Integrating Digitalized Data and Optimization Method for Automated Production Planning in Sewing Lines

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Abstracts: The current global landscape is undergoing a dynamic evolution marked by the onset of the 4th Industrial Revolution. This epochal transformation emphasizes digital transformation as a revolutionary catalyst, fundamentally reshaping businesses. The research presents the digital transformation in industrial sewing manufacturing by applying the Internet of Things (IoT) devices for comprehensive production data collection from sewing lines, alongside integrating data digitization techniques in the industrial sewing process. Moreover, from the data collected, the article proposes an automatic production planning method based on applying a scheduling problem combined with optimization algorithms. Based on that method, it will improve production management efficiency, competitiveness, and labor productivity, creating conditions for sustainable development and promoting global integration.

Keywords: Project Scheduling Problem, Optimization Algorithm, PSO Algorithm, Digital Transformation

1. INTRODUCTION

The recent landscape of digital transformation within businesses is characterized by a robust implementation, facilitating the optimization of production and business processes, heightened operational efficiency, increased profitability, and enhanced negotiation capabilities with partners to formalize economic contracts. In industrial garment production, possessing information systems for monitoring the production process has evolved into a requisite for foreign partners engaging in economic contracts with enterprises. This phenomenon is expediting the digital transformation within industrial garment manufacturing enterprises. Numerous scholarly investigations have elucidated the factors influencing the digital transformation trajectory in businesses. Specifically within industrial garment enterprises, the efficacy of production is directly influenced by two pivotal factors:

- Intelligent production planning
- Encompassing automated planning based on available resources for executing product sewing contracts
- The integration of Internet of Things (IoT) devices for real-time monitoring of work performance
- Consequently, these factors are catalysts prompting industrial garment enterprises to transform digitally and incorporate information technology into their production and business operations.

The infusion of information technology into production planning orchestrates and optimizes resource utilization, thereby enhancing the efficiency of production and business activities. However, the digitization of pertinent data faces significant challenges due to incomplete data descriptions and ineffective digitization methodologies. Consequently, applying calculation and planning models, especially automated planning, encounters impediments. Consequently, a substantial portion of production planning relies on experiential or manual approaches, leading to inherent limitations in precise quantity calculations and allocating labor, resources, and facilities during production. In industrial sewing, producing finished garments involves multiple stages adhering to the industrial sewing line process.

This article elucidates the digital transformation within garment enterprises, focusing on monitoring and assessing production effectiveness across departments and stages over time. Additionally, it outlines methodologies for digitizing data about industrial garment production lines. Leveraging digital data, the article proposes a scheduling and coordination methodology for production plans, incorporating the application of the project scheduling problem with limited resources (Real-RCPSP). The subsequent sections of the article are structured as follows: Part 2 provides a comprehensive review of research pertinent to digital transformation; Part 3 delineates the methodology for integrating IoT devices in industrial garment production and the process of digitizing data related to industrial product production lines; Part 4 expounds on the scheduling problem employed for coordinating production activities based on the Real-RCPSP limited resource project scheduling problem. Part 5 empirically verifies the Real-RCPSP problem [1,2] using real data collected from TNG company. Finally, Part 6 encapsulates conclusions and outlines directions for future research.

2. RELATED WORKS

Many researchers have dedicated their efforts to investigating and implementing digital transformation in the realms of business and manufacturing with the overarching goal of enhancing production efficiency. Extensive studies have identified key factors influencing the digital transformation process in businesses. For instance, Swen and Reinhard [3] underscored three pivotal factors crucial to the success of businesses' digital transformation: the application of new technology, the integration of information and communication technology in operations, and the digital capabilities of leaders. Concurrently, Reis et al. [4] categorized the essence of digital transformation into three domains: technology, organization, and society. In this context, technology underscores the adoption of new technologies, emphasizing the significance of incorporating Internet of Things (IoT) devices in manufacturing processes. Vogelsang et al. [5] further delineated three overarching groups of factors influencing the effectiveness of digital transformation, encompassing business organization (managers, employees, data, customers), environmental factors (corporate culture, industry characteristics, profession, field of activity), and technological considerations (information technology infrastructure, application of new technology, and information security).

Several research endeavors and authorial groups have emphasized the pivotal role played by information technology infrastructure and strategies for its application in determining the success or failure of businesses' digital transformation. Osmundsen et al. [6] identified information technology infrastructure as one of the eight critical factors affecting digital transformation activities. In contrast, the readiness of human resources for digital transformation was underscored by Marzenna et al. [7]. Muhammad and Anton [8] delved into the impact of new technology changes on the digital transformation process, analyzing adaptability, resource allocation, and innovation capabilities as elements positively influencing implementation.

Research findings [9] indicate that digital transformation in businesses typically involves five primary actors: managers, digital transformation human resources, information technology infrastructure, and variables related to digital conversion, such as digital conversion numbers and services. Information technology infrastructure emerges as a particularly influential factor in determining the outcome of businesses' digital transformation processes.

In the context of smart production planning, the authors in a referenced article [1] addressed the challenge of project scheduling with limited resources, specifically the Real-RCPSP. This problem exhibits unique characteristics that render it particularly suited for the industrial garment production field, wherein constraints on project implementation resources and time are intrinsic to various project stages, notably the execution of product sewing contracts. Notably, the problem's constraints signify that higher-skilled resources (workers) can accomplish tasks in shorter durations or with superior quality. The forthcoming sections of this article will leverage the Real-RCPSP problem in conjunction with authentic product production data to facilitate production coordination planning.

3. DIGITIZE DATA OF PRODUCTION LINES

Digital transformation refers to using digital technologies to reshape business models, creating novel opportunities, revenue streams, and value [10]. In the business context, digital transformation denotes the transition from a conventional model to a digital enterprise, achieved through adopting emerging technologies such as big data, the Internet of Things (IoT), and cloud computing. This transformation extends beyond mere technological integration; it encompasses a fundamental shift in operational methods, leadership approaches, work processes, and corporate culture. At its core, digital transformation involves comprehensively reconsidering how organizations integrate people, data, and processes to generate innovative value. Within the domain of industrial garment production, the digital transformation process involves incorporating and integrating IoT devices. These devices serve the dual purpose of enabling managers to consistently update production progress and facilitating smart production planning, thereby enhancing overall work efficiency.

3.1. IoT Device Integration

Enhancing production efficiency necessitates a nuanced understanding of real-time production progress by managers, enabling them to make timely and informed decisions. In the contemporary industrial textile sector, technological advancements have facilitated the integration of industrial sewing machines with Internet of Things (IoT) devices. This integration allows for the systematic collection of data concerning the production process and the operational dynamics of sewing machines over time. Consequently, it enables a granular assessment of the individualized efficiency of each worker and sewing machine, concurrently facilitating the monitoring of the performance of invested equipment. IoT devices affixed to sewing machines have undergone comprehensive research, development, and deployment across various business sewing lines. An example is the Brother devices [11], which have become widely adopted within the industry. The operational sequence of these devices is delineated through the steps illustrated in Figure 1.

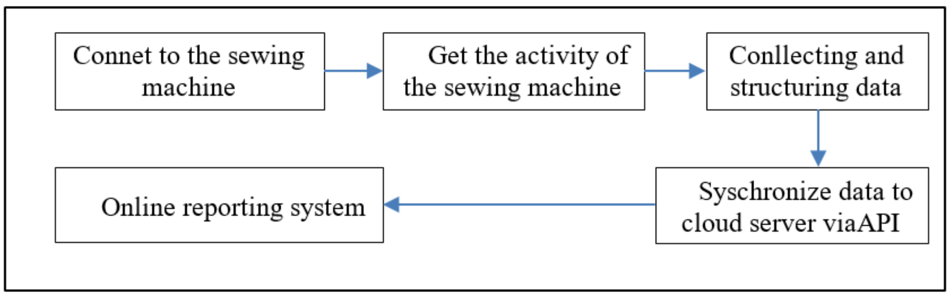

Figure 1. Operational process of Brother IoT device

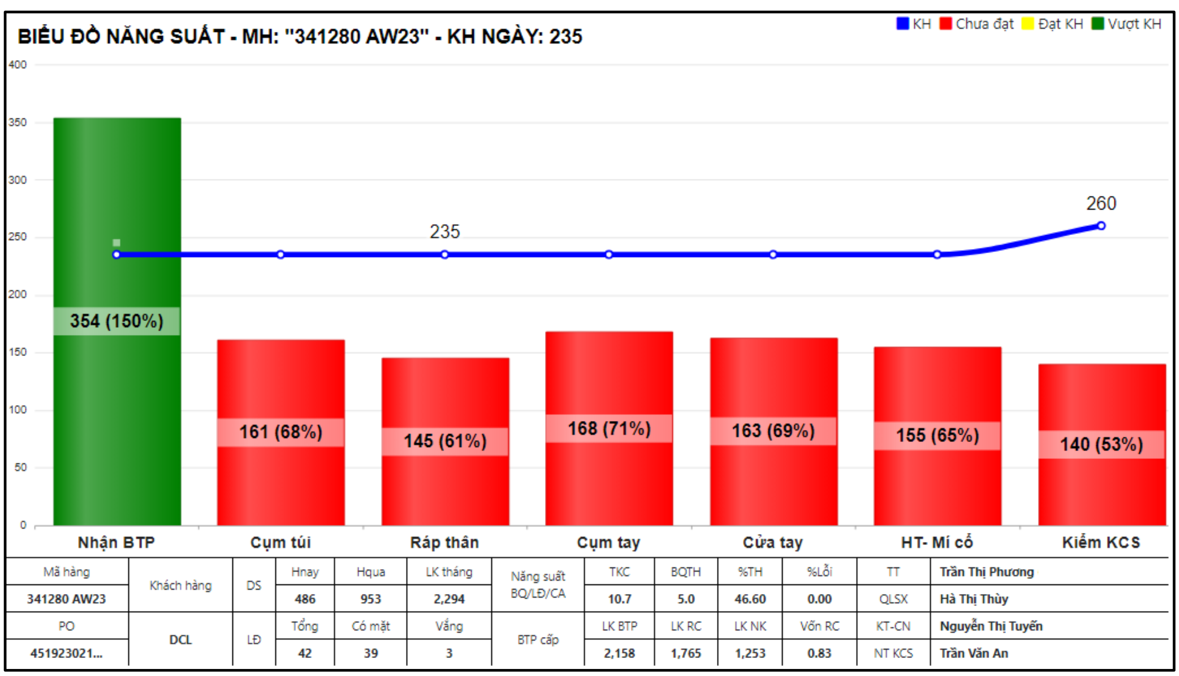

Figure 2. Productivity chart of a sewing line by each stage

The gathered data is transmitted to the Cloud center within the IoT device supplier's system, exemplified here by the Brother device supplier. Manufacturing enterprises can monitor this data through the web interface directly accessible from Brother's system. Alternatively, businesses can develop integrated software to generate customized reports aligning with administrative needs. For instance, they may monitor operational efficiency at specific junctures, such as the conclusion of each sewing line, as depicted in Figure 2. Alternatively, a broader perspective may be adopted to scrutinize the overall operational efficiency of the entire factory, as illustrated in Figure 3. This flexibility allows businesses to tailor their monitoring strategies to meet specific operational and managerial requirements.

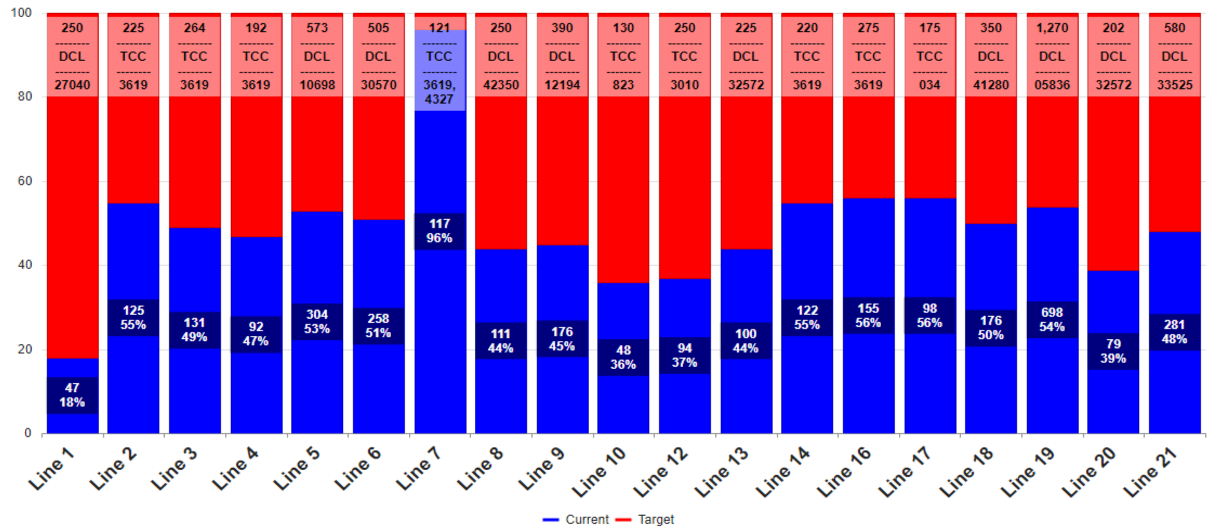

Figure 3. Productivity chart of a company with 21 sewing lines

The integration of data into the Cloud system is achieved through the utilization of application programming interfaces (APIs). The integration process involving IoT data derived from devices, such as those provided by Brother, is carried out using the illustrated steps presented in Figure 4. This delineated sequence underscores the systematic procedures employed to effectively transfer and synchronize IoT-generated data with the Cloud system, ensuring a seamless and structured integration with MIS for comprehensive data utilization.

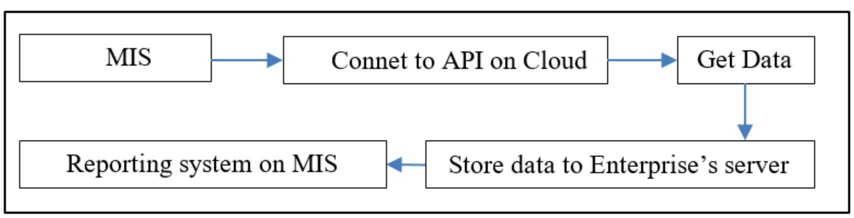

Figure 4. Integrating IoT device data into the enterprise management system

3.2. Production Line Data

Production lines typically operate sequentially, commencing with the processing of input materials at the initial stage and culminating in the creation of finished products at the final stage. Each stage utilizes distinct input materials, and diverse finished products emerge as outputs. Executing a production step necessitates deploying various resources, encompassing equipment, machinery, raw materials, and labor. Significantly, the availability of resources, particularly machinery, equipment, and labor, is often constrained by predefined quantities, and these resources exhibit distinct capabilities.

Consequently, standard production data encompasses the parameters outlined in Table 1 below.

Table 1. Production data parameters

No.	Content
1	Products to be produced
2	Number of products to be produced
3	Number of products in production stage
4	Order of execution of stages
5	Resources needed for each stage
6	Skills (Capability) of Resources
7	Resource type: Resource Consumption (use one time) Renewable resources (machinery, labor, etc.)
8	Capability resource requirements for each stage
9	The execution time of each state of work corresponds to different capacities of the resource
10	The costs

3.3. The Data of Sewing Line

In industrial garment production, fulfilling a contract, particularly involving numerous products of the same type, necessitates the organized deployment of sewing lines to execute the various production stages for the specified product. Each sewing line comprises numerous workers possessing diverse skill levels. The sequencing of sewing stages within a line is systematically arranged based on the priority of the overall production process.

The data associated with each sewing line is fundamental for the manager to formulate a production plan, incorporating details such as contract specifications, labor availability, the qualification of labor, and other pertinent resources. The planning of production on the sewing line is subject to various constraints, as articulated in Table 2 below.

Table 2. Constraints for planning on the horizon

No	Constraint
1	Unique Product Types per Contract: Each contract is associated with a specific product type. This ensures that the production process is tailored to the requirements of a particular product under the contract.
2	Variable Number of Stages per Product Type: Different product types within a contract may entail varying numbers of production stages. This recognizes the unique workflow and complexity associated with each product type.
3	Skill-Specific Worker Requirements: Each stage in the production process requires a worker with a designated skill level. Higher-skilled workers are assumed to perform tasks more efficiently than their lower-skilled counterparts.
4	Skill Level Hierarchy: Workers are categorized into different skill levels, establishing a hierarchy where higher skill levels signify greater proficiency. This hierarchy influences the efficiency and quality of task execution.
5	Priority Relationship between Stages: Stages exhibit a priority relationship, meaning that a subsequent stage cannot commence until the preceding stage is completed. This ensures a sequential and orderly progression through the production process.
6	Worker Assignment Based on Contract: The company has the flexibility to assign workers based on the requirements of each specific contract. This allows for a tailored allocation of skilled resources according to the demands of the contracted product type.
7	Multiple Production Lines (Teams): The company organizes multiple production lines or teams to manage contracts efficiently. Each line operates independently, contributing to the overall execution of the contract. This setup enables parallel processing of different stages or products.

In aligning with the characteristics of sewing line data to apply automatic production planning, the digitization of sewing line data can be orchestrated according to the following rules:

- Project Definition: Each garment contract is treated as a distinct project.
- Task Definition: Each stage of the product within the garment contract is considered an individual task.
- Execution Time: The time required to execute a task corresponds to the execution time of a stage in the sewing line.
- Worker Skill Levels: Workers are categorized into skill levels ranging from 1 to 7. These skill levels directly correlate to the skill levels in the Real-RCPSP (Resource-Constrained Project Scheduling Problem) model.
- Renewable Resource Representation: Each worker is treated as a renewable resource, with each resource possessing a specific skill level in line with the designated worker's proficiency.
- Task Priority: The priority assigned to each stage in the sewing line is construed as the priority of tasks within

the project.

Attaching these rules allows the sewing line data to be effectively digitized and subsequently applied to the Real-RCPSP problem model, facilitating automatic production planning. This digitization ensures a systematic representation of garment contracts, production stages, and associated resources, allowing for efficient scheduling and coordination in the production process.

Example 1:

Digitize data on TNG's garment contracts[17] is shown in Table 3 below.

Table 3. Garment contracts

No.	Contract	Product Type	Product number	Number of task
1	WE1190/1698402 Liner Buy Mar 14-F19	T-shirt	33,693	71
2	FM4013/ 1536181 buy 11/11-F19	swimming trunks	83,340	137

These contracts can be organized by 04 sewing lines with the corresponding number of workers on each line as 37,39,47,41.

By adhering to the guidelines for digitizing sewing line data and contract details presented in Table 3, a standardized dataset conducive to Real-RCPSP problem input is derived, as illustrated in Table 4 below.

Table 4. The dataset of TNG after after digitization

Datasets	Tasks	Resources	Precedence Constraints	Number of skills	Performance time (PT)
TNG1	71	37	1026	6	409
TNG2	71	39	1026	6	325
TNG3	71	41	1026	6	296
TNG4	71	45	1026	6	392
TNG5	137	37	1894	6	1174
TNG6	137	39	1894	6	1052
TNG7	137	41	1894	6	871
TNG8	137	45	1894	6	996

In Table 4, the column *"Performance Time (PT)* " is the total actual contract execution time in hours.

4. THE PROBLEM FOR PRODUCTION SCHEDULING - REAL-RCPSP

The scheduling of projects, economic contracts, or actual production processes invariably encounters constraints such as completion time or the utilization of limited resources. The Resource Constraint Project Scheduling Problem (RCPSP) [12,13] addresses the challenge of scheduling projects with finite resources, a task proven to be NP-Hard, thus precluding the identification of an optimal solution within polynomial time. Employing approximate methods for RCPSP facilitates the discovery of viable scheduling solutions, subsequently reducing project implementation time and cost. The versatility of RCPSP extends to numerous domains, including the economy, military, transportation, and the garment industry.

- A specialized subclass stemming from the RCPSP is the Real-RCPSP problem, characterized by the incorporation of two additional constraints:
- A resource can possess various skills, and each task necessitates an execution resource with the specific abilities to fulfill skill requirements.

A resource matching the task's skill requirements and possessing a higher skill level exhibits superior task performance.

Introducing these two constraints enhances the Real-RCPSP problem's relevance in the planning and executing production processes. The conceptual formulation of the Real-RCPSP problem can be elucidated through the notations presented in Table 5.

Table 5. The notations

Symbol	Description
C_i	The set of tasks need to be completed before task i can be executed
S	The set of all resource's skills S^i: the subset of skills owned by the resource *i*, $S^i \subseteq S$;
S_i	The skill *i;*
t_j	The duration of task *j*
L	The resources used to execute tasks of the project
L^k	The subset of the resources which can be performed task *k*; $L^k \subseteq L$
L_i	The resource i
W	The tasks of the project need to do
W^k	The subset of task which can be executed by the resource *k* , $W^k \subseteq W$
W_i	The task *i*
r^i	The subset of the skill required by task *i*. A resource has the same skill and skill level equal to or greater than the requirement that can be performed.
B_k, E_k	The begin time and end time of the task *k*
$A_{u,v}{}^t$	The variable to identify the resource *v* is running task *u* at time *t;* 1: yes, 0: no;
h_i	The skill level *i*;
g_i	Type of skill *i*;
m	Makespan of the schedule
P	The feasible solution
P_{all}	The set of all solution
$f(P)$:	The function to calculate the makespan of *P* solution
n	Task number
z	Resource number

The Real-RCPSP problem could be state as follow:

$$\mathrm{f(P)} \rightarrow \min \tag{1}$$

where:

$$\boldsymbol{f(P) = \max_{W_i \in W}\{E_i\} - \min_{W_k \in W}\{B_k\}} \tag{2}$$

Subject to the following constraints:

- $S^K \neq \emptyset \quad \forall L_K \in L$ (3)
- $T_{JK} \geq 0 \quad \forall W_J \in W, \ \forall L_K \in L$ (4)
- $E_J \geq 0 \quad \forall W_J \in W$ (5)
- $E_I \leq E_J - T_J \quad \forall W_J \in W,\ J \neq 1,\ W_I \in C_J$ (6)
- $\forall\, \mathbf{W_i} \in \boldsymbol{W^k}\, \exists\, \boldsymbol{S_q} \in \boldsymbol{S^k}:\ \boldsymbol{g_{S_q} = g_{r_i}}$ **and** $\boldsymbol{h_{S_q} \geq h_{r_i}}$ (7)
- $\forall\, \boldsymbol{L_k \in L, \forall q \in m : \sum_{i=1}^{n} A_{i,k}^{q} \leq 1}$ (8)
- $\forall\, \boldsymbol{W_j \in W}\ \exists!\, \boldsymbol{q \in [0,m]},!\ \boldsymbol{L_k \in L}\text{:}\ \boldsymbol{A_{j,k}^{q} = 1}$; **where** $\boldsymbol{A_{j,k}^{q} \in \{0;1\}}$ (9)
- $\boldsymbol{t_{ik} \leq t_{il}}$ **vói** $\boldsymbol{h_k \leq h_l}\ \forall\, \boldsymbol{(r^k, r^l) \in \{S^k \times S^l\}}$ (10)

In the Real-RCPSP problem, each task has additional skill (skill) requirements of the resource needed to perform; each resource is divided into different skill levels.

5. APPLING THE REAL-RCPSP PROBLEM IN INDUSTRIAL SEWING PRODUCTION PLANNING

The Real-RCPSP problem is applied to the digitized sewing line datasets outlined in Table 5 to streamline production coordination in each sewing line. Given that Real-RCPSP falls within the NP-Hard class, and a polynomial-time solution is unattainable, utilizing evolutionary algorithms becomes imperative to derive optimal schedules for each dataset. This study employs the Particle Swarm Optimization (PSO) algorithm [14-16] to ascertain schedules. The outcomes serve as a foundation for formulating a production coordination plan involving allocating resources to execute various stages in industrial garment production.

Integrating the Real-RCPSP problem into the industrial garment production process empowers leaders to devise automated production plans, bypassing traditional manual methodologies rooted in experiential knowledge. The automated production plan is generated dynamically based on input datasets (digitized orders) tailored to the Real-RCPSP problem and the PSO algorithm. Detailed calculations are performed, considering constraints such as labor requirements, execution time, and the quantity of products, thereby enhancing the efficiency and precision of the production planning process.

5.1. PSO Algorithm

Particle Swarm Optimization (PSO) [14-16] is categorized as an evolutionary algorithm. Like its counterparts, PSO conducts a population-based search, initiating with the random initialization of a specified number of individuals within the population. PSO's reliance on two fundamental parameters for each individual in the population sets it apart from other evolutionary algorithms: the position vector (reflecting the individual's experience across generations) and the velocity vector (reflecting the population's collective experience across generations). Each traverses the solution space at a particular velocity. Following each generation, individuals adjust their positions based on the best position attained by the individual in the past and the optimal position of the overall population. This continual adaptation propels the individuals towards more promising search regions within the solution space. The evaluation of each particle in each generation in PSO involves two values: position and velocity. The position is determined as follows:

- $v_i^{k+1} = \omega v_i^k + c_1\, rand_1 \times (pbest_i - x_i^k) + c_2\, rand_2 \times (gbest - x_i^k)$ (11)
- $x_i^{k+1} = x_i^k + v_i^k$ (12)

where:

- v_i^k , v_i^{k+1}: velocity of particle i at generation k and $k+1$
- x_i^k, x_i^{k+1}: position of the particle i at generation k and $k+1$
- ω : inertia weight; c_1, c_2 : speedup coefficients
- $rand_1$, $rand_2$: the values between 0 and 1 randomize generated.
- $pbest_i$: the best position of particle i;
- $gbest$: the best particle position in a population

The detailed implementation steps of the PSO algorithm are shown in Algorithm 1.

Algorithm 1. PSO

Input: $n_{max:}$ the threshold to find local extremal, $t_{max:}$ number of evolution generations.
Output: the best solution g_{best}

Begin
P_{all} ← Init data from iMOPSE dataset and create population.
t = 0
n_f = 0
while (t < t_{max})
t = t + 1
for i=1 to size(P_{all}) do
Caculate the objective value: f(P_i)
end for
for i = 1 to size(P_{all}) do

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            if f(P_i)<f(fitness_i) then
                pbest_i = P_i
                f(pbest_i) = f(P_i)
            end if
        end for
        for i=1 to size(P_all) do
            if(f(P_i) < f(g_best)) then
                g_best = P_i
                f(g_best) = f(P_i)
            end if
        end for
        for i=1 to size(P_all) do
            update velocity vector
            update position vector
        end for
    end while
    return g_best
end
```

f: objective function

5.2. Experimental parameters

The experiment to find a solution using the Real-RPCSP problem and the PSO algorithm is performed with the following parameters:

- Dataset: 08 datasets presented in table 4
- Population size N_p : 70
- Number of generations, N_g : 60,000
- Number of test runs: 20.
- Actual environment: Microsoft Visual Studio 2019, C#

5.3. Experimental results

The test run results can be shown in Table 6 below.

Table 6. Experiment results

Datasets	TNG PT	PSO	Deviating	%
TNG1	409	271	138	33.74%
TNG2	325	246	79	24.31%
TNG3	296	238	58	19.59%
TNG4	392	262	130	33.16%
TNG5	1174	944	230	19.59%
TNG6	1052	949	103	9.79%
TNG7	871	818	53	6.08%
TNG8	996	863	133	13.35%

In Table 6, the "TNG PT" column represents the actual contract performance time (in hours) for TNG Company. In contrast, the "PSO" column signifies the planned execution time (schedule) derived from applying the Real-RCPSP problem model in conjunction with the solution obtained through the PSO algorithm.

Observing Table 5 reveals that employing automatic scheduling through evolutionary methods yields superior contract completion times compared to current practices, showcasing improvements ranging from 6.08% to 33.74%. The variance in execution times can be calculated using a tool, as depicted in the expression illustrated in Figure 5. This demonstrates the automated scheduling approach's efficacy in enhancing the efficiency of the production process.

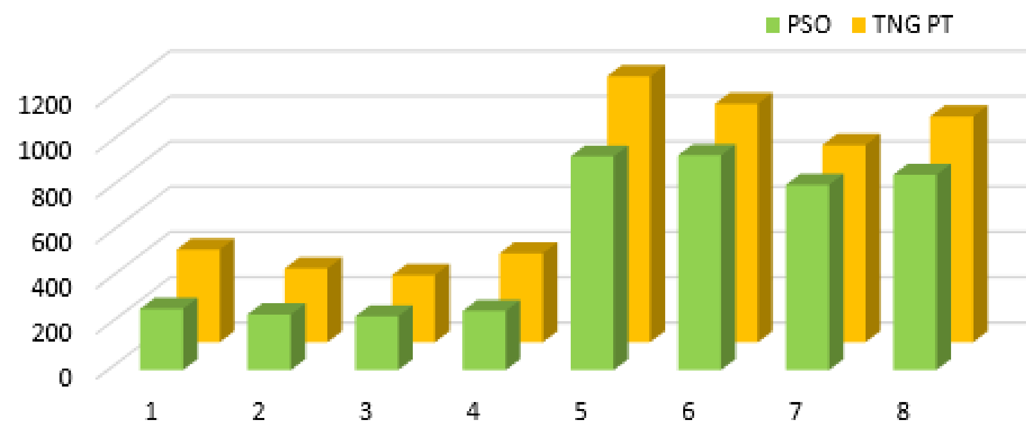

Figure 5. Comparison of execution time between PSO and TNG PT algorithms

The examination's results affirm the feasibility of automatically computing workflow coordination and stage assignments within industrial sewing lines. The industrial sewing data proves to be well-suited for the Real-RCPSP problem model due to the alignment of data and process characteristics. The implementation of an automatic production planning model facilitates the optimization of resources for garment contract execution, leading to a reduction in contract execution time and an enhancement of profits for garment companies.

The automated production planning methodology, grounded in applying Real-RCPSP and approximation algorithms, emerges as an intelligent solution for contemporary production challenges. This approach streamlines production processes and contributes to the growing prevalence of information technology applications in production automation. This trend is anticipated to expand in the foreseeable future.

CONCLUSION

The current era necessitates digital transformation in industrial garment enterprises to enhance the efficiency of production and business activities. Key components of this transformation include integrating IoT devices for monitoring production activities and implementing automatic production coordination planning to streamline the execution of garment contracts. To achieve automated production planning, businesses must digitize their production processes. This paper outlines essential data components for digitization, proposes a process for digitizing production line data, and specifically applies this approach to digitize the sewing line data of TNG company.

In the context of automatic production coordination scheduling, the paper introduces the Real-RCPSP problem and proposes a Particle Swarm Optimization (PSO) algorithm. Experimental application to the TNG dataset demonstrates effective planning, resulting in a notable reduction in contract execution time ranging from 6.08% to 33.74% compared to actual time. Implementing these plans will enhance enterprise profits and operational efficiency, bolstering competitiveness and adaptability in the international business landscape.

Looking ahead, the author plans to explore the Real-RCPSP problem further with practical implementations in various production lines and business enterprises across different sectors. The future work will involve suggesting methods for data digitization in the production process and identifying strategies for deploying automated workflow coordination scheduling systems in manufacturing enterprises.

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