boilers, it can be further reduced by 2.4%; after introducing the demand response mechanism, the carbon emissions are reduced by 44% compared with the baseline scenario. However, the uncertainty of wind and solar power generation will significantly affect the operating efficiency of carbon capture equipment, and thus affect the system's carbon emission level. Cheng Shan et al. (2026) found that compared with the deterministic method, the distributed robust optimization method reduces the amount of abandoned wind and light by 36.4%. but more shared energy storage services need to be purchased to balance the output uncertainty, reflecting the trade-off between environmental benefits and economy.

4.3. Heterogeneity and non-linear effects

The impact of uncertainty on scheduling performance is not evenly distributed but shows significant heterogeneity and nonlinear characteristics. In terms of nonlinear effects, Yao Zongyu et al. (2026) found that as the conservatism level T increased from 1.5 to 3.5, the solution robustness of the robust optimization strategy decreased from 11.94% to 6.18%, but the qualitative robustness decreased from 100% to 97.73%, and the robust cost increased from 1.06% to 2.89%, showing a trade-off relationship of this rise and fall. In the dimension of risk level, as the fluctuation range of sub-process duration increased, the completion rates of all three strategies decreased, but the decrease rate of the robust optimization strategy was much smaller than that of the deterministic strategy, indicating that the robust optimization has stronger anti-interference ability in a high-risk environment. In the dimension of the type of duration distribution, the robust optimization strategy performed best under the right-skewed distribution and worst under the left-skewed distribution, indicating that the effectiveness of the robust optimization strategy is closely related to the distribution form of uncertainty. In terms of heterogeneity, Ma et al. (2024) found that the multi-stage stochastic programming model is much more sensitive to the number of stages than to the number of communities because the non-expected constraints increase exponentially with the number of stages. When the number of stages T increased from 3 to 4, the commercial solver could no longer find the optimal solution within 7200 seconds, while the progressive hedging algorithm could still solve it efficiently. Guo Junhua and Miao Wanying (2026) found that the Pareto frontiers of the three objectives of cost, time, and carbon emissions showed a clear trade-off pattern of "the iron-water combined transport is the most cost-effective, the all-road transport is the most time-effective. and all railway transport is the most emission-effective, and there were significant differences in the optimal transport paths under different values.

4.4. Comprehensive Benefits of Uncertainty Handling

Although handling uncertainty brings additional computational costs and conservatism costs, the existing literature consistently shows that its comprehensive benefits are significant. In the comparative experiment of highway projects, Yao Zongyu et al. (2026) found that the robust optimization strategy can insert time buffers at more critical positions, which is more conducive to resisting risk interference compared with the robust project scheduling method based on artificially designed robustness indicators. Cheng Shan et al. (2026) found that the distributed robust optimization can reduce the scheduling cost by about 15% while ensuring robustness compared with the traditional robust optimization, and can improve the robustness by about 20% compared with the stochastic optimization, verifying its advantage in balancing economy and robustness. The Monte Carlo simulation of Yuan et al. (2021) showed that the robustness level of the distribution - robust model based on the Wasserstein fuzzy set is higher than the preset 95% confidence level, while the deterministic model is only 50.1%, the Gaussian chance-constrained model is 81.8%, and although the robust uncertain-set model reaches 100%, the cost is about 40% higher. This shows that the distributed robust optimization achieves a robustness level close to the most optimistic situation at a moderate cost.

5. Summary and Outlook

Generally speaking, existing studies have reached relatively consistent conclusions in three aspects. At the measurement level, uncertainty can be characterized from two dimensions: parameter fluctuation and event perturbation. The former is applicable to ex-ante absorption optimization, while the latter requires the design of an ex-post response mechanism. At the method level, a method spectrum from conservative to flexible has been formed from fuzzy programming to distributionally robust optimization. Among them, distributionally robust optimization has become the mainstream framework that takes into account both robustness and economy due to its unique advantage of combining historical data and worst-case analysis. At the solution level, metaheuristic algorithms are still the main tools for dealing with large-scale scheduling problems, while data-driven methods such as deep reinforcement learning show increasing competitiveness in dynamic real-time scheduling scenarios.

Looking ahead, the following directions are worth in-depth exploration:

First, the coupled modeling of multiple uncertainties. In practical scenarios, there are often multiple heterogeneous uncertainties, such as parameter ambiguity, event randomness, information incompleteness, etc. - How to characterize and efficiently solve them under a unified modeling framework remains an important challenge. Especially in the distributionally robust optimization framework, how to construct a fuzzy set that can accommodate multi-source uncertainties simultaneously is a

theoretical issue to be further explored.

Second, multi-agent games and distributed decision-making. In systems such as supply chains and multi-microgrids, the goals of each participant are different, and the information is dispersed. How to combine uncertainty optimization with game theory and distributed optimization to design a decentralized scheduling mechanism is an important direction for future research. Cheng Shan et al. (2026) have conducted preliminary exploration in this regard, but there is still a lot of work to be done on uncertainty propagation and equilibrium analysis under the master-slave game framework.

Third, digital twin and online learning. Combining digital twin technology to build a high-fidelity mirror of the physical system and using online learning algorithms to continuously update the scheduling strategy according to real-time data streams is the key path to achieving the autonomous intelligence of the system. The FPN-DRL framework of Jin Yihui and Dong Baoli (2026) provides a reference idea for this, but how to extend this framework to larger-scale industrial scenarios still requires further research.

Fourth, scheduling optimization for sustainability. Under the drive of the "dual carbon" goal, coordinating the optimization of environmental indicators such as carbon emissions with uncertainty and economic goals has become an important direction for scheduling research. Li Wenqiang et al. (2025) and Guo Junhua and Miao Wanying (2026) have conducted exploration in this field, but how to achieve the Pareto optimality of the economic-environment-social three-dimensional goals under different types of uncertainties still requires more systematic research.

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