



Research article

Multi-level shipbuilding standard man-hours calculation model for based on four-dimensional interim product features

Lijun Liu^{1,*}, Jiahao Liu¹, Fei Ren¹, Huisong Meng¹ and Zuhua Jiang²

¹ School of Mechanical and Electrical Engineering, Shaanxi University of Science & Technology, Xian 710021, China

² School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai 200240, China

* **Correspondence:** Email: liulijun@sust.edu.cn; Tel:13379302510.

Abstract: In shipbuilding, man-hour is a unit that is widely used for production planning. Refined and flexible man-hour management is a top pursuit of modern shipyards. However, significant inaccuracies are found in current shipbuilding man-hour data. Refinement is urgently required for the accuracy of design physical quantity, production physical quantity and standard man-hour data. Customized construction demands across ship types and scenarios cannot be supported by this man-hour data. To address this problem, the concept of shipbuilding interim products is introduced in this study. On this basis, a multi-level calculation model for shipbuilding standard man-hours based on the multi-dimensional features of interim products was established. A three-stage progressive framework was incorporated into this model. First, a four-dimensional feature system covering “stage, system, type, and zone” was proposed. Systematic correction of the initial design physical quantity was realized with this system. Second, key production factors were integrated into the model, which included personnel skills, equipment status, and environmental parameters. These parameters were defined as temperature, humidity, and noise levels. On this basis, a multi-dimensional production feature matrix was constructed. Matrix mapping and collaborative conversion from design data to on-site production scenarios were completed by this matrix. Finally, an adaptive man-hour calculation system covering the process and multiple scenarios was established. A practical case of the shipyard of WGQ., Ltd. was used to validate the performance of the proposed model. Satisfactory results were achieved in terms of improving the accuracy of design physical quantity, production physical quantity, and standard man-hour data in the shipbuilding process.

Keywords: shipbuilding man-hours; interim products; design quantity; production quantity; man-hour calculation model

Mathematics Subject Classification: 90B50, 90C90, 62P30

1. Introduction

Shipyard production systems are widely recognized as one of the most complex production systems in the manufacturing industry. A large number of parts, diverse workflows, and intensive labor and resource coordination are involved in this process. Accurate man-hour estimation is therefore essential for shipyard operations. Reliable core support is provided by this estimation for production planning, workload balancing, delivery cycle control, and cost management [1,2]. Mature digital man-hour management systems have been established by internationally leading shipyards. Typical examples include Hyundai Heavy Industries and Mitsubishi Heavy Industries. Design, production, and cost data are integrated within these systems. The traceability and execution efficiency of shipbuilding processes are effectively improved by these systems [3,4].

Current international mainstream shipbuilding man-hour management modes present inherent structural defects, failing to fundamentally address full-chain data fragmentation across design, production and man-hour links, and the inadequate coupling of dynamic production factors. Specifically, Japan's lean mode relies heavily on manual experience with insufficient digital construction; South Korea's intelligent system is limited by unbalanced labor structures and closed system architecture; and the U.S. shipbuilding industry suffers from industrial hollowing-out, hindering standard system implementation and production efficiency improvement. Despite continuous scale expansion, China's shipbuilding industry is plagued by imperfect man-hour standards and pervasive data fragmentation. Most domestic large shipyards are in the digital construction transition stage of man-hour data management and modeling, unable to meet the booming customized shipbuilding demands featuring diverse ship types and construction modes. Severe deviations between design and production physical quantities and low man-hour estimation accuracy restrict the refined management and standardized digital development of shipbuilding man-hour data. Multiple factors, including process complexity, workforce competence, and production organization, affect man-hour estimation accuracy, while cross-link data fragmentation and stochastic production interference remain urgent industrial bottlenecks.

To address these problems, a multi-level calculation model for shipbuilding man-hour data is proposed in this study. The concept of shipbuilding interim products is introduced in this study. It is constructed based on the four-dimensional features of interim products, including stage, system, type, and zone. Three core links of shipbuilding are focused on by the model. These links are design physical quantity, production physical quantity, and standard man-hours. A clear and complete full-process data correction system is constructed by the model. Design physical quantity is first corrected by the model. This is achieved through the establishment of a "stage, system, type, and zone" feature association rule base. A full-process design feature linkage management and control system is also built for this purpose. Then, production physical quantity is calculated by the model. This step is supported by a multi-dimensional production feature matrix. Design features and on-site production factors are integrated within the matrix. Finally, man-hour conversion coefficients are calibrated by the model. This calibration is realized through dynamic iterative optimization of historical production data. Adaptive

updates of coefficients across construction stages and scenarios are achieved through this calibration. Accurate and reliable man-hour management support can be provided for modern shipbuilding practices by this model. It should be noted that, at the algorithm implementation level, the model proposed in this paper mainly relies on methods such as rule-base association and regression analysis to complete feature coefficient calibration and physical quantity conversion. It belongs to the fundamental methods of man-hour data standardization and digital management, and aims to lay a reliable data and feature framework for the subsequent deep integration of intelligent algorithms. A complete intelligent decision-making system has not been realized at the current stage.

Inherent limitations are identified in current shipbuilding man-hour estimation models. Single feature dimensions and insufficient ergonomic mechanism support are common defects. Low physical interpretability is shown by pure data-driven black-box models. A complete full-link conversion framework for design, production and man-hour is also lacking. To address these problems, four-dimensional features of shipbuilding interim products are adopted in this study. A three-stage progressive closed-loop man-hour calculation system is established with two innovations:

(1) A calculation method for four-dimensional feature man-hour impact coefficients is proposed. Feature coefficients are assigned by manual experience in traditional studies. Human workload differences from different welding poses and hull zones cannot be accurately quantified. Neuroengineering sEMG techniques are integrated in this research. Multiple nonlinear fitting models are applied to analyze feature man-hour rules. Coefficient assignment is upgraded to integrate mechanism analysis and measured data. This method is used to support the correction model of design physical quantity. Its accuracy gain is verified through the full-sample measured validation in Section 5.

(2) A three-stage closed-loop man-hour prediction model with full human-machine-environment factors is established. Static geometric features are used only in conventional man-hour models. Process physical constraints and interpretability are missing in these models. A multi-dimensional production feature conversion matrix is built in this study. Dynamic on-site factors are embedded into physical quantity conversion links. An interpretable full-process calculation framework is formed. The model's effectiveness is verified by measured shipyard data and multi-model horizontal comparison.

The structure of this paper is arranged as follows: In Section 2, we review relevant research on shipbuilding man-hour/physical quantity management and existing limitations; in Section 3, we elaborate on the framework of the multi-level calculation model (including four-dimensional features of Interim products and the three-stage framework); in Section 4, we explain the operation logic and implementation methods of the model; and in Section 5, we verify the effectiveness of the model through a shipyard case; Section 6 summarizes research conclusions and prospects for future directions.

2. Literature review

2.1. Analysis of domestic and international man-hour management modes in shipbuilding

In this section, we systematically compare the shipbuilding man-hour management models of China, the United States, Japan, and South Korea. The man-hour estimation methods of each country are taken as the core analytical dimension. The technical route characteristics of different countries are sorted out. The structural shortcomings of each management model are analyzed item by item. The common limitations of mainstream systems are summarized. The research gap is thereby clarified, and the research foundation is laid for the model construction in this paper.

Differentiated technical paths have been formed by the four countries in man-hour estimation methods. The static empirical coefficient method is adopted by Japan, relying on lean production and the Integrated Hull, Outfitting, and Painting (IHOP) mode. The estimation results are highly dependent on historical ledgers and frontline on-site experience [5–7]. Data-driven man-hour control is vigorously promoted by South Korea. Neural network prediction systems, PLM big data collection, and automated work observation are taken as the core means [1,8–10]. The highest digitalization degree among the four countries is thereby achieved. The Product Work Breakdown Structure (PWBS) proposed by the NSRP is relied on by the United States [11,12]. Standardized work breakdown is taken as the unified benchmark for man-hour estimation. The empirical judgment of management personnel and rough physical quantity statistics have long been relied on by China's shipbuilding industry [2,13]. Four typical routes are formed through horizontal comparison. Japan follows an experience-static route, and South Korea follows an end-stage black-box route. The United States follows a route of standardized decomposition but disconnected execution. China follows an experience-extensive route. Productivity measurement frameworks in shipbuilding have been developed to quantify construction efficiency [14]. Notably, a full-chain man-hour calculation framework connecting design physical quantity, production physical quantity, and standard man-hours has not been established by any of the four countries.

The structural shortcomings of each country's man-hour management model are further analyzed. Japan's core limitation is reflected in experience solidification and lagging digital transformation. Its shipbuilding man-hour efficiency has long been internationally leading, reaching 9–15 man-hours/CGT [5]. Lean production principles have been systematically applied to shipbuilding project planning [15]. However, experience-based man-hour data are difficult to be standardized and reused across scenarios. Coupling mechanisms for dynamic factors, such as personnel skill fluctuations and environmental losses, are lacked by the estimation system. Moreover, national digital twin research is mostly focused on hull structure simulation, without in-depth deployment for man-hour control [7,16]. South Korea's shortcomings are concentrated in system closure and labor structure imbalance. Mature man-hour prediction and data management solutions are mainly implemented in large shipbuilding groups. Automated work observation systems based on deep neural networks have been developed to support intelligent ship production [17]. They are difficult to be replicated in small and medium-sized shipyards. Strong dependence on overseas labor is shown by the industry. The stability and consistency of man-hour data are continuously disturbed by the persistent shortage of skilled workers [18]. A systemic disconnection between estimation standards and on-site execution is suffered by the United States. The man-hour management system is separated from the production organization process. Significant man-hour differences are shown by the same operation in workshops, open-air platforms, and on-board erection scenarios. Cost overruns of up to 40.7% were suffered by the Ford-class aircraft carrier program. Delivery delays have been generally experienced by naval vessels under construction. Insufficient shipbuilding capacity and labor gaps have been listed as core shortcomings by the U.S. Department of Defense [19–23]. The first global industrial scale is held by China's shipbuilding industry. However, the scale advantage has not been transformed into a man-hour management advantage. Man-hour estimation is still highly dependent on manual experience, and large estimation deviations are caused. The refined control requirements of multi-ship-type and customized shipbuilding are difficult to meet.

The core features and shortcomings of the four countries' man-hour management models are summarized in Table 1.

Differentiated paths have been formed by the four countries based on their respective industrial foundations. However, consistent common shortcomings are shared by them. Man-hour estimation systems of all countries are still mainly driven by static experience. Multi-dimensional features of interim products and dynamic on-site elements have not been incorporated into a unified quantitative framework. The full-chain calculation path of design physical quantity, production physical quantity, and standard man-hours has not been opened. This common limitation is taken as the core research entry point of this paper. Accordingly, a multi-level man-hour data calculation model is constructed in this paper. Multi-dimensional features of interim products are integrated, and the construction chain is run through by the model. The deficiencies of research are thereby made up.

Table 1. Comparative Analysis of Shipbuilding Man-Hour Management Models in Four Countries.

Country	Core Man-Hour Estimation Method	Typical Features of the Model	Main Structural Shortcomings
Japan	Static empirical coefficient method, relying on the IHOP integrated construction system	Experience-static; man-hour benchmarks are derived from historical ledgers and on-site experience; construction efficiency is internationally leading	Experience is difficult to standardize and reuse; coupling of dynamic influencing factors is lacking; the development of digital man-hour systems is slow
South Korea	Neural network prediction, PLM big data collection, automated work observation	High degree of data-driven management; end-stage intelligent prediction with end-stage black-box characteristics	Technical solutions are limited to large shipyards; labor structure fluctuations affect the stability of man-hour data; model interpretability is insufficient
United States	Man-hour accounting based on the PWBS standardized work breakdown structure	Standardized decomposition with a unified benchmark; a well-established industry specification system	Estimation standards are disconnected from on-site execution; man-hour differences across scenarios are not effectively incorporated into control; cost and schedule control risks of shipbuilding projects are prominent
China	Empirical judgment of management personnel combined with rough physical quantity estimation	Experience-extensive; adaptable to various types of shipyards with a low implementation threshold	Estimation is highly subjective with large deviations; a standardized full-chain calculation framework is lacking, making it difficult to support the refined management of customized shipbuilding

2.2. Research progress in shipbuilding man-hour and physical quantity data management

Extensive studies have been conducted on man-hour estimation and physical quantity management in shipbuilding [1]. Scholars mainly carry out relevant research from three dimensions. These dimensions are design physical quantity, production physical quantity, and man-hour coefficient.

Digital technologies are widely used in design physical quantity optimization. Common technologies include CAD and BIM. These technologies are mainly applied to improve data accuracy and visualization. The integration of CAD systems and material quantity evaluation has been verified. This integration effectively improves data extraction accuracy in the design stage [24]. Model-based approaches are also developed for design data optimization. For example, lightweight weld line generation is a typical method. This method further improves the usability of design data. It also provides effective support for downstream production processes [25]. These studies mainly focus on two core links. One is data extraction optimization in the design stage, and the other is data verification in the design stage. Relatively mature digital design workflows have been formed by these studies. However, there are obvious limitations in research. The linkage between design data, production execution, and man-hour estimation is insufficient.

Extensive studies have been carried out for the shipbuilding production stage. These studies mainly focus on production planning, scheduling, and simulation. Simulation-based production planning systems are widely used in shipyards. Discrete-event simulation models are also commonly adopted. These tools are used to optimize shipyard operations and improve production efficiency [4,26]. Advanced planning systems (APS) are applied to production planning. Constraint-based optimization models are also developed for this field. Machine learning-enhanced constraint satisfaction algorithms have been introduced for long-term planning optimization [27]. They are mainly used for long-term and medium-term production planning [28,29]. Production-oriented modeling methods have been proposed in other studies. These methods are based on geometric and process information of ship structures and can achieve more accurate estimations of production metrics [30]. These methods strengthen the connection between design data and production execution; however, they lack integration with dynamic man-hour estimation mechanisms.

Traditional man-hour estimation approaches have been widely used in shipyards. These approaches are mainly based on three types of methods. They are empirical formulas, work breakdown structures (WBS), and statistical analysis [11,12]. However, these methods have obvious limitations: They often lack adaptability in complex and dynamic production environments. With the development of artificial intelligence, new methods are introduced to this field. Moreover, machine learning and data-driven methods are increasingly applied to man-hour prediction. Neural networks, transfer learning and knowledge discovery methods are widely used. These methods show good performance in improving man-hour prediction accuracy [13,31–33]. Artificial neural networks have also been applied to predict maintenance and repair labor in ship-related operations [34]. For example, transfer learning is used to solve small-sample problems in ship block manufacturing [13]. Hybrid neural network models are applied to achieve more accurate design man-hour prediction [33]. Stochastic optimization methods are also introduced to this field. Two-stage stochastic programming is a typical representative, as it is used to deal with uncertainty in ship block production [35]. These approaches improve the robustness of man-hour estimation. However, they focus on specific shipbuilding processes. Full-process integration of shipbuilding links is not achieved in these methods. Two major research trends are highlighted in other studies. The first is the diversification of feature dimensions for man-hour modeling; the second is the intelligentization of man-hour calculation methods. Digital Twin technology is applied in shipbuilding production management, which realizes real-time synchronization between design and production data. It also improves data accuracy and scientificity of production decision-making [36,37]. Shipbuilding 4.0 puts forward new requirements for production management, which emphasizes data integration, production automation, and intelligent manufacturing [38,39]. However, studies have obvious shortcomings. Relevant research on data correlation, real-time monitoring, and feedback mechanisms is in the early stage [40]. The integration of multi-dimensional features is insufficient in existing models. Full-process data correction across design, production, and man-hour links is not realized.

From the perspective of constructing the feature dimensions of interim products, the Product Work Breakdown Structure (PWBS) framework, as a product-oriented work breakdown structure, has implicitly contained the idea of multi-dimensional classification by construction stage, functional system, structural type, and spatial zone, and this framework has been regarded by subsequent research as the basic logic for shipbuilding task decomposition and resource allocation [5,24]. However, the application of these multi-dimensional features in the literature mainly remains at the level of qualitative production management, such as pallet assembly management based on PWBS, operation

zone division under the zone outfitting method, and stage division in lane-based construction [25,26], and a quantitative correlation model between multi-dimensional features and man-hour consumption has not been established. On the basis of the PWBS multi-dimensional classification logic, we, by introducing sEMG ergonomic experiments and multi-parameter fitting methods, transforms “stage, system, type, and zone” from qualitative classification dimensions into quantifiable man-hour impact calculation parameters for the first time, filling the gap in the quantitative application of multi-dimensional features in the field of man-hour estimation.

In summary, significant progress has been made in feature modeling and intelligent man-hour estimation. However, research still lacks a unified theoretical framework. This framework should integrate multi-dimensional features of interim products. It also needs to cover the full-chain data correction of “design-production-man-hour”. Moreover, most researchers focus on isolated shipbuilding stages or single influencing factors. They fail to capture the dynamic interaction between design features, production conditions, and man-hour consumption [40]. Therefore, a systematic, multi-level and adaptive model needs to be developed. This model should realize the integration of multi-dimensional features. It also needs to achieve full-process data correction across the shipbuilding flow. This demand is the core motivation of the research presented in this paper.

3. Framework

In this section, based on the core role of interim products and their multi-dimensional features in the “design physical quantity, production physical quantity, standard man-hour” chain, a multi-level calculation model for man-hour data is proposed in this study. The model is positioned as a closed-loop prediction model with multi-parameter fitting. Four-dimensional features of interim products and dynamic constraints of human-machine-environment are integrated. The goal of model construction is threefold: Data quality improvement at the design end is achieved; conversion adaptation at the production end is realized; and dynamic man-hour estimation at the management end is enabled. A feedback-capable and self-iterative man-hour data calculation system is formed. In this section, only global inputs, intermediate coupling variables, and final outputs are reviewed. Data flow and macro mathematical conversion logic of the three-stage modules are explained. Detailed formulas, parameter calibration, fitting, and iterative derivation are provided in section 4.

3.1. Analysis of interim products and their multi-dimensional features in shipbuilding

Interim products are a classic concept in shipbuilding. Its theoretical origin can be traced to the 1950s. Group Technology (GT) was transplanted into shipbuilding. In the late 1950s, GT was introduced by the Japanese shipbuilding industry. Similarities of parts in process flows were identified. The whole ship was decomposed into “interim product” families, and these families could be processed by similar manufacturing resources. Thus, one-piece small-batch shipbuilding was transformed into group batch production. On this basis, PWBS was proposed by the U.S. NSRP in 1980. Product Work Breakdown Structure (PWBS) was put forward. A methodology for decomposing shipbuilding tasks was systematically described, which was based on the product perspective. An important foundation was laid for modern interim product management systems [8]. Interim products were further explained by domestic scholars. They are defined as “interim assembly units assembled according to process rules with specific functions”. Levels such as parts, components, blocks, and grand assemblies are

covered. They are used as the core carrier of “hull-outfitting-painting integration” and zone shipbuilding [10–12]. With the development of lean and digital shipbuilding, the concept has been expanded. It has been extended from simple physical decomposition units to digital carriers. Process, logistics, and man-hour information are carried by them. Moreover, block-level interim products are focused on in this study, including flat blocks and curved blocks. Complete process connection can be mapped at this level. Appropriate data granularity is also provided. Feature extraction and model operation are facilitated.

A four-dimensional feature system is proposed in this study. It covers “stage, system, type, and zone”. Its classification logic is consistent with the product-oriented decomposition of PWBS. Shipbuilding is hierarchically decomposed by PWBS from the product perspective. Multi-dimensional classification dimensions are implied. These include construction stage, functional system, structural type, and spatial zone [8,9]. However, previous studies have mainly focused on the application of multidimensional PWBS features. However, the application of PWBS multi-dimensional features has received the most attention in the existing literature. Qualitative management research is also a focus. Examples include production planning, pallet management, and schedule control [10,11]. These features have not been introduced as quantitative parameters into man-hour estimation. On the basis of the PWBS framework, a “feature benchmark system” is constructed. Four dimensions are used: Stage, System, Type, and Zone. Specific definitions and roles are shown in Table 2. For the first time, these four dimensions are transformed from qualitative classification into quantifiable man-hour impact parameters. A mapping extension is realized from “product decomposition structure” to “man-hour calculation feature dimension”. The selection basis is threefold. Structured verification basis is provided for design physical quantity improvement. A design-production connection is built for accurate production physical quantity conversion. Multi-dimensional calculation support is provided for dynamic man-hour estimation. Finally, the foundation is laid for the full-chain calculation model. The chain covers “design physical quantity - production physical quantity - standard man-hour”. Based on this feature benchmark system, the overall logic and three-stage framework are elaborated below. The formation of this feature system is also rooted in the man-hour management engineering practice of WGQ Shipbuilding Co., Ltd. over many years, and has been verified and iteratively improved by long-term actual ship construction data, possessing a solid foundation for engineering application.

Table 2. Definitions and Roles of the Four-Dimensional Features.

Feature Dimension	Definition (Shipbuilding Scenario)	Role
Stage Feature	Construction phase of Interim products (e.g., block manufacturing, grand assembly erection, dock closure)	Reflects the temporality of production processes, matching process requirements and man-hour coefficients of the corresponding stage
System Feature	Ship functional system to which Interim products belong (e.g., hull structure system, outfitting system, power system)	Associated system attributes of design data, distinguishing quantity calculation rules across different systems
Type Feature	Structural form of Interim products (e.g., flat block, curved block, tubular assembly, derived from PWBS hierarchical attributes)	Adapts to process complexity correction of different structures, improving quantity estimation accuracy
Zone Feature	Spatial position of Interim products in the hull (e.g., bow, midship, stern)	Quantifies the impact of operating environment differences (outdoor/cabin, high-altitude/ground) on man-hours

3.2. Framework of the model

3.2.1. Hierarchical Definition of Global Variables

(1) Bottom-Level Basic Input Data

All raw data are extracted from standard drawings and on-site records. These data are divided into three categories.

i. Design Geometry and Physical Quantity Input

Initial design physical quantity Q_{init} is included. Basic process geometry parameters are also provided, including plate thickness, fillet height, and groove type. Groove gap, weld length, material grade, and assembly level are also included too. These data serve as the quantitative foundation for man-hour estimation. The theoretical processing workload is directly reflected.

ii. Four-Dimensional Feature Input of Interim Products

Four classification labels are marked in design documents. These labels are construction stage, structural type, functional system, and hull zone. They are used to quantify process complexity differences.

iii. Dynamic Production Measurement Input from Workshops

Personnel indicators are collected. These include average working years and skill proportions. Qualification numbers are also collected. Environmental indicators are measured, including workshop temperature, humidity, and noise. They are used to characterize on-site efficiency losses.

(2) Intermediate Coupling Variable Set

Intermediate data are generated by three-stage iterative operations. Data transfer functions between stages are undertaken by them. Four types are included.

First stage output: comprehensive correction coefficient K_{corr} and corrected design quantity Q_{corr} .

Second stage intermediate variables: personnel allowance K_p , environmental allowance K_E , and conversion matrix M_{work} .

Second stage output: actual production quantity Q_{prod} matching on-site conditions.

Third stage intermediate variables: dynamic man-hour conversion coefficient Γ .

(3) Final Output Set of the Model

Standardized man-hour vectors T_{std} are divided by trade and assembly level. They can be used for production scheduling and cost accounting. Quota verification and process optimization are also supported.

3.2.2. Overall Framework of the Model

A three-stage progressive man-hour data calculation model is proposed in this study (Figure 1). The model is built based on feature mapping and matrix calculation. Closed-loop feedback is adopted as the supporting mechanism of the model. Production stochastic factors are considered in the model. Dynamic connection of three core links is realized by the model. The links include design quantity correction, production quantity calculation, and man-hour estimation.

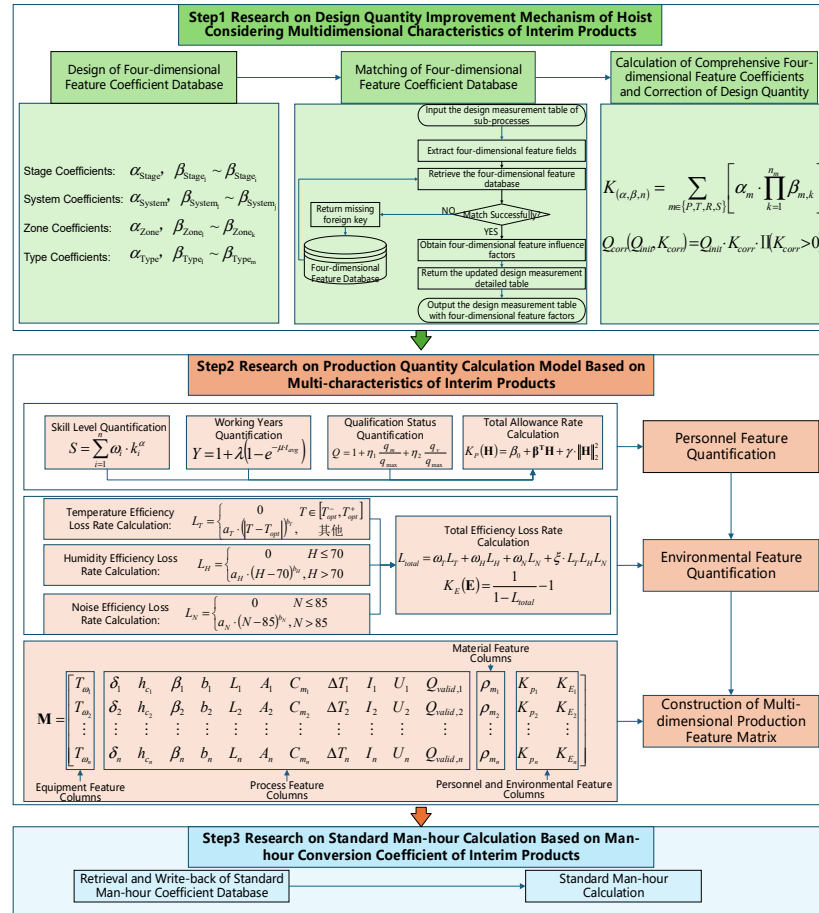


Figure 1. Multi-level Calculation Model for Shipbuilding Man-hours Based on Multi-dimensional Features of Interim Products.

For Stage 1, Design-end data quality is targeted for improvement. A matching mechanism is constructed for interim product features and design parameters. First, original design quantity is taken as input. A four-dimensional feature rule base is established. Systematic inspection and calibration are conducted. Second, coupling influence mechanisms are explored. Four dimensions are included: stage, zone, system, and type. The latest ergonomics and neuroscience achievements are introduced. Weight coefficients and impact coefficients are calculated. A comprehensive correction coefficient is obtained. Then, initial design quantity is corrected. High-quality design quantity data are output.

For Stage 2, accurate conversion between design and production quantity is set as the core. A production physical quantity calculation model is constructed. On-site production features and stochastic factors are reflected by the model. First, corrected design physical quantity is adopted as the model input. Key production factors are integrated into the calculation model. These factors include personnel skills, equipment status, and process parameters. Material attributes and environmental conditions are also covered. A multi-dimensional production feature matrix is built based on this integration. Second, core personnel attributes are quantified in the personnel dimension. These attributes include skill level, working years, and qualification completeness. A personnel allowance rate prediction function is established accordingly. In the environmental dimension, a production

efficiency loss rate model is developed. The model targets three parameters: temperature, humidity, and noise. The environmental allowance rate is derived from this model. Finally, matrix operations are adopted based on the feature matrix. In-depth coupling of design data and on-site production conditions is realized. Quantitative mapping from design to production physical quantity is completed. Dynamic transformation of design data is achieved in this stage. Accurate matching of on-site production features is also realized. Scientific and extensible basic data is provided for subsequent man-hour calculation.

For Stage 3, accurate man-hour calculation and full-process closed loop are set as key tasks. These tasks ensure man-hour estimation adapts to actual production practice. First, a man-hour conversion coefficient library is established. The library is built based on interim product types and four-dimensional features. Different feature combinations are covered by this coefficient library. Man-hour accounting standards for various products are clarified. Relevant processes include assembly, welding and grinding. Second, the coefficient library is combined with corrected production quantity data. Standard man-hours are calculated through this combination. Scenario-adaptive standard man-hour data is generated by the model. Finally, the three stages are connected in a sequential logic. A full-process data closed loop of the three-core links is formed. Seamless connection and accurate transmission of full-link data are realized.

4. Detailed explanation of the model

4.1. Stage 1: Design a Physical Quantity Improvement Mechanism Based on Interim Product Features

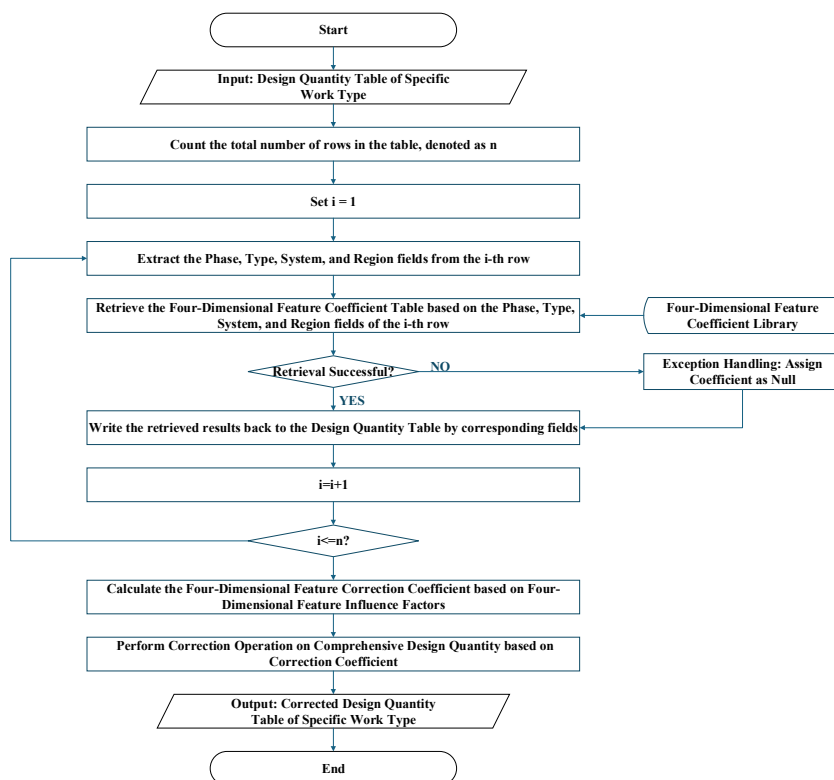


Figure 2. Construction Process of a Design Quantity Improvement Mechanism.

The top-level framework from Section 3.2 is inherited in this section. Standard drawings and PWBS assembly data are taken as inputs. Four-dimensional feature labels are used. sEMG results and industry standards are applied. A standardized mechanism assignment system is constructed. Weight coefficients α and impact factors β are derived. The comprehensive correction coefficient K_{corr} is solved. Original design physical quantity is calibrated. Corrected standardized design physical quantity Q_{corr} is output. This serves as the input for Section 4.2. The overall process is shown in Figure 2.

(1) Trade-Oriented Initial Design Physical Quantity Extraction

Shipbuilding involves the collaboration of multiple trades, and the demand and calculation logic of design quantity vary significantly among trades. The initial extraction of design quantity for specific trades oriented to Interim products relies on the assembly tree decomposition and standard process library, constructing a multi-trade initial design quantity extraction system through a four-step process: hierarchical decomposition - trade matching - data reading - formula calculation.

Hierarchical decomposition follows the logic of assembly tree decomposition, decomposing Interim products stage by stage into grand assembly, medium assembly, small assembly, and steel plate levels, clarifying the ownership relationship of each level, synchronously writing into the design quantity table, and marking the level field. Trade matching calls the standard process library, matching the corresponding trade for each level according to the hierarchical characteristics of Interim products, classifying and organizing the matching results by trade, triggering the “trade-header adaptation” rule, and preloading the exclusive header parameters required for the quantity calculation of the corresponding trade. Data reading directionally reads data from the original design quantity database for different trades, realizing accurate classified collection of multi-trade data. Formula calculation calls the corresponding design quantity calculation formula based on the exclusive header parameters of each trade, calculates the comprehensive design quantity of each trade row by row, and finally outputs the initial design quantity table covering multiple trades.

(2) Definition and Determination of Impact Factors of Four-Dimensional Features of Interim Products

To quantify the impact of the four-dimensional features (stage, system, type, zone) on man-hours, it is necessary to clarify two types of coefficients: The weight coefficients (α) of the four-dimensional features and the impact coefficients (β), which are accurately determined through data processing and machine learning methods (Figure 3).

i. Definition of Four-Dimensional Feature Coefficients

Weight coefficients of four-dimensional features (α): Numerical values used to measure the relative importance of each of the four-dimensional features (stage, system, type, zone) of shipbuilding Interim products in terms of overall man-hour impact, reflecting the contribution ratio of different features to man-hours (such as stage feature weight α_{stage} , type feature weight α_{type} , etc.).

Impact coefficients (β): Quantitative indicators that measure the specific impact degree on man-hours under different conditions or construction stages for a specific feature of shipbuilding Interim products (such as zone impact coefficient β_{zone1} corresponding to “bow zone”, type impact coefficient β_{type1} corresponding to “curved block”, etc.).

ii. Determination process

A. Initial assignment of weight coefficients α

Four dimensions are independent. No information overlap exists. Equal weight assignment is adopted. The formula is shown in Equation (1).

$$\alpha_m = \alpha_{stage} = \alpha_{type} = \alpha_{zone} = \alpha_{system} = 0.25 \quad (1)$$

This equal weight is set by GTT principles. It serves as a benchmark. Dynamic correction can be made by the entropy weight method or principal component analysis.

B. Mechanism assignment method: Type dimension (welding posture) mechanism modeling

a. Mechanism assumption

Type dimension describes process attributes. The core factor is welding posture. sEMG shows muscle load grows nonlinearly. S-curve characteristics are fitted. The Logistic model is selected.

b. Boundary conditions

Flat welding: open space, no constraint. Baseline value $F_{\text{flat}} = 1.00$.

Overhead welding: narrow space, severe constraint. Endpoint value $F_{\text{end}} = 2.19$.

c. Curve equation and parameters

The Logistic growth model is adopted. The formula is shown in Equation (2).

$$\beta_{1,c} = F(x) = \frac{F_{\max}}{1 + \exp(-k(x - x_0))} \quad (2)$$

Parameters are set as follows. $F_{\max} = 2.19$. It is calibrated by sEMG %MVIC extreme values. $k = 1.5$ is the curve steepness coefficient. $x_0 = 1.1$ is the growth inflection point.

Four levels are mapped: $x = 1, 2, 3, 4$.

d. Interpolation solution

The type dimension impact factor $\beta_{1,c}$ is obtained. It is shown in Table 3.

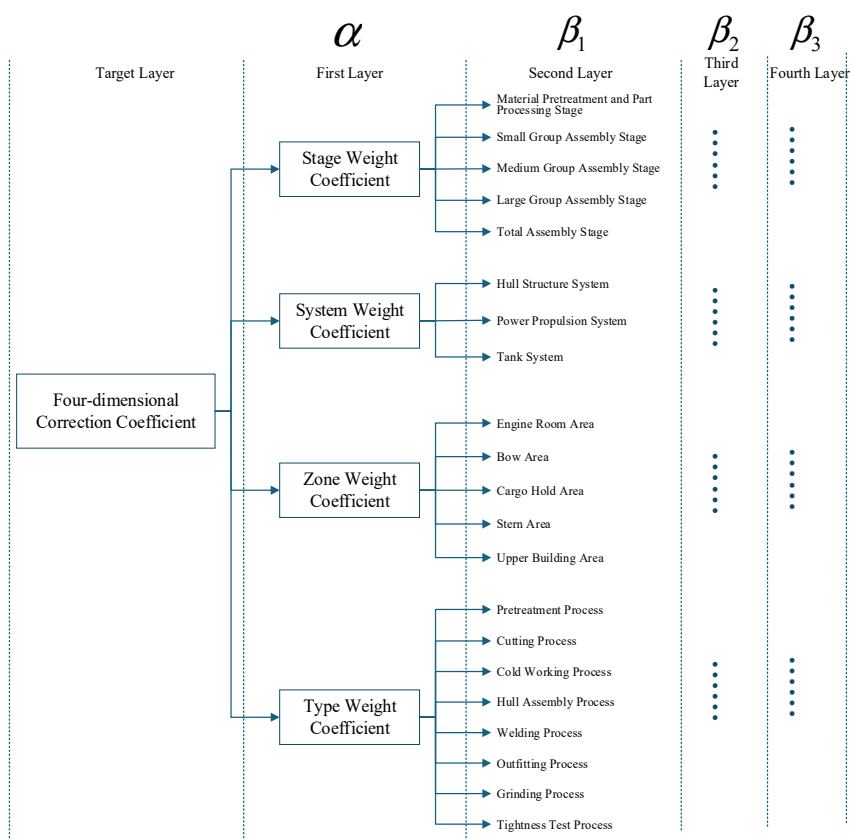


Figure 3. Four-Dimensional Feature Rule Base.

Table 3. Type Dimension Impact Factor Interpolation Table.

Welding Posture	x	Calculation Formula	$\beta_{1,c}$
Flat	1	$2.19/[1 + \exp(-1.5 \times (1 - 1.1))]$	1.01 (Baseline)
Vertical	2	$2.19/[1 + \exp(-1.5 \times (2 - 1.1))]$	1.32
Horizontal	3	$2.19/[1 + \exp(-1.5 \times (3 - 1.1))]$	1.78
Overhead	4	$2.19/[1 + \exp(-1.5 \times (4 - 1.1))]$	2.19 (Endpoint)

e. Simplified mechanism assignment for other three dimensions

The same approach is used. Only fitting models and boundary values differ, which are shown in Table 4.

Table 4. Simplified Mechanism Assignment for Other Three Dimensions.

Dimension	Fitting Model	Levels	Baseline	Endpoint	Calibration Source
Zone (j = 2)	Exponential $F(x) = ae^{bx} + c$	5 (superstructure→stern)	1.00	2.47	5-level measured data regression
System (j = 3)	Logistic	4 (structure→power)	1.00	2.85	4-level Logistic regression
Stage (j = 4)	Quadratic $F(x)=ax^2 + bx + c$	7 (part→erection)	1.00	2.65	7-level polynomial regression

C. Four-dimensional feature matching mechanism

After calibration, an automatic matching process is established. Labels are extracted from DAP drawings. Corresponding α and β are read. Data are written back to the design physical quantity table. Standardized parameter input is provided for batch correction coefficient K_{corr} .

(3) Correction Calculation of Design Quantity Oriented to Interim Products

After calibration of α and β , a two-stage mathematical model is constructed. First, comprehensive correction coefficient K_{corr} is built. Linear superposition and nonlinear multiplication are used. Second, a logical indicator function is introduced. Negative coefficients are excluded. Original design physical quantity Q_{init} is corrected. Corrected value $L = Q_{corr}$ is the unique upstream input for Stage 2. The formulas are shown in Equations (3) and (4).

$$K_{corr}(\alpha, \beta, n) = \sum_{m \in \{P, T, R, S\}} \left[\alpha_m \cdot \prod_{k=1}^{n_m} \beta_{m,k} \right] \quad (3)$$

$$L = Q_{corr}(Q_{init}, K_{corr}) = Q_{init} \cdot K_{corr} \cdot \mathbb{I}(K_{corr} > 0) \quad (4)$$

where α is the weight coefficient of four-dimensional features; β is the impact coefficient; n is the decomposition level; m traverses four dimensions; k is the sub-condition index; n_m is the total category number; Q_{corr} is the corrected design physical quantity; Q_{init} is the original value; K_{corr} is the correction coefficient; and $\mathbb{I}(\cdot)$ is the indicator function, which equals 1 when the condition is satisfied and 0 otherwise. Negative correction coefficients are excluded.

Feature factor weights are considered. Historical data are used for training. Correction is executed row by row. A design physical quantity correction table is generated, which includes original quantity, impact factors, correction coefficient, and corrected quantity.

4.2. Stage 2: Production Physical Quantity Calculation via a Multi-dimensional Feature Matrix

This stage follows the process of “design feature extraction to quantification of man-machine-environment factors to matrix construction and operation to quantity integration” (corresponding to Figure 4), focusing on the accurate conversion from design quantity to production quantity, solving the problem of “disconnection between design data and production scenarios”.

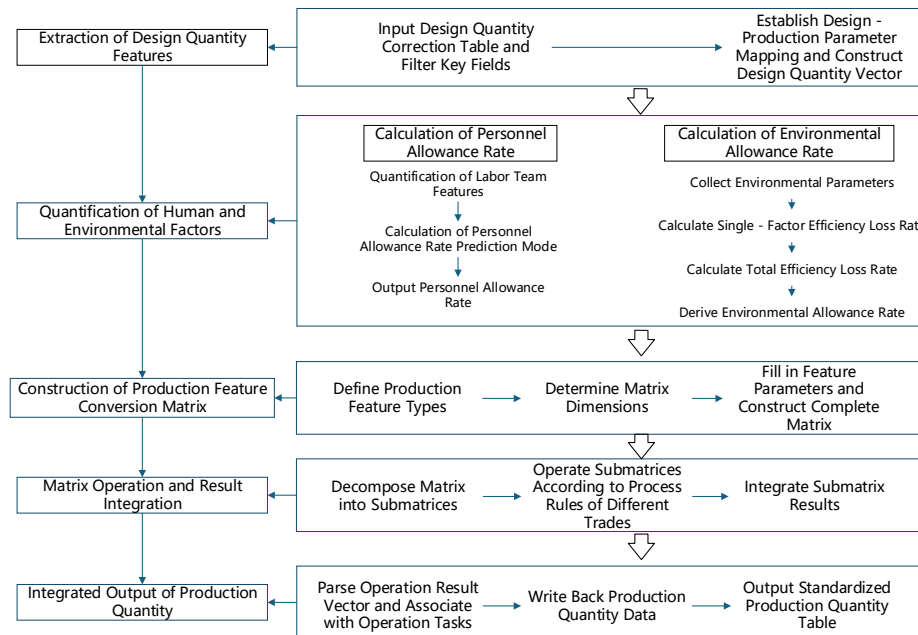


Figure 4. Production Quantity Data Calculation Framework.

(1) Extraction of Design Quantity Features

Design quantity is the basis for production quantity calculation, and key features need to be extracted to construct the “data base dimension” for production quantity calculation. Data input and screening take the design quantity correction table as input, screening fields such as “corrected design quantity, trade, groove parameters, and assembly number”. Parameter mapping and vector construction establish a mapping relationship between “design quantity fields and production quantity parameters”, extract relevant columns to construct a design quantity vector, and generate the basic matrix of the production material calculation conversion matrix.

(2) Calculation of Allowance Rates for Personnel and Environmental Factors

Personnel skill level and operating environment (temperature/humidity/noise, etc.) significantly affect production efficiency. It is necessary to quantify the personnel allowance rate and environmental allowance rate to provide adjustment basis for the “man-environment” dimension for production quantity correction, as shown in Figure 5.

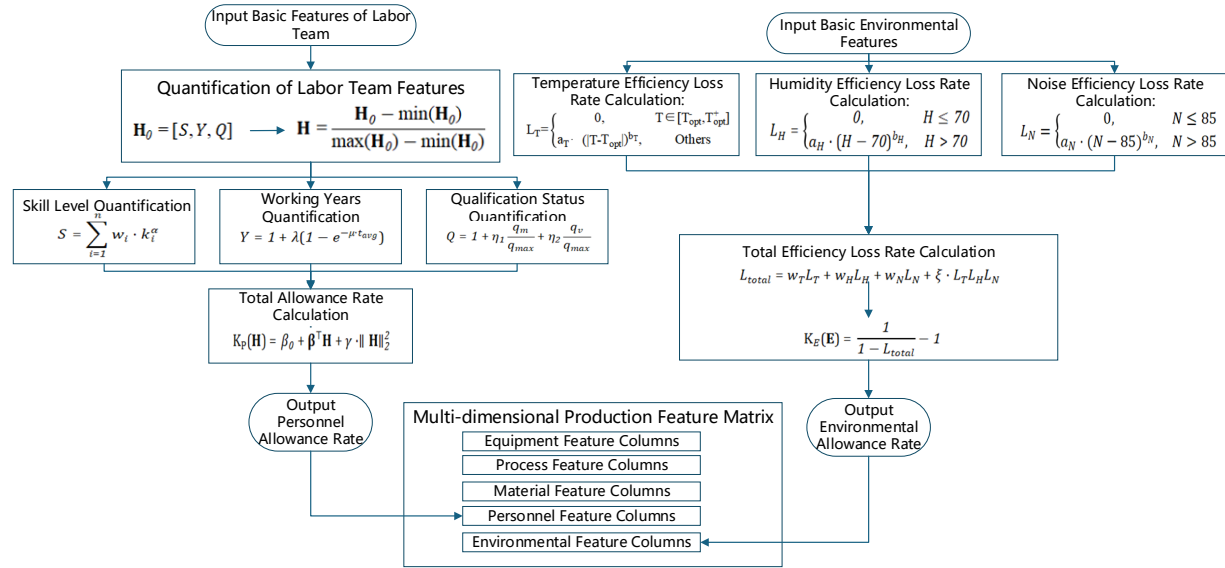


Figure 5. Calculation Methods of Allowance Rates for Personnel and Environmental Factors.

i. Calculation of Personnel Allowance Rate

The personnel allowance coefficient K_P quantifies three dynamic factors, including team skills, working years, and qualifications. Four steps are followed. First, raw data are collected, and a 3D feature vector H_0 is built. Second, sub-item formulas are established, and single feature indicators are obtained. Third, min-max standardization is applied, and the normalized vector H is obtained. Fourth, a multiple regression model with L2 regularization is built, and all features are coupled. Thus, final personnel allowance is obtained, which serves as a fixed column parameter.

$$S = \sum_{i=1}^n w_i \cdot k_i^\alpha \quad (5)$$

$$Y = 1 + \lambda(1 - e^{-\mu \cdot t_{avg}}) \quad (6)$$

$$Q = 1 + \eta_1 \frac{q_m}{q_{max}} + \eta_2 \frac{q_v}{q_{max}} \quad (7)$$

$$H_0 = [S, Y, Q] \quad (8)$$

$$H = \frac{H_0 - \min(H_0)}{\max(H_0) - \min(H_0)} \quad (9)$$

$$K_P(H) = \beta_0 + \beta^T H + \gamma \cdot \|H\|_2^2 \quad (10)$$

where: I is the skill level index; I is the proportion; I_i is the benchmark coefficient; α is the nonlinear amplification parameter; t_{avg} is the average working years; λ is the experience gain limit; μ is the decay rate; q_m is the mandatory qualifications; q_v is the value-added qualifications; q_{max} is the upper limit; η_1, η_2 are weights; β is the feature weight vector; β_0 is the intercept; and γ is the regularization coefficient.

ii. Calculation of Environmental Allowance Rate

The environmental allowance coefficient K_E quantifies three conditions, including temperature, humidity, and noise. Optimal ranges are defined. Nonlinear functions are used beyond ranges. Basic losses and synergistic losses are superimposed. Total loss rate is obtained. The conversion formula is applied.

$$L_T = \begin{cases} 0, & T \in [T_{opt}^-, T_{opt}^+] \\ a_T \cdot (|T - T_{opt}|)^{b_T}, & \text{Others} \end{cases} \quad (11)$$

$$L_H = \begin{cases} 0, & H \leq 70\% \\ a_H \cdot (H - 70\%)^{b_H}, & H > 70\% \end{cases} \quad (12)$$

$$L_N = \begin{cases} 0, & N \leq 85\text{dB} \\ a_N \cdot (N - 85)^{b_N}, & N > 85\text{dB} \end{cases} \quad (13)$$

$$L_{total} = w_T L_T + w_H L_H + w_N L_N + \xi \cdot L_T L_H L_N \quad (14)$$

$$K_E(E) = \frac{1}{1 - L_{total}} - 1 \quad (15)$$

where: $T_{opt}^- = 20^\circ\text{C}$, $T_{opt}^+ = 25^\circ\text{C}$; a_T , b_T are temperature parameters; a_H , b_H are humidity parameters; 70% is the humidity threshold; 85 dB is the noise threshold; a_N , b_N are noise parameters; w_T , w_H , w_N are weights; ξ is the interaction coefficient; and L_{total} is the total efficiency loss rate.

(3) Construction of a Multi-dimensional Production Feature Conversion Matrix

The calculation of production quantity needs to integrate design quantity, production factors, and process rules, constructing a “multi-dimensional, full-factor” conversion matrix to realize the structured integration of “design features - production factors - man-machine-environment conditions”, as shown in Figure 6.

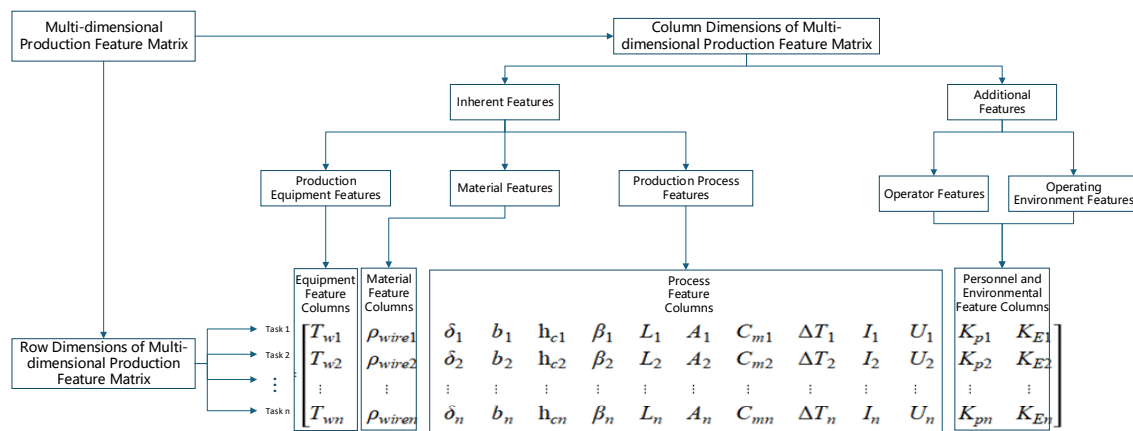


Figure 6. Construction Method of Multi-dimensional Production Feature Conversion Matrix.

i. Definition of Feature Types and Parameters

From the perspective of “trade relevance”, production features are divided into two categories, clarifying the core parameter scope covered by each type:

Intrinsic features (trade-related): Features strongly associated with the processes of specific trades, including production equipment features (such as welding equipment type, assembly equipment accuracy), production process features (such as welding groove parameters, painting process flow), and material features (such as steel grade, welding wire specification).

Additional features (trade-irrelevant): Features that generally affect the production efficiency of all trades, including operator features (such as skill level, qualification status) and operating environmental features (such as temperature, humidity, noise).

ii. Dimensions and Structure of the Production Quantity Conversion Matrix

Definition of matrix dimensions:

Row dimension: Divided by “trade operation task/batch”, with a total of n rows, corresponding to n trade operation tasks (such as “block A welding task 1”, “block A welding task 2”, etc.).

Column dimension: Columned by “feature type”, including equipment feature column, process feature column, material feature column, personnel feature column, and environmental feature column, realizing the structured organization of multi-dimensional features.

iii. Example of Multi-dimensional Production Feature Matrix for Welding Trade

Taking the welding trade as an example, the construction logic of the multi-dimensional production feature matrix is detailed in combination with its process characteristics, including the definition of feature parameters and matrix form:

(a) Definition of Production Feature Parameters for Welding Trade

For the welding process, the parameters of “intrinsic features” and “additional features” are refined and defined. The meaning and physical significance of each parameter are shown in Table 5.

Table 5. Definition of Production Feature Parameters for Welding Trade.

Feature Type	Feature Parameter	Parameter Meaning	Physical Significance
Production Equipment Features (Intrinsic)	T_w	Welding type	Match welding equipment according to welding type
Production Process Features (Intrinsic)	δ	Plate thickness (mm)	Base metal thickness, affecting weld cross-sectional area A
	h_e	Fillet height	Weld reinforcement, participating in man-hour/quantity calculation
	β, b	Groove angle, groove gap	Determine the calculation formula of weld cross-sectional area A
	L	Weld length (mm)	Total welding length
	A	Weld area (indirect variable)	Calculated from plate thickness and groove parameters
	C_m	Specific heat capacity of welding wire	Extracted from process library/material table
	ΔT	Welding wire melting temperature difference	Extracted from process library
	I	Welding current	Core parameter of welding process
	U	Welding voltage	Core parameter of welding process
	Q_{valid}	Effective heat input (indirect variable)	Calculated from current, voltage, etc.
Material Features (Intrinsic)	ρ_m	Welding wire material	Density of welding wire
Operator Features (Additional)	K_p	Personnel impact coefficient	Personnel allowance rate
Operating Environment Features (Additional)	K_E	Environmental impact coefficient	Environmental allowance rate

(b) Form of Welding Production Quantity Conversion Matrix

Based on the above parameter definitions, the production quantity conversion matrix M_{welding} for the welding trade can be expressed as:

$$M_{\text{welding}} = \begin{bmatrix} T_{w1} & \delta_1 & b_1 & h_{c1} & \beta_1 & L_1 & A_1 & C_{m1} & \Delta T_1 & I_1 & U_1 & \rho_{\text{wire}1} & K_{p1} & K_{E1} \\ T_{w2} & \delta_2 & b_2 & h_{c2} & \beta_2 & L_2 & A_2 & C_{m2} & \Delta T_2 & I_2 & U_2 & \rho_{\text{wire}2} & K_{p2} & K_{E2} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ T_{wn} & \delta_n & b_n & h_{cn} & \beta_n & L_n & A_n & C_{mn} & \Delta T_n & I_n & U_n & \rho_{\text{wire}n} & K_{pn} & K_{En} \end{bmatrix} \quad (16)$$

where each row corresponds to one welding operation task, and each column is sequentially the equipment feature column (T_w), process feature column (core process parameters such as δ , b , h_c , β , L , A , C_m , ΔT , I , U , Q_{valid}), material feature column (ρ_{wire}), personnel feature column (K_p), and environmental feature column (K_E), realizing the matrix expression of "equipment - process - material - man - environment" full factors for welding tasks.

(4) Calculation of a Multi-dimensional Production Feature Matrix Model

A computable mapping is established in this subsection. The mapping runs from the multi-dimensional production feature matrix to the production quantity column vector. Geometric, thermal and man-environment parameters are carried simultaneously by the matrix M_{welding} . These parameters have different dimensions. Direct matrix multiplication would cause dimensional confusion, and physical meaning would be distorted. A stepwise calculation chain is therefore adopted, including sub-matrix extraction, element-wise operation, and result fusion. First, the geometric parameter sub-vector is extracted, and the weld cross-sectional area is calculated. Second, the thermal parameter sub-vector is extracted, and the effective heat input is calculated. Finally, the geometric and thermal quantities are coupled with the allowance coefficients. The production quantity column vector Q_{prod} is then output.

Step 1: Weld Cross-sectional Area Sub-matrix Operation

The weld cross-sectional area A is the basic geometric quantity. It is used to calculate welding wire volume and heat input. For a V-groove, the area of a single weld is formed by two parts. They are the groove cross-sectional area and the reinforcement area. The calculation formula is shown in Equation (17).

$$A = \delta b + \frac{(\delta - p)^2 \tan \beta}{2} + \frac{2}{3} h_c \quad (17)$$

where: δ is the plate thickness (mm); b is the groove gap (mm); p is the groove reference thickness (mm); β is the groove angle ($^\circ$); and h_c is the fillet height (mm).

Equation (17) is mapped into vector operation form for batch calculation. Let δ , b , β , and h_c be $n \times 1$ column vectors. Geometric parameters are extracted from columns 2, 3, 5, and 6 of the matrix M_{welding} . The weld cross-sectional area vector A is then calculated in batch. The Hadamard product is adopted, which denotes element-wise multiplication and is marked as $\circ$.

$$A = \delta \circ b + \frac{(\delta - p) \circ (\delta - p) \circ \tan \beta}{2} + \frac{2}{3} h_c \quad (18)$$

where: 1 is an $n \times 1$ all-one column vector. Dimensional compatibility between the scalar p and vector operations is ensured by this vector. A is an $n \times 1$ column vector, and its i -th element corresponds to the cross-sectional area of the i -th weld (mm^2).

Step 2: Effective Heat Input Sub-matrix Operation

The effective heat input Q_{valid} represents the heat energy absorbed per unit weld length. It is a key thermal variable connecting welding process parameters with quantity consumption. Based on the Joule heating principle, Q_{valid} is determined by welding current I , welding voltage U , wire resistivity and thermal efficiency coefficient η . Let I and U be $n \times 1$ column vectors. They are extracted from columns 10 and 11 of the matrix M_{welding} . The effective heat input vector Q_{valid} is then expressed as follows.

$$Q_{\text{valid}} = I \circ U + I^2 \circ \frac{\rho_{\text{wire}} \circ L_{\text{wire}}}{S} \quad (19)$$

where: η is the welding thermal efficiency coefficient, set as 0.75 in this study. This value refers to measured data of CO₂ gas shielded welding in the Welding Handbook. L is the weld length column vector (mm), extracted from column 7 of the matrix. v is the welding speed (mm/s), set as 5.0 mm/s based on typical WPS parameters. Q_{valid} is an $n \times 1$ column vector, and its i -th element corresponds to the effective heat input of the i -th weld (J).

Step 3: Production Quantity Fusion Calculation

The production quantity Q_{prod} comprehensively reflects the actual workload required by welding tasks. Geometric volume, thermal demand, personnel efficiency correction, and environmental loss correction are coupled. Let ρ_m be the welding wire density column vector (kg/mm³). Let K_P and K_E be the personnel and environmental allowance coefficient vectors. They are extracted from columns 13 and 14 of the matrix. The production quantity column vector Q_{prod} is calculated as follows:

$$Q_{\text{prod}} = \left(\frac{A \circ L \circ \rho_m \circ C_m \circ \Delta T}{Q_{\text{valid}}} \right) \circ K_P \circ K_E \quad (20)$$

where: C_m is the specific heat capacity of the welding wire (J/(kg·°C)), set as 460 J/(kg·°C). ΔT is the melting temperature difference of the welding wire (°C), set as 1500 °C. The numerator term represents the total energy required to heat the weld metal to its melting point (J). A dimensionless thermal-geometric coupling coefficient is obtained after division by Q_{valid} . Personnel and environmental allowance corrections are then superimposed. Finally, an $n \times 1$ production quantity column vector is output.

(5) Integrated Output of Production Quantity

Production quantity needs to be associated with tasks/processes to form a standardized production quantity table. Vector parsing and task association clarify the tasks corresponding to vector elements, associating the relevant fields of the design quantity correction table; data write-back and table construction add a "production quantity" field to the design quantity correction table and write back the calculation results; data closed-loop and application realize the data closed-loop between design and production, providing standardized results for the integration of multi-trade production data.

4.3. Stage 3: Dynamic Standard Man-Hour Estimation

In this stage, we follow the process of "targeted extraction of key production quantity data to dynamic man-hour conversion coefficient matching to accurately calculate of standard man-hours", solving the problem of static traditional man-hour coefficients, and realizing the transformation of standard man-hours from "empirical estimation" to "data-driven calculation", which is a key link connecting production quantity and man-hour management.

(1) Targeted Extraction of Key Production Quantity Data

Taking the production quantity table output in Stage 2 as the data source, extract the “stage column” (such as grand assembly, medium assembly), “trade column” (such as welding, assembly), and “production quantity column” (such as weld length, structural part weight), eliminating redundant fields. Furthermore, verify data validity, such as checking the unity of units and rationality of values of welding data, correcting abnormal items, and forming a three-dimensional data set of “stage - trade - production quantity” to lay the foundation for subsequent calculations.

(2) Retrieval and Matching of Dynamic Man-hour Conversion Coefficients

A two-dimensional dynamic man-hour conversion coefficient library of “stage + trade” is constructed. Coefficients are stored by this dimension and regularly updated based on historical data, process upgrades, etc. Retrieve the coefficient library using “stage + trade” (such as “grand assembly + welding”) as the keyword: If the matching is successful, call the coefficient; if the matching fails, estimate the coefficient by analogy with similar scenarios, input it into the library after expert review, and mark it as “to be verified”, realizing the dynamic improvement of coefficients.

(3) Standard Man-hour Formula Operation and Result Output

The production quantity column vector Q_{prod} is obtained from Equation (20). It is matched with the dynamic man-hour conversion coefficient Γ . The standard man-hours are then calculated as follows:

$$T_{\text{std}} = Q_{\text{prod}} \odot \Gamma \quad (21)$$

where: Γ is the dynamic man-hour conversion coefficient vector with the same dimension as Q_{prod} . Each element is matched from the coefficient library by the “stage + trade” combination. The coefficients are fitted from historical production data of the shipyard. A typical value is $\Gamma = 7.7 \times 10^{-5}$ h/mm³ for grand assembly welding. The operator $\odot$ denotes the Hadamard element-wise product.

Parameters are substituted row by row for calculation, and result rationality is verified. Deviations beyond $\pm 15\%$ of the mean value are traced back and corrected. Finally, the standard man-hours are written back to the production quantity table. A full-chain data table is formed, which provides support for production planning and cost accounting.

5. Case Study

To verify the effectiveness of the proposed model, a case study is conducted. Block construction data from WGQ Shipyard are used for this verification. In this section, we detail the case design, verification process, and result analysis, and strictly follow the academic expression norms established previously.

5.1. Case Description and Data Sources

A two-stage verification design is adopted in this section. Full-process feasibility and full-condition estimation accuracy are verified. The design combines case demonstration and full-scale validation.

(1) Full-process case demonstration. Blocks 222 and 232 of WGQ Shipyard are taken as the case objects. The data flow of the three-stage progressive chain is fully demonstrated. The chain covers design quantity calculation, production quantity calculation and standard man-hour estimation. Intermediate results of each stage are also shown. The implementability of the model under real shipyard data structures is verified. It should be noted that Blocks 222 and 232 are used exclusively

for the full-process data chain demonstration, aiming to verify the implementability of the model under real shipyard data structures, while the estimation accuracy of the model is independently and rigorously validated on the full-sample dataset described below (Section 5.2).

(2) Full-scale accuracy validation. A total of 2,567 block man-hour records are used as the unified dataset. These records are accumulated by WGQ Shipyard over half a year. First, the estimation accuracy of the complete model, which integrates the four-dimensional feature correction module and the man-machine-environment production feature conversion matrix, is verified entry by entry against the measured actual man-hours. Then, horizontal accuracy comparison is conducted with four mainstream baseline methods. The same data division and the same evaluation protocol are used. Statistical significance tests are also performed (Section 5.3).

5.2. Verification Process

(1) Design Physical Quantity Correction Case

The multi-trade design quantity correction follows a four-step workflow, including decomposition, matching, integration, and calculation. Accurate collection of multi-trade quantities is achieved by this workflow. The assembly tree is decomposed into multiple levels for interim products, ranging from grand assembly down to steel plate. Data storage is optimized by this hierarchical decomposition, and ownership relationships of each level are also clarified. Stage information is extracted in the process trade matching step, the standard process library is retrieved for trade matching of each level, and matching results are written back to the hierarchical table subsequently.

Row data of the same trade are integrated based on matching results; the mapping library is called to construct dynamic table headers. Raw data are extracted and cleaned from the original database, and the processed data are written into the design physical quantity table. Trade-specific calculation formulas are invoked for comprehensive calculation, and the initial design physical quantity table is generated through this step.

A matching mechanism for four-dimensional feature impact factors is constructed. In-depth adaptation between design quantity and production scenarios is realized by this mechanism, which follows three core steps: extraction, retrieval, and write-back. Four-dimensional feature fields are extracted directionally in the first step, including stage, system, type, and zone dimensions. The pre-established coefficient library is traversed in the second step, and adaptive weight coefficients α and impact coefficients β are retrieved. Matching status is judged in the result processing step, missing features are supplemented simultaneously, and calculated impact factors are written back to the design quantity table. Multi-trade cyclic processing is performed for all involved trades, and a multi-trade design quantity correction table is generated and output, with four-dimensional impact factors fully included.

Design quantity correction calculation is completed through three steps, including coefficient calculation, quantity correction, and result output. Quality improvement of design quantity data is achieved in this process. Correction coefficients (K_{corr}) are calculated with the model formula, with four-dimensional impact factors used as the input of calculation. Initial design physical quantity is adjusted with the correction coefficients, accuracy of the corrected data is verified strictly in this step, and a complete corrected design physical quantity table is output, as shown in Table 6.

Table 6. Welding Trade Design Quantity Correction Table (Partial Data).

Block	Stage	Assembly No.	Trade	Part Name 1	Part Name 2	Plate Thickness 1 (mm)	Material 1	Groove 1	Plate Thickness 2 (mm)	Material 2	Groove 2	Weld Length (mm)	Fillet Height	Welding Position	Weld Flatness	Comprehensive Design Quantity	Four-Dimensional Feature Correction Coefficient	Corrected Design Quantity
222	Grand Assembly	222&LOCK	Welding	222-852A	222-851A	12	AH32	0	16	AH32	0	11092	6.5	L	Flat	11092	1.05	11646.6
222	Grand Assembly	222&LOCK	Welding	222-TT11B	222-FR61C	12	AH32	0	16	AH32	0	1380	6.5	L	Flat	1380	1.05	1449
222	Grand Assembly	222&LOCK	Welding	222-TT11B	222-FR60C	12	AH32	0	16	AH32	0	1380	6.5	L	Flat	1380	1.05	1449
222	Grand Assembly	222&LOCK	Welding	222-TT11B	222-FR95C	12	AH32	0	16	AH32	0	1380	6.5	L	Flat	1380	1.05	1449
222	Grand Assembly	222&LOCK	Welding	222-TT11B	222-TB62C	12	AH32	0	16	AH32	0	3276	6.5	L	Flat	3276	1.05	3439.8
222	Grand Assembly	222&LOCK	Welding	222-TT11B	222-851A	12	AH32	0	16	AH32	0	1965	6.5	L	Flat	1965	1.05	2063.25
222	Grand Assembly	222&LOCK	Welding	222-BK11C	222-851A	12	AH32	0	16	AH32	0	1600	6.5	L	Flat	1600	1.05	1680
222	Grand Assembly	222&LOCK	Welding	222-8K12C	222-851A	12	AH32	0	16	AH32	0	200	6.5	L	Flat	200	1.05	210

Table 7. Welding Trade Production Quantity Table (Partial Data).

Block	Stage	Assembly No.	Trade	Part Name 1	Part Name 2	Plate Thickness 1 (mm)	Material 1	Groove 1	Plate Thickness 2 (mm)	Material 2	Groove 2	Weld Length (mm)	Fillet Height	Welding Position	Weld Flatness	Comprehensive Design Quantity	Four-Dimensional Feature Correction Coefficient	Corrected Design Quantity	Production Quantity
222	Grand Assembly	222&LOCK	Welding	222-852A	222-851A	12	AH32	0	16	AH32	0	11092	6.5	L	Flat	11092	1.05	11646.6	55321
222	Grand Assembly	222&LOCK	Welding	222-TT11B	222-FR61C	12	AH32	0	16	AH32	0	1380	6.5	L	Flat	1380	1.05	1449	6883
222	Grand Assembly	222&LOCK	Welding	222-TT11B	222-FR60C	12	AH32	0	16	AH32	0	1380	6.5	L	Flat	1380	1.05	1449	6883
222	Grand Assembly	222&LOCK	Welding	222-TT11B	222-FR95C	12	AH32	0	16	AH32	0	1380	6.5	L	Flat	1380	1.05	1449	6883
222	Grand Assembly	222&LOCK	Welding	222-TT11B	222-TB62C	12	AH32	0	16	AH32	0	3276	6.5	L	Flat	3276	1.05	3439.8	16339
222	Grand Assembly	222&LOCK	Welding	222-TT11B	222-851A	12	AH32	0	16	AH32	0	1965	6.5	L	Flat	1965	1.05	2063.25	9800
222	Grand Assembly	222&LOCK	Welding	222-BK11C	222-851A	12	AH32	0	16	AH32	0	1600	6.5	L	Flat	1600	1.05	1680	7980
222	Grand Assembly	222&LOCK	Welding	222-8K12C	222-851A	12	AH32	0	16	AH32	0	200	6.5	L	Flat	200	1.05	210	840

Table 8. Welding Trade Standard Man-hour Table (Partial Data).

Block	Stage	Assembly No.	Trade	Part Name 1	Part Name 2	Plate Thickness 1 (mm)	Material 1	Groove 1	Plate Thickness 2 (mm)	Material 2	Groove 2	Weld Length (mm)	Fillet Height	Welding Position	Weld Flatness	Comprehensive Design Quantity	Corrected Design Quantity	Production Quantity	Standard Man-hours	Actual Man-hours
222	Grand Assembly	222&LOCK	Welding	222-852A	222-851A	12	AH32	0	16	AH32	0	11092	6.5	L	Flat	11092	11646.6	55321	4.260	4.300
222	Grand Assembly	222&LOCK	Welding	222-TT11B	222-FR61C	12	AH32	0	16	AH32	0	1380	6.5	L	Flat	1380	1449	6883	0.530	0.630
222	Grand Assembly	222&LOCK	Welding	222-TT11B	222-FR60C	12	AH32	0	16	AH32	0	1380	6.5	L	Flat	1380	1449	6883	0.530	0.630
222	Grand Assembly	222&LOCK	Welding	222-TT11B	222-FR95C	12	AH32	0	16	AH32	0	1380	6.5	L	Flat	1380	1449	6883	0.530	0.630
222	Grand Assembly	222&LOCK	Welding	222-TT11B	222-TB62C	12	AH32	0	16	AH32	0	3276	6.5	L	Flat	3276	3439.8	16339	1.258	1.420
222	Grand Assembly	222&LOCK	Welding	222-TT11B	222-851A	12	AH32	0	16	AH32	0	1965	6.5	L	Flat	1965	2063.25	9800	0.755	0.910
222	Grand Assembly	222&LOCK	Welding	222-BK11C	222-851A	12	AH32	0	16	AH32	0	1600	6.5	L	Flat	1600	1680	7980	0.614	0.751
222	Grand Assembly	222&LOCK	Welding	222-8K12C	222-851A	12	AH32	0	16	AH32	0	200	6.5	L	Flat	200	210	840	0.077	0.092

(2) Production Physical Quantity Calculation Case

The design quantity correction table of the target block is preprocessed first, and key feature parameters are extracted from the preprocessed data. These parameters include weld length, plate specifications and part quantity, which are associated with on-site production factors. The association is established based on interim product four-dimensional features, and production factors include personnel skill levels and environmental parameters. Dimensionality reduction is performed on personnel and environmental data, with principal component analysis adopted for this process. Key influencing factors are screened out through this process: Core personnel factors include skill level, working years and qualification, while key environmental factors include temperature, humidity, and noise.

Feature quantification is conducted for personnel allowance rate calculation, and quantification standards are formulated for all core personnel features. Skill level classification, working years, and qualification are covered in these standards. The range 5–10 years of working experience is set as the benchmark for quantification, homogeneous groups are divided via K-Means clustering algorithm, and a multiple linear regression model is established based on grouped data. For example, a welding team with 80% senior members is selected, and all members of this team have over 5 years of working experience. A 3% skill efficiency improvement is achieved by this team, and the corresponding correction coefficient is determined as 0.97.

Seasonal historical data are input for environmental allowance rate calculation, and single-factor efficiency loss models are established based on optimal ranges. The optimal temperature range is set as 20–25°C for the model, the optimal humidity range is defined as 40–60%, and noise level below 85dB(A) is set as the optimal condition. Total production efficiency loss rate is obtained by linear superposition, and the environmental allowance rate is derived from the total loss rate.

Multi-source feature data are integrated for matrix construction, including design features, allowance rates, and process features. Core process features include welding current, voltage, and assembly accuracy, and a multi-dimensional production feature conversion matrix is constructed. Structural assembly is taken as an example to explain matrix elements, which include geometric dimensions, assembly sequence, skill efficiency coefficients, and environmental impact coefficients. Matrix decomposition and sub-operation are performed on the matrix. Subsequently, row-by-row and element-by-element calculations are executed, following the process rules of corresponding trades. Sub-matrices of geometric quantities and material consumption are covered, and production physical quantity results of each trade are generated. The welding trade production quantity is shown in Table 7.

(3) Standard Man-Hour Estimation Case

Key data dimensions are screened from the production quantity table first, and core data of construction stage, trade, and production quantity are extracted. Stage data include grand assembly and medium assembly construction phases, while production quantity data cover weld length and fillet height parameters. "Stage-trade-quantity" associations are clarified through data extraction, with grand assembly welding parameter association as a typical example.

A conversion coefficient matching mechanism is constructed in the second step, and "stage + trade" is set as the key word for coefficient library retrieval. A typical retrieval key is "grand assembly + welding" in this case, the man-hour conversion coefficient library is queried with the key, and corresponding standard man-hour conversion coefficients are matched. The coefficient for Block 222 grand assembly welding is 0.000077, missing coefficients are estimated by analogy with similar

scenarios, supplemented after expert review and verification, and valid coefficients are written back to the production quantity table.

Model calculation is executed in the final step of man-hour estimation, and production quantity data are associated with matched conversion coefficients. Production quantity includes design quantity and corrected production quantity, and parameters are substituted into the standard man-hour calculation formula. The formula is defined as standard man-hours = production quantity $\times$ conversion coefficient. Row-by-row calculation is performed for all data entries, calculation results are filled into the “standard man-hours” column, and data of a single trade are verified after the initial calculation. Cyclic processing is performed for other trades, including assembly and cutting, and an interim product table with standard man-hour data is output. As shown in Table 8, the calculated man-hours of Block 222 are also highly consistent with the corresponding actual records, with an average ratio of calculated to actual man-hours of about 0.86; the accuracy of the model is collectively covered by the full-sample statistics in Section 5.3.

(4) Model Parameter Sensitivity Analysis

The three-stage man-hour calculation model contains several core input parameters. They include the four-dimensional feature weight α and the condition impact factor β . The personnel allowance coefficient KP, the environmental allowance coefficient KE, and the man-hour conversion coefficient Γ are also included. All parameters are calibrated by sEMG physiological experiments, industry quotas, or workshop measurements. Calibration deviations are directly transmitted to the corrected design quantity Q_{corr} . The production quantity Q_{prod} and the final standard man-hours T_{std} are also affected, and man-hour estimation errors are caused.

A sensitivity analysis of all core parameters is conducted in this subsection. Sensitivity quantification methods for manufacturing environmental cost are referred to. Disturbance effects of different parameters on standard man-hours are distinguished quantitatively. High-sensitivity core parameters and low-sensitivity secondary parameters are identified. The priority of on-site parameter calibration is clarified, and the overall estimation error is reduced. A controlled variable method is adopted: Other parameters are fixed while a single parameter is slightly disturbed. The sensitivity coefficient of each parameter is calculated, and the influence of parameter fluctuation on standard man-hours is quantified. A quantitative basis is provided for parameter iteration and data collection frequency optimization.

The general relative sensitivity calculation method is followed. The sensitivity coefficient S_i is defined as the relative change amplitude of the output standard man-hours T_{std} . A relative disturbance is applied to a single input parameter X_i . The formula (22) is:

$$S_i = \frac{T_{std}(X_i + \Delta X_i) - T_{std}(X_i)}{T_{std}(X_i)} \quad (22)$$

where: S_i is the sensitivity coefficient of the i -th input parameter; $T_{std}(X_i)$ is the baseline standard man-hours under original parameters; $T_{std}(X_i + \Delta X_i)$ is the standard man-hours after parameter disturbance; and ΔX_i is the disturbance offset of the input parameter X_i . A larger $|S_i|$ indicates a more severe influence of the parameter on estimation results, and higher parameter sensitivity is indicated. A smaller $|S_i|$ indicates lower sensitivity.

Parameters are varied, and the results are compared with the initial values. Figure 7(a) shows the sensitivity curves of the man-environment coefficients and the man-hour conversion coefficient. Figure 7(b) shows the disturbance sensitivity curves of the four-dimensional weight parameters.

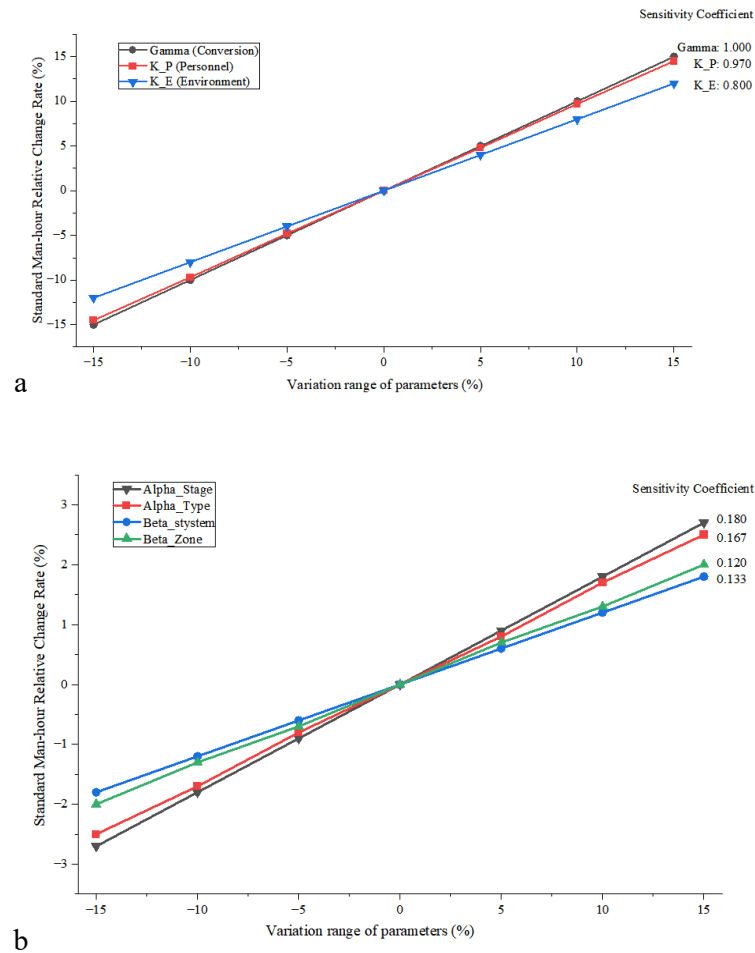


Figure 7. Sensitivity Curves of Core Model Parameters. (a) Man-Environment and Conversion Coefficients; (b) Four-Dimensional Weight Parameters.

5.3. Discussion

Actual man-hour records of nine typical blocks are used for result analysis. These blocks are Blocks 206, 329, 439, 521, 621, 721, 834, 921, and 990 of WGQ Shipyard. The actual man-hour data are sourced from on-site measured ledgers. Calculated man-hours are first aligned with actual man-hours task by task. Abnormal on-site records are then removed, including missed check-in reports and cross-day splitting errors. Finally, 2,567 valid samples are obtained. Various interim products are fully covered, including flat blocks, curved blocks, grand assemblies, and medium assemblies. The result analysis is divided into three parts. In Section 5.3.1, calculated man-hours are directly compared with actual man-hours, and estimation accuracy is verified. In Section 5.3.2, the proposed model is compared with traditional quota and mainstream machine learning models. Qualitative and quantitative comparisons are conducted, and inherent shortcomings of each method are clarified. In Section 5.3.3, mechanism, accuracy, and engineering value are analyzed comprehensively. The advancement and practicability of the model are verified.

5.3.1. Direct Comparison with Actual Man-hour Data

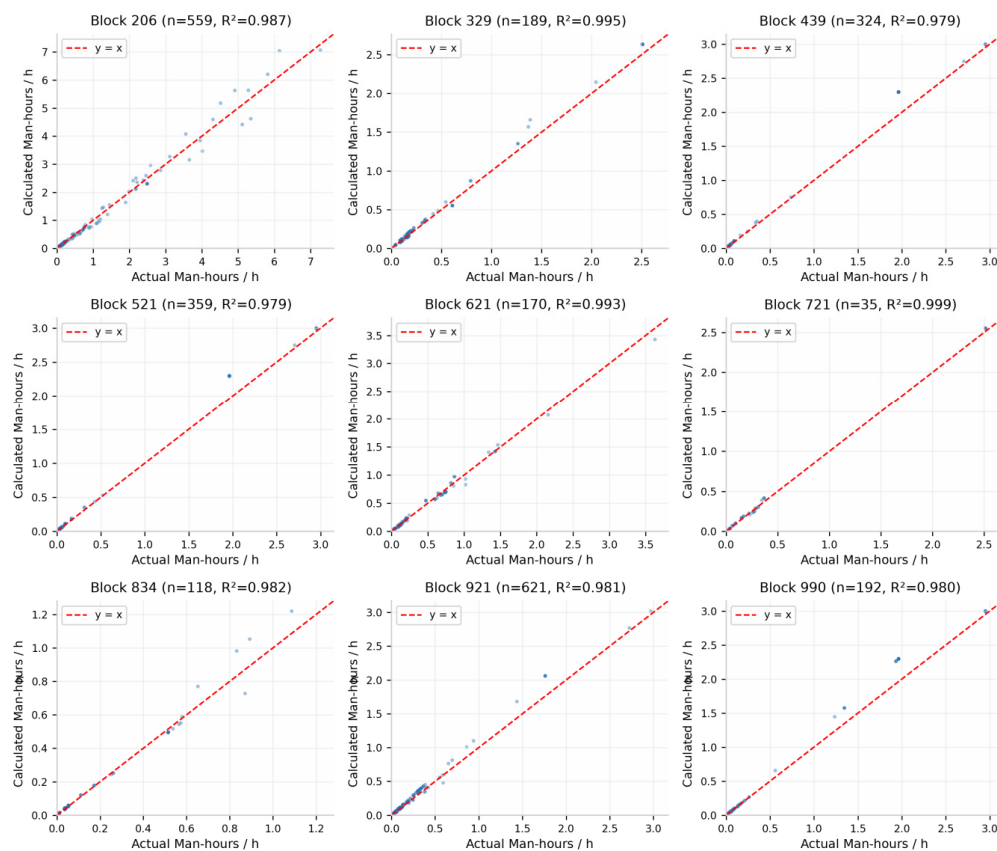
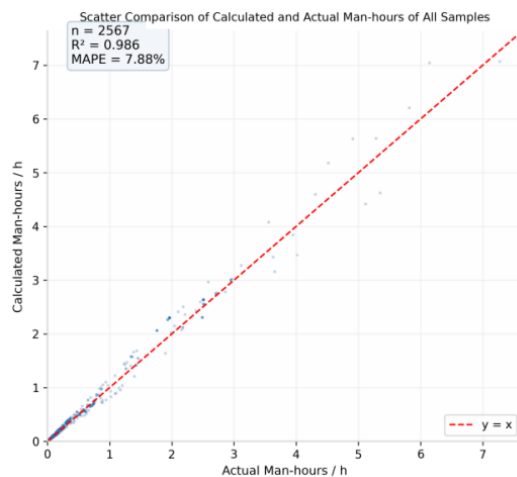
Calculated man-hours are directly compared with actual man-hours entry by entry. Actual man-hours are taken as the ground truth. Four indicators are used for quantitative evaluation, including R^2 , RMSE, MAE, and MAPE. Estimation accuracy details are given block by block in Table 9. Scatter plots of calculated versus actual man-hours are drawn in Figures 8 and 9. The agreement degree is shown intuitively. Model accuracy is directly verified from the perspective of practical fit.

Table 9. Measured Accuracy Details of Nine Blocks.

Block No.	Valid Samples	R^2	RMSE	MAPE
206	559	0.987	0.096	8.1%
329	189	0.995	0.052	10.3%
439	324	0.979	0.086	8.0%
521	359	0.979	0.081	6.1%
621	170	0.993	0.035	9.7%
721	35	0.999	0.024	8.1%
834	118	0.982	0.030	6.6%
921	621	0.981	0.033	8.7%
990	192	0.980	0.105	4.3%
Total	2,567	0.986	0.073	7.88%

The measured results are analyzed as follows: Under unified verification of 2,567 actual man-hour records, the calculated man-hours are highly consistent with actual man-hours. R^2 is 0.986 and MAPE is 7.88%. RMSE is 0.073 and MAE is 0.023. The average ratio of calculated to actual man-hours is 1.034. No systematic overestimation or underestimation is observed. For each block, MAPE ranges from 4.3% to 10.3%, and R^2 values are all higher than 0.97. As shown in Figures 8 and 9, sample points are densely distributed on both sides of the $y = x$ reference line. Consistency between calculated and actual man-hours is intuitively verified. Reliable accuracy is achieved by the model.

Scatter Comparison of Calculated and Actual Man-hours of Nine Typical Blocks

**Figure 8.** Scatter Comparison of Calculated and Actual Man-hours of Nine Typical Blocks.**Figure 9.** Scatter Comparison of Calculated and Actual Man-hours of All Samples ($n = 2,567$, $R^2 = 0.986$).

5.3.2. Comparison with Other Estimation Methods

Current shipbuilding man-hour estimation follows three mainstream technical routes, including traditional quota methods, shallow machine learning, and transfer learning. Significant differences exist in modeling logic, input systems, and condition adaptability. A structured qualitative comparison is conducted to identify inherent shortcomings. Five core engineering evaluation dimensions are used. They are modeling driven logic, feature input system, parameter calibration means, dynamic condition coupling capability, and model interpretability. Four representative estimation schemes are compared, with the 2,567 measured samples as the benchmark. The comparison dimensions and results are shown in Table 10.

Table 10. Multi-dimensional Qualitative Comparison of Different Man-hour Estimation Methods.

Method	Modeling Driven Logic	Feature Input System	Parameter Calibration Means	Dynamic Condition Coupling	Model Interpretability	Inherent Limitations
Traditional WBS Process Quota Method	Pure on-site experience induction	Only single geometric parameter of components	Manual ledger-based empirical assignment	No personnel or environmental loss correction	Extremely low; errors cannot be traced	Solidified static coefficients; poor generalization across ship types
Single-feature BP Neural Network	Pure data-driven black-box fitting	A few geometric dimension features	Gradient backpropagation without process constraints	Only static geometric coupling; on-site dynamic losses ignored	Low; black box without process physical meaning	Physiological losses missing; errors surge under condition fluctuations
PSO-BP Optimized Neural Network	Pure data-driven black-box fitting	Multiple static geometric features	Particle swarm optimization without physical mechanism support	Only static geometric coupling; on-site dynamic losses ignored	Low; black box without process physical meaning	No human-factor mechanism support; no direction for deviation optimization
TR-PSO Transfer Learning Model	Pure data transfer fitting driven	Multiple static geometric features	Transfer fine-tuning without physiological experiment calibration	Only static geometric coupling; on-site dynamic losses ignored	Low; black box without process physical meaning	Complete design-production quantity conversion chain missing
Proposed Four-dimensional Feature Multi-level Coupling Model	Hybrid drive of sEMG ergonomic mechanism and measured data	Four-dimensional interim product features plus dynamic personnel and environmental factors	Piecewise regression calibration based on welding sEMG load experiments	Full-dimensional dynamic coupling of skills, temperature, humidity and noise	High; all coefficients correspond to actual process meanings	No obvious inherent shortcomings; accuracy and practicability balanced

The underlying defects of each method are analyzed based on the comparison results.

Traditional WBS quota methods rely on historical production ledgers, and man-hour coefficients are solidified. Moreover, only basic geometric parameters are used for estimation, including plate thickness and weld length. Workload differences are not distinguished. These differences arise from construction stages, hull zones, and welding postures. Quota deviations accumulate continuously when new ship types are added. Personnel turnover and workshop environment changes also worsen the deviations. This method suits only old shipyards with single products and stable environments. Flexible customized shipbuilding demands cannot be met.

Single-feature BP and PSO-BP models are pure data-driven black-box algorithms. Only component geometry is used as the input variable. Dynamic production factors are not incorporated, including personnel skill levels and workshop temperature and humidity. Internal weights have no physical meaning related to shipbuilding processes or ergonomics. Error sources cannot be located when deviations from on-site man-hours occur. Process and quota optimization can hardly be guided.

The TR-PSO transfer learning model relieves small-sample training difficulties, and source domain data are used. However, its modeling boundary is limited to final man-hour prediction of blocks. A full-chain framework covering design quantity correction and production quantity

conversion is not built. No sEMG human load experiments support the feature assignment process. Man-hour loss differences cannot be quantified for different welding postures and operating zones. Inherent gaps exist in its estimation logic.

The proposed multi-level coupling model takes four-dimensional features as the core. sEMG experiments are introduced to quantify physiological workload losses. A three-stage progressive closed-loop architecture is built. Multi-factor coupling correction of man, machine, and environment is realized through the multi-dimensional production feature matrix. All calculation parameters have clear physical meanings of shipbuilding processes. The model is verified on 2,567 measured samples of nine blocks. Grand and medium assemblies, multiple trades, and dynamic workshop scenarios are simultaneously adapted. Systematic shortcomings of the methods are remedied.

A quantitative comparison is further conducted on the qualitative basis. Actual man-hours are used as the benchmark, and the same 2,567 measured samples are used for all methods. Four mainstream methods are tested together with the proposed model. They are the traditional WBS quota method, the single-feature BP neural network, the PSO-BP optimized neural network, and the TR-PSO transfer learning model. Four error indicators are uniformly adopted, including R^2 , RMSE, MAE, and MAPE. The horizontal comparison results are shown in Table 11.

Table 11. Quantitative Comparison of Measured Accuracy of Different Estimation Methods.

Model	R^2	RMSE	MAE	MAPE
Traditional WBS Process Quota Method	0.334	0.503	0.391	18.69%
Single-feature BP Neural Network	0.665	0.357	0.272	13.02%
PSO-BP Optimized Neural Network	0.755	0.305	0.215	10.11%
TR-PSO Transfer Learning Model	0.872	0.221	0.158	9.85%
Proposed Four-dimensional Feature Multi-level Coupling Model	0.986	0.073	0.023	7.88%

The quantitative comparison results are analyzed as follows: The traditional WBS quota method shows the highest overall error, and its MAPE reaches 18.69%. The core reason is the poor adaptability of static quotas. Many curved blocks, cross-zone operations, and skill-differentiated teams are included in the samples. Estimation is completed only by fixed geometric coefficients, so condition adaptability is seriously insufficient. Accuracies of single-feature BP and PSO-BP models are improved, with MAPEs of 13.02% and 10.11% respectively. However, single geometric input is used without ergonomic constraints, and an obvious error ceiling exists. The TR-PSO model improves fitting under small-sample scenarios, but its MAPE is still 9.85%. This value is 1.97 percentage points higher than the proposed model. Under unified verification with the same samples, R^2 of the proposed model reaches 0.986 and MAPE is reduced to 7.88%. The error is reduced by about 57.8% compared with the traditional WBS method. The error is reduced by about 20.0% compared with the best baseline TR-PSO. Stronger prediction stability and accuracy are fully proved. The three-stage architecture integrates four-dimensional feature correction and full-factor man-machine-environment coupling. Man-hour data calculated by this method are closer to actual measured values.

To further verify the statistical significance of the accuracy improvement, paired-samples t-tests are conducted on the entry-by-entry absolute errors $|T_{\text{calc}} - T_{\text{actual}}|$ between the proposed model and each baseline method over the same 2,567 measured samples. The results show that the mean absolute error of the proposed model (0.023 h) is significantly lower than that of the traditional WBS quota method (0.391 h, $t(2566) = 62.35$, $p < 0.001$), the single-feature BP neural network (0.272 h, $t(2566)$

= 48.54, $p < 0.001$), the PSO-BP optimized neural network (0.215 h, $t(2566) = 42.63$, $p < 0.001$), and the TR-PSO transfer learning model (0.158 h, $t(2566) = 34.37$, $p < 0.001$). The accuracy advantage of the proposed model over all baseline methods is therefore statistically significant, rather than a random fluctuation of the sample set.

5.3.3. Comprehensive Analysis

Based on the qualitative mechanism comparison and quantitative verification, three conclusions are drawn.

(1) At the mechanism level, four-dimensional features of interim products are taken as the core. sEMG ergonomic experiments and man-machine-environment dynamic coupling are integrated. Inherent shortcomings of existing methods are overcome. They include static solidification of quota methods, black-box non-interpretability of machine learning, and missing links of transfer learning.

(2) At the accuracy level, calculated man-hours are highly consistent with actual man-hours. R^2 is 0.986 and MAPE is 7.88%. The proposed model significantly outperforms the traditional WBS method (MAPE 18.69%). It also outperforms the TR-PSO transfer learning model (MAPE 9.85%). The verification is upgraded from “changes are generated” to “accuracy is proved”.

(3) At the engineering value level, model outputs can be directly connected to shipyard production management systems. Data support is provided for production scheduling, cost accounting, quota verification, and team allocation. All parameters have clear physical meanings of shipbuilding processes, so on-site calibration and iteration are facilitated. The three dimensions mutually confirm each other. Advancement and engineering practicability of the proposed multi-level man-hour calculation model are demonstrated.

6. Conclusions

In this study, we focus on the data deviation between design physical quantity, production physical quantity and standard man-hours in the shipbuilding process. Traditional shipbuilding man-hour calculation methods are difficult to meet the needs of refined production management due to defects of missing multi-dimensional feature association, data fragmentation, and static empirical estimation, and cannot effectively bridge the disconnection between design outputs and on-site production dynamics. In this study, we present a novel multi-level standard man-hours calculation model for shipbuilding, constructed based on the four-dimensional feature system of shipbuilding Interim products covering stage, system, type, and zone.

The proposed model fills the research gap of full-process data correction in shipbuilding man-hour management, and forms three core theoretical contributions. Verified by actual block construction data from WGQ Shipyard, the model can effectively improve full-process data accuracy, provide reliable data support for shipyard production planning, cost control and refined management, and offer constructive guidance for the standardization and digitalization of shipbuilding man-hour data management.

There are some limitations in this study, which provide directions for future study. First, the validation scope of the proposed model is relatively narrow, only limited to specific ship blocks and a single shipyard. Second, the quantification of partial production factors in the model is simplified, with calculation precision to be further optimized. In the future, using the methodology verified through this

study, we will extend model validation to more ship types and shipyards, optimize factor quantification methods, and further advance the generalizability and practical application value of the model.

Author contributions

Liu Lijun: Conceptualization, Supervision, Funding acquisition, Writing – review & editing, Project administration. Liu Jiahao: Methodology, Formal analysis, Investigation, Data curation, Software (if applicable), Writing – original draft. Ren Fei: Investigation, Data curation, Validation, Visualization. Meng Huisong: Investigation, Validation, Writing – review & editing. Jiang Zuhua: Supervision, Resources, Writing – review & editing.

Use of Generative-AI tools declaration

During the preparation of this manuscript, the authors used ChatGPT for language polishing and expression improvement. All AI-assisted content was critically reviewed and revised by the authors, who take full responsibility for the final published version.

Acknowledgments

The authors are very grateful to those who provided valuable comments on this article.

Conflict of interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

1. M. Hur, S. Lee, B. Kim, S. Cho, D. Lee, D. Lee, A study on the man-hour prediction system for shipbuilding, *J. Intell. Manuf.*, **26** (2015), 1267–1279. <https://doi.org/10.1007/s10845-013-0858-3>
2. A. M. Rashwan, Estimation of ship production man-hours, *Alex. Eng. J.*, **44** (2005), 527–533.
3. S. Cho, J. M. Lee, J. H. Woo, Development of production planning system for shipbuilding using component-based development framework, *Int. J. Nav. Archit. Ocean Eng.*, **13** (2021), 405–430. <https://doi.org/10.1016/j.ijnaoe.2021.05.001>
4. Y. Okubo, T. Mitsuyuki, Ship production planning using shipbuilding system modeling and discrete time process simulation, *J. Mar. Sci. Eng.*, **10** (2022), 176. <https://doi.org/10.3390/jmse10020176>
5. N. S. Krishnan, A scientific approach to measure shipbuilding productivity, *Marit. Aff.*, **8** (2012), 136–149. <https://doi.org/10.1080/09733159.2012.690565>
6. D. Okumus, S. Fariya, S. Tamer, S. Gunbeyaz, G. Yildiz, R. Kurt, et al., The impact of fatigue on shipyard welding workers' occupational health and safety and performance, *Ocean Eng.*, **285** (2023), 115296. <https://doi.org/10.1016/j.oceaneng.2023.115296>
7. A. Bordbar, M. Tadros, A. Nazemian, M. Aung, K. Georgoulas, P. Louvros, et al., Digitalisation of shipyard production planning: a review of simulation, optimisation, AI, and digital twin methods (2010–2025), *J. Mar. Sci. Eng.*, **14** (2026), 396. <https://doi.org/10.3390/jmse14040396>

8. M. Ramirez-Peña, F. J. A. Fraga, J. Salguero, M. Batista, Assessing sustainability in the shipbuilding supply chain 4.0: A systematic review, *Sustainability*, **12** (2020), 6373. <https://doi.org/10.3390/su12166373>
9. K. Kim, M. Choi, H. Seo, J. Lee, J. Kim, S. Kim, A mixed integer linear programming model for rapid rescheduling in ship and offshore unit design projects, *J. Mar. Sci. Eng.*, **13** (2025), 222. <https://doi.org/10.3390/jmse13020222>
10. S. Park, J. H. Huh, Study on PLM and big data collection for the digital transformation of the shipbuilding industry, *J. Mar. Sci. Eng.*, **10** (2022), 1488. <https://doi.org/10.3390/jmse10101488>
11. W. A. Z. Wan Abd Rahman, N. I. Mohd Zaki, M. K. Abu Husain, A review of work breakdown structure and man-hours estimation method used in shipbuilding production, *Int. J. Mech. Eng. Technol.*, **10** (2019), 1141–1158.
12. W. A. Z. Wan Abd Rahman, N. I. Mohd Zaki, M. K. Abu Husain, Work breakdown structure application for man-hours calculation in hull construction shipbuilding in Malaysia, *Cogent Eng.*, **6** (2019), 1599524. <https://doi.org/10.1080/23311916.2019.1599524>
13. J. Li, P. Lin, D. Song, Z. Yan, B. Yang, L. Zhou, Time prediction in ship block manufacturing based on transfer learning, *J. Mar. Sci. Eng.*, **12** (2024), 1977. <https://doi.org/10.3390/jmse12111977>
14. P. Z. Roque, J. M. Gordo, A measurement of shipbuilding productivity, in: *Maritime Technology and Engineering 5 Volume 1*, CRC Press, 2021, 801–809. <https://doi.org/10.1201/9781003216582-91>
15. J. Emblemståg, Lean project planning in shipbuilding, *J. Ship Prod. Des.*, **30** (2017), 79–88. <https://doi.org/10.5957/jspd.30.1.130054>
16. X. Jing, C. Cheng, J. Liu, S. Yue, S. Li, Y. Chen, et al., Shipbuilding workshop and storage yard scheduling: A literature review, *Mar. Struct.*, **107** (2026), 103988. <https://doi.org/10.1016/j.marstruc.2025.103988>
17. T. Shinoda, T. Tanaka, H. Okamoto, D. Umemoto, A method of automated work observation for ship production using deep neural networks, paper presented at *SNAME Maritime Convention 2021*. <https://doi.org/10.5957/smc-2021-041>
18. China Institute of International Studies, The development choices behind South Korea’s “foreign labor dispute”, 2026.
19. U.S. Department of Defense, National Defense Industrial Strategy (NDIS), Washington, D.C.: DoD, 2024.
20. R. O’Rourke, Navy Ford (CVN-78) Class Aircraft Carrier Program: Background and Issues for Congress, Washington, D.C.: Congressional Research Service, 2025.
21. U.S. Government Accountability Office, Navy Shipbuilding: Increased Use of Leading Practices Could Improve Timeliness, Washington, D.C.: GAO, 2024.
22. China Association of the National Shipbuilding Industry, In 2024, China’s shipbuilding completions, new orders and orderbook accounted for 55.7%, 74.1% and 63.1% of the global market share respectively, Xinhua News Agency, 2025.
23. C. Liang, X. Li, W. Niu, Y. Zhang, Internet of Things driven digital twin for intelligent manufacturing in shipbuilding workshops, *Future Internet*, **17** (2025), 368. <https://doi.org/10.3390/fi17080368>

24. W. S. Ruy, H. K. Kim, Y. J. Cho, D. E. Ko, Implementation of welding material quantity evaluation system combined with ship design CAD system, *Int. J. Nav. Archit. Ocean Eng.*, **9** (2017), 219–226. <https://doi.org/10.1016/j.ijnaoe.2016.10.004>
25. K. Kwon, J. Lee, D. Mun, Lightweight model-based weld line generation and its applications to support the construction of ships and offshore plants, *J. Mar. Sci. Eng.*, **11** (2023), 554. <https://doi.org/10.3390/jmse11030554>
26. Y. G. Lee, S. Ju, J. H. Woo, Simulation-based planning system for shipbuilding, *Int. J. Comput. Integr. Manuf.*, **33** (2020), 626–641. <https://doi.org/10.1080/0951192X.2020.1775304>
27. D. H. Kwak, Y. I. Cho, S. W. Choe, H. J. Kwon, J. H. Woo, Optimization of long-term planning with a constraint satisfaction problem algorithm with a machine learning, *Int. J. Nav. Archit. Ocean Eng.*, (2022), 100442. <https://doi.org/10.1016/j.ijnaoe.2022.100442>
28. S. H. Nam, H. Q. Shen, C. Ryu, J. G. Shin, SCP-matrix based shipyard APS design: Application to long-term production plan, *Int. J. Nav. Archit. Ocean Eng.*, **10** (2018), 741–761. <https://doi.org/10.1016/j.ijnaoe.2017.10.003>
29. S. Ju, J. H. Woo, Integration of long-term planning and mid-term scheduling of shipbuilding, *Prod. Plan. Control*, **34** (2023), 524–542. <https://doi.org/10.1080/09537287.2021.1940344>
30. W. S. Choi, D. H. Kim, J. H. Nam, M. J. Kim, Y. B. Son, Estimating production metric for ship assembly based on geometric and production information of ship block model, *J. Mar. Sci. Eng.*, **9** (2021), 39. <https://doi.org/10.3390/jmse9010039>
31. J. H. Jeong, J. H. Woo, J. G. Park, Machine learning methodology for management of shipbuilding master data, *Int. J. Nav. Archit. Ocean Eng.*, **12** (2020), 428–439. <https://doi.org/10.1016/j.ijnaoe.2020.03.005>
32. J. Li, M. Sun, D. Han, J. Wang, X. Mao, X. Wu, A knowledge discovery and reuse method for time estimation in ship block manufacturing planning using DEA, *Adv. Eng. Inform.*, **39** (2019), 25–40. <https://doi.org/10.1016/j.aei.2018.11.005>
33. C. Wang, D. Hua, J. Peng, L. Huang, Prediction of ship production design man-hour based on WGAN-GP and HEOA-BP neural network, *J. Ship Prod. Des.*, **41** (2025), 93–101. <https://doi.org/10.5957/jspd.04240011>
34. P. A. M. Fruytier, A. K. Dev, Predicting ship maintenance and repair labor with artificial neural networks, *J. Ship Prod. Des.*, **38** (2022), 9–18. <https://doi.org/10.5957/jspd.10200027>
35. Y. Genç, M. Kafali, U. B. Çelebi, Approximate estimation of man-day in ship block production: A two-stage stochastic program, *Pol. Marit. Res.*, **31** (2024), 146–158. <https://doi.org/10.2478/pomr-2024-0015>
36. J. Liu, Y. Zhang, Z. Liu, J. Leng, H. Zhou, S. Gu, et al., Digital twins enable shipbuilding, *Alex. Eng. J.*, (2024), 107915. <https://doi.org/10.1016/j.aej.2024.09.007>
37. Z. Kunkera, T. Opetuk, N. Hadžić, N. Tošanović, Using digital twin in a shipbuilding project, *Appl. Sci.*, **12** (2022), 12721. <https://doi.org/10.3390/app122412721>
38. X. Zhang, D. Chen, Shipbuilding 4.0: A systematic literature review, *Appl. Sci.*, **14** (2024), 6363. <https://doi.org/10.3390/app14146363>
39. V. Stanić, M. Hadjina, N. Fafandjel, T. Matulja, Toward Shipbuilding 4.0 – An Industry 4.0 changing the face of the shipbuilding industry, *Brodogradnja*, **69** (2018), 111–128. <https://doi.org/10.21278/brod69307>

40. G. Alblas, J. Pruijn, Are current shipbuilding cost estimation methods ready for a sustainable future? A literature review of cost estimation methods and challenges, *Int. Shipbuild. Prog.*, **71** (2024), 3–28. <https://doi.org/10.3233/ISP-230009>



AIMS Press

© 2026 the Author(s), licensee AIMS Press. This is an open access article distributed under the terms of the Creative Commons Attribution License (<https://creativecommons.org/licenses/by/4.0>)