Linguistic and Philosophical Investigations
ISSN: 1841-2394, e-ISSN: 2471-0881
Vol 23 (1), 2024
pp. 1745 - 1764

Development of an Intelligent Hybrid Meta-Heuristic Allocation Model for Organizing the Dredging Vessels in Iranian Ports

Amirabbas Mohammadi, Ali Rajabzadeh Ghatari*, Maryam Shoar, Vahid Baradaran

[1]Department of Industrial Management, North Tehran Branch, Islamic Azad University, Tehran, Iran, Amirabbas.mohammadi@iau.ac.ir

[2]Professor, Department of Industrial Management , Tarbiat Modares University, Tehran, Iran
Corresponding author email : Alirajabzadeh@modares.ac.ir

[3]Assistant Professor, Department of Industrial Management, North Tehran Branch, Islamic Azad University, Tehran, Iran

[4]Associatied Professor, Department of Industrial Engineering, North Tehran Branch, Islamic Azad University, Tehran, Iran

Abstract

The organization of dredging ships has an important place in the operation of ports and maritime organizations. The main goal of the current research is to organize Iran's dredging ships, considering risk management. This research uses artificial intelligence techniques in a Matlab programming environment to design a hybrid meta-heuristic model. The studied population of this research can be divided into two general groups: the first includes expert professors in industrial engineering, industrial management, port logistics management, and marine engineering (i.e., academic experts), and the second group comprises managers and professionals working in ports and maritime organization (i.e., industry experts). Their opinions were collected using a combination of non-probability targeted (judgmental) and snowball sampling methods in the spring of 2024. The main findings of this research are those of applying the research model to the country's dredging ships in Iran Ports and Maritime Organization, taking into account risk management, which is as follows the performance of reducing the time of dredging operations in various ports (I1) is equal to 0.07; the risk control aimed at increasing security in ports (I2) is equal to 0.10; marine traffic conditions improvement Index (I3) is equal to 0.06; allocation according to the number of existing dredges and their capacity (I4) is equal to 0.17; allocation according to the environmental conditions of the region (I5) is equal to 0.07 and allocation for reducing the cost of dredging projects in ports (I6) is equal to 0.13. These results, considering risk management, caused the organization of the country's dredging ships to be improved by 25%. Finally, suggestions are provided for the benefit of managers and professionals working in ports and maritime organizations as well as academic experts in fields like industrial engineering, industrial management, port logistics management, and marine engineering.

Keywords: Allocation; Meta-heuristic; Interpretive Structural Modeling; Data mining; Artificial intelligence; Supply Chain Management; Iran Ports and Maritime Organization

Received: 10 May 2024 **Revised**: 11 June 2024 **Accepted:**29 June 2024

Introduction

Ports are one of the most important and strategic points in any country, as they provide the country's needs, and that is why this research considers dredging and the allocation of existing dredgers in the country to the ports. Due to the scarcity of dredgers in the country, ports are faced with sedimentation, and the docking of domestic and foreign ships and the export and import in ports has become difficult. Therefore, the allocation of dredging vessels, the port type, and the amount of exports and imports in ports have become important issues. According to the classifications and previous studies, ports in Iran have been divided into three categories: southwest ports, southeast ports, and northern ports. The rate of sedimentation in these ports and their importance, location, and strategic status differ. Therefore, the limited number of dredging ships in Iran has increased the importance of allocating dredging ships to each of the ports, which constitute a large part of the strategic points for export and import in the country.

The first model of dredging systems was made of a pile and a big bucket. By holding a candle, they fixed the vessel in a place in the water, and they poured the shipping materials at sea level into a big bucket by the effort and strength of human capital and then sent the bucket to the shore or deep waters (Shoshtrizadeh et al., 2017).

In fact, dredging was initially aimed at increasing the depth of rivers and canals for easier movement of ships by stirring and mixing materials on the surface of the water and using the energy of water flow to transport materials. In the Middle Ages, the Dutch invented a model of dredging called bag and spoon (Fazlullahi, 2020). At the end of the 16th century, new dredging ships that were known as mud mills were built in the Netherlands. In the 18th century, when the steam engine came into use, surprising developments occurred in the shipbuilding industry and dredging machines. In 1867, the first suction dredger was produced. Afterward, during the 19th and 20th centuries, dredges with great diversity in their structure were proposed, and various types of dredges, including suction, cutting, and pulling dredgers, were designed and used and are still in use (Negarestan, 2018).

In fact, the necessity of dredging aqueducts to access freshwater sources dates back to very distant times. However, the necessity of dredging waterways dates back to when humans started carrying goods and passengers in rivers and beaches by building boats. The history of dredging in rivers such as the Nile, Tigris, and Indus dates back thousands of years ago (Mirzaei and Dezfuli, 2023). Historical documents show that the canal between the Tigris and Euphrates Rivers and between the Nile River and the Red Sea were created around 600 BC. Nikao II started the construction of the latter. Infantry and prisoners of war mainly carried out these dredging approaches. Dredging and increasing the depth of canals and rivers for better movement of ships was initially done by stirring and mixing the bed materials and using the water flow energy to transport the materials. For example, in the Indus River, stems of trees were attached to the back of wooden boats to mix the mud of the bed in the river water, and then, the water flow transported them over long distances (Koh Bezan, 2020).

The first dredging systems consisted of piles and a large bucket. The candle kept the boat fixed in the water, and the seabed materials were poured into a big bucket by human beings, and then the bucket was dragged to the shore or deep waters (Fateminezhad and Ghiathi, 2021). In the Middle Ages, a more advanced type of this device called a bag and spoon, was invented in Holland. The device required three operators. One of them would place the spoon in a suitable place on the bed, and the second one would pull the spoon with the help of a rope. The third person used a rope to guide and stabilize the vessel. Dredging ships, in its true sense, were built at the end of the 16th century in Holland, where they were called mud mills. It had two large wheels that lifted the dredged material from the seabed with a blade and dumped it on a chute. Grab dredgers were first made in Italy. With the invention of the steam engine by James Watt in the 18th century, great changes occurred in the shipbuilding and dredging industry (Derakhshan, 2023).

In fact, modern dredging in Iran is relatively new. Before the victory of the Islamic Revolution in Iran, the Ports and Maritime Organization often used the power and expertise of foreign organizations to dregate ports. According to the Algerian agreement (1970) that was signed to resolve the dispute between Iran and Iraq for the ownership of Arvandrud before the Islamic revolution in Iran, due to the lack of dredging vessels, the Iranian government handed over the dredging rights of Arvandrud to Iraq for 5 years and at the same time obliged the Ports and Maritime Organization to equip their dredging vessels. Iran's dredging ships were gradually created during the last four decades (Iran Ports and Maritime Organization, 2022).

The research background in Iran

Molakhah et al. (2023) suggested that the best section for dredging was in a span of about 8 km from the Kurdan diversion dam to the Qazvin Highway Bridge. To optimally assess the dredging cross-section of the Kurdan river bed, GIS software and HEC-4RAS were used to create the geometry model of the river in the desired area. Then, the data available from the previous years were fitted, and the flow and sediment were calculated for different return periods. In the end, a hydraulic model of the river was built. Then, three sections with an approximate length of 1.5 km were selected to be dredged with equal volumes. Finally, the speed changes, erosion, and sedimentation were examined, and the best section of the river was determined for dredging, taking into account the lowest speeds and the lowest erosion in the river.

Mirzaei and Dezfuli (2023) compared different dredging techniques technically and economically in the studied port, i.e., Imam Khomeini port. This research, which was presented at the national conference of new approaches to removing the obstacles in the country's construction industry, various dredging techniques, which are mostly mechanical and hydraulic, were examined in terms of construction management and execution, time cost, quality, and necessary machinery and equipment.

Sharifi et al. (2022) investigated the optimized allocation of berths in a situation where the fuel consumption required for the movement of ships is considered by the managers of terminals and shipping lines when deciding about the operation of the vessel allocation. They chose the Shahid Rajaei Port as the case and presented a mathematical model suitable for the physical and operational characteristics of this port. Then, they used the exact method of Augmented Epsilon Constraint (AEC) to solve the model. As the presented mathematical model was too complex to be solved, the NSGA-II (multi-objective Non-Dominated Sorting Genetic Algorithm II) meta-heuristic was used to solve the problems with real dimensions. In the end, the results obtained and the statistical analyses performed indicated the acceptable performance of the proposed mathematical multi-objective optimization model in reducing the waiting time of the fuel consumption of the ships.

Afshari and Mirzapour (2022) reported that in addition to container ships that have been widely noted in the literature, the transportation of bulk goods also has a significant share in international trade. On the other hand, as any bulk goods are transported by different ships, all types of bulk carriers cannot be serviced in all berths; therefore, this research, aiming at allocating several berths to bulk carriers in bulk terminals, proposed a mixed integer model to minimize the total cost of waiting times, operations and the cost of allocating berths to carriers. As many factors can affect the arrival and service time of each ship, the mentioned parameters were considered as triangular fuzzy numbers in this study. Jiménez method has been used to de-fuzzify the model. Finally, some numerical examples were solved using IBM ILOG CPLEX 12.10 to validate the model and the results were presented.

Abroad research

Chou et al. (2024) reported that the Department of Civil and Construction Engineering, National University of Science and Technology in Taiwan, used a chatbot based on deep learning with natural language processing to evaluate supportive risk management in river dredging projects. Among the main results of the study above is that choosing the right dredger for river dredging projects depends on the technical and economic characteristics of the dredger types and their environmental effects. Knowing the techniques of transporting and transferring dredged sediments to the disposal site is one of the important issues for managing the risk of supporting river dredging projects in Taiwan and when investigating the environmental effects of dredging activities. The advantages of river dredging projects in Taiwan are filling the hollows created underwater or on land and replacing good, suitable, and quality materials with weak underwater materials.

Martin et al. (2024) analyzed multi-port continuous berth allocation based on the Adaptive Large Neighborhood Search (ALNS) algorithm proposed by Denmark Technical University. The findings of the mentioned research showed that the objectives of allocating a continuous wharf with multiple ports in Denmark are: Construction of several ports and recovery of dock land; creating a route for laying pipes and underwater cables and maintaining them; increasing or improving the waterways of ports and sea channels. The allocation advantages in the coastal areas of Denmark are that they provide safe access between the sea and the port (access channel), Increase the depth and capacity of port berths, and develop sea transportation.

Tunçel et al. (2023) employed the bow-tie fuzzy approach with SLIM (Success Likelihood Index Method) and Quantitative Risk Assessment (QRA), proposed by the Marine Transportation Engineering and Management Group, Istanbul Technical University in Turkey, to evaluate the anchor dredging in cargo ships. In fact, the main result of the mentioned study is that dredging and anchoring activities have important goals in Turkey's maritime transportation. During the last three decades, the implementation of dredging projects in ports, estuaries, and rivers of Turkey has been growing, and based on the application of comprehensive quantitative risk assessment method in risk assessment for anchor dredging, the quality of anchor dredging operations in cargo ships in Turkey has increased. Dredging advantages in the docks of the coastal areas of Turkey are the development of the marine environment; Extraction of agricultural resources, coastal protection, and land reclamation.

Bai et al. (2021) analyzed the efficiency of trailing suction hopper dredging using the cumulative strategy and project management framework for dredging (PMFD) proposed by the State Laboratory of Simulation and Safety of Hydraulic Engineering, Tianjin University, China. According to the findings of this research, trailing suction hopper dredging is suggested for maintaining the existing depths based on the rate of sedimentation and other influencing parameters and the preparation of the initial hydrographic map. In China, trailing suction hopper dredges are performed based on the depth of the area, the dredger vessel's trough, the existing obstacles, the type of bed, and its degree of hardness, among others. The advantages of dredging in the docks of the coastal areas of China are: Increasing the depth and capacity of rivers or lakes or even harbor basins; filling the pits that are created underwater or on land; and coastal protection and land reclamation.

Research method

The research methodology is quantitative analysis with the use of hybrid meta-heuristic algorithms. As it is exploratory, we do not have to use hypotheses. The information required for this research is collected through field and library studies, observation, interviews, and technical meetings held with experts. In general, operations research mainly uses modeling, especially mathematical models. The use of mathematical models is the core of operation research. In general, operation research models require performing the following 5 phases. This research uses hybrid meta-heuristic algorithms to build and solve the model and find the optimal solution:

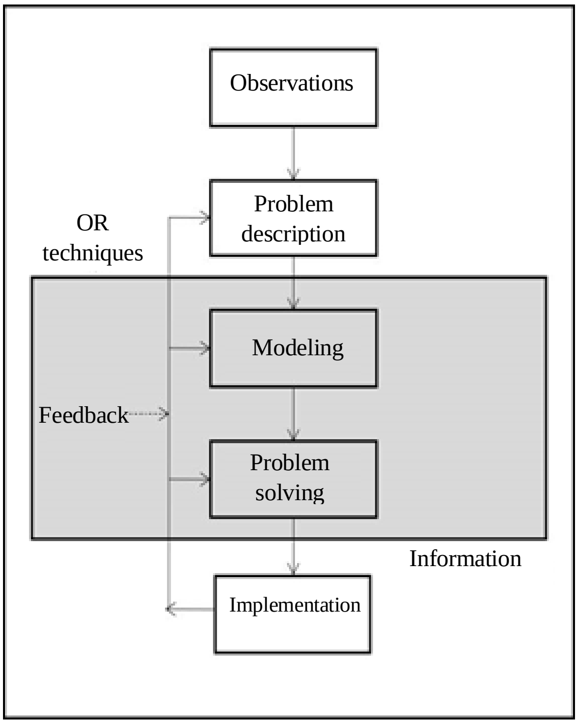


Figure 1. Steps to reach the optimal solution by hybrid meta-heuristic algorithms

The research data collection methods and tools

As in all scientific research, the library method is used. However, other research may have used it in some parts of the research process. In this research, due to the importance of the study subject, both the library and field methods are used. The research method is library in terms of collecting information. While it is a field study, as it reviews the literature and records of the problem and the research subject and collects information, authors inevitably have met human and organizational societies and held regular meetings with experts, ports and maritime organizations, and contracting organizations equipped with dredging vessels. In addition, they have exploited meetings with experts, questioning, interviews, and observations and have collected, categorized, and analyzed information.

Statistical population and the sample

Regarding the nature of the research, we do not have a population or a sample. In general, the results of this research are generalizable and usable in all ports of the country. In the following, the general specifications of the country's ports (including capacities, depth, etc.) are presented:

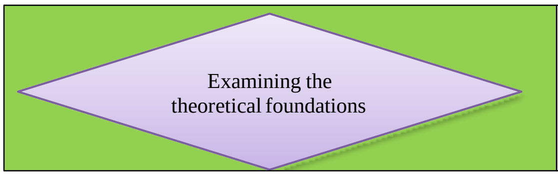
Table 1. The general specifications of the country's ports

Port name	Subordinate ports	The length of the main channel (km)	Pond depth (m)	The number of wharfs (post)	Berth depth (m)	Maximum shipping capacity (Tons)	Capacity to accept goods (million tons)
Anzali Port	-	0.8	5	17	5-9	12000	13.6
Amirabad port	Port of NEKA	1	6	15	6.5	8000	7.5
Nowshahr port	Faridoonkar port	1.8	5	10	4-6	10000	2.8
Bandar Imam Khomeini	Shadegan, Sajafi port	78	14	40	9-14	150000	60

Khorramshahr port	-	115	-	21	5.5	10000	4
Abadan port	Arvandkenar, Chavibdeh port	92	5.5	5	5.5	5000	0.6
Bushehr port	Asaluyeh Khark Ganaveh Kangan Deylam Dayyer	15	6	15	4.5-11.5	50000	9.8
Chabahar port	Geishab Khark Ganaveh Kangan Deylam Dayyer	2.8	12	10	4-12	80000	9.5
Shahid Rajaee Port	Kish port Qeshm port	8.3	14	35	5-17	200000	132
Bahonar Port	Haqqani Sirik Tiyab Jask Hormuz	-	10.5	12	5-10	50000	2.7
Lengeh port	-	0.6	5.5	3	5.5	10000	2.7

Techniques and tools of the research data analysis

In the next phase, since implementing the allocation of dredging ships to the ports and identifying environmental risks are among the goals of this research, and in order to achieve these goals, we investigated the country's ports and then, taking into account the steps of scientific research in operations, collected data relating to the allocation and ports of the country and the identification of risks in this area. Then, a mathematical model for allocation using hybrid meta-heuristic algorithms is presented. According to the collected data and identified variables and limitations, the data was analyzed first by using Rapid Miner or IBM SPSS Modeler, and then we used Matlab to implement and solve the allocation model by using meta-heuristics algorithms and to reach the optimal solution. Finally, the flowchart of the research data analysis steps is presented:



The theoretical foundations of the research are examined to identify the input and output themes of the research model.

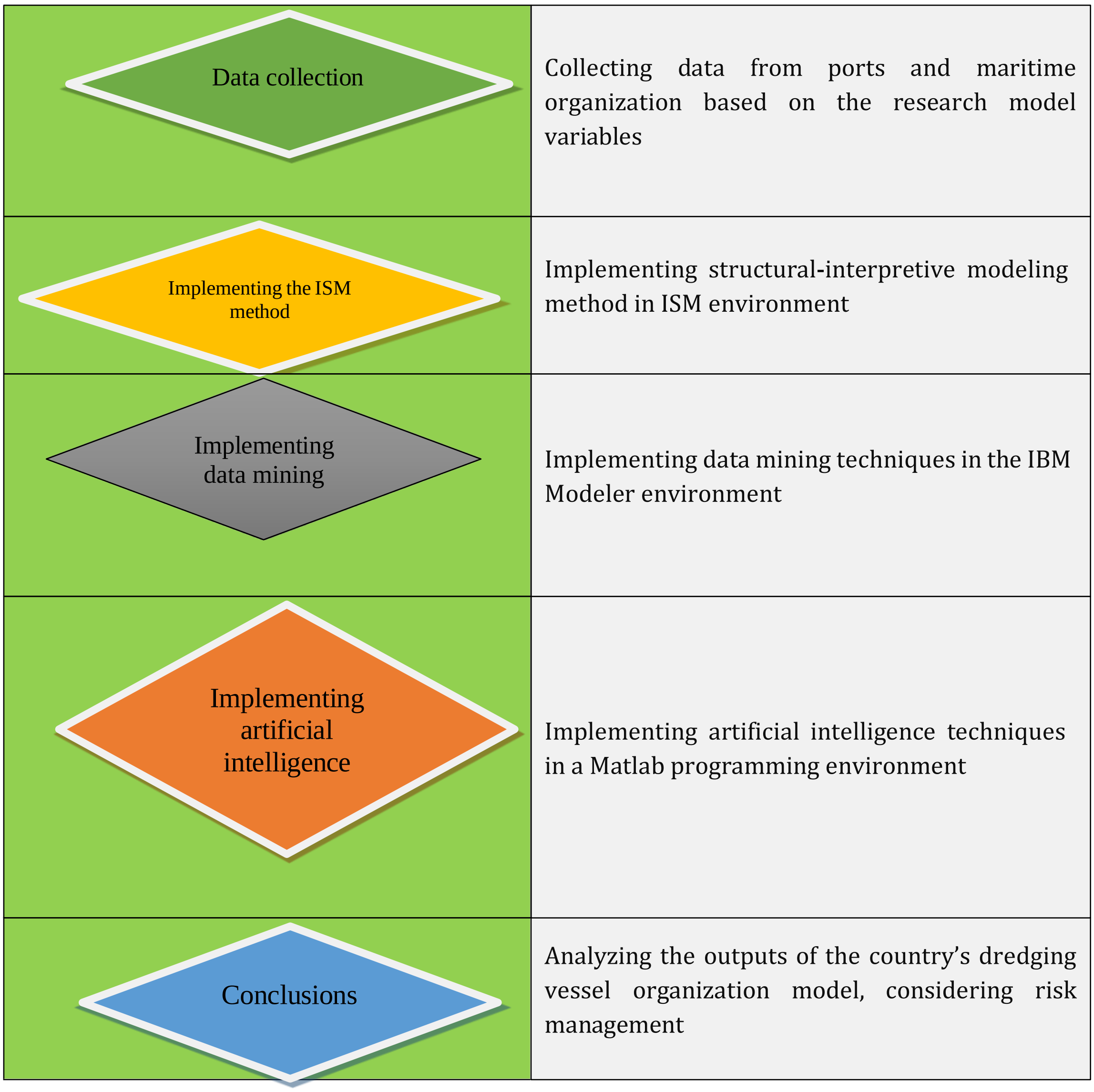


Figure 2. The flowchart of the research data analysis steps

Analyzing data by meta-heuristic algorithms

Most real-world search and optimization problems include complexities such as non-convexity, nonlinearities, discontinuities, mixed nature of variables, multiple fields, and large dimensions, which a combination of them makes classical algorithms provably inefficient and impractical or unenforceable (Danamazraeh and Parand, 2023).

To the extent of our knowledge, there is no mathematical algorithm to find the optimal solution for all these problems in a limited computational time. Therefore, in order to solve such problems, search and optimization algorithms are usually developed by using certain heuristics, which, while they lack strong mathematical foundations, are good at reaching an approximate solution in a reasonable amount of time. These techniques, called meta-heuristics, do not guarantee finding the exact optimal solution, but they can lead to an almost optimal solution in a computationally efficient way. Due to this practical appeal and the ease of implementation, meta-heuristics are gaining popularity in several applied fields. Most meta-heuristics techniques have a random nature and imitate a natural, physical, or biological principle similar to the search or optimization process (Qhahramani Nahar and Samadi, 2023).

A meta-heuristic approach is particularly relevant to solving problems in search and optimization. They describe a method that exploits one or more heuristics and, therefore, inherits all three of the properties mentioned above. Therefore, a meta-heuristic method Seeks to find a near-optimal solution rather than trying to find the exact optimal solution. There is no precise reason to converge to the optimal solution. They are usually computationally faster than exhaustive search. They have an iterative nature and often use random operations in their search process to modify one or more initial candidate solutions; they usually take random samples from the search space. Since many real-world optimization problems are complex due to their inherent applications, classical optimization algorithms may not always be applicable and may not be fair in solving such problems pragmatically. Meta-heuristics usually are categorized as follows (Danamazraeh and Parand, 2002; Sadeghian, 2002):

Deterministic techniques versus random techniques: Deterministic techniques follow a certain path from random initial solution(s). Therefore, they are sometimes referred to as path techniques. Stochastic techniques (or discontinuous techniques) allow probabilistic jumps from the current solution(s) to the next solution. Greedy techniques versus non-greedy ones: Greedy algorithms usually search in the neighborhood of the current solution and move to a better solution immediately after finding a better solution. This behavior often leads to a local optimum. Non-greedy techniques either remain the same before updating solution(s) for some iterations or have a mechanism to start from a local optimum. However, greedy behavior is the optimal strategy to deal with convexity problems. Memory-based versus memoryless techniques: Memory-based techniques keep records of past solutions and their paths and use them for direct search. A popular memory-based method is called Tabu Search. It is a different neighborhood technique: Some meta-heuristics, such as simulated annealing and Tabu search, allow a limited set of moves from the current solution. However, many meta-heuristics use operators and parameters to provide the possibility of creating multiple neighborhoods. For example, particle swarm optimization manages this through different swarm topologies. Dynamic versus static objective function: A meta-heuristic that updates the objective function depending on the current search needs is classified as dynamic. Other meta-heuristics use their operators to control the search.

Most meta-heuristics are population-based, random, and non-greedy and use a static objective function (Danamazraeh and Parand, 2002).

Most meta-heuristics follow a similar sequence of operations and, therefore, can be defined in a common general framework. To determine a meta-heuristic, at least five schemes (SP, GP, RP, UP, TP) and four parameters (N, μ, λ, ρ) are required. Individual plans may include one or more parameters of their own (Danamazraeh and Parand, 2002; Qhahramani Nahar and Samadi, 2002):

Table 2. The steps of data analysis with meta-heuristic algorithms

In phase 1, the counter will be reset to zero. It is clear from the iteration loop of meta-heuristics that they are iterative procedures.
In phase 2, an initial set of N solutions in the St set will be created. Often, solutions are generated randomly between the lower and upper bounds of the variables. For combinatorial optimization problems, random permutations of entities can be generated. When problem-specific knowledge of good initial solutions is available, they may be included along with a few random solutions to enable exploration.
Phase 3 evaluates each of the N members of the set using the provided objective and constraint functions. Constraint violations, if any, should be considered here to provide an evaluation plan that will be exploited in the next steps of the algorithm. One way to define the constraint violation CV(x|p) is that ≼α≻ is equal to |α| If α < 0, and 0 otherwise. Before adding the values of different constraints, they should be normalized. The objective function f(x) and the constraint violation value CV(x|p) can both be submitted to the next steps for the actual evaluation of the solutions.
Phase 4 selects the best member of the set St and stores it as x∗t. This phase requires pairwise comparison with the set members. One of the ways to compare two solutions, A and B, in constrained optimization problems is to use the following parameterless strategy to select the winner:

If A and B are possible, the researcher chooses the case that has a lower target value, i.e., f. If A is possible and B is not, he chooses A and vice versa. If A and B are impossible, he chooses one that has a lower CV value.
In phase 5, the algorithm enters a loop until the termination plan (TP) is met. The loop consists of steps 6 to 12. TP may involve achieving a predetermined target value (ft) and is satisfied when f(x∗t) ≤ fT. TP may contain a predetermined number of iterations T, thereby setting the termination condition t≤T. Other TPs are also possible, and it is one of the five designs that the user will select.
Phase 6 uses the selection plan (SP) to select μ solutions from the set of St. SP should analyze St carefully and select better solutions with respect to the f and CV. The meta-heuristic will vary greatly based on the SP being exploited—the solutions of μ form a new set of Pt.
In phase 7, Pt solutions are exploited to create a new set of λ solutions using a production plan (GP). This scheme provides the basic search operation of a meta-heuristic algorithm. Designs are different for function optimization and combinatorial optimization problems. The created solutions are stored in the Ct collection.
In phase 8, the worse or random solutions St are selected to be replaced by the replacement plan (RP). The solutions to be replaced are stored in Rt. In some meta-heuristic algorithms, Rt can be Pt (requiring ρ = μ) and replace exploited solutions to create new ones. To make the algorithm greedier, Rt can be the worst μ member from St.
In phase 9, *ρ* selected solutions from St have to be replaced with *ρ* other solutions. Here, a set of at most (μ+λ+ρ) combinatorial solutions Ct ∪ Rt ∪ Pt is exploited to select ρ of the solution by employing the update (UP) scheme. If Rt = Pt, then the combination of solutions does not need to contain both Rt and Pt to avoid duplication of solutions. UP can choose the best ρ solution among them. A set of combinations of solutions from Ct ∪ Rt or Ct ∪ Pt or simply Ct is also allowed. Suppose the members of Rt are included in the hybrid set of solutions. In that case, the meta-heuristic algorithm has the property of elite-preserving, which is desired in an efficient optimization algorithm. RP and UP have important roles in determining the ability of the meta-heuristics to withstand or overcome adverse conditions or harsh tests (robustness). The greedy approach of replacing the worst solutions with the best solutions may lead to faster yet premature convergence. Maintaining diversity in candidate solutions is an essential aspect to consider when designing RP and UP.
Phase 10 evaluates each of the new members of St, and phase 11 updates the best member x∗t by using the best members of the updated St. When the algorithm meets TP, the best current solution is declared as the near-optimal solution.

The above meta-heuristic can also represent a single solution optimization procedure with a setting of N = 1, which results in μ = ρ = 1. If a new unitary solution is created in phase 7, then λ = 1. In this case, SP and RP are simple procedures for selecting the singleton solution in St. Thus; it results in St = Rt = Pt. The generation plan (GP) can employ a Gaussian distribution or other distributions to select a solution in the neighborhood of the single-trunk solution in St. The updating plan (UP) consists of selecting a single solution from two solutions Ct ∪Rt (preserving the elites) or selecting the new solution from Ct alone and replacing it with Pt. Various types of meta-heuristics are presented (Qhahramani Nahr and Samadi, 2023; Sadeghian, 2023):

Table 3. Meta-heuristic algorithms

Name	Abbreviation	Category	The introduction year
Simulated Annealing	SA algorithm	Based on the physics laws	1983

Tabu Search	TS algorithm	Neighborhood-based	1989
Genetic Algorithm	GA algorithm	Evolution-based	1992
Evolutionary algorithm	EA algorithm	Evolution-based	1994
Cultural Algorithm	CA algorithm	Evolution-based	1994
Particle Swarm Optimization	PSO algorithm	Crowd-based	1995
Differential-evolution	DE algorithm	Evolution-based	1995
Variable Neighborhood Search	VNS algorithm	Movement-based	1997
Guided Local Search	GLS algorithm	Movement-based	1998
Clonal Selection Algorithm	CSA algorithm	Evolution-based	2000
Harmony Search	HS algorithm	Evolution-based	2001
Memetic Algorithm	MA algorithm	Evolution-based	2002
Iterative Local Search	ILS algorithm	Movement-based	2003
Artificial Bee Colony	ABC algorithm	Based on collective intelligence	2005
Ant Colony Optimization	ACO algorithm	Based on collective intelligence	2006
Glowworm Swarm Optimization	GSO algorithm	Crowd-based	2006
Imperialistic Competitive Algorithm	ICA algorithm	Socio-political	2007
Biogeography Based Optimization	BBO algorithm	Socio-political	2008
Teaching-Learning-Based Optimization	TLBO algorithm	Based on social behavior	2011
Animal Migration Optimization	AMO algorithm	Crowd-based	2013
Artificial Root Foraging Algorithm	ARFA algorithm	Nature based	2014
Coral Reefs Optimization Algorithm	CROA algorithm	Nature-based	2014
Social Engineering Optimizer	SEO algorithm	Socio-political	2018
Future Search Algorithm	FSA algorithm	Socio-political	2019
Political Optimizer	PO algorithm	Socio-political	2020
Rain Optimization Algorithm	ROA algorithm	Inspired by nature	2020

After understanding the role of each of the five designs and choosing their appropriate size, different meta-heuristic optimization algorithms can be created. All five designs may include random operations, thereby randomizing the resulting algorithm. Most problems in nature have multiple (possibly conflicting) goals that must be met. Many of these problems are often considered as single-objective optimization problems by transforming all the objectives into one. The general multi-objective optimization (MOP) problem can be formally defined as follows (Danamazraeh and Parand, 2023):

Let the vector $x^*=[x^*1, x^*2, ..., x^*n]T$

Which meets *the* following inequalities:

$gi(x)\leq 0$ for $i=1,2,...,m$, which meets the following *p* equalities

$hi(x)\leq 0$ for $i=1,2,...,p$, which optimizes the following vector function

$f(x)=[f1(x),f2(x),...,fk(x)]T$

While having several objective functions, the optimality concept changes because in multi-objective optimization problems, the researcher is really trying to find good agreements instead of a single solution, which is common in global optimization (Qhahramani Nahar and Samadi, 2023).

Finally, the research method of "organizing dredging vessels in the country considering risk management by using Matlab programming environment" includes all the systematic steps of data collection and classification and logical analysis to achieve the research goal. Afterward, the population, the sample, and the data collection method will be selected, and the validity and reliability of the localization tools used in the research elements will be explained. Then, the data analysis method is examined.

Data analysis based on artificial intelligence techniques in Matlab programming environment

According to the implementation of artificial intelligence techniques (hybrid meta-heuristic model based on artificial intelligence, ISM, and data mining) in the Matlab programming environment to develop the prediction model of the research input data, a smart algorithm was implemented in the Ports and Maritime Organization. Applying the intelligent algorithm, five stages for the design of an intelligent system were presented:

The first step: Identifying the input and output variables of the algorithm - after finalizing the initial model of the hybrid meta-heuristic model based on artificial intelligence, ISM and data mining were used to define the input and output variables of the algorithm. The algorithm input variables using the artificial intelligence of the Matlab environment are The first input variable: Reducing the dredging operation time in various ports (I1); the Second input variable: Risk control aimed at increasing security in ports (I2); The third input variable: The improvement index of maritime traffic conditions (I3); Fourth input variable: Allocation based on the number of existing dredges and their capacity (I4); The fifth input variable: Allocation based on to the environmental conditions of the region (I5); The sixth input variable: Allocation based on cost reduction due to dredging projects in ports (I6); and the output variable of the algorithm is the performance of "organizing the country's dredging vessels taking into account risk management." According to the initial model of the research and applying the documents of Iran Ports and Maritime Organization and experts' opinions to evaluate that model, it is possible to compile the input and output variables of the smart algorithm implemented in the Ports and Maritime Organization.

The second step: Defining qualitative variables using linguistic adverbs and assigning numbers and fuzzy sets and membership functions to them - the table of linguistic variables, fuzzy values , and membership functions of triangular and trapezoidal numbers related to the input and output variables of the algorithm in three and five spectrums show that:

Table 4. Linguistic variables relating to the output variable of the main research module

Linguistic variable	Membership functions of triangular and trapezoidal numbers
Unimportant	(0, 0.025, 0.05)
Very weak	(0.05, 0.10, 0.15)
Weak	(0.1, 0.2, 0.3)
Medium	(0.3, 0.5, 0.7)
Good	(0.7, 0.8, 0.9)
Very Good	(0.85, 0.9, 0.95)
Excellent	(0.925, 0.95, 1, 1)

Intelligent system training data
0, 0, 0, 0, 0, 0, 0
0-0.025, 0-0.025, 0-0.025, 0-0.025, 0-0.025, 0-0.025, 0.05
0.025-0.05, 0.025-0.05, 0.025-0.05, 0.025-0.05, 0.025-0.05, 0.025-0.05, 0.1
0.05-0.075, 0.05-0.075, 0.05-0.075, 0.05-0.075, 0.05-0.075, 0.05-0.075, 0.15
0.075-0.10, 0.075-0.10, 0.075-0.10, 0.075-0.10, 0.075-0.10, 0.075-0.10, 0.2
0.10-0.15, 0.10-0.15, 0.10-0.15, 0.10-0.15, 0.10-0.15, 0.10-0.15, 0.25
0.15-0.25, 0.15-0.25, 0.15-0.25, 0.15-0.25, 0.15-0.25, 0.15-0.25, 0.3
0.25-0.30, 0.25-0.30, 0.25-0.30, 0.25-0.30, 0.25-0.30, 0.25-0.30, 0.35
0.30-0.35, 0.30-0.35, 0.30-0.35, 0.30-0.35, 0.30-0.35, 0.30-0.35, 0.4
0.35-0.4, 0.35-0.4, 0.35-0.4, 0.35-0.4, 0.35-0.4, 0.35-0.4, 0.45
0.40-0.45, 0.40-0.45, 0.40-0.45, 0.40-0.45, 0.40-0.45, 0.40-0.45, 0.5
0.45-0.5, 0.45-0.5, 0.45-0.5, 0.45-0.5, 0.45-0.5, 0.45-0.5, 0.55
0.50-0.55, 0.50-0.55, 0.50-0.55, 0.50-0.55, 0.50-0.55, 0.50-0.55, 0.6
0.55-0.6, 0.55-0.6, 0.55-0.6, 0.55-0.6, 0.55-0.6, 0.55-0.6, 0.65
0.60-0.65, 0.60-0.65, 0.60-0.65, 0.60-0.65, 0.60-0.65, 0.60-0.65, 0.7
0.65-0.7, 0.65-0.7, 0.65-0.7, 0.65-0.7, 0.65-0.7, 0.65-0.7, 0.75
0.70-0.75, 0.70-0.75, 0.70-0.75, 0.70-0.75, 0.70-0.75, 0.70-0.75, 0.8
0.75-0.80, 0.75-0.80, 0.75-0.80, 0.75-0.80, 0.75-0.80, 0.75-0.80, 0.85
0.8-0.85, 0.8-0.85, 0.8-0.85, 0.8-0.85, 0.8-0.85, 0.8-0.85, 0.9
0.85-0.9, 0.85-0.9, 0.85-0.9, 0.85-0.9, 0.85-0.9, 0.85-0.9, 0.925
0.90-0.95, 0.90-0.95, 0.90-0.95, 0.90-0.95, 0.90-0.95, 0.90-0.95, 0.95

0.95-1, 0.95-1, 0.95-1, 0.95-1, 0.95-1, 0.95-1, 0.975
1, 1, 1, 1, 1, 1, 1

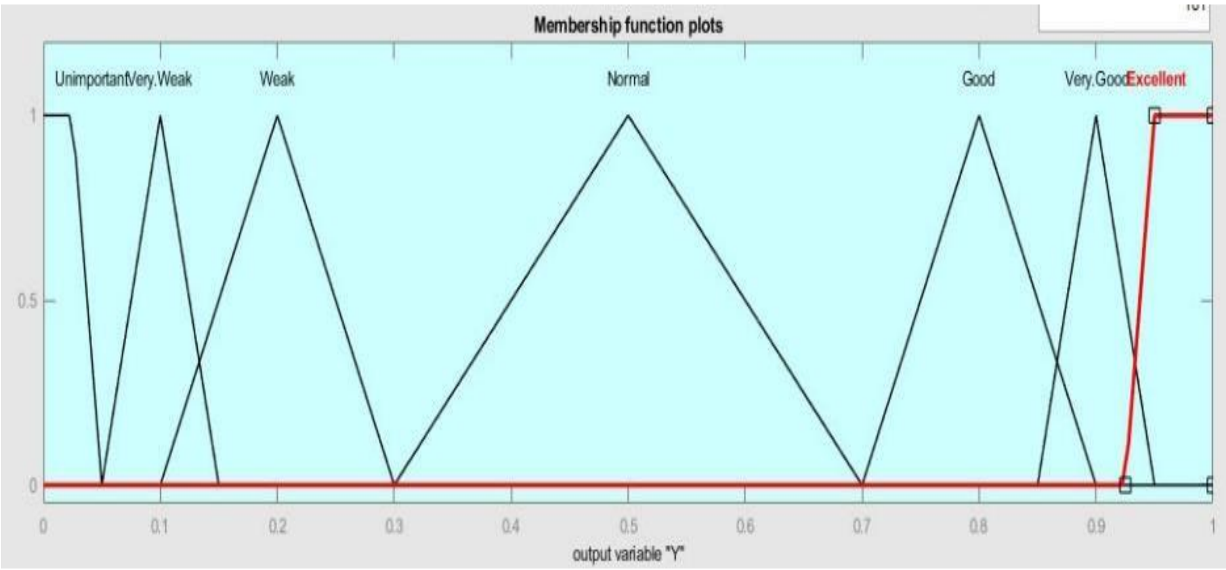


Figure 3. Sub-categorization of themes and determination of fuzzy values associated with linguistic variables (membership functions of triangular and trapezoidal numbers)

The third step is designing the knowledge base of the intelligent system - this stage includes extracting expert rules, evaluating them by experts, and creating a fuzzy rule base. Finally, due to the existence of 6 main variables, each of which has three states, the number of main module fuzzy rules in the algorithm is equal to 729 (3 to the power of 6). The figure associated with the fuzzy rule bases of the main module is as follows:

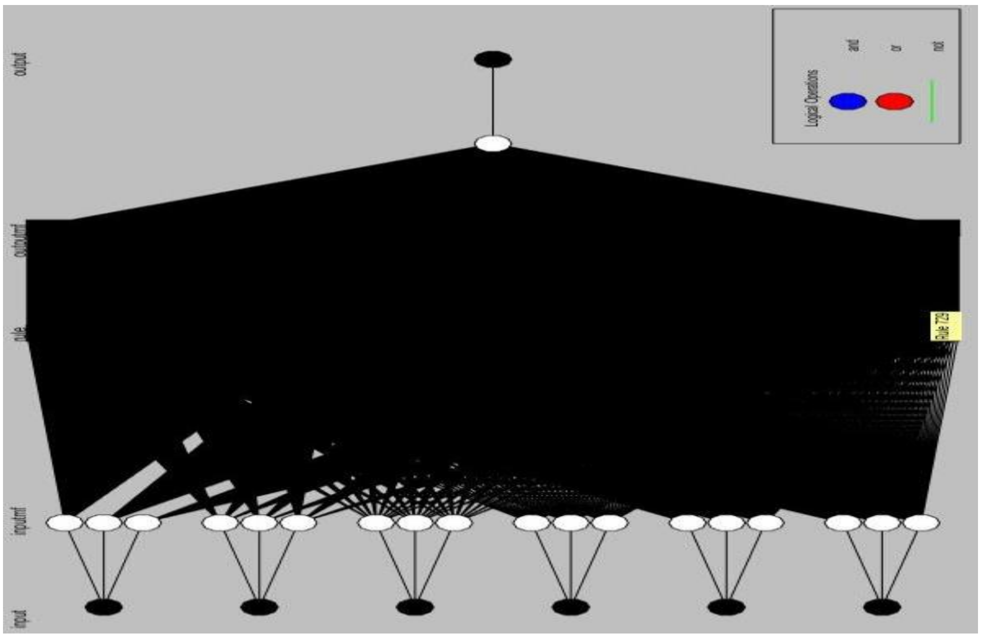


Figure 4. The way the fuzzy rules in the knowledge base of the main research module are generated

The fourth step: Algorithm inference engine design - the Neuro-Fuzzy toolbox in the MATLAB programming environment allows to infer based on the rules in the intelligent algorithm knowledge base. The average error of the test data was determined based on 10 series of calculation error measurements (Epoch) in the inference engine, and the hybrid optimization method (Hybrid) was used, which benefits the high accuracy of the artificial intelligence calculations. At this stage, the wtaver method was chosen for de-fuzzification, which converts fuzzy numbers and sets them into a definite value for the actual performance of the algorithm. The figure below shows the inference engine of the algorithm:

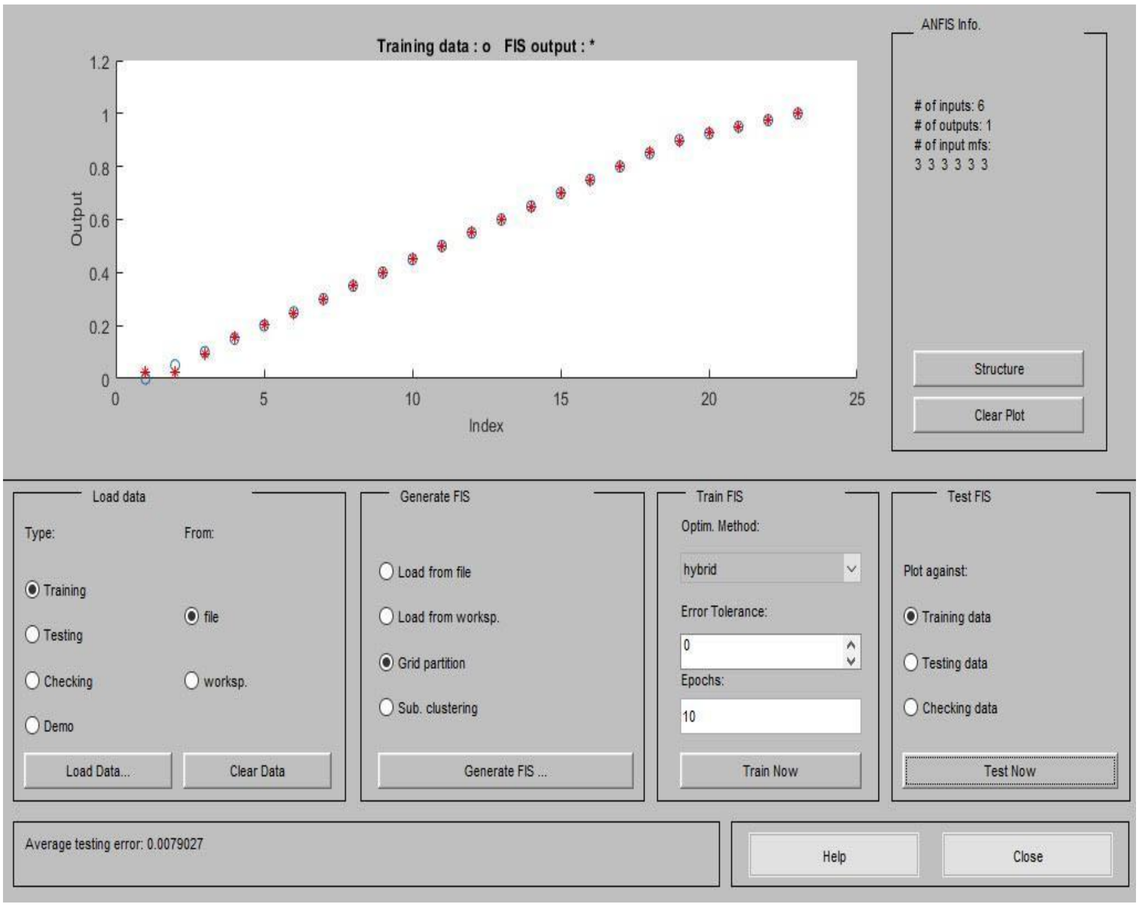


Figure 5. The intelligent algorithm of the inference engine

Matlab R2017B can be employed to make inferences based on the rules in the intelligent system knowledge base. Based on 10 repetitions to test the training data, the inference engine of the system calculated the average error of the test data equal to 0.0079 (less than 1%), which indicates the high accuracy of the artificial intelligence calculations of the research.

The fifth step describes how to exploit the intelligent algorithm implemented in the ports and maritime organization and analyze its outputs. To analyze the behavior of the output variable of the system, one can analyze the outputs of the hybrid meta-heuristic model based on artificial intelligence, ISM, and numerical (exact) and linguistic data mining. In order to determine the weight of the system input values, the information related to the weight of each of the main research variables is provided:

Table 5. Information relating to the weight of each of the main research variables

The research input variables	Data mining predictive weight	ISM penetration coefficient	The combined weight for smart algorithm
Reducing dredging operation time in different ports (I1)	0.13	0.56	**7.28%**
Risk control aimed at increasing security in ports (I2)	0.14	0.72	**10.01%**
The Improvement Index of Maritime Traffic Conditions (I3)	0.12	0.50	**6%**
Allocation according to the number of existing dredges and their capacity (I4)	0.18	0.94	**16.92%**
Allocation according to the environmental conditions of the region (I5)	0.10	0.72	**7.2%**
Allocation aimed at reducing the dredging projects costs in ports (I6)	0.16	0.83	**13.28%**

In fact, the following figure analyzes the behavior of the input and output variables of the main module:

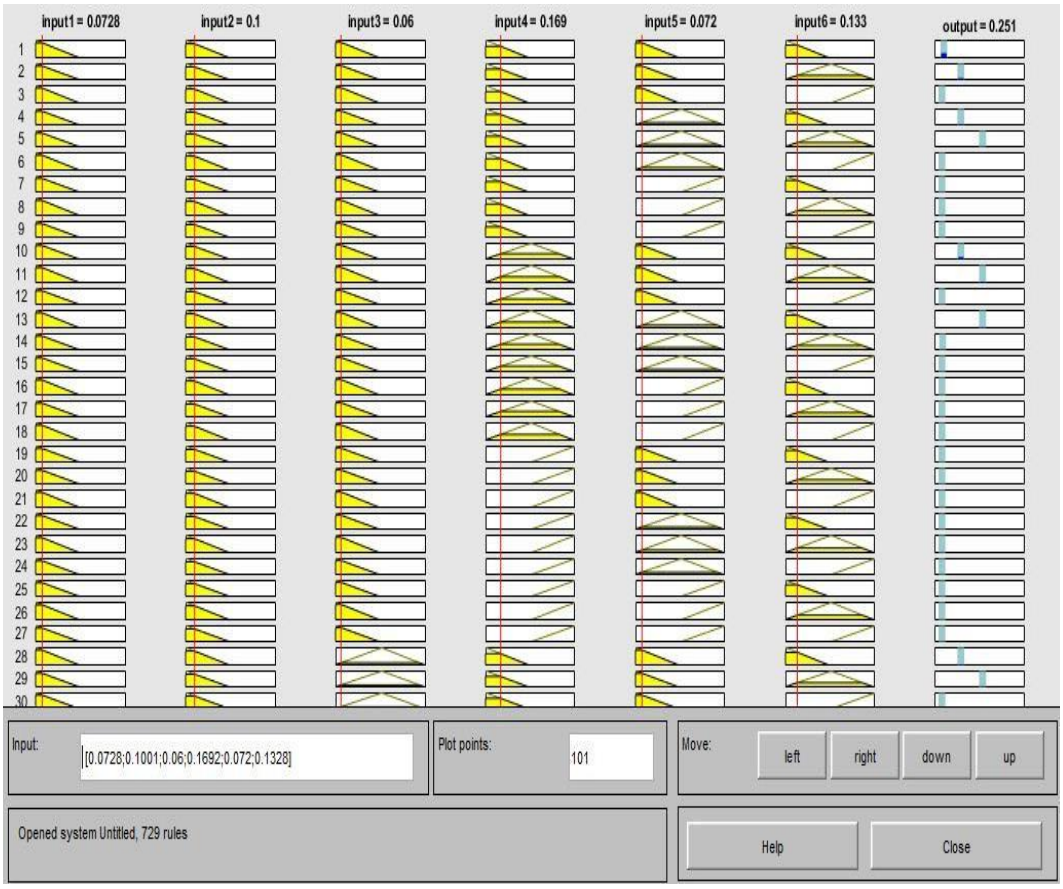


Figure 6. Numerical and linguistic analysis of the output variable behavior of the system

According to the rules of the knowledge base of the algorithm main module and based on calculating the weight of each of the main variables using the documents of Iran Ports and Maritime Organization and the opinions of experts as well as according to the average error of the test data (which is less than 1%) using the smart algorithm implemented in Iran Ports and Maritime Organization, the objective function of "organizing the dredging ships of the country taking into account risk management" can be numerically and accurately stated as follows:

Y.O = 0.0728 I1 + 0.1001 I2 + 0.0600 I3 + 0.1692 I4 + 0.0720 I5 + 0.1328 I6

For organizing the country's dredging vessels considering risk management, if "reducing dredging operation time in various ports" (I1) is 0.07, "risk control aimed at increasing security in ports (I2)" is 0.10, "marine traffic conditions improvement Index (I3) is 0.06; "allocation according to the number of existing dredges and their capacity (I4)" is 0.17; "allocation according to the environmental conditions of the region (I5)" is 0.07; and "allocation according to the cost reduction of dredging projects in ports (I6) is 0.13; then, the improvement of "organizing the country's dredging ships taking into account risk management" will be equal to 0.25, which indicates 25% improvement in the objective function. In other words, implementing the results of the current research in Iran Ports and Maritime Organization, organizing the country's dredging ships, and taking into account the management risk will be improved by 25%. After designing and implementing the intelligent system, aimed at validating the algorithm, the outputs and answers of the intelligent system were compared using a separate measuring tool with the documents of Iran Ports and Maritime Organization and experts' opinions, and the result can be observed based on the rules of the intelligent system and the average responses of the experts. Since the documents of Iran Ports and Maritime Organization and experts' opinions are expressed in terms of a five-point membership function (MF), to validate the algorithm, the percentage difference between the outputs of the intelligent system and the average of the documents of Iran Ports and Maritime Organization and the opinions of experts can be used to validate the algorithm. The final difference between the outputs of the intelligent system and the average of the documents of Iran Ports and Maritime Organization and the opinions of experts is equal to 0.065, which is not significant, i.e., there is no significant difference between the average of the documents of Iran Ports and Maritime Organization and the opinions of experts and the outputs of the "Smart Algorithm."

Conclusion

The main findings of the research to achieve the research goals according to the research background are as follows. One of the most important results of the current research is exploring the position of the "port dredging operation management" component in organizing the country's dredging vessels, taking into account risk management. In fact, managing port dredging operations has an important role in organizing the country's dredging vessels, taking into account risk management, as the component of "port dredging operations management" is based on criteria such as Minimizing dredging costs, reducing the operation cost of dredging ships in various ports; maximizing the number of dredging projects carried out by dredging vessels; reducing dredging operation time in different ports. In fact, reducing the dredging operation time in different ports (V.A4) for the component of "port dredging operation management" has a predictive weight equal to 0.13. Moreover, the possible relationship between reducing the dredging operation time in different ports (V.A4) for the component of "port dredging operation management" and the research objective function (Y.O) is equal to 72%.

Another most important result of the present research is exploring the position of the "traffic management in ports" component in organizing dredging ships in the country, taking risk management into account. In fact, traffic management in ports has an important role in organizing dredging ships in the country, taking into account risk management, as the component "traffic management in ports" is determined based on criteria such as maintaining the balance of dredging plans between ports and different vessels; Application of marine traffic service based on dredging depth; traffic control based on the location and type of use of each port; the improvement index of maritime traffic conditions. In fact, the indicator of the improvement of maritime traffic conditions (V.Cd) for the component "traffic management in ports" has a predictive weight equal to 0.13. In addition, the possible relationship between the improvement index of marine traffic conditions (V.Cd) for the "traffic management in ports" component and the research objective function (Y.O) is calculated to equal 52%.

In addition, one of the most important results of the current research is exploring the position of "berth allocation management in ports" in organizing dredging ships in the country, taking into account risk management. The component of "management of Berth Allocation in Ports" is based on criteria such as allocation according to reducing the cost of dredging projects in ports; Allocation according to the difference in dredging operation time in each port; allocation according to the environmental conditions of the region; Allocation according to the number of existing dredges and their capacity. In fact, allocation according to the number of existing dredgers and their capacity (V.D4) for the component "Management of Berth Allocation in Ports" has a predictive weight equal to 0.18; Allocation according to cost reduction of dredging projects in ports (V.D1) for the component "Wharf Allocation Management in Ports" has a predictive weight equal to 0.16. The possible relationship between the allocation according to the number of existing dredges and their capacity (V.D4) for the component "Management of Berth Allocation in Ports" and the objective function of the research (Y.O) is measured equal to 64%.

The other main result of the research is obtained by using the hybrid meta-heuristic model based on artificial intelligence. Based on ten repetitions to test the training data (epochs), the average error of the test data in the inference engine of the system is equal to 0.0079 (less than 1%), which shows the very high accuracy of the artificial intelligence calculations of the research: If "reducing the dredging operation time in various ports (I1) is 0.07; risk control aimed at increasing security in ports (I2) is 0.10; marine traffic conditions improvement Index (I3) is 0.06; allocation according to the number of existing dredges and their capacity (I4) is 0.17; allocation according to the environmental conditions of the region (I5) is 0.07; and allocation according to the reduction of the cost of dredging projects in ports (I6) is 0.13; then, the improvement of "organizing the country's dredging ships taking into account risk management" will be equal to 0.25 (i.e., 25% optimality of the objective function). In other words, implementing the results of the current research in Iran Ports and Maritime Organization, the organization of the country's dredging ships, taking into account risk management, will be improved by 25%.

On the other hand, one of the most important results of the research is the logic and alignment of its results in organizing the country's dredging ships, taking into account risk management with the results of other valid research so that our findings relating to "management of berth allocation in ports" are consistent with the results of Martin (2024), Agra & Rodrigues (2022), and Correcher et al. (2018), as it has given special attention to the allocation according to the number of existing dredges and their capacity and allocation aimed at reducing the cost of dredging projects in ports and allocation with respect to the difference in dredging operation time in each port.

The findings relating to the variable of "port dredging operation management" in this research are consistent with the results of Bai et al. (2021), Ban & Bebić (2023) and Chou et al. (2024), as it examines reducing the dredging operations cost of dredging ships in different ports, maximizing the number of dredging projects carried out by dredging ships and reducing the dredging operation time in different ports.

The findings relating to the variable of "risk management of coastal projects" in the present study are consistent with the results of Lamii et al. (2022) and Cullum et al. (2018), as it gives special attention to reducing the risk of limiting the capacity of dredging vessels, reducing the risk of maximum permitted wave height (tides) and the risk control aimed at increasing security in ports.

Findings relating to the variable of "traffic management in ports" in the present study are consistent with the results of Zhen et al. (2018), Ksciuk et al. (2022), and Andersen et al. (2021), as it examines maintaining the balance of dredging plans between ports and different vessels, traffic control based on the location, type and the use of each port and the improvement index of maritime traffic conditions.

The findings relating to the variable of “requirements based on the side costs of the dredging vessels” in the present study are consistent with the results of researchers like Ksciuk et al. (2022), Shabani et al. (2023) and Bai et al. (2021), as it gives especial attention to the lease of the dredgers, paying attention to insurance, certificates and the wage crew.

The findings relating to the variable of “requirements for selecting the method and type of dredging ships” in this research are consistent with the results of Luter et al. (2021), Tunçel et al. (2023), and Wei et al. (2023), as it examines the environmental conditions of the region and the type and the depth of dredging materials.

References

1. Ahmadi, Rahleh, 2022, The evaluation of factors influencing the improvement of traffic safety level in Arvand Rud river with dredging approach, 21st Iranian National Hydraulic Conference, Ahvaz.

2. Afshari, Azita., Mirzapour Al Hashem, Seyyed Mohammad Javad, 2022, A model for the allocation of several continuous berths in bulk terminals under fuzzy uncertainty conditions, the 8th International Conference on Logistics and Supply Chain (Transformative, Innovative and Basic Knowledge Ecosystems), Tehran.

3. Jafari Yerki, Tanin, 2023, Book: risk management and value engineering in project management, publisher: Miyad Andisheh, Publication Year: 2023.

4. Derakhshan, Ali, 2023, Investigating environmental geotechnical challenges (dredging), 7th International Conference on Applied Research in Science and Engineering.

5. Radkhah, Alireza and Igdari, Sohail, 2021, Investigating physical and ecological effects caused by dredging and sand extraction in river systems, 17th Congress of Soil Sciences of Iran and 4th National Conference on Water Management in Hakimaneh Soil Regeneration Farm and Hakmarovai Hakimane Ab, Karaj.

6. Sargazi, Sima., Mish Mast Nahi, Hassan and Ahmadzadeh, Hamed, 2022, The berth allocation problem with the aim of reducing the total service time of the ship under the conditions of uncertainty, the 21st Conference of Fuzzy Systems of Iran.

7. Sharifi, Sadegh., Hosseini, Seyed Farzad and Zarei, Hassan, 2022, The wharf allocating problem in container terminals considering the fuel consumption of vessels, case study: Shahid Rajaee Port of Iran, Transportation Engineering Quarterly, Volume: 13, No. 3.

8. Shafiei, Omid, 2021, Book: combining equipment allocation and cost-time balance problems by using multi-criteria genetic algorithm, publishers: Modares Educational Group (affiliated to M. F. H. Simai Golestan Afarinesh), Sangh and Danesh, Publication year: 2021.

9. Shoushtari Zadeh Naseri, Ali et al., 2017, Book: dredging using water injection method: World Association of Water Transport Infrastructures of the Maritime Navigation Commission (translation and editing), Publisher: Ports and Maritime Organization, Publication year: 2018.

10. Azizi, Bahram, 2023, Construction project risk management book (principles, tools and applications), publisher: Raz Nahan, Publication year: 2023.

11. Fateminezhad, Mohammad Javad and Ghiasi, Reza, 2021, Investigating the distribution of suspended sediments during the dredging of the port basin, the 7th International Conference on Mechanics, Construction, Industries and Civil Engineering, Tehran.

12. Fardani, Mohammad Hossein, 2019, The best allocation model book in construction plans, Publisher: Contemporary Knowledge and Research, Publication year: 2019.

13. Fazlullahi, Mohammad Reza, 2020, The impact of access channel dredging on the performance of container ports under the tide influence, The 11th National Conference on Civil Engineering, Architecture and Urban Development, Babol city, Iran.

14. Karimi, Zahra, 2023, Book: Risk in planning, or risk management in planning, or risk management, publisher: Sanjesh and Danesh, Publication year: 2023.

15. Koh Bezan, Shahin, 2019, Book: Introduction to understanding dredging vessels, publisher: Top Works, Publication year: 2020.

16. Moulakhah Khalilabad, Mohammad and Moulakhah Khalilabad, Farzaneh, 2023, Determining the suitable dredging sites for organizing the Kurdan river by using a mathematical model, The Third International Conference on Architecture, Civil Engineering, Urban Planning, Environment and Horizons of Islamic Art in Declaration of the Second Step of the Revolution, Tabriz.

17. Mirzaei Sheshjovani, Vahid and Dezfouli, Abdul Karim, 2023, Technical and economic comparison of different dredging techniques in ports, Case study: Imam Khomeini Port of Iran, National Conference of New Approaches in Removing Obstacles in the Construction Industry of the Country: Special Focus: Civil (Structural, Geotechnical and Construction Management), Architecture and Urban Planning, Ahvaz.

18. Negarestan, Hossein, 2017, Book: Environmental assessment of dredging materials discharge, Case study: maintenance dredging of Chabahar and Amirabad ports, publisher: Ports and Maritime Organization, Publication year: 2018.

19. Hedayati Far, Mohsen, 2023, Book: New implementation techniques and methods in risk management of construction projects, publisher: Academic Jihad of Amir Kabir University of Technology, Publication year: 2023.

20. Documents of Iran Ports and Maritime Organization, https://www.pmo.ir/fa/laws-%D9%82%D9%88%D8%A7%D9%86%DB%8C%D9%86-%D9% 88-%D9%85%D9%82%D8%B1%D8%B1%D8%A7%D8%AA.

21. Documents of Iran Maritime Industrial Organization (Sadra), https://sadra.ir/project/.

22. Heydari, Mohsen, 2023, Book: The key success factors in firefighting crisis management with the structural-interpretive modeling design to determine the interaction of factors with it, publisher: Azar Barzin, Publication year: 2023.

23. Bashash Alanegh, Ali and Nasim Nouri, 2019, Book: Data mining in technical and engineering fields, humanities, basic sciences: data mining in SPSS (Volume 3), Publisher: Salehian, Publication year: 2020.

24. Danamzareh, Hassan and Korosh Parand, 2023, Book: Meta-heuristic algorithms with emphasis on genetic algorithm, Publisher: Arvan, Publication year: 2023.

25. Sadeghian, Bahareh, 2023, An introductory book on meta-heuristic data mining, Publisher: Barakat Kausar, Publication year: 2023.

26. Karamizadeh, Sasan, 2023, The training book of data mining with Rapidminer, Publisher: Dibagaran Cultural and Artistic Institute of Tehran, Publication year: 2023.

27. Ghahramani Nahar, Javaid and Pariya Samadi Parvizenjad, 2023, Book: Meta-heuristic algorithms in solving optimization problems, Publisher: Pourhossein,Publication year: 2023.

28. Bai, Shuo, et al. 2021. Productivity analysis of trailing suction hopper dredgers using stacking strategy. Automation in Construction. Volume 122, February 2021, 103470

29. Ban, Dario & Jure Bebić, 2023. An introduction of future fuels on working ship for GHGs reduction: Trailing suction hopper dredger case study. Journal of Cleaner Production30 March 2023

30. Chou, Jui-Sheng, et al. 2024. Deep learning-based chatbot by natural language processing for supportive risk management in river dredging projects. Engineering Applications of Artificial Intelligence12 January 2024

31. Guo, Liming, et al. 2023. Column generation for the multi-port berth allocation problem with port cooperation stability. Transportation Research Part B: Methodological14 March 2023

32. Lin, Bowen, et al. 2024. A novel method for the evaluation of ship berthing risk using Automatic Identification System (AIS) data. Ocean Engineering. Volume 293, 1 February 2024, 116595

33. Luter, Heidi M. et al. 2021. Assessing the risk of light reduction from natural sediment resuspension events and dredging activities in an inshore turbid reef environment. Marine Pollution Bulletin11 June 2021

34. Lv, Yaqiong, et al. 2024. Dynamic berth allocation under uncertainties based on deep reinforcement learning towards resilient ports. Ocean & Coastal Management28 March 2024

35. Martin-Iradi, Bernardo, et al. 2024. An adaptive large neighborhood search heuristic for the multi-port continuous berth allocation problem. European Journal of Operational Research6 February 2024

36. Tunçel, Ahmet Lutfi, et al. 2023. An extended fuzzy bow-tie approach with SLIM to assess risk for anchor dredging in cargo ships. Ocean Engineering4 July 2023

37. Vijayan, K. et al. 2021. Shock transmission through universal joint of cutter suction dredger. Ocean Engineering21 May 2021

38. Wang, Bin, et al. 2020. Research on predicting the productivity of cutter suction dredgers based on data mining with model stacked generalization. Ocean Engineering12 September 2020

39. Wei, Changyun, et al. 2023. PPLC: Data-driven offline learning approach for excavating control of cutter suction dredgers. Engineering Applications of Artificial Intelligence4 July 2023

40. Xu, Xianfeng, et al. 2024. Port berth allocation and micro grid cluster joint optimization scheduling based on master-slave game. Journal of Cleaner Production11 April 2024.

41. Alshami H, Bin Abdul Hamid M S R. An Insight into the Impact of Blockchain Characteristics and Applications on the Ship Management Companies. sjamao 2024; 6 (2) :8-17

42. Davoudizadeh R, Hosseini Seno S A. Analyzing Advantages and Benefits of Information Technologies in Organizations. sjis 2020; 2 (1) :7-19