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RESEARCH ARTICLE

Optimizing shipbuilding production project scheduling under resource constraints using genetic algorithms and fuzzy sets

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ABSTRACT

This study explores the application of Genetic Algorithms (GA) in optimizing shipbuilding production processes in the presence of uncertain environments. The research addresses two key aspects: firstly, the integration of GA RCPSP (Resource-Constrained Project Scheduling Problem) with techniques for managing uncertainty in shipbuilding production; and secondly, the analysis of Pareto optimal solutions generated by GA to achieve optimal scheduling in the shipbuilding context. The proposed framework aims to minimize project completion time and maximize resource utilization by incorporating probabilistic models, scenario analysis to handle uncertainties. Furthermore, the study focuses on evaluating the trade-offs between project completion time, resource allocation, and cost through the analysis of Pareto optimal solutions, using visualization techniques and sensitivity analyses to support decision-making processes. The findings contribute to enhancing shipbuilding production by providing a comprehensive approach for effectively managing uncertainty, improving resource allocation, and reducing project duration through the integration of GA RCPSP and uncertainty management techniques.

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Introduction

The shipbuilding industry, which is estimated to reach a global shipbuilding market value of $145.67 billion in 2023 (Statista, 2023), is one of the capital-intensive and heavy industries that creates substantial employment opportunities and makes a significant contribution to the global economy. In recent years, the global supply of merchant ships has been dominated by China, the Republic of Korea and Japan, which together have a 94% market share in the shipbuilding industry

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(UNCTAD, 2022). The shipbuilding industry is a highly complicated sector with a multifaceted value chain encompassing the design, construction, and installation of diverse vessels (Lee et al., 2020). The production process within a shipyard represents one of the most intricate manufacturing systems (Okubo & Mitsuyuki, 2022). In the shipbuilding industry, competitiveness is multifaceted, encompassing various dimensions, including shipbuilding expenses, delivery timelines, ship quality, after sales services, and financing terms (Ecorys, 2009; Jiang & Strandenes, 2012). Shipbuilding is characterized by a complex production system with intricate work and organizational structures, extended lead times, and diverse resource requirements (Liu et al., 2011). The modern shipbuilding industry continually faces new challenges and market demands, necessitating ongoing improvements in the shipbuilding process to enhance fabrication efficiency amidst numerous uncertainties on the factory floor. Consequently, shipyards are compelled to continuously develop and implement novel production technologies and methodologies to effectively schedule the complex shipbuilding process (Hadžić, 2019).

The shipbuilding industry, which operates under an Engineering-to-Order (ETO) production mode, is a representative example of a project-based industry. Shipbuilding projects possess distinct characteristics such as complex product structures, multiple manufacturing stages, long production cycles, tight deadlines, jobbing work, concurrent execution of multiple projects, frequent modifications in engineering designs, and so on (Mao et al., 2020). Effective production planning plays a crucial role as it directly impacts construction costs and project duration. Moreover, given the limited time available for comparing multiple plans, production resource constraints must be taken into account (Okubo & Mitsuyuki, 2022). The shipbuilding production is a complex and lengthy process, which demands careful planning and timely decision-making. Characteristic of an intermittent process like shipbuilding is a large number of working activities of different duration (Ljubenkov et al., 2008). With the rapid development of technology, it has been affecting in ship production process (Mao et al., 2020). The primary challenge in shipbuilding processes lies in enhancing productivity at shipyards by developing new production technologies and effectively managing them (Lee et al., 2020). Labor plays a critical role in shipbuilding industry productivity, making it difficult to estimate workloads and schedules while considering worker allocation. Given the characteristics of the ETO industry, design and scheduling changes frequently occur during production. Furthermore, managing long-term production plans poses challenges. Process managers oversee the control of each task according to predefined schedules, making it difficult to negotiate and coordinate with other processes and increasing the possibility of making inefficient decisions (Goo et al., 2019). In a multi-project environment, all construction tasks are consolidated into an overall shipyard-level plan that analyzes available capabilities and resources over the planning horizon. Since all ships are built using shared resources in a competitive manner, it is necessary to plan the aggregate utilization of resources across all projects in order to create a reliable master schedule for each production stage and the entire project (Liu et al., 2011). In a distributed manufacturing environment, accomplishing such a complex shipbuilding project requires cross-enterprise cooperation. Multi-project parallelism and distributed manufacturing introduce numerous project coordination tasks. The complexity of shipbuilding projects and the extensive coordination required exponentially increase the difficulty of project control (Mao et al., 2020). For most shipbuilding enterprises, project execution is generally inefficient, as evidenced by poor coordination, underutilization of resources, cost overruns, and project delays, all of which have a significant impact on the enterprise's reputation within the industry. The root cause of these performance issues is the lack of effective project scheduling methods that align with the characteristics of current shipbuilding projects involving distributed manufacturing, collaborative decision-making, and dynamic scheduling (Mao et al., 2020). To ensure competitiveness and sustainability, shipyards must continuously monitor and enhance productivity, efficiency, and quality while reducing overall production costs (Rubeša et al., 2023).

Shipbuilding production is a complex process that requires careful planning and timely decision-making. It involves numerous working activities of varying durations, following an intermittent process. In a multi-project environment, all building tasks are consolidated into an overall shipyard-level plan. This plan analyzes available capabilities and resources over the planning horizon. However, coordinating multiple projects and managing distributed manufacturing poses significant challenges. It exponentially increases the difficulty of controlling the shipbuilding project due to its inherent complexity and extensive coordination requirements. Hence, it is imperative to employ efficient project planning and scheduling techniques in order to enhance the optimization of resource utilization, encompassing resource allocation and comprehensive resource utilization strategies. Given the finite

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resources available to enterprises for their production endeavors, meticulous planning of both temporal and quantitative aspects of project resources becomes indispensable. Shipbuilding faces the RCPSP, which involves optimizing the allocation of limited resources within a project's time constraints. This complex challenge requires efficient management of manpower, materials, and equipment to ensure timely completion of ship construction, addressing the industry's unique operational requirements. Additionally, GAs, a metaheuristic inspired by natural evolution and used to solve complex optimization problems, are used for RCPSPs because they can handle multiple constraints simultaneously, explore and exploit the solution space, utilize a population-based approach, and iteratively improve solutions. These algorithms are well-suited for optimizing complex scheduling problems by considering task dependencies, resource availability, and limits. GAs generate and evaluate a population of potential solutions, selecting and combining individuals through genetic operations like crossover and mutation. This iterative process continues until a termination criterion is met, aiming to find an optimal or near-optimal solution in a large search space. By representing project schedules as chromosomes and using genetic operations, GAs explore various combinations to find efficient project schedules that balance resource allocation, task dependencies, and project objectives (Akan, 2017; Han et al., 2017; Hu et al., 2019; Jeong et al., 2018; Mao et al., 2020). Furthermore, precisely estimating the duration of activities in terms of project management in the ship production process can be challenging due to the unique nature of each order. In such cases, fuzzy set theory effectively handles uncertainty and provides more accurate modeling of real-world problems compared to deterministic methods by addressing uncertainty and vagueness, using approximate knowledge (Kahraman & Kaya, 2010). Zadeh's (1965) development of fuzzy set theory introduced membership functions, assigning degrees of membership within the interval [0,1] to elements therefore, thanks to the membership functions of fuzzy sets being defined for project duration in scheduling, it becomes possible to provide a wider range of feasible cluster solutions for projects operating in uncertain environments (Akan & Bayar, 2022). Therefore, effective project planning and scheduling, along with the utilization of artificial intelligence techniques such as GAs and fuzzy set theory, can significantly contribute to overcoming the challenges of shipbuilding production and optimizing resource allocation in this complex and resource-intensive industry. Additionally, the aim of this study is to comprehensively explore the integration of genetic algorithm into shipbuilding production processes under uncertainty, providing actionable insights for efficient resource utilization and timely project completion. By addressing the two research questions, the article strives to bridge the gap between theoretical concepts and practical implementation, providing insights into the adaptation of GA to real-world shipbuilding scenarios. With the motivation to investigate and provide valuable insights into the following research questions:

(RQ1) How can the application of GA RCPSP be applied to the shipbuilding production process in the presence of an uncertain environment?

(RQ2) How can the analysis of Pareto optimal solutions be performed using the set generated by the Genetic Algorithm for the GA RCPSP in the context of the shipbuilding production process?

Furthermore, a shipbuilding process consists respectively of the stages of shipowner's decision, design and contracting, engineering and approval, material procurement, fabrication and assembly, outfitting and installation, testing and trials, certification and documentation, delivery and commissioning, and post-delivery support (Kim et al., 2005; Özyiğit, 2006). The manufacturing phase is prone to minor variations, primarily characterized by pivotal procedures such as block erection, prioritized block assembly, exterior assembly, and painting (Park et al., 2002) nevertheless, the manufacturing phase may vary due to different production arrangements adopted by shipyards based on ship type and outsourcing decisions (Stopford, 2009). Therefore, the application of this study focuses on the following stages of ship production process such as plate cutting and assembly of components, surface cleaning and grinding operations of plates, preparation of profiles, preparation of cut single-piece plates, surface preparation, and bending operations, assembly of small groups and pre-fabrication, panel manufacturing, component panel manufacturing, grouped panel production, block production, block assembly on the slipway, and launching the steel ship into the sea.

Additionally, the rest of the research is structured as follows: Section 2 provides a comprehensive literature review. In Section 3, the methodology is presented in detail. Section 4 demonstrates the application of the study method to perform. The final section encompasses the discussion of the findings, drawing conclusions based on the results obtained, and providing suggestions for future research endeavors.

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Literature Review

This section considers the application of the GA RCPSP within fuzzy environment in the context of the shipbuilding industry.

The studies in regard to the use of RCPSP: Kolisch (1995) introduced ProGen, an algorithm for solving RCPSP. The algorithm was utilized to solve the problem using the priority rule method. To enable comparison with other researchers, Kolisch & Spracher (1996) developed the PSPLib Project Scheduling Library. Özdamar & Ulusoy (1996) proposed an iterative scheduling algorithm that improved project duration through forward/backward planning transitions obtained from Local Constraint-Based Analysis. This algorithm demonstrated an average project duration deviation of 1%. Boctor (1996) explored the multi-mode RCPSP, generating 21 heuristic methods to solve it. Sprecher & Drexl (1998) devised a branch and bound algorithm and a parallel scheduling algorithm for solving the multi-mode RCPSP. Reyck & Herroelen (1998) developed a branch and bound algorithm for the RCPSP, incorporating minimum and maximum delays between activities as activity precedence constraints. Schirmer (1998) evaluated a case-based approach for the RCPSP by comparing it with other algorithms using PSPLib data. Hartmann & Kolisch (2000) proposed a simulated annealing-based method within the X-Pass approach for solving RCPSP. Brucker & Knust (2000) introduced a new lower bound for the RCPSP, minimizing workforce utilization in the RCPSP through constraint propagation and linear programming. Abbasi et al. (2006) presented a simulated annealing algorithm based on time maximization to minimize workforce utilization and enhance scheduling reliability in the RCPSP. Shadrokh & Kianfar (2007) aimed to minimize the cost of resource capacity and project completion time by addressing the resource investment problem within the RCPSP category. Homberger (2007) proposed a multi-agent approach and a restart evolution method for the Resource-Constrained Multi-Project Scheduling problem. Adhau et al. (2012) developed a negotiation-based multi-agent method utilizing an auction approach to prevent resource intersections and generate optimal solution sets. Adhau et al. (2013) excluded resource transportation cost and time from their solution to facilitate comparison with previous methods. Furthermore, recent studies provide novel methods and algorithms, RCPSP. Etgar et al. (2018) achieved near-optimal solutions for multi-release work plans using clustering-based techniques. Chand et al. (2018) proposed genetic programming-based hyper-heuristics, while Muñoz et al. (2018) showcased the effectiveness of the Bienstock-Zuckerberg algorithm for project scheduling problems. Zhu et al. (2019) introduced a discrete oppositional multi-verse optimization algorithm for the multi-skill RCPSP, demonstrating superior performance. Servranckx & Vanhoucke (2019) focused on RCPSP with alternative subgraphs, highlighting the benefits of using a set of schedules. Vanhoucke & Coelho (2019) presented a solution algorithm for RCPSP with activity splitting and setup times. Tesch (2020) proposed event-based mixed-integer programming formulations for RCPSP, while Shariatmadari & Nahavandi (2020) enhanced schedule robustness using resource buffers. Wang et al. (2020) integrated information and data flow for RCPSP in construction scheduling. Guo et al. (2021) introduced a decision tree approach leveraging project indicators and predictions to identify the best priority rule. Asadujjaman et al. (2021) proposed a hybrid immune genetic algorithm for net present value-based RCPSP, outperforming existing methods. Saad et al. (2021) presented a quantum-inspired genetic algorithm that surpassed other evolutionary algorithms for RCPSP. Van Eynde & Vanhoucke (2022) developed a theoretical framework for assessing instance complexity, while Zhou et al. (2022) introduced a hybrid approach for multi-objective scheduling problems. Akhbari (2022) proposed a mathematical model integrating multiple modes. Xu & Bai (2023) presented an algorithm using a hybrid genetic algorithm and sensitivity analysis to analyze the impact of dynamic resource disruptions on project makespan. Zhang et al. (2023) developed a specific RCPSP model for water conservancy project scheduling, combining priority rule-based heuristics and hybrid genetic algorithms. Issa et al. (2023) proposed a heuristic method for reassessing scheduling interruption categories in RCPSP, providing decision choices to optimize project makespan. Akan (2023) analyzed the maritime logistics operation process by applying RCPSP approach in the "to-be" process stage in terms of business process management perspective.

The studies in regard to the use of GA-RCPSP: Sprecher et al. (1995) addressed semi-active, active, and non-delay scheduling without precedence relations. Hartmann (1998) incorporated problem-specific knowledge through permutation-based encoding, priority-based assignment, and rule-based priority scheme. Hartmann (2001) extended the concept of problem representation importance by incorporating two local searches. Alcaraz & Maroto (2001) utilized crossover techniques and a two-point passage. Hartmann (2002) aimed to minimize resource imbalances and achieve optimal results quickly. Toklu (2002) directly operated on the scheduling problem for the RCPSP. Kim et al. (2003) developed a hybrid GA with a fuzzy logic controller. Hindi et al. (2002) incorporated a crossover strategy related to the maintenance of order. Coelho & Tavares (2003) introduced a new crossover operator and activity representation. Valls et al. (2004) developed a hybrid GA with a peak passage operator. Tseng & Chen (2006) proposed a hybrid metaheuristic model combining Ant Colony Optimization, GA, and Local Search strategies. Ranjbar & Kianfar (2007) incorporated a resource utilization ratio and a local search method. Franco et al. (2007) minimized resource consumption using object-oriented programming and two-point crossover. Valls et al. (2008) introduced a hybrid GA with a local improvement operator. Goncalves et al. (2008) addressed the multi-project RCPSP. Chang et al. (2008) enhanced the decision support capability of the GA. Van Peteghem & Vanhoucke (2008, 2010) used two populations to minimize activity completion time and improve mode selection. Montoya-Torres et al. (2009) suggested a multi-string object-oriented GA model. Tseng & Chen (2009) proposed a two-phase genetic local search algorithm. Magalhaes-Mendes (2011) introduced a two-level GA. Khanzadi et al. (2011) presented a GA for large-scale projects. Palencia & Delgadillo (2012) applied a GA approach to a bus assembly line. Ponz-Tienda et al. (2012) demonstrated the effectiveness of an adaptive GA. Afshar-Nadjafi et al. (2013) integrated intelligent local search into the GA and organized sub-activities based on resource usage, employing a unified approach within each set. Devikamalam & Jane (2013) optimized resource allocation and reduced costs. Kim (2013) utilized an elitist GA. Tasan & Gen (2013) employed a fuzzy logic control-based automatic adjustment strategy. Huang et al. (2013) developed formulas to estimate completion time and minimize cost in project scheduling with fuzzy activity durations, along with constructing different fuzzy models and analyzing GAs. Aziz (2013) focused on minimizing project duration and maximizing net present value. Cheng et al. (2014) used a fuzzy clustering method and Differential Evolution algorithm. Sawant (2016) developed a GA to minimize resource usage. Zhang et al. (2008) also addressed resource usage minimization. Furthermore, in recent years, the GA RCPSP method has been widely used in many fields (e.g., García-Nieves et al., 2018; Muritiba et al., 2018; Chand et al. 2019; Zamani, 2019; Chaleshtarti et al., 2020; Liu et al., 2020; Snauwaert & Vanhoucke, 2021; Zaman et al., 2021; Aramesh et al., 2022; Hua et al., 2022; Myszkowski & Laszczyk, 2022; Coelho & Vanhoucke, 2023; Xu & Bai, 2023; Zhang et al., 2023).

The studies in regard to the use of fuzzy sets in project scheduling: Hapke & Slowinski (1996) proposed a fuzzy scheduling procedure for RCPSPs using fuzzy duration parameters and generating prioritized fuzzy orders. Bhaskar et al. (2011) introduced a parallel scheduling scheme based on priority rules for fuzzy activity durations in RCPSP. Long & Ohsato (2008) presented the fuzzy critical chain method for project scheduling. Çebi & Otay (2015) suggested a multi-objective linear programming model for minimizing project duration and cost in fuzzy project scheduling. Knyazeva et al. (2015) proposed a fuzzy heuristic priority algorithm for the fuzzy-constrained project scheduling problem in RCPSP. Birjandi et al. (2019) presented a hybrid fuzzy approach, FPND, combining PSO, BPSO, and GA, to minimize project end cost in the fuzzy RCPSP-MR problem, showcasing its effectiveness through comparisons and numerical examples.

The studies in regard to the production planning in shipbuilding: Cho & Chung (1996) introduced the part assembly chart, a semantic network representation system that utilized case-based and rule-based logic for ship block assembly planning. This system incorporated structural and geometric information, as well as cutting, bending, and welding operations. Lee et al. (1997) conducted research on ship production planning and scheduling, incorporating various disciplines such as operations management, artificial intelligence, and information technology. Their work focused on reducing scheduling time, selecting optimal schedules through simulation, and transferring technology from academia to industry. Kim et al. (2002) proposed a Constraint Satisfaction Problem-based algorithm to minimize unplanned blocks and balance workload in block assembly scheduling. Hiekata et al. (2010) introduced a method to improve design quality in ship production processes using statistical analysis and process ontology. Park & Seo (2010) developed GA-based approaches to solve storage location assignment problems in shipbuilding. Cha & Roh (2010) focused on process planning simulation models, particularly the simulation core. Soong et al. (2011) investigated ship production management strategies using various business tools and key performance indicators. Formentini & Romano (2011) proposed an information transfer model based on Value Analysis for multi-project environments. Yuguang et al. (2016) developed a real-time shipment and block assembly system for effective production control. Hwang et al. (2014) developed an intelligent simulation model for shipbuilding production planning and decision-making. In Joo & Kim (2014) presented a GA-based scheduling model for timely delivery of ship blocks. Park et al. (2014)

integrated process mining and data envelopment analysis for performance evaluation in ship block production processes. Kwon & Lee (2015) formulated a spatial scheduling problem for large assembly blocks in shipyard assembly lines. Back et al. (2016) defined a shipyard production simulation data model using an iterative procedure. Yuguang et al. (2016) developed a discrete particle swarm optimization algorithm for ship production assembly lines. Wang et al. (2016) proposed an integer programming model for ship block production considering uncertain factors. Dong et al. (2016) developed a flexible two-stage queue model for optimal cost-effectiveness in ship maintenance and construction. Mei et al. (2016) created an impact factor system for evaluating production processes in flexible intermediate product manufacturing. Furthermore, Hu et al. (2019) developed a guided local search algorithm for the 2D-RCPSP, Yang & Liu (2018) introduced a hybrid algorithm for fuzzy blocking flow shop scheduling, and Zhong (2017) proposed an improved genetic algorithm for multi-objective hull assembly line balancing. Li et al. (2021) integrated job scheduling, workshop layout, and transportation tasks for green manufacturing in marine crankshaft production using a genetic algorithm. Mao et al. (2020) presented an agent-based framework for collaborative planning and scheduling in shipbuilding projects. Other studies focused on improving time estimation precision (Li et al., 2019), shipbuilding block assembly line scheduling (Cho et al., 2022), and large-scale shipyard scheduling problems (Han et al., 2017). Jeong et al. (2018) proposed efficient spatial arrangement planning for shipyards, while Ge & Wang (2021) addressed block spatial scheduling optimization and scheduling strategies for irregular curved blocks. These studies collectively advance optimization techniques in shipbuilding, covering scheduling, resource utilization, spatial arrangement, and time estimation.

Accordingly, the contribution of this study is that the utilization of a GA approach to address the RCPSP in the context of shipbuilding, considering a fuzzy environment has not been studied in the existing academic literature.

Methodology

Resource Constraint Project Scheduling Problem

The RCPSP is a method that evaluates the activities of a project using limited resources without violating precedence relationships, aiming for the most suitable or optimal solution among mathematical methods. The RCPSP is a type of problem that is frequently studied in the literature and generates solutions using different methods. Due to the presence of two different constraints, activity priorities and resource constraints, it is considered more challenging than other problems. The RCPSP falls into the problem class classified as NP (Non-Polynomial) - Hard in the Strong Sense (Blazewicz et al., 1983) in the literature. Resources are the elements used for the realization of a project. The types of resources expressed in projects are as follows: Renewable resources have limited availability but do not deplete with usage. They can be reused after an activity. Non-renewable resources are limited and deplete with usage. When project duration and resource usage are constrained, they are doubly constrained. Non-renewable resources can be discrete if divisible into units, or continuous if indivisible. During the execution of activities that constitute projects, there is a relationship between the resources assigned and used for these activities. Usually, it is expressed as a Time-Cost Trade-Off, where it is expected that increasing the use of a resource in an activity will lead to a decrease in the activity duration. Due to the continuous and discrete nature of resource utilization, it is referred to as a continuous and discrete function of cost-time. In the case of discreteness, it is expressed as a mode corresponding to the cost-time pair. Project scheduling problems with multiple modes are also referred to as multi-modal problems. Another type of interaction is when the activity duration is fixed, but the resources can have different usages, which is called Resource-Resource Trade-Off. RCPSP models are examined in two categories as the Single-Mode RCPSP assumes fixed and unchanged project activity durations and assigned resource quantities, while the Multi-Mode RCPSP allows for variable and not fixed activity durations and assigned resource quantities. The RCPSP with multiple projects can be formulated in Eq. (1-5) as follows (Kolisch & Spracher, 1996; Ulusoy, 2002; Satıç, 2014; Akan, 2017).

$$min\ Z = \frac{\sum_{t=EFT_{jq}}^{LFT_{jq}} tX_{qjt}}{Q} \tag{1}$$

$$\sum_{t=EFT_j}^{LFT_j} X_{jt} = 1, j = 0, 1, \dots, n+1 \tag{2}$$

$$\sum_{t=EFT_i}^{LFT_i} tX_{imt} \leq \sum_{t=EFT_j}^{LFT_j} (t - d_j) X_{jt}, j = 1, \dots, n+1 \text{ and } i \in P_j \tag{3}$$

$$\sum_{j=1}^{j} k_{jr} \sum_{r=t}^{t+d_j-1} X_{jt} \leq K_r, r \in R, t = 1, \dots, r \tag{4}$$

$$X_{jt} = \begin{cases} 1, & if\ the\ activity\ j\ is\ finished\ at\ the\ end\ of\ the\ period\ t \\ 0, & for\ other\ situations, \end{cases} \tag{5}$$

where;

t the time index $t = 1, \dots, T$

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j the activity index $j = 1, \ldots, J$

R the set of renewable resources

d_j the duration of activity j^{th}

P_j the set of the predecessors of the activity j^{th}

EFT_j the earliest finish time of activity j^{th}

LFT_j the latest finish time of activity j^{th}

k_{jr} the amount of resource usage per unit time from resource r for activity j^{th}

K_r the unit time upper limit of resource utilization for renewable resource r

M_j the mode number of the activity j^{th}

q the project index $q = 1, \ldots, Q$

Eq. (1) aims to minimize the objective function and project delays. Eq. (2) requires the scheduling of each activity j^{th}. Eq. (3) represents the constraint that activity j^{th} can start only when its dependent activities, X_{it}, i and P_j are completed. Eq. (4) represents the constraint that ensures the precedence relationship between activity j^{th} and its predecessor activity i^{th} is satisfied. Eq. (5) defines the resource constraint per unit of time for each activity, where the variable X_{jt} is defined within the time interval $\{EFT_j, LFT_j\}$.

In essence, the presence of multiple projects does not fundamentally differ from having a single project in the context under consideration. The decision variables and constraints remain unchanged for both single and multiple projects. However, the objectives of the projects may differ. For instance, while one project may solely aim to minimize project duration, another project may seek to minimize both duration and cost simultaneously. When addressing multiple projects, two approaches can be adopted: treating each project as an independent entity with its distinct start and finish nodes, or merging them into a unified project for evaluation. The integration of all projects allows for the creation of a single start and finish node. In this particular study, the two projects were integrated into a unified project, necessitating adjustments to the activity and resource relationships accordingly.

Genetic Algorithm (GA)

The GA technique, developed by Holland (1975) and further enhanced by Goldberg (1989), is an intuitive method inspired by the Theory of Evolution. It models the processes of inheritance, including crossover, mutation, and selection, to transmit inherited information to subsequent generations. GAs offer broad applicability and provide accurate, convenient, and efficient solutions for various problems GAs aim to address complex problems in various domains and fall under the category of metaheuristic techniques (Haupt & Haupt, 2004). One such application is RCPSPs. GAs consist of key elements: chromosome populations, fitness-based selection, crossover for generating new generations, and random mutations. GAs utilize fitness functions to evaluate chromosome quality. GAs differ from traditional optimization methods in several aspects. GAs utilize probabilistic rules, objective functions, sets of points for solution search, and parameter codes instead of direct manipulation. Haupt & Haupt (2004) classify GAs as metaheuristic techniques, primarily employed for addressing complex problems. With its advantages GAs demonstrate versatility in handling both continuous and discrete variables, operating without derivative information, exploring solutions concurrently with large samples, adapting well to problems with many variables, being suitable for parallel computing, overcoming local optima in complex solution variables, providing a list of optimal variable solutions, encoding variables for optimization, and working with numerical, experimental, or analytical functions. However, GAs may not be the best approach for every problem. Traditional methods may suffice for simple problems. Consider using GAs for large populations or when past experience indicates their efficacy (Goldberg, 1989). GA concepts possess the following characteristics (Coley, 1999; Mitchell, 1999; Haupt & Haupt, 2004):

- Gen represents a section of the solution in GAs, which corresponds to a project activity in RCPSP.
- Chromosome encodes a solution in GAs. It represents a scheduling solution in RCPSP, using random key, activity list, or other methods.
- Population is the number of solutions being searched simultaneously. A larger population increases the chances of finding the optimal solution, but population size should be adjusted to prevent excessive solution time.
- Generation is the process of producing solutions through successive iterations.
- Fitness Function evaluates solutions to recognize the desired solution. It can be a combination of objectives for problems with multiple goals.
- Selection chooses chromosomes for the next generation based on fitness functions.
- Crossover modifies chromosome programming from one generation to another, creating more qualified individuals.

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- Mutation creates a new solution by making slight changes to existing information. Mutation can occur after crossover or independently and includes operations like reversal, displacement, insertion, and reciprocal exchange.

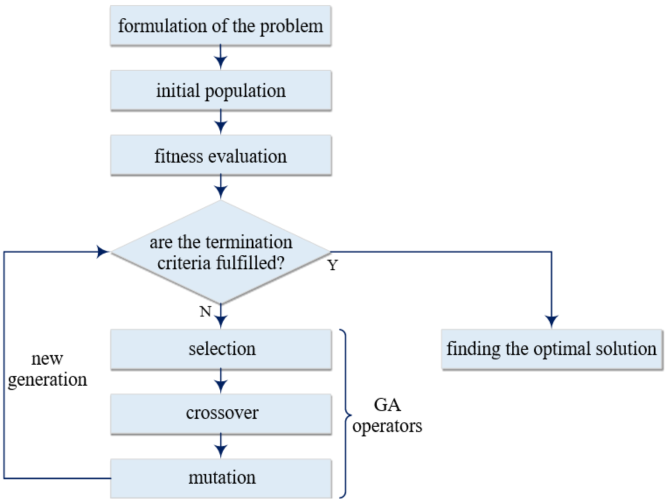

Figure 1. GA diagram

Generally, the operational principles of a standard GA can be summarized in Figure 1 as follows (Coley, 1999; Mitchell, 1999; Haupt & Haupt, 2004).

- Generating a solution population by encoding possible solutions. The population size is determined considering the complexity and depth of the problem.
- Evaluating the fitness of each chromosome in the population using a fitness function. The evolution process involves determining the quality of chromosomes through this function, which is problem-specific and critical to the success of the GA.
- Creating a new population by applying crossover and mutation operators to selected chromosomes. Crossover promotes diversity, while mutation influences individual solutions.
- Updating the population by replacing old chromosomes with newly generated ones, maintaining a fixed population size.
- Assessing the success of the population by calculating the fitness values of the new chromosomes.
- Iterating the process to produce improved generations within a specified time frame.
- Eventually, the solution is obtained by identifying the best individuals in the population during the generation computation.

Defuzzification Method in Fuzzy Sets

The trapezoidal fuzzy numbers defined as $\tilde{A} = (a, b, c, d)$ in fuzzy sets $A \in F(R)$, Wang (2009) proposed the widely used a centroid defuzzification method in computed by Eq. (6), which is based on trapezoidal numbers in fuzzy sets.

$$\tilde{X}_0(\tilde{A}) = \frac{1}{3}\left[a + b + c + d - \frac{dc - ab}{(d+c)-(a+b)}\right] \quad (6)$$

Application

In this study, the ship block construction problem in the shipyard was solved using a GA in a fuzzy duration environment with the RCPSP method. Subsequently, a solution set consisting of 32 solutions was generated based on 8 different scenarios within the framework of the shipyard's gradually decreasing 4 capacities. The solutions in this set were evaluated using the Pareto optimal curve method to find the solutions for the optimal shipyard capacity-project completion time. In addition, infeasible and unimplementable solutions were also searched and evaluated within the solution set in Figure 2. Accordingly, the solution steps were as follows:

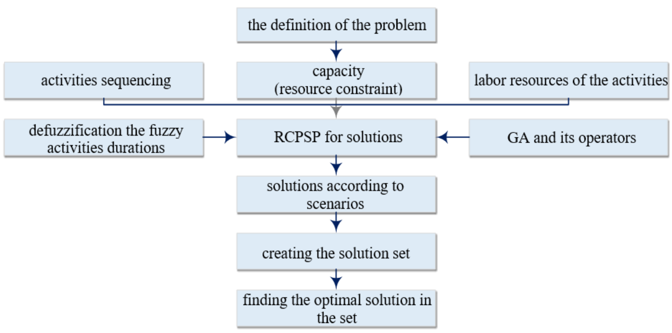

Figure 2. Proposed methodology follows

Since the problem is solved based on the RCPSP methodology, the objective function is specifically defined as RCPSP.

The block construction plans for ships A and B are available, and they were prepared according to the plans provided. The gradually decreasing shipyard capacity values are listed in Table 1. Additionally, Appendices includes the activity list, resource workforce values, activity precedence relationships indicating the activity sequencing, and information about which workstation the activities will be processed for the block construction of ships A and B also, they present the fuzzy trapezoidal duration assigned to the project activities. These data are also required for solving the RCPSP.

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In Table 1, the capacity, resource supply, and constraints of workstations in the shipyard are allocated. Capacity1 represents the actual capacity of the shipyard for the work stations as WS 02, WS 04, WS 05, WS 09 and WS 12. Capacity 2 is obtained by reducing Capacity 1 by 75 workers, Capacity 3 is obtained by reducing Capacity 2 by reducing 75 workers, and Capacity 4 is obtained by reducing Capacity 3 by an additional 75 workers.

Since the problem is solved using a GA in the resource-constrained project scheduling framework, deterministic processing with durations is necessary. Due to the fuzzy duration representation of activity durations, the fuzzy durations of activities are transformed into deterministic durations through defuzzification considering the membership function of fuzzy trapezoidal numbers with known weights. Appendices provide the fuzzy trapezoidal durations of the block construction activities for ships A and B and their corresponding defuzzified values.

Table 1. The capacity, resource supply, and constraints of workstations in the shipyard

Work Station (WS)	**Resource (workforce)**	**Capacity 1** ***(person/day)***	**Capacity 2** ***(person/day)***	**Capacity 3** ***(person/day)***	**Capacity 4** ***(person/day)***
WS 02 (Cutting)	Resource 1 (Cutting workforce)	10	10	10	10
WS 04 (Prefabrication)	Resource 2 (Prefabrication Workforce)	115	100	85	70
WS 05 (Panel Production)	Resource 3 (Panel Production Workforce)	115	100	85	70
WS 09 (Block Production)	Resource 4 (Block Production Workforce)	270	240	210	180
WS 12 (Slipway)	Resource 5 (Slipway Workforce)	135	120	105	90
Total		645	570	495	420

Table 2. The solution scenarios of the problem

Scenario	**Description**	**Capacity 1**	**Capacity 2**	**Capacity 3**	**Capacity 4**
A	Normal project programming	*A1*	*A2*	*A3*	*A4*
B	20% workforce increase for WS 04 (Prefabrication) and WS 05 (Panel Production)	*B1*	*B2*	*B3*	*B4*
C	3 workers (12%) increase in critical activities 295 and 297	*C1*	*C2*	*C3*	*C4*
D	3 workers (12%) increase in critical activities 274, 299, 300 and 301	*D1*	*D2*	*D3*	*D4*
E	3 workers (12%) increase in critical activities 274, 295, 297, 299, 300 and 301	*E1*	*E2*	*E3*	*E4*
F	5 workers (20%) increase in critical activities 295 and 297	*F1*	*F2*	*F3*	*F4*
G	5 workers (20%) increase in critical activities 274, 299, 300 and 301	*G1*	*G2*	*G3*	*G4*
H	5 workers (20%) increase in critical activities 274, 295, 297, 299, 300 and 301	*H1*	*H2*	*H3*	*H4*

With all the necessary data provided, the solution sets are generated using the GA in the RCPSP. In this study, the GA, which is a metaheuristic method, is employed for solving the RCPSP. Therefore, the mutation rate, selection rate, crossover, population size, and generation parameter values of the GAs are determined, and the problem-solving process starts with these parameter values. Multiple solutions were generated for each solution with different GA parameter values, and the solutions with the best local values were included in the solution set. The

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assumptions in line with the structure of the GA RCPSP can be stated as follows:

- Activity durations are deterministic, converting fuzzy durations into precise values
- The amount of resources used per unit of time in activities is constant.
- A resource assigned to an activity cannot be used by another activity until the completion of that activity.
- There are no breaks or discontinuities between the start and finish of activities.
- The defined activities cannot be canceled and must be completed.
- The resources used for the execution of activities are considered as renewable resources.
- Subsequent activities cannot start before the completion of preceding activities.
- RCPSP literature can be classified into groups aiming to minimize project duration, project cost, or achieve a multi-objective optimal solution considering time and cost.
- *Initialization of the Initial Population*: Activities were assigned randomly within a given period based solely on their priority constraints. The scheduling period used was the longest completion time of the project. Start times were sorted in descending order based on the activity constraints, creating the initial activity sequence.
- *Chromosome Structure*: Chromosomes were constructed using the activity list design method. Genes in the chromosome represented the starting order of activities. Activity starts and finish times were determined based on the activity sequence and resource capacities.
- *Generation of the Initial Population*: The initial population was randomly generated according to the activity priority rule. Serial scheduling was employed to order the project's activities.
- *Fitness Function*: The fitness function evaluated the chromosomes based on the project's duration.
- The objective was to minimize the project's duration while considering all resource constraints.
- *Crossover Operation*: Single-point sequential crossover method was used.
- *Mutation Operation*: Single-point mutation operator was applied with varying mutation parameters.
- *Selection Operation*: Elitist selection mechanism was employed to choose the best individuals for the next generation.
- *Termination of the Algorithm*: The algorithm stopped after reaching a specified generation count.
- *Software Solution*: The Genetic Algorithm Project Scheduler (Satıç, 2014) was used to compute the RCPSP.

Based on these 8 different scenarios, a solution set consisting of 32 solutions, representing the shipyard's capacity-project completion time combinations, is generated. In this study, various solution scenarios were generated for ship block construction, considering the problem scenarios. Solutions were then produced based on these scenarios. These scenarios are classified as follows. The solution set for these scenarios is presented in Table 2.

In the context of a ship block construction project where a GA-based resource-constrained project scheduling method is applied in a fuzzy time environment, the solutions obtained based on different project capacities are provided in Table 3. When evaluating the project completion times in the solution set, the following observations can be made:

- *Normal Project Completion Time:* The project's normal completion time, without any resource constraints, is 462 days.
- *Scenario A:* Normal Project Scheduling: In this scenario, the project completion time remains the same at 462 days for the capacities of shipyard numbers 1, 2, and 3. Despite a gradual decrease in the shipyard's capacity, there is no increase in the project completion time. However, for the solution based on the capacity of shipyard number 4, the project completion time increases by 20 days to 482 days.
- *Scenario B:* 20% Workforce Increase for WS 04 and WS 05: In this scenario, the project completion time remains the same at 461 days for the capacities of shipyard numbers 1, 2, and 3. There is no increase in the project completion time despite the gradual decrease in the shipyard's capacity. Furthermore, with the increase in workforce, the project duration is reduced by 1 day. However, for the solution based on the capacity of shipyard number 4, the project completion time increases by 11 days to 473 days.
- *Scenario C:* 3-Person (12%) Increase for Activities 295 and 297: In this scenario, the project completion time remains the same at 445 days for the capacities of shipyard numbers 1, 2, and 3. Despite the decrease in the

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shipyard's capacity, there is no increase in the project completion time. By increasing the resources for activities 295 and 297, the project completion time is reduced by 17 days. However, for the solution based on the capacity of shipyard number 4, the project completion time decreases by 6 days to 456 days.

- *Scenario D:* 3-Person (12%) Increase for Activities 274, 299, 300, and 301: In this scenario, the project completion time decreases by 17 days to 445 days for the capacity of shipyard number 1, by 14 days to 448 days for the capacity of shipyard number 2, by 13 days to 449 days for the capacity of shipyard number 3, and increases by 11 days to 473 days for the capacity of shipyard number 4.
- *Scenario E:* 3-Person (12%) Increase for Activities 274, 295, 297, 299, 300, and 301: In this scenario, the project completion time decreases by 30 days to 432 days for the capacities of shipyard numbers 1 and 2, by 29 days to 433 days for the capacity of shipyard number 3, and increases by 7 days to 469 days for the capacity of shipyard number 4.
- *Scenario F:* 5-Person (15%) Increase for Activities 295 and 297: In this scenario, the project completion time decreases by 26 days to 436 days for the capacities of shipyard numbers 1, 2, and 3, and decreases by 6 days to 456 days for the capacity of shipyard number 4.
- *Scenario G:* 5-Person (15%) Increase for Activities 274, 299, 300, and 301: In this scenario, the project completion time decreases by 21 days to 441 days for the capacities of shipyard numbers 1 and 2, by 19
- *Scenario H:* 5-Person (15%) Increase for Activities 274, 295, 297, 299, 300, and 301: In this scenario, the project completion time decreases by 47 days to 415 days for the capacity of shipyard number 1, decreases by 43 days to 419 days for the capacity of shipyard number 2, decreases by 41 days to 421 days for the capacity of shipyard number 3, and decreases by 13 days to 449 days for the capacity of shipyard number 4.

According to the results of the project computation in Table 3:

- For *Capacity 1*, which is 645 persons/day; the project completion duration is 462 days for *A1*, 461 days for *B1*, 445 days for *C1*, 445 days for *D1*, 432 days for *E1*, 436 days for *F1*, 441 days for *G1* and 415 days for *H1*.
- For *Capacity 2*, which is 570 persons/day; the project completion duration is 462 days for *A2*, 461 days for *B2*, 445 days for *C2*, 448 days for *D2*, 432 days for *E2*, 436 days for *F2*, 441 days for *G2* and 419 days for *H2*.
- For *Capacity 3*, which is 495 persons/day; the project completion duration is 462 days for *A3*, 461 days for *B3*, 445 days for *C3*, 449 days for *D3*, 433 days for *E3*, 436 days for *F3*, 443 days for *G3* and 421 days for *H3*.
- For *Capacity 4*, which is 420 person/day; the project completion duration is 482 days for *A4*, 473 days for *B4*, 456 days for *C4*, 473 days for *D4*, 469 days for *E4*, 456 days for *F4*, 471 days for *G4* and 449 days for *H4*.

The Pareto optimal curve method is applied to the solution set to identify optimal solutions and infeasible solutions, which are then interpreted. After 32 different scenarios consisting of shipyard capacity and project completion times were computed by proposed methodology, a convex solution set of Pareto optimality is obtained as shown in Figure 2. Accordingly, solutions within the region that does not lie on the convex Pareto curve are observed not to be optimal solutions.

Table 3. The comparison of project completion durations

Scenario	**Capacity 1**	**Capacity 2**	**Capacity 3**	**Capacity 4**
	645 persons/day	***570 persons/day***	***495 persons/day***	***420 persons/day***
An	462 days	462 days	462 days	482 days
Bn	461 days	461 days	461 days	473 days
Cn	445 days	445 days	445 days	456 days
Dn	445 days	448 days	449 days	473 days
En	432 days	432 days	433 days	469 days
Fn	436 days	436 days	436 days	456 days
Gn	441 days	441 days	443 days	471 days
Hn	415 days	419 days	421 days	449 days

Note: $n=(1, \ldots, 4), n \in N$

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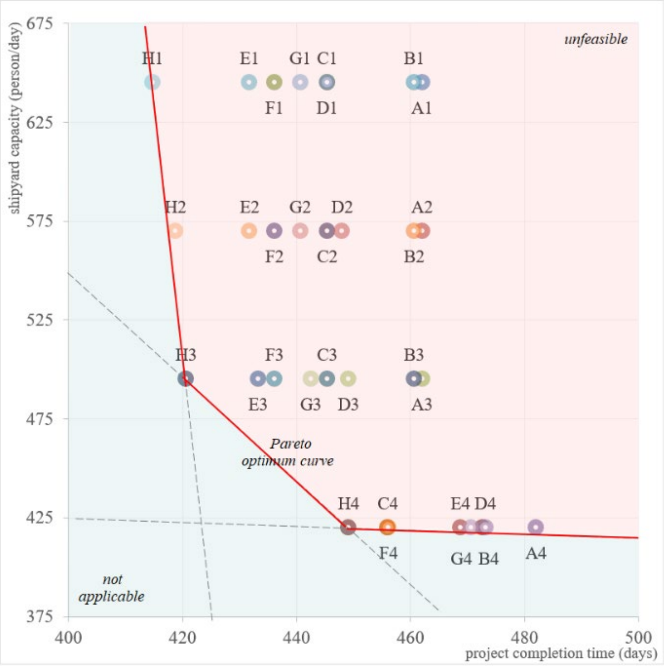

Figure 2. The Pareto optimal curve and the capacity-time solution set

The solutions located on the Pareto optimal curve are represented by *H1*, *H3*, *H4*, and *F4*. Therefore, the optimal solution should be sought within this boundary. Upon examining these solutions: Scenario *H1* is the solution with the shortest duration and the highest capacity supply. Scenario *H3* is one of the optimal solutions. Scenario *H4* is one of the optimal solutions. Scenario *F4* is the solution with the longest duration and the lowest capacity supply. Furthermore, comparing *H3* and *H4*, in *H3*, the project completion time is 421 days with a shipyard capacity of 495 persons/day, whereas in *H4*, the project completion time is 449 days with a shipyard capacity of 420 persons/day. Although the solutions within the space that is not on the convex Pareto curve are not optimal solutions, their preference or prioritization will be evaluated by the shipyard. On the other Project delays lead to increased costs, while early completion yields cost savings. As the resources allocated from the shipyard capacity decrease, the gains in cost increase up to a certain threshold. Scenarios *A4*, *B4*, *D4*, *E4*, and *G4* of the shipyard do not exhibit value gains but rather result in losses. Scenarios *A1*, *A2*, and *A3* do not yield any gains or losses. Other solutions show gains. The largest value loss occurs in scenario *A4* with shipyard capacity number 4, whereas the greatest value gain is observed in scenario *H1* with shipyard capacity 1.

Results and Discussion

This study addresses the RCPSP in the context of block construction of ships in shipyards, aiming to optimize capacity utilization. The RCPSP becomes particularly important in competitive environments or situations with limited resources. The problem objectives in RCPSP include minimizing costs, minimizing project duration, and optimizing the trade-off between costs and time.

The flow time values are the same for all jobs at workstation WS 02 in the entire capacity of the shipyard. This is because the station operates at full capacity and there is no idle workforce available. Additionally, this station has the shortest processing time among all production workstations. On the other hand, workstation WS 09 has the highest flow time value among the production workstations, which is proportional to the decrease in its capacity. Furthermore, when the shipyard's capacity decreases, this workstation still has the highest flow time value, and the job flow at this workstation becomes intermittent when the shipyard operates at capacity 4. Considering the block construction times of both ships and the conditions at their workstations, the flow time of *ship B*, which is being constructed, is longer than that of *ship A*. When evaluating the solution set based on the makespan (total project completion time), both projects are expected to be completed within 462 days under normal conditions. However, solutions that exceed this duration result in longer makespan values. The project completion times range from a maximum of 482 days to a minimum of 415 days. Therefore, a decrease in the shipyard's capacity leads to longer project durations. While projects can be completed within the normal or shorter time frame for shipyard capacities 1, 2, and 3, the makespan, or total project completion time, increases for capacity 4. This pattern is observed in other solution alternatives as well. When the project's completion time exceeds the normal completion time, the lateness values in this solution set become greater than zero, resulting in tardiness. An increase in tardiness is observed as the resource constraint decreases. Among the solutions in the solution set, the solution obtained with the shipyard's capacity 4 shows the highest tardiness value. For other solution scenarios, the tardiness values are lower. In contrast, no tardiness occurs for capacities 1, 2, and 3, and the lateness values are smaller than zero due to projects being completed earlier than the normal completion time. The solution set includes projects with completion times reduced to 415 days, and the solution with the smallest earliness value is generated by *H1*. Solutions *C4*, *F4*, and *H4* show earliness values for

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capacity 4 and for other capacities, which means the projects are completed earlier. All solutions in the solution set aim to minimize the completion time for the due dates of the projects. For capacities 1, 2, and 3, the completion time occurs earlier than the project's total completion time. However, for capacity 4, the completion time is later than the project's total completion time with a certain tardiness value. In the block construction process, for delayed projects, especially in capacity 4 of the shipyard, the critical ratio can be used to prioritize the completion of preferred projects or projects that need to be completed early in order to prevent delays in project delivery. However, in this study, the completion time of *ship B* is later than that of *ship A*, so such a delivery priority is disregarded. For solutions in capacities 1, 2, and 3 of the shipyard, the resource histogram shows similar values for the makespan, which is the normal completion time of the project. However, in capacity 4 of the shipyard, as the workforce supply provided by the shipyard decreases, the resource distribution changes, resulting in an increase in the makespan of the project. Therefore, the resource distribution chart shows a spread towards the completion time of the project.

In the literature, GA RCPSP method has been widely used in many fields (e.g., Muritiba et al., 2018; Chand et al. 2019; Liu et al., 2020; Zaman et al., 2021; Hua et al., 2022; Zhang et al., 2023) however, neither GA RCPSP nor RCPSP in fuzzy environment has been proposed as a methodology for the shipbuilding except for the study of Akan (2017), but there is a study that proposes a project scheduling problem with spatial resource constraints (Hu et al., 2019) for RCPSP methodology in shipbuilding. . On the other hand, RCPSP are widely applied in many fields with integrating extension methods such as branch and bound (Bianco & Caramia, 2012), fuzzy mixed integer nonlinear programming (MILP), and GA and particle swarm optimization (PSO) (Birjandi & Mousavi, 2019), ant colony optimization (ACO) (Dridi et al., 2019), fuzzy clustering chaotic-based differential evolution (Cheng et al., 2014), genetic programming based hyper-heuristic (Chand et al., 2018), memetic algorithm (Rahman et al., 2022), hybrid simulation and optimization (Wang et al., 2020), multi-agent-based cooperative (Li et al., 2021), exact linear programming binary formulation (García-Nieves et al., 2019), Improvement of the critical chain method (Tian et al., 2020), nondominated sorting genetic algorithm II (NSGA-II) (Laszczyk & Myszkowski, 2019), and column generation (Changchun et al., 2018).

In production planning and management, scheduling operations play a crucial role. Finding the best schedule can be challenging, depending on the project environment, performance criteria, and process constraints. GAs are a viable method for addressing RCPSPs, which belong to the *np-hard in the strong sense* class. While intuitive approaches don't guarantee optimal solutions, metaheuristic methods like GAs have shown better results. These problems offer combinatorial solutions, and GAs provide efficient and effective solutions. GAs use genetic operators, including crossover, mutation, and selection, to create the solution set. The mutation rate, ranging from 0% to 100%, influences the best solution time, with rates of 50% to 70% yielding optimal results. Selection operators prioritize the project completion time, typically with selection rates of 10% to 20% for the best local value. The population rate, representing the global solution set, is usually set between 100 and 200. As the population size increases, the solution space grows, resulting in longer solution times. The number of generations affects the algorithm's runtime and the quality of the best local solution. Generally, 1,000 to 2,000 generations are preferred, with 1,000 generations often leading to the best solutions. GAs search for solutions within a population rather than a single set. Mutated and selected new generations maintain the problem objectives, and the final generation with improved solution sets achieves the best result. Traditional methods for resource-constrained project scheduling, such as first come first served, fail to consider future resource requirements. In contrast, GAs prioritize critical activities and schedule remaining activities randomly, adhering to priority rules and project-wide constraints. The scheduling process generates a population of solutions, which is then refined using genetic operators until the desired number of generations is reached. GAs require computer resources even for simple projects. The algorithm's design involves methods, encoding, creation, population initialization, genetic operators (crossover, mutation, selection), and a fitness function. Genetic parameters, including population size, generation count, mutation rate, and project activity count, impact the algorithm's runtime.

In terms of practical implications, shipbuilding projects often face uncertainties such as unexpected delays, material shortages, or workforce fluctuations. This means that shipbuilders can plan and allocate resources more effectively, taking into account potential disruptions, and thereby improving the overall project success rate. On the analysis side, stakeholders can visually understand the impact of different scheduling decisions and the trade-offs involved. In addition, shipbuilding production efficiency is improved by optimizing the allocation of resources and tasks, resulting in reduced project completion times while maintaining effective resource utilization. This optimization is critical due to the limited and expensive resources in shipbuilding. GAs can be used to optimize allocation, ensuring that the right resources are assigned to tasks at the right time. This minimizes waste and idle time, ultimately resulting in cost savings. These actions have a significant financial impact, leading to a faster return on investment and improved overall business performance.

Conclusion

This study optimizes ship production processes through the RCPSP, focusing on cost minimization, project duration reduction, and optimal cost-time optimization. Utilizing GA and fuzzy set theory, it enhances project planning for efficient resource allocation in competitive, resource-intensive shipbuilding. The framework integrates probabilistic models and scenario analysis to optimize project completion time and resource utilization.

The study's major contributions to the literature can be summarized as follows:

i) The solution of GA RCPSP method in fuzzy environment was carried out.

ii) The analysis of Pareto optimal solutions was carried out.

iii) The application of this study has been carried out in shipbuilding industry.

Overall, it was observed that the utilization of a GA approach to address the RCPSP in the context of shipbuilding, considering a fuzzy environment can be applied to ship production plan during the shipbuilding process. With this study, GA RCPSP with fuzzy environment in shipbuilding process planning can be a contribution for the literature of the shipbuilding process.

The main limitation of this study is that the method GA RCPSP can be designed different aspects to optimize alternative solutions with GA designed architecture. Regarding future research, the problem can be applied by different designed GA RCPSP methodologies or alternative metaheuristic RCPSP solutions methods or other methods. The focus will be on the development of methods for the parallel inclusion of fuzzy numbers in the model. A shipyard will engage in holistic planning by considering all shipbuilding projects within the shipyard's production planning process.

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Compliance With Ethical Standards

Authors' Contributions

EA: Manuscript design, Drafting, Writing, Data analysis.
GA: Manuscript design, Drafting, Writing, Data analysis.
Both authors read and approved the final manuscript.

Conflict of Interest

The authors declare that there is no conflict of interest.

Ethical Approval

For this type of study, formal consent is not required.

Data Availability Statement

All data generated or analyzed during this study are included in this published article and its supplementary information files.

Supplementary Materials

Supplementary data to this article can be found online at https://doi.org/10.33714/masteb.1324266

References

Abbasi, B., Shadrokh, S., & Arkat, J. (2006). Bi-objective resource-constrained project scheduling with robustness and makespan criteria. *Applied mathematics and Computation*, *180*(1), 146-152. https://doi.org/10.1016/j.amc.2005.11.160

Adhau, S., Mittal, M. L., & Mittal, A. (2012). A multi-agent system for distributed multi-project scheduling: An auction-based negotiation approach. *Engineering Applications of Artificial Intelligence*, *25*(8), 1738-1751. https://doi.org/10.1016/j.engappai.2011.12.003

Adhau, S., Mittal, M. L., & Mittal, A. (2013). A multi-agent system for decentralized multi-project scheduling with resource transfers. *International Journal of Production Economics*, *146*(2), 646-661. https://doi.org/10.1016/j.ijpe.2013.08.013

Marine Science and Technology Bulletin

Afshar-Nadjafi, B., Rahimi, A., & Karimi, H. (2013). A genetic algorithm for mode identity and the resource constrained project scheduling problem. *Scientia Iranica*, *20*(3), 824-831. https://doi.org/10.1016/j.scient.2012.11.011

Akan, E., & Bayar, S. (2022). Interval type-2 fuzzy program evaluation and review technique for project management in shipbuilding, *Ships and Offshore Structures*, *17*(8), 1872-1890, https://doi.org/10.1080/17445302.2021.1950350

Akan, E. (2023). A holistic analysis of maritime logistics process in fuzzy environment in terms of business process management. *Business Process Management Journal*, *29*(4), 1116-1158. https://doi.org/10.1108/BPMJ-08-2022-0368

Akan, E., (2017). *Tersanelerde Gemi Üretim Yönetimi Modeli: Marmara Bölgesinde Bir Uygulama*. [PhD Thesis. İstanbul University].

Akhbari, M. (2022). Integration of multi-mode resource-constrained project scheduling under bonus-penalty policies with material ordering under quantity discount scheme for minimizing project cost. *Scientia Iranica*, *29*(1), 427-446. https://doi.org/10.24200/sci.2020.54286.3680

Alcaraz, J., & Maroto, C. (2001). A robust genetic algorithm for resource allocation in project scheduling. *Annals of operations Research*, *102*, 83-109. https://doi.org/10.1023/A:1010949931021

Aramesh, S., Aickelin, U., & Akbarzadeh Khorshidi, H. (2022). A hybrid projection method for resource-constrained project scheduling problem under uncertainty. *Neural Computing and Applications*, *34*(17), 14557-14576. https://doi.org/10.1007/s00521-022-07321-2

Asadujjaman, M., Rahman, H. F., Chakrabortty, R. K., & Ryan, M. J. (2021). An immune genetic algorithm for solving NPV-based resource constrained project scheduling problem. *IEEE Access*, *9*, 26177-26195. https://doi.org/10.1109/ACCESS.2021.3057366

Aziz, R. F. (2013). Optimizing strategy software for repetitive construction projects within multi-mode resources. *Alexandria Engineering Journal*, *52*(3), 373-385. https://doi.org/10.1016/j.aej.2013.04.002

Back, M. G., Lee, D. K., Shin, J. G., & Woo, J. H. (2016). A study for production simulation model generation system based on data model at a shipyard. *International Journal of Naval Architecture and Ocean Engineering*, *8*, 496e510. https://doi.org/10.1016/j.ijnaoe.2016.05.005

Bhaskar, T., Pal, M. N., & Pal, A. K. (2011). A heuristic method for RCPSP with fuzzy activity times. *European Journal of Operational Research*, *208*(1), 57-66. https://doi.org/10.1016/j.ejor.2010.07.021

Bianco, L., & Caramia, M. (2012). An exact algorithm to minimize the makespan in project scheduling with scarce resources and generalized precedence relations. *European Journal of Operational Research*, *219*(1), 73-85. https://doi.org/10.1016/j.ejor.2011.12.019.

Birjandi, A., & Mousavi, S. M. (2019). Fuzzy resource-constrained project scheduling with multiple routes: A heuristic solution. *Automation in Construction*, *100*, 84-102. https://doi.org/10.1016/j.autcon.2018.11.029

Birjandi, A., Mousavi, S. M., Hajirezaie, M., & Vahdani, B. (2019). A new weighted mixed integer nonlinear model and FPND solution algorithm for RCPSP with multi-route work packages under fuzzy uncertainty. *Journal of Intelligent & Fuzzy Systems*, *37*(1), 737-751. https://doi.org/10.3233/JIFS-181293

Blazewicz, J., Lenstra, J. K., & Rinnooy Kan, A. H. G. (1983). Scheduling subject to resource constraints: Classification and complexity. *Discrete Applied Mathematics*, *5*, 11-22. https://doi.org/10.1016/0166-218X(83)90012-4

Boctor, F. F. (1996). A new and efficient heuristic for scheduling projects with resource restrictions and multiple execution modes. *European Journal of Operational Research*, *90*(2), 349-361. https://doi.org/10.1016/0377-2217(95)00359-2

Brucker, P., & Knust, S. (2000). A linear programming and constraint propagation-based lower bound for the RCPSP. *European Journal of Operational Research*, *127*(2), 355-362. https://doi.org/10.1016/S0377-2217(99)00489-0

Çebi, F., & Otay, İ. (2015). A fuzzy multi-objective model for solving project network problem with bonus and incremental penalty cost. *Computers & Industrial Engineering*, *82*, 143-150. https://doi.org/10.1016/j.cie.2015.01.007

Cha, J. H., & Roh, M. I. (2010). Combined discrete event and discrete time simulation framework and its application to the block erection process in shipbuilding. *Advances in Engineering Software*, *41*, 656-665.

Chaleshtarti, A. S., Shadrokh, S., Khakifirooz, M., Fathi, M., & Pardalos, P. M. (2020). A hybrid genetic and Lagrangian relaxation algorithm for resource-constrained project scheduling under nonrenewable resources. *Applied Soft Computing*, *94*, 106482. https://doi.org/10.1016/j.asoc.2020.106482

Chand, S., Huynh, Q., Singh, H., Ray, T., & Wagner, M. (2018). On the use of genetic programming to evolve priority rules for resource constrained project scheduling problems. *Information Sciences*, *432*, 146-163. https://doi.org/10.1016/j.ins.2017.12.013

Chand, S., Singh, H., & Ray, T. (2019). Evolving heuristics for the resource constrained project scheduling problem with dynamic resource disruptions. *Swarm and Evolutionary Computation*, *44*, 897-912. https://doi.org/10.1016/j.swevo.2018.09.007

Chang, C. K., Jiang, H. Y., Di, Y., Zhu, D., & Ge, Y. (2008). Time-line based model for software project scheduling with genetic algorithms. *Information and Software Technology*, *50*(11), 1142-1154. https://doi.org/10.1016/j.infsof.2008.03.002

Changchun, L., Xi, X., Canrong, Z., Qiang, W., & Li, Z. (2018). A column generation based distributed scheduling algorithm for multi-mode resource constrained project scheduling problem. *Computers & Industrial Engineering*. *125*, 258-278. https://doi.org/10.1016/j.cie.2018.08.036

Cheng, M. Y., Tran, D. H., & Wu, Y. W. (2014). Using a fuzzy clustering chaotic-based differential evolution with serial method to solve resource-constrained project scheduling problems. *Automation in Construction*, *37*, 88-97. https://doi.org/10.1016/j.autcon.2013.10.002

Cho, K. K., & Chung, D. S. (1996). An automatic process-planning system for block assembly in shipbuilding. *CIRP Annals*, *45*(1), 41-46. https://doi.org/10.1016/S0007-8506(07)63013-3

Cho, Y. I., Nam, S. H., Cho, K. Y., Yoon, H. C., & Woo, J. H. (2022). Minimize makespan of permutation flowshop using pointer network. *Journal of Computational Design and Engineering*, *9*(1), 51-67. https://doi.org/10.1093/jcde/qwab068

Coelho, J., & Tavares. L. (2003). *Comparative analysis of meta–heuristics for the resource constrained project scheduling problem*. Technical report, Department of Civil Engineering, Instituto Superior Tecnico, Portugal.

Coelho, J., & Vanhoucke, M. (2023). New resource-constrained project scheduling instances for testing (meta-) heuristic scheduling algorithms. *Computers & Operations Research*, *153*, 106165. https://doi.org/10.1016/j.cor.2023.106165

Coley, D. A. (1999). *An introduction to Genetic Algorithms for Scientists and Engineers*. World Scientific.

Devikamalam, J., & Jane Helena, H. (2013). Resource scheduling of construction projects using genetic algorithm, *International Journal of Advanced Engineering Technology*, *4*(3), 113-119.

Dong, F., Deglise-Hawkinson, J. R., Van Oyen, M. P., & Singer, D. J. (2016). Dynamic control of a closed two-stage queueing network for outfitting process in shipbuilding. *Computers & Operations Research*, *72*, 1-11. https://doi.org/10.1016/j.cor.2015.05.002

Dridi, O., Krichen, S., & Guitouni, A. (2014). A multiobjective hybrid ant colony optimization approach applied to the assignment and scheduling problem. *International Transactions in Operational Research*, *21*(6), 935-953. https://doi.org/10.1111/itor.12071

Ecorys. (2009). *Study on competitiveness of the European shipbuilding industry: Within the framework contract of sectoral competitiveness studies* – ENTR/06/054. Final report.

Etgar, R., Gelbard, R., & Cohen, Y. (2018). Feature assignment in multi-release work plan: accelerating optimization using gene clustering. *Computers & Industrial Engineering*, *118*, 123-137. https://doi.org/10.1016/j.cie.2018.02.036

Formentini, M., & Romano, P. (2011). Using value analysis to support knowledge transfer in the multi-project setting. *International. Journal of Production Economics*, *131*, 545–560. https://doi.org/10.1016/j.ijpe.2011.01.023

Franco, E. D., Zurita, F. L. Z., & Delgadillo, G. M. (2007). A genetic algorithm for the resource constrained project scheduling problem (RCPSP). *Revista Investigación & Desarrollo*, 7(1), 39-50.

García-Nieves, J. D., Ponz-Tienda, J. L., Ospina-Alvarado, A., & Bonilla-Palacios, M. (2019). Multipurpose linear programming optimization model for repetitive activities scheduling in construction projects. *Automation in Construction*, *105*, 102799. https://doi.org/10.1016/j.autcon.2019.03.020

García-Nieves, J. D., Ponz-Tienda, J. L., Salcedo-Bernal, A., & Pellicer, E. (2018). The multimode resource-constrained project scheduling problem for repetitive activities in construction projects. *Computer-Aided Civil and Infrastructure Engineering*, *33*(8), 655-671. https://doi.org/10.1111/mice.12356

Ge, Y., & Wang, A. (2021). Spatial scheduling for irregularly shaped blocks in shipbuilding. *Computers & Industrial Engineering*, *152*, 106985. https://doi.org/10.1016/j.cie.2020.106985

Goldberg, D. A. (1989). *Genetic Algorithms in search optimization and machine learning*. Addison-Wesley Publishing.

Goncalves, J. F., Mendes, J. J. M., & Resende, M. G. C. (2008). A genetic algorithm for the resource constrained multi-project scheduling problem. *European Journal of Operational Research*, *189*, 1171–1190. https://doi.org/10.1016/j.ejor.2006.06.074

Goo, B., Chung, H., & Han, S. (2019). Layered discrete event system specification for a ship production scheduling model. *Simulation Modelling Practice and Theory*, *96*, 101934. https://doi.org/10.1016/j.simpat.2019.101934

Guo, W., Vanhoucke, M., Coelho, J., & Luo, J. (2021). Automatic detection of the best performing priority rule for the resource-constrained project scheduling problem. *Expert Systems with Applications*, *167*, 114116. https://doi.org/10.1016/j.eswa.2020.114116

Hadžić, N. (2019). Analytical solution of the serial Bernoulli production line steady-state performance and its application in the shipbuilding process. *International Journal of Production Research*, *57*(4), 1052-1065. https://doi.org/10.1080/00207543.2018.1500042

Han, D., Yang, B., Li, J., Sun, M., Zhou, Q., & Wang, J. (2017). A three-layer parallel computing system for shipbuilding project scheduling optimization. *Advances in Mechanical Engineering*, *9*(10), 1687814017723297. https://doi.org/10.1177/1687814017723297

Hapke, M., & Slowinski, R. (1996). Fuzzy priority heuristics for project scheduling. *Fuzzy sets and systems*, *83*(3), 291-299. https://doi.org/10.1016/0165-0114(95)00338-X

Hartmann, S. (1998). A competitive genetic algorithm for resource-constrained project scheduling. *Naval Research Logistics (NRL)*, *45*(7), 733-750. https://doi.org/10.1002/(SICI)1520-6750(199810)45:7%3C733::AID-NAV5%3E3.0.CO;2-C

Hartmann, S. (2001). Project scheduling with multiple modes: a genetic algorithm. *Annals of Operations Research*, *102*(1-4), 111-135. https://doi.org/10.1023/A:1010902015091

Hartmann, S. (2002). A self-adapting genetic algorithm for project scheduling under resource constraints. *Naval Research Logistics (NRL)*, 49(5) 433-448. https://doi.org/10.1002/nav.10029

Hartmann, S., & Kolisch, R. (2000). Experimental evaluation of state-of-the-art heuristics for the resource-constrained project scheduling problem. *European Journal of Operational Research*, *127*(2), 394-407. https://doi.org/10.1016/S0377-2217(99)00485-3

Haupt, R. L., & Haupt, S. E. (2004). *Pratical genetic algorithms*. 2nd ed. Wiley-Interscience Publication.

Hiekata, K., Yamato, H., & Tsujimoto, S. (2010). Ontology based knowledge extraction for shipyard fabrication workshop reports. *Expert Systems with Applications*, *37*, 7380-7386. https://doi.org/10.1016/j.eswa.2010.04.031

Hindi, K. S., Yang, H., & Fleszar, K. (2002). An evolutionary algorithm for resource-constrained project scheduling. *IEEE Transactions on Evolutionary Computation*, *6*, 512-518. https://doi.org/10.1109/TEVC.2002.804914

Holland, J. H. (1975). Adaptation in natural and artificial systems. The MIT Press.

Homberger, J. (2007). A multi-agent system for the decentralized resource-constrained multi-project scheduling problem. *International Transactions in Operational Research*, *14*(6), 565-589. https://doi.org/10.1111/j.1475-3995.2007.00614.x

Hu, S., Zhang, Z., Wang, S., Kao, Y., & Ito, T. (2019). A project scheduling problem with spatial resource constraints and a corresponding guided local search algorithm. *Journal of the Operational Research Society*, *70*(8), 1349–1361. https://doi.org/10.1080/01605682.2018.1489340

Hua, Z., Liu, Z., Yang, L., & Yang, L. (2022). Improved genetic algorithm based on time windows decomposition for solving resource-constrained project scheduling problem. *Automation in Construction*, *142*, 104503. https://doi.org/10.1016/j.autcon.2022.104503

Marine Science and Technology Bulletin

Huang, W., Oh, S. K., & Pedrycz, W. (2013). A fuzzy time-dependent project scheduling problem. *Information Sciences, 246*, 100-114. https://doi.org/10.1016/j.ins.2013.05.026

Hwang, I. H., Kim, Y., Lee, D. G., & Shin, J. G. (2014). Automation of block assignment planning using a diagram-based scenario modeling method. *International Journal of Naval Architect Ocean Engineering*, *6*, 162-174. https://doi.org/10.2478/IJNAOE-2013-0170

Issa, S. B., Patterson, R. A., & Tu, Y. (2023). Solving resource-constrained project scheduling problems under different activity assumptions. *Computers & Industrial Engineering*, *180*, 109170. https://doi.org/10.1016/j.cie.2023.109170

Jeong, Y. K., Ju, S., Shen, H., Lee, D. K., Shin, J. G., & Ryu, C. (2018). An analysis of shipyard spatial arrangement planning problems and a spatial arrangement algorithm considering free space and unplaced block. *The International Journal of Advanced Manufacturing Technology*, *95*, 4307-4325. https://doi.org/10.1007/s00170-017-1525-1

Jiang, L., & Strandenes, S. P. (2012). Assessing the cost competitiveness of China's shipbuilding industry. *Maritime Economics & Logistics*, *14*, 480-497. https://doi.org/10.1057/mel.2012.17

Joo, C. M., & Kim, B. S. (2014). Block transportation scheduling under delivery restriction in shipyard using meta-heuristic algorithms. *Expert Systems with Applications*, *41*, 2851-2858. https://doi.org/10.1016/j.eswa.2013.10.020

Kahraman, C., & Kaya, I. (2010). A fuzzy multicriteria methodology for selection among energy alternatives. *Expert Systems with Applications*, *37*(9), 6270–6281. https://doi.org/10.1016/j.eswa.2010.02.095

Khanzadi, M., Soufipour, R., & Rostami, M. (2011). A new improved genetic algorithm approach and a competitive heuristic method for large-scale multiple resource-constrained project-scheduling problems. *International Journal of Industrial Engineering Computations*, *2*(4), 737-748. https://doi.org/10.5267/j.ijiec.2011.06.009

Kim, H., Kang, J., & Park, S. (2002). Scheduling of shipyard block assembly process using constraint satisfaction problem. *Asia Pacific Management Review*, *7*(1), 119-138.

Kim, H., Lee, S. S., Park, J. H., & Lee, J. G. (2005). A model for a simulation-based shipbuilding system in a shipyard manufacturing process. *International Journal of Computer Integrated Manufacturing*, *18*(6), 427-441. https://doi.org/10.1080/09511920500064789

Kim, J. L. (2013). Genetic algorithm stopping criteria for optimization of construction resource scheduling problems. *Construction Management and Economics*, *31*(1), 3-19. https://doi.org/10.1080/01446193.2012.697181

Kim, K. W., Gen, M., & Yamazaki, G. (2003). Hybrid genetic algorithm with fuzzy logic for resource-constrained project scheduling. *Applied Soft Computing*, *2*(3), 174-188. https://doi.org/10.1016/S1568-4946(02)00065-0

Knyazeva, M., Bozhenyuk, A., & Rozenberg, I. (2015). Resource-constrained project scheduling approach under fuzzy conditions. *Procedia Computer Science*, *77*, 56-64. https://doi.org/10.1016/j.procs.2015.12.359

Kolisch, R., & Spracher A. (1996). PSPLIB - A project scheduling problem library. *European Journal of Operational Research*, *96*, 205-216. https://doi.org/10.1016/S0377-2217(96)00170-1

Kolisch, R. (1995). *Project scheduling under resource constraints*. Springer.

Kwon, B., & Lee, G. M. (2015). Spatial scheduling for large assembly blocks in shipbuilding. *Computers & Industrial Engineering*, *89*, 203–212. https://doi.org/10.1016/j.cie.2015.04.036

Laszczyk, M., & Myszkowski, P. B. (2019). Improved selection in evolutionary multi–objective optimization of multi–skill resource–constrained project scheduling problem. *Information Sciences*, *481*, 412-431. https://doi.org/10.1016/j.ins.2019.01.002

Lee, J. K., Lee, K. J., Park, H. K., Hong, J. S., & Lee, J. S. (1997). Developing scheduling systems for Daewoo Shipbuilding: DAS project. *European Journal of Operational Research*, *97*, 380-395. https://doi.org/10.1016/S0377-2217(96)00205-6

Lee, Y. G., Ju, S., & Woo, J. H. (2020). Simulation-based planning system for shipbuilding. *International Journal of Computer Integrated Manufacturing*, *33*(6), 626-641. https://doi.org/10.1080/0951192X.2020.1775304

Li, H., Duan, J., & Zhang, Q. (2021a). Multi-objective integrated scheduling optimization of semi-combined marine crankshaft structure production workshop for green manufacturing. *Transactions of the Institute of Measurement and Control*, *43*(3), 579-596. https://doi.org/10.1177/0142331220945917

Li, F., Xu, Z., & Li, H. (2021b). A multi-agent based cooperative approach to decentralized multi-project scheduling and resource allocation. *Computers & Industrial Engineering*, *151*, 106961. https://doi.org/10.1016/j.cie.2020.106961

Li, J., Sun, M., Han, D., Wang, J., Mao, X., & Wu, X. (2019). A knowledge discovery and reuse method for time estimation in ship block manufacturing planning using DEA. *Advanced Engineering Informatics*, *39*, 25-40. https://doi.org/10.1016/j.aei.2018.11.005

Liu, J., Liu, Y., Shi, Y., & Li, J. (2020). Solving resource-constrained project scheduling problem via genetic algorithm. *Journal of Computing in Civil Engineering*, *34*(2), 04019055. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000874

Liu, Z., Chua, D. K. H., & Yeoh, K. W. (2011). Aggregate production planning for shipbuilding with variation-inventory trade-offs. *International Journal of Production Research*, *49*(20), 6249-6272. https://doi.org/10.1080/00207543.2010.527388

Ljubenkov, B., Dukic, G., & Kuzmanic, M. (2008). Simulation methods in shipbuilding process design. *Strojniski Vestnik*, *54*(2), 131-139.

Long, L. D., & Ohsato, A. (2008). Fuzzy critical chain method for project scheduling under resource constraints and uncertainty. *International Journal of Project Management*, *26*(6), 688-698. https://doi.org/10.1016/j.ijproman.2007.09.012

Magalhaes-Mendes, J. (2011). A two-level genetic algorithm for the multi-mode resource-constrained project scheduling problem. *International Journal of Systems Applications, Engineering & Development*, *3*(5), 271-278.

Mao, X., Li, J., Guo, H., & Wu, X. (2020). Research on collaborative planning and symmetric scheduling for parallel shipbuilding projects in the open distributed manufacturing environment. *Symmetry*, *12*(1), 161. https://doi.org/10.3390/sym12010161

Mei, Y., Ye, J., & Zeng, Z. (2016). Entropy-weighted ANP fuzzy comprehensive evaluation of interim product production schemes in one-of-a-kind production. *Computers & Industrial Engineering*, *100*, 144-152. https://doi.org/10.1016/j.cie.2016.08.016

Mitchell, M. (1999). *An introduction to genetic algorithms.* 5th ed. MIT Press.

Montoya-Torres, J. R., Gutierrez-Franco, E., & Pirachicán-Mayorga, C. P. (2009). Project scheduling with limited resources using a genetic algorithm. *International Journal of Project Management*, *28*, 619–628. https://doi.org/10.1016/j.ijproman.2009.10.003

Muñoz, G., Espinoza, D., Goycoolea, M., Moreno, E., Queyranne, M., & Letelier, O. R. (2018). A study of the Bienstock–Zuckerberg algorithm: applications in mining and resource constrained project scheduling. *Computational Optimization and Applications*, *69*, 501-534. https://doi.org/10.1007/s10589-017-9946-1

Muritiba, A. E. F., Rodrigues, C. D., & da Costa, F. A. (2018). A path-relinking algorithm for the multi-mode resource-constrained project scheduling problem. *Computers & Operations Research*, *92*, 145-154. https://doi.org/10.1016/j.cor.2018.01.001

Myszkowski, P. B., & Laszczyk, M. (2022). Investigation of benchmark dataset for many-objective multi-skill resource constrained project scheduling problem. *Applied Soft Computing*, *127*, 109253. https://doi.org/10.1016/j.asoc.2022.109253

Okubo, Y., & Mitsuyuki, T. (2022). Ship production planning using shipbuilding system modeling and discrete time process simulation. *Journal of Marine Science and Engineering*, *10*(2), 176. https://doi.org/10.3390/jmse10020176

Özyiğit, İ., 2006, *Gemi İnşaatında Planlama ve Üretim Kademeleri* [MSc Thesis. Yıldız Teknik University].

Palencia, A. E. R., & Delgadillo, G. E. M. (2012). A computer application for a bus body assembly line using Genetic Algorithms, *International Journal Production Economics*, *140*(1), 431-438. https://doi.org/10.1016/j.ijpe.2012.06.026

Park, C., & Seo, J. (2010). Comparing heuristic algorithms of the planar storage location assignment problem. *Transportation Research Part E: Logistics and Transportation Review*, *46*, 171–185. https://doi.org/10.1016/j.tre.2009.07.004

Park, C., Chung, K. H., Park, J. C., Cho, K. K., Baek, T. H., & Son, E. I. (2002). A spatial scheduling application at the block paint shop in shipbuilding: The HYPOS project. *Production Planning & Control*, *13*(4), 342-354. https://doi.org/10.1080/09537280276010830

Park, J., Lee, D., & Zhu, J. (2014). An integrated approach for ship block manufacturing process performance evaluation: Case from a Korean shipbuilding company. *International. Journal of Production Economics*, *156*, 214–222. https://doi.org/10.1016/j.ijpe.2014.06.012

Ponz-Tienda, J. L., Yepes, V., Pellicer, E., & Moreno-Flores, J. (2012). The resource leveling problem with multiple resources using an adaptive genetic algorithm. *Automation in Construction*, *29*, 161–172. https://doi.org/10.1016/j.autcon.2012.10.003

Rahman, H. F., Servranckx, T., Chakrabortty, R. K., Vanhoucke, M., & El Sawah, S. (2022). Manufacturing project scheduling considering human factors to minimize total cost and carbon footprints. *Applied Soft Computing*, *131*, 109764. https://doi.org/10.1016/j.asoc.2022.109764

Ranjbar, M. R., & Kianfar, F. (2007). Solving the discrete time/resource trade-off problem in project scheduling with genetic algorithms. *Applied Mathematics and Computation*, *191*, 451–456. https://doi.org/10.1016/j.amc.2007.02.109

Reyck, B., & Herroelen, W. (1998). A branch-and-bound procedure for the resource-constrained project scheduling problem with generalized precedence relations. *European Journal of Operational Research*, *111*, 152-174.

Rubeša, R., Hadjina, M., Matulja, T., & Bolf, D. (2023). The shipyard technological level evaluation methodology. *Brodogradnja: Teorija i praksa brodogradnje i pomorske tehnike*, *74*(3), 91-106. https://doi.org/10.1016/S0377-2217(97)00305-6

Saad, H. M., Chakrabortty, R. K., Elsayed, S., & Ryan, M. J. (2021). Quantum-inspired genetic algorithm for resource-constrained project-scheduling. *IEEE Access*, *9*, 38488-38502. https://doi.org/10.1109/ACCESS.2021.3062790

Satıç, U. (2014). *Çok kaynak kısıtlı projelerin sezgisel yöntemlerle çizelgelenmesi.* [MSc Thesis. Yıldız Teknik University].

Sawant, V. C. (2016). Genetic algorithm for resource constrained project scheduling. *International Journal of Science and Research*, *5*(6), 733-750 https://doi.org/10.1002/(SICI)1520-6750(199810)45:7%3C733::AID-NAV5%3E3.0.CO;2-C

Schirmer, A. (1998). Case-based reasoning and improved adaptive search for project scheduling. *Naval Research Logistics*. *47*, 201-222. https://doi.org/10.1002/(SICI)1520-6750(200004)47:3%3C201::AID-NAV2%3E3.0.CO;2-L

Servranckx, T., & Vanhoucke, M. (2019). Strategies for project scheduling with alternative subgraphs under uncertainty: similar and dissimilar sets of schedules. *European Journal of Operational Research*, *279*(1), 38-53. https://doi.org/10.1016/j.ejor.2019.05.023

Shadrokh, S., & Kianfar, F. (2007). A genetic algorithm for resource investment project scheduling problem, tardiness permitted with penalty. *European Journal of Operational Research*, *181*(1), 86-101. https://doi.org/10.1016/j.ejor.2006.03.056

Shariatmadari, M., & Nahavandi, N. (2020). A new resource buffer insertion approach for proactive resource investment problem. *Computers & Industrial Engineering*, *146*, 106582. https://doi.org/10.1016/j.cie.2020.106582

Snauwaert, J., & Vanhoucke, M. (2021). A new algorithm for resource-constrained project scheduling with breadth and depth of skills. *European Journal of Operational Research*, *292*(1), 43-59. https://doi.org/10.1016/j.ejor.2020.10.032

Soong, Y. J., Woo, J. H., & Shin., J. G. (2011). Research on systematization and advancement of shipbuilding production management for flexible and agile response for high value offshore platform. *International Journal of Naval Architect Ocean Engineering*, *3*, 181~192. https://doi.org/10.2478/IJNAOE-2013-0061

Sprecher, A., & Drexl, A. (1998). Multi-mode resource-constrained project scheduling by a simple, general and powerful sequencing algorithm. *European Journal of Operational Research*, *107*(2), 431-450. https://doi.org/10.1016/S0377-2217(97)00348-2

Sprecher, A., Kolisch, R., & Drexl, A. (1995). Semi-active, active, and non-delay schedules for the resource-constrained project scheduling problem. *European Journal of Operational Research*, *80*, 94-102. https://doi.org/10.1016/0377-2217(93)E0294-8

Statista. (2023). *Size of the global shipbuilding market in 2020 and 2021, with a forecast through 2030*. Retrieved on July 1, 2023, from https://www.statista.com/statistics/1102252/size-of-the-global-shipbuilding-market/

Stopford, M. (2009). *Maritime economics*. Routledge.

Tasan, S. O., & Gen, M. (2013). An integrated selection and scheduling for disjunctive network problems. *Computers & Industrial Engineering*, *65*(1), 65-76. https://doi.org/10.1016/j.cie.2011.12.022

Tesch, A. (2020). A polyhedral study of event-based models for the resource-constrained project scheduling problem. *Journal of Scheduling*, *23*(2), 233-251. https://doi.org/10.1007/s10951-020-00647-6

Tian, M., Liu, R. J., & Zhang, G. J. (2020). Solving the resource-constrained multi-project scheduling problem with an improved critical chain method. *Journal of the Operational Research Society*, *71*(8), 1243-1258. https://doi.org/10.1080/01605682.2019.1609883

Toklu, Y. C. (2002). Application of genetic algorithms to construction scheduling with or without resource constraints. *Canadian Journal of Civil Engineering*, *29*, 421-429. https://doi.org/10.1139/l02-034

Tseng, L. Y., & Chen, S. C. (2006). A hybrid metaheuristic for the resource-constrained project scheduling problem. *European Journal of Operational Research*, *175*(2), 707-721. https://doi.org/10.1016/j.ejor.2005.06.014

Tseng, L. Y., & Chen, S. C. (2009). Two-phase genetic local search algorithm for the multimode resource-constrained project scheduling problem. *IEEE Transactions on Evolutionary Computation*, *13*(4), 848-857. https://doi.org/10.1109/TEVC.2008.2011991

Ulusoy, G., & Özdamar, L. (1996). A framework for an interactive project scheduling system under limited resources. *European Journal of Operational Research*, *90*(2), 362-375. https://doi.org/10.1016/0377-2217(95)00360-6

Ulusoy, G. (2002). Proje planlamada kaynak kısıtlı çizelgeleme. In M. Köksalan, & N. Erkip (Eds.), *Yöneylem Araştırması – Halim Doğrusöz'e Armağan* (pp. 89-128). ODTÜ Basım.

UNCTAD. (2022). *Review of Maritime Transport 2022*. United Nations Publications.

Valls, V., Ballestin, F., & Quintanilla, M. S. (2004). Justification and RCPSP: A technique that pays. *European Journal of Operational Research*, *165*(2), 375-386. https://doi.org/10.1016/j.ejor.2004.04.008

Valls, V., Ballestin, F., & Quintanilla, S. (2008). A hybrid genetic algorithm for the resource-constrained project scheduling problem. *European Journal of Operational Research*, *185*(2), 495-508. https://doi.org/10.1016/j.ejor.2006.12.033

Van Eynde, R., & Vanhoucke, M. (2022). A theoretical framework for instance complexity of the resource-constrained project scheduling problem. *Mathematics of Operations Research*, *47*(4), 3156-3183. https://doi.org/10.1287/moor.2021.1237

Van Peteghem, V., & Vanhoucke, M. (2008). *A genetic algorithm for the multi-mode resource-constrained project scheduling problem*. Working Papers of Faculty of Economics and Business Administration, Ghent University, Belgium 08/494. Ghent University, Faculty of Economics and Business Administration.

Van Peteghem, V., & Vanhoucke, M. (2010). A genetic algorithm for the preemptive and non-preemptive multi-mode resource-constrained project scheduling problem, *European Journal of Operational Research*, *201*(2), 409-418. https://doi.org/10.1016/j.ejor.2009.03.034

Vanhoucke, M., & Coelho, J. (2019). Resource-constrained project scheduling with activity splitting and setup times. *Computers & Operations Research*, *109*, 230-249. https://doi.org/10.1016/j.cor.2019.05.004

Wang, C., Mao, P., Mao, Y., & Shin, J. G. (2016). Research on scheduling and optimization under uncertain conditions in panel block production line in shipbuilding. *International Journal of Naval Architecture and Ocean Engineering*, *8*(4), 398-408. https://doi.org/10.1016/j.ijnaoe.2016.03.009

Wang, H. W., Lin, J. R., & Zhang, J. P. (2020). Work package-based information modeling for resource-constrained scheduling of construction projects. *Automation in Construction*, *109*, 102958. https://doi.org/10.1016/j.autcon.2019.102958

Wang, Y. M. (2009). Centroid defuzzification and the maximizing set and minimizing set ranking based on alpha level sets. *Computers & Industrial Engineering*, *57*(1), 228-236. https://doi.org/10.1016/j.cie.2008.11.014

Xu, J., & Bai, S. (2023). A reactive scheduling approach for the resource-constrained project scheduling problem with dynamic resource disruption. *Kybernetes*, *In press*. https://doi.org/10.1108/K-09-2022-1339

Yang, Z., & Liu, C. (2018). A hybrid multi-objective gray wolf optimization algorithm for a fuzzy blocking flow shop scheduling problem. *Advances in Mechanical Engineering*, 10(3), 1687814018765535. https://doi.org/10.1177/1687814018765535

Yuguang, Z., Bo, A., & Yong Z. (2016). A PSO algorithm for multi-objective hull assembly line balancing using the stratified optimization strategy. *Computers & Industrial Engineering*, *98*, 53-62. https://doi.org/10.1016/j.cie.2016.05.026

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, *8*(3), 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X

Zaman, F., Elsayed, S., Sarker, R., Essam, D., & Coello, C. A. C. (2021). An evolutionary approach for resource constrained project scheduling with uncertain changes. *Computers & Operations Research*, *125*, 105104. https://doi.org/10.1016/j.cor.2020.105104

Zamani, R. (2019). An effective mirror-based genetic algorithm for scheduling multi-mode resource constrained projects. *Computers & Industrial Engineering*, *127*, 914-924. https://doi.org/10.1016/j.cie.2018.11.031

Zhang, H., Xu, H & Peng, W. (2008) A Genetic Algorithm for Solving RCPSP. *2008 International Symposium on Computer Science and Computational Technology*, China. pp. 246-249. https://doi.org/10.1109/ISCSCT.2008.255

Zhang, S., Song, X., Shen, L., & Xu, L. (2023). Complicated time-constrained project scheduling problems in water conservancy construction. *Processes*, *11*(4), 1110. https://doi.org/10.3390/pr11041110

Zhong, Y. G. (2017). Hull mixed-model assembly line balancing using a multi-objective genetic algorithm simulated annealing optimization approach. *Concurrent Engineering*, *25*(1), 30-40. https://doi.org/10.1177/1063293X16666204

Zhou, T., Long, Q., Law, K. M., & Wu, C. (2022). Multi-objective stochastic project scheduling with alternative execution methods: An improved quantum-behaved particle swarm optimization approach. *Expert Systems with Applications*, *203*, 117029. https://doi.org/10.1016/j.eswa.2022.117029

Zhu, L., Lin, J., & Wang, Z. J. (2019). A discrete oppositional multi-verse optimization algorithm for multi-skill resource constrained project scheduling problem. *Applied Soft Computing*, *85*, 105805. https://doi.org/10.1016/j.eswa.2022.117029