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Research on the Application of Intelligent Algorithm in the Balance Optimization of Manufacturing Production Line

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Abstract: Against the backdrop of the manufacturing industry's transformation toward flexibility and intelligence, production line balancing optimization has become a core objective for improving production efficiency and reducing operational costs. Traditional balancing methods rely heavily on static analysis and empirical decision-making, leaving them unable to accommodate production scenarios featuring multiple product variants, small batch sizes, and short delivery cycles. This paper systematically reviews the core optimization objectives and constraints of production line balancing problems, analyzes the underlying mechanisms and implementation pathways of mainstream intelligent optimization algorithms—including genetic algorithms, simulated annealing, particle swarm optimization, and ant colony algorithm in production line balancing, and discusses the advantages and limitations of different algorithms in combination with specific scenarios such as bottleneck station identification, cycle time optimization, and operation element allocation. Through case comparison and application effect analysis, the remarkable results of intelligent algorithms in reducing production cycle time, improving linebalance rate, and enhancing flexible response ability are revealed, providing theoretical basis and practical reference for manufacturing enterprises to achieve dynamic balance and intelligent scheduling of production lines.

Keywords: Intelligent Algorithm; Production Line Balance; Manufacturing; Optimize Scheduling; Genetic Algorithms; Industrial Intelligence

1. Introduction

1.1 Background of the Study

Since the launch of reform and opening-up, China has established a complete industrial base, but in the context of intensified global competition and increasing downward pressure on the economy, the traditional manufacturing industry is facing severe challenges of transformation and upgrading Strategy, the inevitable requirement to promote the overall development of the manufacturing industry towards high-quality development. Manufacturing enterprises mostly adopt assembly line production mode, decompose the entire production process into several processes, according to the sequence and process for production, each process has special personnel responsible for operation and management, can reduce waste and repetitive labor in the production process, and improve production efficiency. However, after subdividing the operations, the imbalance of the work load of each station is unavoidable in practice, which further leads to the reduction of production efficiency of enterprises. Line balancing has always been at the heart of assembly line optimization research, and many companies are aware of its importance and have set up an Industrial Engineering (IE) department to be responsible for the fine management and continuous optimization of the production site. In recent years, the application of computer simulation technology in the manufacturing industry has provided a powerful tool for production line balancing, which can simulate the operation of the production line in a virtual environment, intuitively understand the problems of the production line without actual operation, and then conduct more targeted analysis and optimization of the production line.

The goal is to reasonably allocate the operation content of each process under the premise of meeting the priority of operations and resource constraints, so as to balance the load of the workstation and minimize the production cycle, so as to improve equipment utilization, reduce work-in-progress inventory, and shorten the production cycle. In the traditional mass production mode, the production line balance mostly relies on industrial engineering methods, and relatively static balance is achieved through process analysis, time measurement and empirical adjustment. However, with the increasing personalization of market demand and the acceleration of product iteration, traditional rigid production lines have been difficult to adapt to the manufacturing environment with multi-variety mixed flow production and frequent order fluctuations, and the production line balance problem has gradually evolved to dynamic, random and multi-objective optimization.

In recent years, intelligent technologies—represented by artificial intelligence, big data, and the Internet of Things—have been gradually integrated into manufacturing systems, offering new methodologies for balancing optimization. With its self-learning, adaptive and strong optimization capabilities, the intelligent optimization algorithm can efficiently solve large-scale, nonlinear and multi-constraint combinatorial optimization problems, and shows significant advantages in dynamic scheduling, resource allocation, bottleneck resolution and other aspects. Focusing on the concrete applications of intelligent algorithms in production line balancing, this paper elaborates on their optimization mechanisms, applicable scenarios, and implementation pathways, in order to provide decision-making support for manufacturing enterprises to achieve intelligent production scheduling and lean production.

1.2 Significance of the study

The global manufacturing industry is experiencing the fourth industrial revolution with "intelligent manufacturing" as the core. As the core carrier of manufacturing systems, production line operational efficiency directly determines enterprise competitiveness. Statistics show that the imbalance of the production line can lead to a 15%~30% reduction in equipment utilization, an increase in work-in-progress inventory by more than 20%, and an extension of the delivery cycle by about 25%. Therefore, line balance optimization has always been the focus of research in the field of industrial engineering and production management.

With consumption upgrading and competition intensifying, the production mode of enterprises has gradually shifted from "production to sales" to "sales and production", and a production line often needs to handle multiple types of products at the same time. Traditional balancing methods based on static beats and fixed processes are difficult to cope with practical challenges such as frequent line changes, process conflicts, and fluctuating working hours. Intelligent algorithms provide more flexible and efficient solutions for production line balancing through simulation modeling, real-time data perception and dynamic optimization, which has become an important technical direction for the current smart factory construction.

2. Overview of Production Line Balance Problems

2.1 Overview of Production Line Balancing

Line Balance refers to the reasonable adjustment of the process and the balanced distribution to each station of the production line, so that the production time of each station is as equal as possible, so as to reduce unnecessary waiting time in the production process and improve the production line production efficiency. According to different classification principles, there are many types of production lines, for example, according to different processing objects, they can be divided into single-variety, multi-variety, and mixed variety production lines. Regardless of the classification principle, the production line has common basic characteristics: first, the production line should try to make the running time of each station the same to avoid wasting time; second, arrange according to the priority relationship of the process, and reasonably correspond the process to each station; Third, the production rhythm of each station on the production line is similar, and the processing time of each station cannot exceed the cycle time of the production line to prevent the accumulation of tasks in the production process. Fourth, generally speaking, most of the products on the production line are single varieties or fixed multi-varieties, and the production process is basically the same, and the process on each station is basically fixed. Production line balance is crucial for the entire production line and even the enterprise, if the production line is not balanced, it will reduce production efficiency. Solutions to the Assembly Line Balancing Problem (ALBP) generally start with in-depth analysis of existing line processes, with continuous improvement implemented based on analysis results Production line balancing is a process of continuous optimization, and the balanced and optimized production line will inevitably generate new bottleneck stations, which is an object that needs to be continuously optimized.

Depending on fixed preconditions and optimization objectives, ALBP can be divided into three classic categories. ALBP-I.: The production cycle rate remains unchanged, and the minimum number of stations is calculated when the constraints are met. Design your production line by considering how to achieve maximum production efficiency with the least cost, how the production capacity of the production line can meet market demand, and maximize production efficiency. The forecast information of known market demand at this stage is equivalent to finding the minimum number of workstations given a given cycle time. ALBP-II.: Given a fixed number of workstations, the objective is to minimize the line takt time while satisfying all constraints. This applies to the operational phase, where large-scale equipment relocation or layout adjustment is impractical, and efficiency gains must come from runtime compression. ALBP-III.: Given fixed workstation counts and takt time, the objective is to further equalize workloads across stations. This line balancing process includes longitudinal and horizontal balancing, I.E. minimizing the load variance between stations and minimizing the load variance of different products passing through the same station. Through longitudinal balance, the production time between different stations is the same as much as possible; Through horizontal balance, the load of different products through the station is as close as possible to reduce the fluctuation of production time in the station.

2.2 Traditional Balancing Methods and Their Limitations

Traditional methods such as heuristic rules, mathematical planning, simulation analysis, etc., are classic tools for manufacturing system optimization, and have strong practicability and effectiveness in single product and stable cycle scenarios. Among them, heuristic rules rely on the principle of priority allocation formed by experience summary, which can quickly obtain feasible solutions. Mathematical planning has a theoretical rigor at the theoretical level by establishing an accurate model to solve the optimal allocation scheme. Simulation analysis can effectively evaluate the performance of different configuration schemes by simulating the operation process of the production line. However, as the manufacturing industry shifts towards multi-variety, low-batch, and customization, these traditional methods exhibit significant limitations in navigating complex production environments:

Firstly, traditional methods rely heavily on fixed working hour data and static parameter assumptions, making it difficult to adapt to the common fluctuations in working hours in actual production. In the real production environment, the operating time is affected by multiple factors such as worker proficiency, material supply status, and equipment status, and there is a certain degree of randomness. However, traditional optimization methods usually use fixed standard working hours for calculation, which cannotreflect this dynamic change, resulting in deviations in the optimization results during actual execution and greatly reducing the balance effect.

Secondly, when dealing with multi-variety mixed flow production scenarios, the solution ability of traditional methods is obviously insufficient. Multi-variety mixed-flow production lines need to consider complex constraints such as process differences, switching costs, and priority relationships of different product types at the same time. In particular, mathematical programming methods increase exponentially in solution complexity as the scale of the problem expands, and it is often impossible to obtain a feasible solution within an acceptable time.

Third, the optimization results of traditional methods are mostly in local optimization, and it is difficult to achieve global optimization. Although heuristic rules have high computational efficiency, they are essentially greedy algorithms and are difficult to jump out of the local optimal solution space. Although mathematical planning can theoretically achieve global optimization, when facing large-scale combinatorial optimization problems, approximate solutions often have to be used due to the limitation of computing resources, and it is also difficult to ensure the global optimality of the solution.

Lack of dynamic adaptability: They lack real-time sensing and online adjustment capabilities. When abnormal situations such as equipment failures, emergency orders, and material shortages occur, traditional methods need to re-collect data, build models, and solve them, which is time-consuming and cannot meet the needs of real-time scheduling. However, the frequency of changes in the modern manufacturing environment is accelerating, and the production line needs to have rapid response capabilities, and traditional methods are obviously insufficient in this regard.

In addition, the implementation of traditional methods usually requires the deep participation of professionals, relying on expert experience for model construction and parameter adjustment, which is highly manual and limits the scalability and sustainability of its popularization and application. As production systems become more complex, it is becoming increasingly difficult to rely solely on human experience for adjustments.

In summary, although traditional methods still have their application value in specific scenarios, their limitations are becoming increasingly prominent in the face of dynamic, complex, and changeable modern production environments. This has prompted the manufacturing industry to seek smarter, more adaptive, and more resilient optimization methods, and the rise of intelligent algorithms offers new possibilities to break through these limitations. By integrating real-time data, learning from historical experience, and adaptive adjustment strategies, intelligent algorithms bring new solutions to the balance optimization of production lines, which can better meet the needs of digital and intelligent transformation of the manufacturing industry.

3. Application Status of Intelligent Algorithm in Production Line Balancing

In terms of intelligent algorithms, early researchers can obtain theoretical optimal solutions by establishing mathematical models and using accurate algorithms such as 0-1 integer programming, branch definition method, shortest path method, and goal programming method. However, while exact algorithms guarantee optimality, they suffer from extreme computational complexity: even small-scale problems require oversized models and prohibitively long solving times. To reduce computation time while ensuring solution quality, most subsequent research adopted heuristic and meta-heuristic algorithms, including genetic algorithms (GA), particle swarm optimization (PSO), whale optimization algorithm (WOA), ant colony optimization (ACO), tabu search (TS), and simulated annealing (SA).Relevant advances are summarized as follows:. Yang and Hsu improved the imperial competition algorithm to the global optimization algorithm for the linear equilibrium rate problem, and used the example of steel coil packaging line to verify the advantages of the improved algorithm in accelerating convergence and finding the global optimal solution [1]. Leiber and Reinhart designed a two-layer optimization method through nested genetic algorithms, which takes into account both the selection of production resources and the layout to optimize the balance of the assembly line [2]. Nagy et al established a multi-objective task model based on production efficiency, training, and equipment cost, and used analytic hierarchy process to evaluate each index, and then solved it with a multi-level simulated annealing algorithm [3]. Aydogan et al proposed an improved particle swarm algorithm to optimize the U-line balance problem for the randomness of assembly line task execution time. Multi-objective optimization algorithms are widely used in manufacturing, energy, computing, and other fields, and the Pareto optimal solution is obtained through improved strategies, which provides a strong basis for system optimization [4]. Jing et al. optimized the high output torque and low torque pulsation as the optimization goals, and optimized the response surface method and the multi-objective genetic algorithm MOGA to obtain the optimal structural parameters [5]. Wei took the temperature and pressure drop performance of spiderweb-shaped microchannels as objective functions, used a multi-objective genetic algorithm to generate Pareto solutions, and selected the final optimal solution via the TOPSIS method, significantly improving microchannel comprehensive performance [6]. Liu et al. established the kinematics model and error model of agricultural machinery with the goal of minimizing the comprehensive error, and optimized the Arctic puffin algorithm by using Latin hypercube sampling and fitness memory to optimize the optimized parameters to reduce external interference and improve the smoothness of the pavement [7]. Wen et al.

proposed a new variable-length two-chromosome multi-objective optimization method for large-scale Hadoop cluster virtual machine placement, which designed the two-chromosome structure by combining variable-length chromosomes with non-dominated sequencing genetic algorithms, and introduced two-stage crossover and mutation operations to enhance it To solve the diversity of spatial exploration, this method can effectively respond to dynamic resource requirements and improve the resource management efficiency of Hadoop clusters [8]. Han et al. constructed an upper-level optimization model targeting maximum new energy generation and minimum wind-solar-storage total investment cost, and a lower-level model targeting guaranteed evening peak power supply for receiving grids, and performed multi-objective optimization via the NSGA-II algorithm to obtain the Pareto frontier [9]. Liu et al. improved the standard whale optimization calculation by introducing Tent chaos mapping and adaptive nonlinear dynamic inertia weights to plan the multi-target point path [10]. Li et al. proposed a multi-objective white shark optimization algorithm, established a multi-objective optimization model with edge node computing resource margin and load balancing status as indicators, and solved the load balancing problem of nodes [11]. Defersha and Rooyani developed a two-stage genetic algorithm for solving the problem of flexible workshop scheduling [12]. Abedi et al proposed a multi-population multi-objective memetic algorithm for energy-efficient job shop scheduling considering machine aging effects [13].

4. Challenges and Prospects

4.1 Current Challenges

1. Data Quality and Real-Time Challenges: Key data such as working hours, equipment status, and material supply on the production line have significant volatility and uncertainty. Missing sensor data, transmission delays, or noise issues can lead to algorithm models being optimized based on inaccurate or incomplete "facts", and the resulting scheduling schemes are often discounted or even cause new confusion when actually executed.
2. The challenge of insufficient algorithm generalization ability: Mainstream intelligent optimization algorithms (e.g., GA, PSO) require deep customization for specific production lines' product processes and equipment layouts. This highly scenario-dependent feature makes it difficult for algorithms to migrate directly to other production lines, greatly limiting the feasibility of large-scale replication and promotion.
3. The challenge of the lack of human-machine collaboration mechanism: As a "digital brain", how to effectively integrate the optimization scheme output of intelligent algorithms with the "craftsman experience" of on-site operators is still an unsolved problem. On the one hand, it is difficult for algorithms to quantify and utilize tacit knowledge (such as subtle characteristics of equipment); On the other hand, when algorithmic decisions conflict with human experience or face sudden anomalies, there is a lack of smooth human intervention and arbitration mechanism, which affects the actual acceptance and operational flexibility of the system.
4. The challenge of high cost of system integration: Integrating intelligent algorithm platforms with existing industrial software such as manufacturing execution systems and enterprise resource planning faces complex problems such as inconsistent data protocols, different interface standards, and the need to re-adapt business processes. This leads to long integrated development cycles, high investment costs, and subsequent O&M and upgrades also bring continuous burdens, posing a high technical threshold and financial pressure on many enterprises, especially small and medium-sized enterprises.

4.2 Future Research Directions

1. Dynamic balance driven by digital twins

By building a high-fidelity virtual model synchronized with the physical production line in real time, combined with real-time data and simulation prediction, theproduction line balancecan be changed from a static design to an adaptive process that can be adjusted online and optimized, and can actively respond to various production disturbances.

2. Application of deep learning and reinforcement learning

The deep neural network is used to automatically extract complex features and patterns in production data, and then through continuous interaction between reinforcement learning and the environmenttolearn and evolve optimal scheduling strategies, so as to achieve an adaptive and intelligent balance that does not rely on fixed rules.

3. Multi-objective collaborative optimization

The optimization goal expands from a single efficiency indicator to multi-dimensional sustainable goals such as energy efficiency, human factors engineering, product quality, and cost. Algorithms need to find the best balance between these potentially conflicting goals to maximize the overall value.

4. Cloud-edge collaborative computing architecture

Deploy lightweight models close to the edge of the production line to handle real-time scheduling to ensure immediate response; Perform complex model training and big data analysis in the cloud. This architecture combines real-time control with global optimization, improving the agility and scalability of the system.

5. Conclusion

Intelligent algorithms provide a new way for manufacturing line balance optimization with efficiency, flexibility and strong adaptive capabilities. This paper systematically analyzes the core principles, technical characteristics and applicable scenarios of mainstream intelligent algorithms such as genetic algorithms, simulated annealing, and particle swarm optimization, and combines them with practical application cases in auto parts, electronic assembly and other industries, and verifies its remarkable results in improving the linebalance rate, shortening the production cycle time, and enhancing flexible response. Practice shows that compared with traditional methods, intelligent algorithms can more effectively deal with multi-constraint and multi-objective optimization problems and achieve continuous performance improvement in dynamic environments.

Looking forward to the future, with the deep coupling and integration innovation of the Internet of Things, digital twins, 5Gcommunication and artificial intelligence technologies, the production line balance will move towards a new stage of intelligent development. Its core features are reflected in three aspects: first, real-time perception, through ubiquitous sensor network and edge computing, to achieve millisecond-level data collection and feedback of production status; the second is dynamic optimization, relying on digital twin models and adaptive algorithms to simulate production disturbances in real time and adjust strategies to achieve forward-looking balance; The third is autonomous decision-making, the system will be able to independently generate and execute optimal scheduling instructions based on multi-objective collaboration and reinforcement learning, gradually reducing the dependence on manual intervention.

In the face of this trend, manufacturing companies need to adopt a pragmatic and forward-looking strategy. First of all, it is necessary to deeply analyze its own production mode, product characteristics and existing information foundation, scientifically evaluate the applicability and input-output ratio of different intelligent algorithms, and avoid the blindness of technology selection. Secondly, it is recommended to adopt the path of "overall planning and step-by-step implementation", which can start fromthe pilot of local production lines orspecific links, accumulate data and experience, and then gradually promote it to the whole process. In the process of promotion, it is necessary to simultaneously consolidate the data foundation, improve the standard system and cultivate compound talents. The ultimate goal is to build a dynamic optimal balance between cost control, operational efficiency and market flexibility through the synergistic evolution of technology and management, so as to build the core competitiveness of a future-oriented sustainable manufacturing system.

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