Operation Optimization of Complex Industrial Processes

Subjects: Engineering, Industrial
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The operation optimization of complex industrial processes is a dynamic multi-objective optimization problem. These problems cover industrial areas such as steel, chemicals, and energy. Specifically, they address operation optimization problems under uncertain environments in production processes, with production metrics as the optimization objectives and controllable variables as the decision variables. They consider changing factors in production processes, operational metrics, and constraints on production metrics, establishing dynamic models for solving these problems. Unlike static models, these objectives and constraints change over time, similar to how the Pareto set (PS) and Pareto front (PF) in dynamic multi-objective optimization problems (DMOPs) can change over time.

Keywords: complex industrial processes ; operation optimization ; data-driven ; dynamic optimization ; industrial systems ; combinatorial optimization problem

1. Introduction

In reality, this is a challenging problem because researchers cannot easily create the dynamic models for relevant operating variables. Traditionally, controllers in various complex industrial systems are based on mechanism models. Therefore, dynamic control strategies often rely on the dynamic characteristics of mathematical models of physical systems. Given the dynamic features of a particular system, different control systems can be designed to counteract disturbances applied to the system. This operation simplifies external interferences in industrial systems through assumptions, which are then extended to complex nonlinear systems. However, these approximations and simplifications could be more practical and limit the performance of these systems. Due to the complexity of industrial production processes, traditional mechanism modeling methods are no longer sufficient to provide references for the dynamic optimization and control of production processes. Therefore, establishing dynamic models for the optimization of operational metrics in complex industrial production processes, while ensuring production objectives and promptly optimizing control when the system undergoes dynamic changes, has become an urgent problem in the current context.

The emergence of the big data age has somewhat mitigated the difficulties associated with dynamic multi-objective optimization problems. With the advancement of industrial automation, many sensors are being applied in complex industrial processes. Massive industrial data are crucial in industrial control, leading industrial informatization and intelligence developments. These data are integrated into various aspects of industrial design, processes, production, and management, enabling intelligent functions such as description, diagnosis, prediction, decision-making, and control in industrial systems. In reference [1], combining the advantages and applications of data-driven methods with the benefits and necessities of dynamic optimization has been emphasized. This integration supports the secure and rapid development of complex industrial systems. It not only enables high-precision and real-time predictions but also forms the application foundation for the dynamic operational optimization of future industrial systems. Specifically, recent issues in industrial systems include state monitoring and fault detection for system equipment, the prediction of critical parameters in the production process, and the monitoring and prediction of product quality, among others. Data-driven modeling and dynamic optimization control of problems in industrial production processes through the analysis of historical or real-time measurement data have gained widespread attention across various industries. References [2][3][4][5] systematically summarize data-driven predictions in different industrial systems, revealing the characteristics and effects of various prediction methods in different industrial sectors. These prediction methods have played a significant role in the dynamic optimization and control of complex industrial processes. They can enhance the production safety index in industrial processes, reduce the maintenance and operation costs of industrial equipment, and improve industrial production efficiency.

In addition, system dynamics is also an effective solution for handing complex industrial processes. Its core is to model and analyze the feedback loop and time delay in the system to reveal the inherent dynamic behavior and complexity of the system. That is to say, system dynamics pays more attention to the dynamic characteristics of the whole and the interaction between the elements, which is the key to determining the behavior of dynamic systems. Different from the traditional modeling methods, system dynamics considers the influence of the time delay of a decision or action on the system so that it can be used to deal with complex dynamic behaviors such as nonlinearity and historical dependence. However, system dynamics models usually require a deep understanding of the system's internal structure and dynamic behavior. This requires specialized knowledge and skills, and building such a model can be complex and time-consuming. Therefore, verifying a system dynamics model is usually difficult because it requires complex simulations and experiments. In summary, although the results of system dynamics models usually have good interpretability, it may be more difficult to establish these models when the internal structure and dynamic behavior of a system are very complex.

Data-driven control strategies are different from system dynamics. Data-driven methods can usually learn patterns directly from a large amount of historical data without the need for in-depth understanding of the internal structure and dynamic behavior of a system and are more suitable for dealing with problems such as large amounts of data, high dimensionality, and complex internal structures. Their emergence has rapidly transformed the direction of the traditional industrial control field. This transformation has helped overcome the inherent limitations of mechanism models when applied to dynamic optimization problems, reducing the control system's dependence on the internal structure of traditional models. Additionally, due to the abundance of data, numerous heterogeneous data sources, and the temporal properties of data, data-driven strategies have found widespread application in complex industrial processes such as petrochemicals and steel metallurgy. Currently, it has become common practice to combine data-driven strategies with traditional multi-objective optimization methods to address these new dynamic optimization challenges, and the latest developments in this field are summarized in references [6][7][8][9]. Given the backdrop of industrial big data, these references provide strategies for dynamic data-driven optimization. Researchers like Jin and Wang have discussed the importance of dynamic data-driven optimization in industrial production processes, emphasizing real-time model updates, which serve as a reference for future work in dynamic data-driven optimization.

From the perspective of rapidly increasing data volumes, early industrial processes typically employed mechanism modeling methods. As the volume of data grows beyond a certain extent, models that combine mechanism analysis with data-driven approaches tend to be more accurate than traditional mechanism models. In recent years, industrial big data technologies have experienced rapid development, leading to a significant increase in data volumes. Using data-driven models and methods can produce good results.

2. Review of Dynamic Problems in Complex Industrial Processes

Many factors in complex industrial systems, such as solid nonlinearity, multivariable coupling, dynamic changes in operating conditions, and unknown industrial progress and processes, make further control and optimization of industrial systems very difficult. Different industrial systems have different priorities and evaluation indicators; specific analyses are needed for different industrial processes. Therefore, understanding the production process of complex industries and analyzing it independently and in a customized manner plays an essential role in the monitoring, control, and optimization of complex industrial systems.

Taking an industrial process in a complex industry as an example, this research analyzes and discusses different industrial production processes and puts forward operation optimization problems in different processing industries. In recent years, with the rapid development of the industrial Internet, the scope of application of industrial data modeling is expanding. With the deepening concentration of data analysis, the scope of application of data-driven modeling is also developing towards diagnosis and prediction. From the initial solution of energy consumption problems to the predictive maintenance of production equipment to the optimization of production processes, data-driven modeling plays a vital role. **Figure 1** is the application of data-driven modeling in complex industrial processes under the rapid development of data volumes.

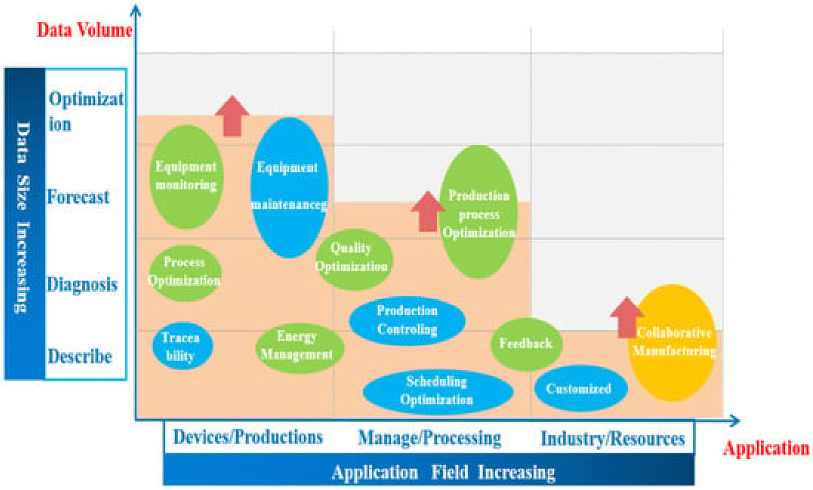

Figure 1. Application of data-driven modeling in complex industrial processes.

Industrial systems are becoming increasingly complex, and safety-related accidents occasionally occur. Significant hazards and frequent accidents highlight the necessity of condition monitoring. The complex industrial model based on data-driven optimization refers to equipment operation data such as for manufacturing, processing, equipping, and testing as part of the production process. It then extracts these data by establishing real-time and comprehensive data acquisition systems. The data are aggregated, calculated, and analyzed in the cloud. This enables condition monitoring, early warning prediction, and industrial equipment performance optimization. The rapid development of big industrial data is significant for controlling and optimizing complex industrial production processes.

Table 1 shows that monitoring and controlling issues in complex industrial processes have become increasingly crucial in recent years. In the steel industry, most scholars focus on enhancing the quality of strip steel, specifically improving steel performance. The pressing need is to increase production efficiency while ensuring steel quality. In the chemical industry, researchers primarily concentrate on predicting crucial parameters in chemical production processes and the safe and rational management of chemical pollutants. Clearly, process control in the chemical industry is vital for energy conservation and enhancing production efficiency. Simultaneously, the safe disposal of chemical pollutants is a significant concern. Most researchers are interested in petroleum production and dynamic risk prediction. As a critical energy source promoting rapid development, petroleum necessitates ensuring safe production while maintaining production efficiency. This leads to researchers addressing issues related to fault detection in oil extraction equipment and oil quality monitoring, proposing corresponding solutions. Additionally, with the growing environmental awareness of industrial processes, wastewater discharge and treatment in the petroleum and chemical industries have become crucial aspects worthy of attention.

Table 1. The research status of complex industrial systems.

Reference Resources	Published Time/Year	Research Problem
Cao [10]	2021	Stress–strain produced by steel heat
Wang [11], He [12], Liu [13], Sala [14], Song [15], Fang [16], Xin [17]	2014–2023	Prediction of molten steel temperature
Zhou [18], Wang [19], Zang [20]	2022–2023	Prediction of oxygen demand
Wang [21]	2017	Prediction of ladle furnace temperature
Takalo-Mattila [22], Chen [23], Li [24], Wu [25], Zhao [26], Xie [27], He [28], Boto [29], Chen [30], Xu [31], Orta [32], Carneiro [33], Wang [34]	2021–2023	Prediction of steel properties
Zou [35], Feng [36], Liu [37], Wang [38], Qian [39]	2021–2023	Prediction of molten steel composition
Wang [40]	2022	Energy efficiency
Lee [41]	2021	Motor equipment load
Huang [42], Yu [43]	2022–2023	Modeling and prediction of inventory change

Reference Resources	Published Time/Year	Research Problem
Zhou [44], Esche [45], Zhu [46], Li [47], Bouaswaig [48], Zhong [49]	**2020–2023**	**Prediction of key process parameters**
Bai [50]	**2023**	**Fault monitoring of chemical process equipment**
Ye [51], Zeng [52], Gatlan [53], Rico-Rodriguez [54]	**2020–2022**	**Emission and utilization of pollutants**
Zhu [55], Rau [56], Zang [57]	**2021–2023**	**Prediction of energy efficiency**
Chen [58], Furrer [59], Han [60]	**2020–2023**	**Prediction of chemical production**
Liu [61], Liu [62], Chai [63], Mamudu [64], Tariq [65], Zhang [66], Keramea [67]	**2021–2023**	**Prediction of reservoir production and dynamic risk**
Ahmad [68][69], dos Santos [70], Tan [71], Yin [72]	**2020–2022**	**Discharge and utilization of petroleum wastewater**
Guzman [73], He [74]	**2021–2023**	**Detection of oil quality**
Mamudu [75], Yang [76]	**2022–2023**	**Fault monitoring of oil production equipment**
Subasi [77], de Moura [78], Zhao [79], Jiang [80]	**2020–2023**	**Prediction of oil reservoir permeability**

However, efficiency is crucial while striving to simplify processes and reduce operational costs. Pursuing higher efficiency can sometimes conflict with achieving the required production quality. Therefore, striking an appropriate balance is crucial. Moreover, production processes often face a trade-off between efficiency and resource utilization. Maximizing efficiency might lead to increased resource consumption, whereas prioritizing resource conservation may negatively impact overall productivity. Ensuring sustained, high-quality production while minimizing resource consumption is a significant challenge. Addressing these challenges requires complex, intelligent technologies and optimization methods. Artificial intelligence, machine learning, and advanced control algorithms are critical in analyzing complex data from various devices and providing real-time insights into the production process. By leveraging these technologies, industrial factories can optimize their operations, make data-driven decisions, and balance efficiency, quality, and resource utilization.

The combinatorial optimization problem in the industrial production process must also be discussed. Combinatorial optimization problems involve finding the optimal solution in a set of possible solutions. These problems usually involve scheduling, path selection, resource allocation, and other aspects, which are the critical problems to be solved in industrial production processes. Due to the variability in customer demands, hybrid manufacturing systems (HMSs) have gained interest from academic and industrial sectors. An HMS, which merges traditional manufacturing units with functional areas, enhances adaptability in terms of fulfilling customer requirements. For example, in production scheduling, it is often necessary to determine the order and time of production to maximize production efficiency or minimize production costs. This involves a typical combinatorial optimization problem: arranging the order and time of production to achieve the optimization goal under the given production task and resource constraints. Omer Faruk Yilmaz et al. [81] explored a multi-objective scheduling problem in HMS and proposed an optimization model to achieve three objectives: (i) minimization of average flow time, (ii) reducing the maximum number of workers, and (iii) minimization of the maximum number of workers changing. Later, Omer Faruk Yilmaz et al. [82] studied an integrated dual-objective u-shaped assembly line balancing and part-feeding a problem based on the heterogeneity of workers. An optimization model was established to express the problem to be solved. Experiments show that by improving workers' skill levels, the quality of Pareto optimal solutions increased by 30% in comparative indicators.

In summary, the data-driven dynamic multi-objective optimization method can be combined with combinatorial optimization techniques to find the optimal solution that satisfies multiple optimization objectives by searching and learning from many possible solutions. At the same time, dynamic optimization can also deal with time-varying optimization problems so that the solution can adapt to changes in the production environment. Therefore, incorporating combinatorial optimization problems into a data-driven dynamic multi-objective optimization framework will help us better understand and solve practical industrial production problems.

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