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Prediction of Iran's monthly average temperature with time series methods and regionalizing area using ANN, LSTM, and GRU artificial neural networks

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ABSTRACT

This paper investigates the accuracy of five artificial neural networks, namely ANN, LSTM, and GRU, in predicting monthly temperature data. The study employs the monthly temperature data set of 31 meteorological stations in Iran as its time series data set, which is partitioned into five regions with distinct climates to ensure accurate temperature predictions. Three metrics, including MSE, MAE, and R2Score, are used to measure the prediction error of each neural network. The results indicate that the Stacked LSTM neural network outperforms other artificial neural networks in terms of predicting monthly temperature data, making it the most appropriate method for this purpose. Notably, the ANN neural network exhibits the lowest accuracy in predicting monthly temperature data among the examined neural networks. This study highlights the effectiveness of Stacked LSTM neural networks in time series analysis and prediction and provides valuable insights for the application of artificial neural networks in this domain.

1. Introduction

Climate change caused by rapid development activities is currently occurring at a faster rate than ever before [2, 15, 16]. In this regard and according to the report of the World Meteorological Organization, the average temperature of the earth in 2021 was about 1.08 ± 0.13 degrees Celsius higher than the average temperature of the earth in the years 1850 to 1900 [28]. These climatic fluctuations lead to floods, storms, droughts [13], and such phenomena [17]. Other consequences of climate change include rising sea levels [8], change in the rainfall pattern [2], reduction in the capacity and quality of underground water [3], reduction in the quality and yield of agricultural products [6], Negative effects on food production [1], desertification of beaches and the destruction of ports [2], and the reduction of snow cover can be mentioned [20].

In the meantime, among Middle Eastern countries, the consequences of climate change are very severe. And this is also valid about Iran [23]. Some surveys conducted by the Iranian Meteorological Organization in 2016 indicate that the average temperature of Iran has increased with a slope of 0.4 degrees Celsius during

the 50-year statistical period from 2015 to 2017. In recent years, Iran has also faced problems such as the reduction of drinking water resources (reduction in the capacity and quality of underground water) and the occurrence of numerous floods; Now, considering the steep climate changes in Iran, as well as the destructive and irreparable effects that global warming has on nature and the lives of humans and living beings, it seems necessary to investigate and forecast the weather and climate situation. The necessity of weather forecasting is that with the predictions made about the future weather condition of Iran, it is possible to adopt a solution and strategy to slow down this process.

To investigate and predict the weather, we must study the factors and variables of the weather that play the greatest role in the weather and climate. Temperature is one of the most important climate variables and can be effective in discovering and revealing extreme climate events. In fact, the increase in temperature can affect various aspects of human life, including industry, transportation, and agriculture.

So far, we have chosen temperature as our prominent variable, which has an ultimate impact on weather

conditions and climate changes, for investigation and prediction. It should be noted that methods such as regression have been used to check and predict weather data.

Employing techniques that rely on neural networks constitutes another approach of studying and forecasting weather data. Neural networks are a type of mathematical structure that can show the correlation between the inputs and outputs of any system based on non-linear effects. Neural networks are used for prediction and have parallel processing, learning, and generalization capabilities [1]. These networks are capable of investigating intricate phenomena by modeling the human brain [19]. The utilization of methods founded on neural networks, such as the LSTM method, has been the subject of extensive research and investigation in the field of weather data analysis and prediction [11, 25-27]. In this research, temperature data have been predicted and estimated with High accuracy. For example, Toth and his colleagues investigated the amount of precipitation in the Sio River basin in Italy with a neural network method. The mentioned research shows the superiority of the neural network in predicting the amount of precipitation [4]. Pritpal and Bhogeswar were also able to accurately predict the amount of monsoon rainfall in India with neural networks. Their model has an input layer, an output layer, and a hidden layer [4].

Also, Mekanik and his colleagues showed a higher correlation and a lower error of the neural network method by predicting the amount of precipitation in large climate models using two neural networks and linear regression methods [9]. In this regard, we have used the LSTM method, which is a type of neural network; since the LSTM method has a low speed due to having many gates, we have used GRU layers to increase the speed and compensate for this slowness [8]. This research considers the importance of forecasting temperature in many decision-making processes, including crisis management and water resources management, and utilizes neural networks to investigate and predict this variable based on its optimal performance. At first, we partitioned Iran into different regions in the data section and the studied region, then we will collect the temperature data of the weather stations for each region from the Tutiempo site. In the methods section, we will explain LSTM, GRU, Bi-LSTM, Stacked-LSTM, and ANN neural network methods. Finally, in the last section, we will investigate the collected data and the studied region using the proposed methods and obtain separate forecasts for each of the partitioned areas of Iran, followed by an analysis of the results.

2. METHODS

2.1. Data and the studied area

The studied area in this article is Iran. This research examines the average temperature parameter using a time series spanning 17 years from 2006 to 2022 [7,9].

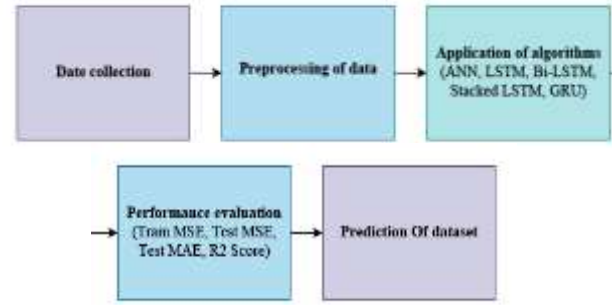


Figure 1: Overview of this study - the first stage consists of data collection, the next stage is data cleaning (the process of fixing or removing incorrect, corrupted, incorrectly formatted, duplicate, or incomplete data), the middle stage is implementation of the algorithm, in the fourth stage we calculated the error for each algorithm and in the last stage we predict the discussed data.

The data consists of 203 monthly observations from each of the 30 selected weather stations, with at least one station representing each province in Iran. (Due to the limited data from weather stations in Golestan, Qom, Semnan, and Alborz provinces, they are not included in the analysis.) It should be noted that the mentioned data were collected from the Tutiempo website.

Since Iran is a vast country, it has diverse climates and weather conditions. For example, the northwestern regions of Iran have relatively low temperatures, while the central and southern regions experience very high temperatures. Therefore, to facilitate a more accurate study and analysis of temperature patterns in Iran, the country has been divided into five climatic regions based on the proximity of the collected temperature data, each characterized by unique weather patterns.

The first region, encompassing the cities of Rasht, Bandar-e Anzali, Ramsar, and Nowshahr, is characterized by a moderate and humid climate. The second region, comprising the cities of Urmia, Tabriz, Ardabil, Zanzan, Sanandaj, Kermanshah, Ilam, Arak, Khorramabad, Hamadan, Yasuj, and Shahr-e Kord, is known for its cold and mountainous climate. The third region, which includes the cities of Ahvaz, Abadan, Bushehr, and Bandar Abbas, experiences high temperatures and a warm and humid climate. The fourth region, occupied by the cities of Birjand, Mashhad, Bojnourd, Isfahan, Tehran, and Qazvin, has a moderate climate with cold and humid winters and hot and dry summers. Finally, the fifth region, comprising the cities of Yazd, Kerman, Shiraz, and Zahedan, is characterized by a hot and dry climate.

To analyze and forecast the weather patterns in each region, the average data of the weather stations within each region are calculated. This climatic division is

illustrated in the figure below, with Iran located approximately at geographical coordinates of 25-40 degrees N latitude and 45-65 degrees E longitude.

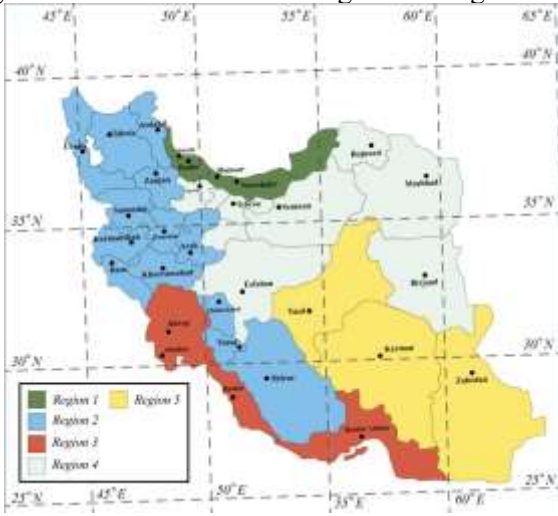


Figure 2: The partitioned figure of Iran along with selected stations

From now on, we will refer to region one as R1, region two as R2, region three as R3, region four as R4, and region five as R5 for brevity. According to Table 1, which was obtained based on the collected data; The average temperature of the R1 region is equal to 17.055 centigrade. Also, the minimum and maximum temperatures in the R1 region are 1.2 and 29.5 degrees Celsius. According to the following table, the maximum, minimum, and average temperature in each region is:

Table 1: Temperature table in the regions of the studied area

Region	Max Temperature (°C)	Average Temperature (°C)	Min Temperature (°C)
Region 1	29.5000	17.0554	1.2000
Region 2	33.9000	14.1240	-11.8000
Region 3	40.7000	26.7050	9.1000
Region 4	34.0000	16.0755	-7.6000
Region 5	35.5000	19.3278	-0.8000

2.2. Artificial neural network

Artificial neural networks are composed of three layers, namely input, hidden, and output layers. The input layer is responsible for transmitting data to the network, while the hidden layer processes the data. Finally, the output layer processes the input vector and provides output and performance information. ANN consists of numerous interconnected processing elements called neurons that work in unison to solve a problem. The structure of ANN is shown in figure 4. Recurrent Neural Networks (RNN) are a type of artificial neural network that receives the output of the network along with the next input, which is then fed

back to the network. RNN neural networks have internal memory, which allows them to retain previous inputs and use this memory to process a sequence of inputs. The recurrent neural network is a type of artificial neural network that utilizes a recurrent loop to retain the data obtained. In Recurrent Artificial Neural Network (RNN), the order of input data is essential, but this arrangement is maintained only until one consecutive data point. For example, the neural network does not refer to the previous seven data points to predict the future, which results in decreased accuracy in predicting data with long sequences such as financial markets or monthly weather data. To resolve this issue, a new structure for recurrent neural networks was proposed, called Long-Short Term Memory (LSTM), designed to address the gradient fading problem [4]. In this structure, the neural network uses more previous data for training, enabling the use of distant previous data. The LSTM recurrent neural network overcomes the back-propagation problem in normal recurrent neural network models, where the gradient descent cannot use the error of a long time ago to optimize the weights of the data network based on current data. The neurons used in the LSTM recurrent neural network consist of four sections: Cell, Input gate, Output gate, and Forget gate.

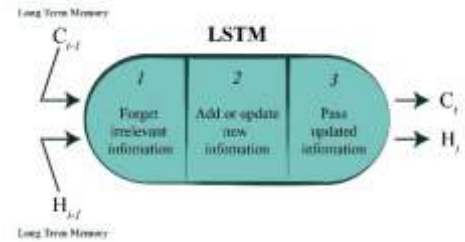


Figure 3: LSTM artificial neural network

In a neuron of the first LSTM, we have to decide whether to keep the previous data or not, this decision is made using the following equation, this process is done in the first part (Forget gate).

$$f_t = \sigma(\alpha_t \cdot U_f + H_{t-1} \cdot W_f)$$

$$\sigma(z) = 1/(1 + e^z)$$

- α_t : input to the current timestamp.
- U_f : weight associated with the input
- H_{t-1} : The hidden state of the previous timestamp
- W_f : It is the weight matrix associated with hidden state

The output of the function is a value between 0 and 1; When this value is multiplied by the previous state, it is determined whether the memory should be cleared or not.

$$C_{t-1} \cdot f_t = 0 : \text{forget everything}$$

$$C_{t-1} \cdot f_t = C_{t-1} : \text{forget nothing}$$

In the second part, or the input gate, we measure the importance of the information in the new inputs.

$$i_t = \sigma$$

$$\sigma(z) = 1/(1 + e^z)$$

- α_t : Input at the current timestamp t
- U_i : Weight matrix of input
- H_{t-1} : A hidden state at the previous timestamp
- W_i : Weight matrix of input associated with hidden state

Now we send the obtained values to a cell as new information. We call this information N and calculate it with the following method:

$$N_t = \tanh$$

In the LSTM neuron section, the tanh activation function is employed. When the new information value is negative, it gets eliminated from the cell, whereas if it is positive, it gets added. It is crucial to mention that the information addition does not represent the numerical sum of the values; instead, the operation is computed using the following approach:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot N_t$$

Finally, in the third part (Output gate) of the neuron, we deliver output to the next neurons, this output is calculated by the following method:

$$o_t = \sigma(\alpha_t \cdot U_o + H_{(t-1)} \cdot W_o)$$

$$\sigma(z) = 1/(1 + e^z)$$

The output value is between 0 and 1, now we have to calculate the Hidden state value (Hidden state function is the same function that makes long-term memory):

$$H_t = o_t \cdot \tanh(C_t)$$

Unlike other LSTM models that process input data in either the forward or backward direction, Bi-LSTM processes data simultaneously in both directions. As a result, this artificial neural network has access to both past and future information, which can enhance the accuracy of predictions. Figure \ref{fig:four} shows the structure of the Bi-LSTM artificial neural network. Stacked LSTM is a type of LSTM neural network architecture that consists of several LSTM layers stacked on top of each other. Each layer in the stack processes the output of the previous layer, allowing the network to learn more complex representations of the inputs. The structure of the Stacked LSTM artificial neural network is shown in Figure 4.

The GRU neural network architecture is commonly used in processing sequential data tasks, including natural language processing, speech recognition, and time series prediction. Compared to the LSTM neural network, the GRU network has a simpler structure, which enables faster training and requires fewer parameters [5]. Additionally, some studies have shown that the GRU neural network outperforms LSTM in terms of CPU time convergence. The structure of the GRU recurrent neural network is shown in Figure 4.

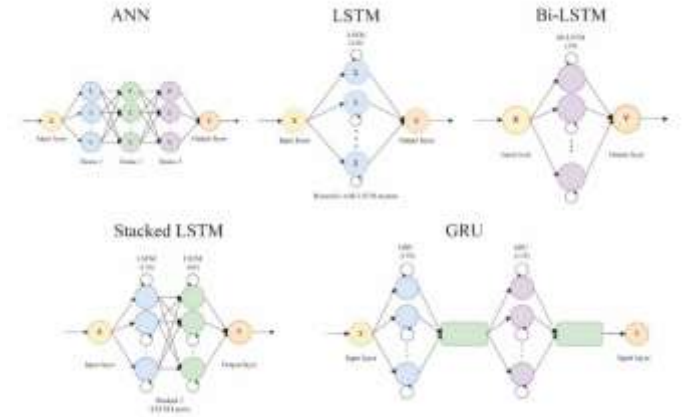


Figure 4: Structure and Layers of ANN, LSTM, Bi-LSTM, Stacked LSTM, GRU neural networks

3.REULTS AND DISCUSSION

Following the methodology outlined in the previous section, we collected monthly temperature data from various regions of Iran and analyzed and predicted them using different artificial neural networks, including LSTM, GRU, Bi-LSTM, Stacked LSTM, and ANN. It is worth mentioning that the dataset for each region consisted of 203 monthly temperature data points. To train the LSTM, Bi-LSTM, Stacked LSTM, and GRU neural networks, we utilized 167 data points out of the 203 collected data points. Subsequently, we predicted the temperature for the remaining 36 months in each region and evaluated the accuracy of the forecast using Train MSE, Test MSE, MAE, and R2 Score criteria. For the ANN neural network, we employed 163 data points for training and predicted the temperature for the remaining 41 months. In the following sections, we present the results obtained for all regions. We will begin by examining the results obtained from the ANN neural network.

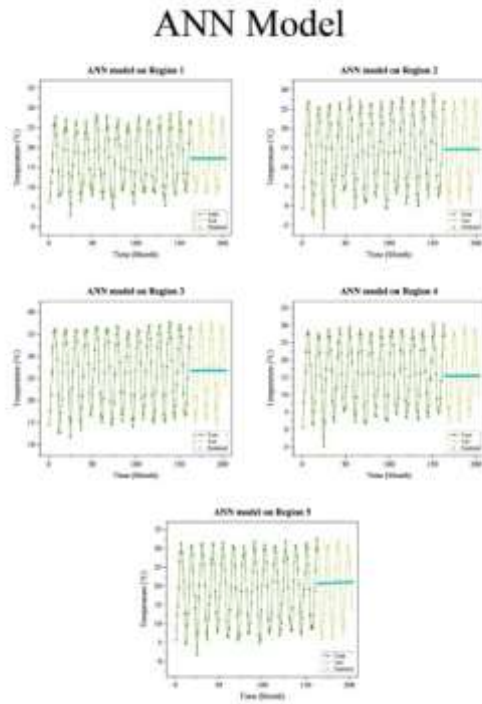


Figure 5: Temperature prediction charts for the next 41 months of all regions based on ANN

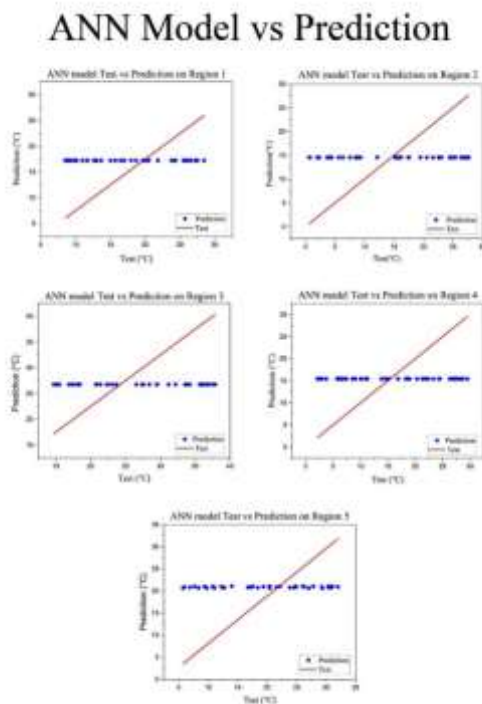


Figure 6: ANN Model Test vs Prediction on all Regions

After analyzing Figures 5 and 6, it is evident that the data predicted by ANN lacks accuracy and significantly deviates from the actual values. Therefore, drawing conclusions from these predicted data is not feasible.

Moving forward, we will examine the results and graphs obtained from the prediction of data in five distinct regions of Iran using the LSTM neural network.

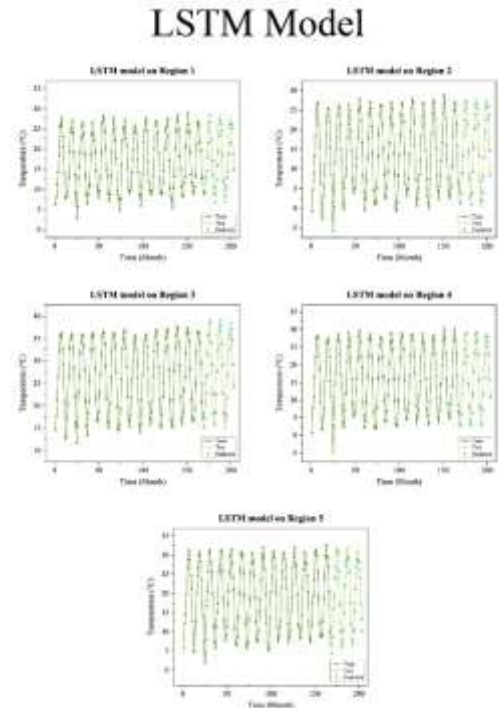


Figure 7: Temperature forecast charts for the next 37 months of all regions based on the LSTM neural network

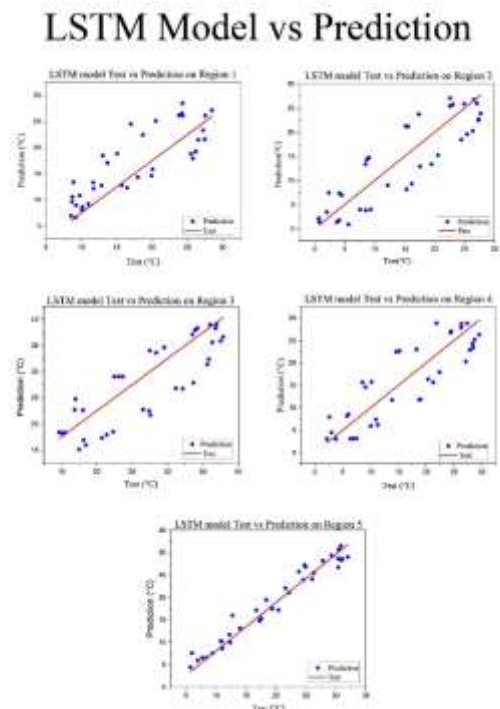


Figure 8: The LSTM Model Test vs Prediction on all regions

According to the figure 7 and the predicted and obtained data, the mean Test MSE (Mean squared error) of the predicted data of five regions is equal to

0.0285. And the average Test MAE value for the five mentioned regions is equal to 0.1308. In table 2, Train MSE, Test MSE, Test MAE, and R2score data are written for the five discussed areas.

Table 2: LSTM Train MSE, Test MSE, Test MAE and R2 Score

Region	Train MSE	Test MSE	Test MAE	R2 Score
Region 1	0.0520	0.0520	0.1870	0.9420
Region 2	0.0031	0.0036	0.0403	0.9663
Region 3	0.0189	0.0189	0.1117	0.9800
Region 4	0.0338	0.0338	0.1604	0.9641
Region 5	0.0343	0.0343	0.1544	0.9641
Average	0.0284	0.0285	0.1308	0.9633

The results and graphs obtained from predicting data in five distinct regions of Iran using the Bi-LSTM neural network will now be investigated.

Bidirectional LSTM Model

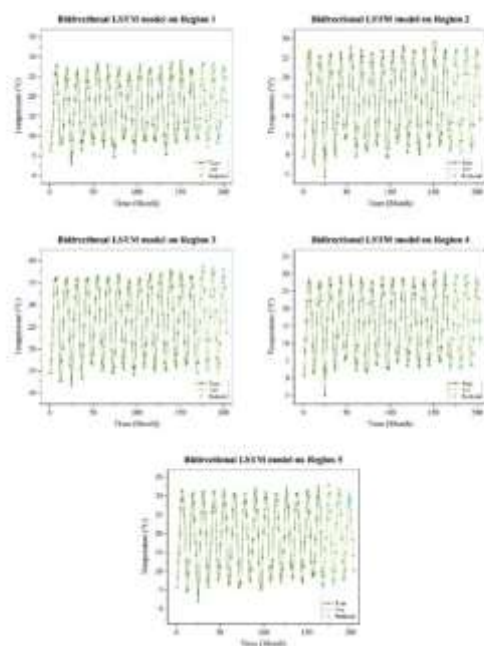


Figure 9: Temperature forecast charts for the next 37 months for all regions based on the Bi-LSTM

Bidirectional Model vs Prediction

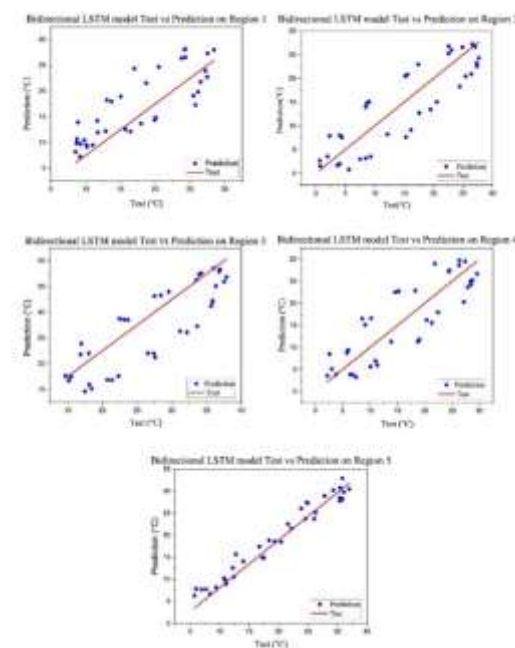


Figure 10: Bi-LSTM Model vs Prediction on all Regions

According to the figure 9 and 10, the mean Test MSE (Mean squared error) of the predicted data of five regions is equal to 0.0313. And the average Test MAE value for the five mentioned regions is equal to 0.1324. In the blew table, Train MSE, Test MSE, Test MAE, and R2score data are written for the five discussed areas.

Table 3: Bi-LSTM Train MSE, Test MSE, Test MAE and R2 Score

Region	Train MSE	Test MSE	Test MAE	R2 Score
Region 1	0.0658	0.0658	0.2095	0.9266
Region 2	0.0028	0.0030	0.0314	0.9773
Region 3	0.0192	0.0192	0.1165	0.9797
Region 4	0.0312	0.0312	0.1494	0.9668
Region 5	0.0371	0.0371	0.1553	0.9611
Average	0.0312	0.0313	0.1324	0.9623

The results and graphs obtained from predicting data in five distinct regions of Iran using the Stacked LSTM neural network will now be investigated.

Stacked Model

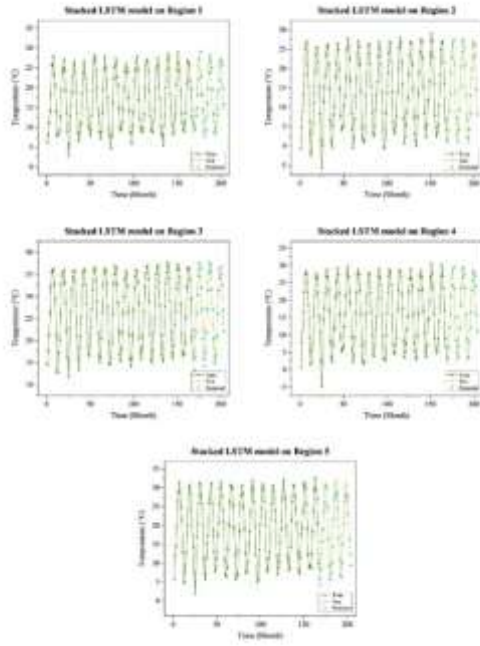


Figure 11: Temperature forecast charts for the next 37 months for all regions based on the Stacked LSTM

Stacked LSTM Model vs Prediction

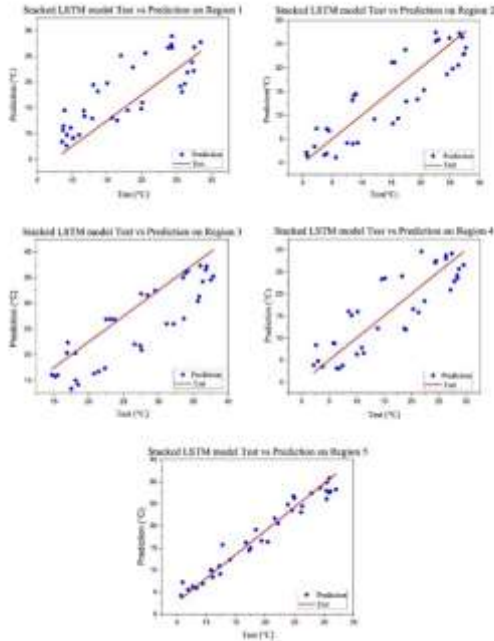


Figure 12: Stacked LSTM Model vs Prediction on all Regions

According to the figure 11 and 12, the average Test MSE (Mean squared error) of the predicted data of five regions is equal to 0.0278. And the average Test MAE value for the five mentioned regions is equal to 0.1239. In Table 4, Train MSE, Test MSE, Test MAE, and R2score data are written for the five discussed areas.

Table 4: Stacked LSTM Train MSE, Test MSE, Test MAE and R2 Score

Region	Train MSE	Test MSE	Test MAE	R2 Score
Region 1	0.0500	0.0500	0.1838	0.9442
Region 2	0.0035	0.0038	0.0322	0.9773
Region 3	0.0161	0.0161	0.0952	0.9829
Region 4	0.0342	0.0342	0.1587	0.9636
Region 5	0.0350	0.0350	0.1494	0.9634
Average	0.0278	0.0278	0.1239	0.9663

The results and graphs obtained from the prediction of data in five distinct regions of Iran using the GRU neural network will now be examined.

GRU Model

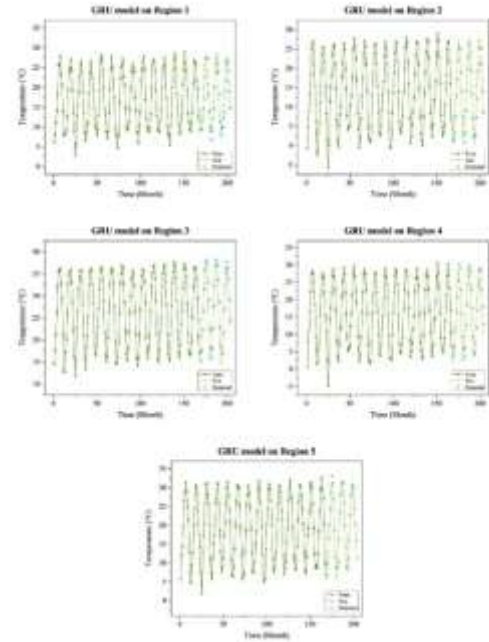


Figure 13: Temperature forecast charts for the next 37 months for all regions based on the GRU

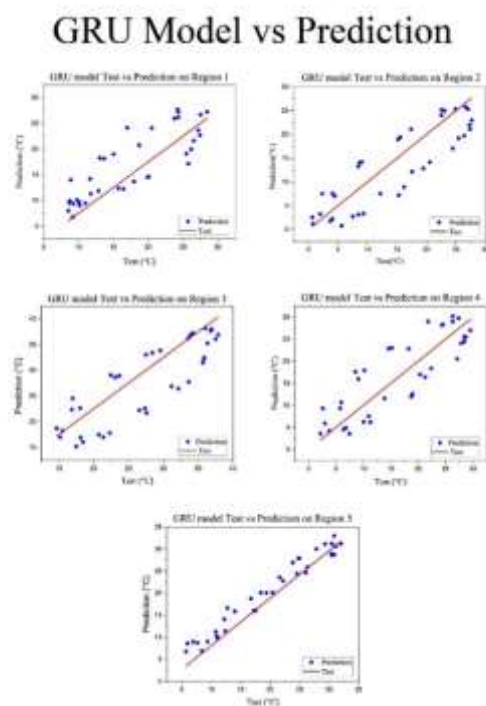


Figure 14: GRU Model vs Prediction on all Regions

Based on the chart above and the predicted and actual data, the mean Test MSE (Mean Squared Error) for the predicted data across five regions is 0.0423. Additionally, the average Test MAE (Mean Absolute Error) value for the same regions is equal to 0.1307. The table below displays the Train MSE, Test MSE, Test MAE, and R2 Score data for the five regions under consideration.

Table 5: GRU Train MSE, Test MSE, Test MAE and R2 Score

Region	Train MSE	Test MSE	Test MAE	R2 Score
Region 1	0.0482	0.0482	0.1728	0.9462
Region 2	0.0028	0.0030	0.0314	0.9720
Region 3	0.0192	0.0192	0.1165	0.9807
Region 4	0.0312	0.0312	0.1494	0.9561
Region 5	0.0371	0.0371	0.1553	0.9563
Average	0.0312	0.0313	0.1324	0.9623

In conclusion, we conducted a comparison between the latest predicted data generated by various neural networks, including ANN, LSTM, Bi-LSTM, Stacked LSTM, and GRU, with their corresponding real data. The table below presents the results of this comparison. It is important to note that for the ANN neural network, the last predicted data corresponds to the 41st month, while for other neural networks, it corresponds to the 37th month, which aligns with the month of January 2023.

Table 6: Comparing the latest data predicted by ANN, LSTM, Bi-LSTM, Stacked LSTM, and GRU neural networks with the corresponding real data

Regi on	ANN	LST M	Bi-LST M	Stack ed	GRU	Real data
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	LST M					
Regi on 1	17.25	14.70	14.98	15.782	14.75	7.575
	78	34	07	6	83	0
Regi on 2	14.58	8.325	9.062	8.1036	8.557	-
	95	5	9		6	0.6667
Regi on 3	26.77	24.52	23.73	22.114	24.30	14.20
	92	39	86	5	98	00
Regi on 4	15.49	11.00	11.60	11.315	12.84	0.716
	05	89	07	3	74	7
Regi on 5	21.10	10.07	10.24	9.2997	11.36	4.575
	74	51	25		95	0

4. Conclusions

The present study aims to investigate the accuracy of different artificial neural network-based methods in predicting monthly temperature in various regions of Iran. Monthly temperature is considered as the most significant weather criterion for prediction purposes. To achieve this goal, we employed five different neural network models, namely ANN, LSTM, Bi-LSTM, Stacked LSTM, and GRU. The accuracy of these models was evaluated based on three criteria, including R2Score, MAE, and MSE. To provide a comprehensive and accurate comparison, the models were tested in five distinct regions of Iran, each featuring a unique weather pattern. The accuracy of the models was determined based on the extent to which they minimized R2Score, MAE, and MSE criteria.

Our results indicate that the Stacked LSTM neural network model outperforms the other models in terms of accuracy, as it produced the lowest train and test MSE and MAE values. In contrast, the synthetic ANN model had the lowest accuracy, rendering its predictions almost unusable. Furthermore, the Bi-LSTM and GRU models demonstrated the best R2Score accuracy. Based on our findings, we conclude that the Stacked LSTM neural network model is the most appropriate method for predicting monthly temperature data in the studied regions of Iran..

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Investigation of the pitch motion of a semi-submersible offshore platform combining conventional mooring systems using genetic algorithms

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ABSTRACT

The Mooring systems play a significant role in the hydrodynamic behaviour of the floating offshore platforms. This research examines the role of mooring systems in regulating the pitch motion of semi-submersible platforms, given their growing application in deep-water operations. Excessive platform movements can compromise structural stability and operational performance. To analyze platform motion, numerical simulations of the AmirKabir semi-submersible platform were conducted under various mooring configurations using nonlinear time-domain analysis. Two optimization approaches were employed: a numerical trial-and-error method and a genetic algorithm based on stochastic selection, both utilizing numerical modeling to define the fitness function. The predicted outcomes from the genetic algorithm align with those obtained from numerical methods in reducing platform pitch motion. Three mooring configurations derived from the genetic algorithm demonstrate an approximately 32% improvement over numerical models. The results indicate that combining catenary and taut mooring lines yields optimal behavior in controlling the pitch motion of semi-submersible platforms.

1. Introduction

Oceans and seas furnish essential natural resources, such as crude oil and natural gas beneath the seabed. Floating structures designed for exploration and extraction in deep waters have gained popularity with recent discoveries of large offshore oil and gas fields. Over the past decades, the demand for floating platforms (including Floating Production Storage and Offloading units (FPSOs), semi-submersibles, spars, and tension-leg platforms) has increased. A critical component of these floating platforms is the mooring system, crucial for preserving the structure's position under specific environmental conditions to safely conduct operations like drilling, extraction, offloading, and power generation (e.g., offshore wind turbines). Designing such systems presents difficulties for

engineers across various aspects, including design, engineering, construction, installation, operation, inspection, monitoring, maintenance, and repair [1].

As illustrated in Figure 1, a semi-submersible platform is a specialized floating structure designed for offshore drilling, oil extraction, heavy lifting, accommodation, or a combination of these functions. Once oil wells are drilled and completed by drilling vessels, semi-submersible platforms are deployed to the field and connected to permanent mooring systems. Semi-submersibles are stable and cost-effective platforms. As offshore oil and gas development has progressed into deeper waters, the use of semi-submersible platforms has become increasingly popular due to their large deck space for accommodating heavy equipment

and the ease of integrating the topside structure alongside the quay.



Figure 1. Semi-submersible platform [2].

Marine moorings are crucial components of floating platform station-keeping systems developed for offshore oil and gas exploration and extraction. Beyond anchoring the floating structure at a designated location, the mooring system restricts platform movements to ensure the integrity and performance of drilling and production facilities, such as production risers, drilling risers, and their centralization. Marine mooring systems can be designed for a wide range of conditions, from harsh environments like the North Sea to milder settings like the Gulf of Thailand or West Africa, and for water depths ranging from a few meters to over 3,000 meters.

Moorings systems can be classified as either catenary or taut, depending on their profiles and configurations. As illustrated in Figure 2, a catenary mooring system features a mooring line profile in which part of the line lies statically on the seabed due to its own weight. These systems are commonly used, particularly in shallow to moderate water depths.

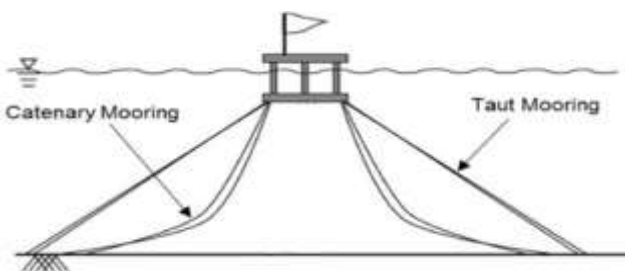


Figure 2. Types of tensile-moorings systems [3].

In contrast, a taut mooring system does not have any portion of the line resting on the seabed; instead, the

lines stretch directly from anchors on the seabed to fairleads on the floating structure. As a result, taut mooring systems have a smaller operational radius and require shorter lines compared to catenary systems. However, because the lines are taut, the platform's offset and dynamic responses are more significantly affected by line tension. In shallow water, this can lead to excessive stiffness and an undesirably high line tension. Therefore, taut mooring systems are more suitable for deep or ultra-deep water applications. Typically, a semi-submersible platform uses 8, 12, or 16 mooring lines, arranged evenly in four groups and connected from four columns to the seabed [4].

Extensive research has been conducted on analyzing and optimizing mooring lines for offshore platforms. In one study, Hermawan and Furukawa investigated the dynamic behavior of multi-component mooring lines for analyzing the motion of a floating offshore structure. They developed a coupled three-dimensional dynamics model using the lumped mass method, allowing the motion of segment connection points and including anchors and clump weights. This model facilitates the analysis of simultaneous interlocking-segment line motions to solve three-dimensional dynamic responses of multi-component mooring lines. The model integrates hydrodynamic loads, line-seabed interaction, elasticity, current effects, and dragging anchor motions. It is coupled with a ship-type floating offshore structure and validated by comparing it with equivalent models based on conventional numerical methods. The study concluded that the model could successfully provide realistic predictions of the motion of floating structures and highlighted the significant impact of lateral mooring line motion on mooring line tension [5].

In another study, Feng et al. developed and examined a model for dynamic mooring lines by integrating a boundary element model for a two-dimensional floating body with a coupled mooring line model. The boundary model was formulated in the time domain using the Rankine approach, and a reflection potential was introduced to simulate wave reflection caused by seabed slope. This newly developed model was validated through comparisons with available data. Subsequently, the dynamic response analysis was conducted under different seabed conditions. Compared to a flat seabed, a sloping seabed induced asymmetrical configurations in the mooring lines and

caused significant effects on the motion responses of the floating body [6].

In another study, Trubat et al. investigated the mooring forces of floating offshore wind turbines primarily driven by platform motions through yaw motion. Conventional dynamic analyses typically consider only the hydrodynamic mooring forces induced by wave-generated linear motion. Using the FloaWDyn aero-servo-hydro-elastic model, the impact of wave hydrodynamic loads on catenary lines and the platform system was assessed and simulated for various sea states, both with and without wave forces. Stress variations and increases in standard deviation were analyzed across multiple scenarios. It was found that the extended tension range of the mooring system (by 5% under extreme sea conditions) affects damage during mooring load events and compromises the fatigue resistance of the mooring lines [7].

In another study, Okoubaka et al. applied a genetic algorithm to assess the feasibility of optimizing the geometry and dimensions of a floating platform designed to host sloped wave energy converters. In this research, frequency-domain analysis was used to conduct sensitivity tests regarding the search starting point, selection of optimized variables, number of iterations, simulation time, and the contents of the search space. The results indicated that the number of iterations required for convergence increases with the number of optimized variables. Furthermore, for the studied platform geometry, no universally optimal unit was identified. Instead, various combinations of characteristic features in response to wave forces were comparatively evaluated. Ultimately, it was observed that when the solution space is controlled and contains a subset of known potential solutions for improving system performance, computation time, energy absorption efficiency, and the range of improvement are enhanced. Additionally, the optimized genetic algorithm tends to favor platform geometries for which the wave resonance response aligns with dominant wave climate frequencies. A key contribution of this study lies in the controlled manipulation of the variable space for a subset of potential solutions that enhance system performance. This controlled approach leads to improvements in computational time, energy absorption efficiency, and the optimal operational state of the platform [8].

In another investigation, Mariares Casimiro et al. proposed a novel framework for the multi-objective

optimization of mooring systems for floating renewable energy platforms by employing a surrogate model based on random forest algorithms combined with a genetic algorithm. This framework, applied to the optimization of the mooring system for a floating wind turbine, demonstrates how this approach can support strategic design decision-making in real-world problems faced by the renewable energy sector. The framework utilizes validated numerical models of the mooring system to train the surrogate model, resulting in an efficient computational optimization routine that enables exhaustive exploration of the search space. This framework presents a wide range of optimal solutions and illustrates how design changes affect the trade-offs between two competing objectives, while also minimizing both cost and cumulative fatigue of the mooring system [9].

Youliang Zhao et al. investigated the design and optimization of a mooring system for a floating platform—a task that typically relies heavily on engineering experience and time-consuming numerical simulations. A novel hybrid approach, BPNN-FEM, combining a Back Propagation Neural Network (BPNN) and a modified Finite Element Method (FEM) model, was proposed to facilitate more efficient statistical prediction and dynamic stress series forecasting in mooring systems with multiple design variables under irregular sea states. The accuracy of this approach was validated using several statistical error metrics. This method offers a more cost-effective alternative to intensive numerical simulations for optimizing the design of floating platform systems. An optional mooring configuration was proposed based on maximum safe operations, drift constraints of the platform, and the safety performance of mooring lines. A semi-submersible platform deployed in deep water was used as a case study to demonstrate the proposed hybrid approach. The platform consisted of twelve mooring lines, and the design variables included the mooring radius, azimuthal spacing of the mooring lines, and lengths of various segments of the mooring lines. Environmental loads were also considered in this optimization process. The predicted results aligned well with those obtained through the FEM [10].

Currently, numerous studies are being conducted on the mooring of offshore platforms. Each researcher considers specific environmental and structural conditions to enhance platform mobility and improve mooring performance. Based on the unique capabilities

of each mooring type, this study investigates the combined use of taut and catenary moorings, independently, to improve the pitch motion of an offshore semi-submersible platform. The objective is to identify an optimal combination that minimizes platform motion as effectively as possible.

In this article, we analyzed the pitch motion of a semi-submersible offshore platform and employed the Genetic Algorithm (GA) as an optimization tool for the analysis and design process. Pitch motion is considered one of the critical parameters in the performance of semi-submersible platforms and is influenced by factors such as wind forces, wave action, and ocean currents. Based on the conducted analysis, it was found that accurately modeling this type of motion requires complex modeling and precise computation. Therefore, the use of artificial intelligence techniques such as the Genetic Algorithm demonstrates high potential in optimization and identifying influential parameters. By simulating the natural processes of selection and inheritance, the Genetic Algorithm is capable of conducting a more targeted search within the solution space and providing acceptable results.

In this study, various methodologies for simulating and analyzing pitch motion were investigated, and several strategies were proposed to enhance the accuracy and efficiency of the analyses. The results demonstrated that employing the Genetic Algorithm significantly reduces prediction errors and improves the operational conditions of offshore platforms.

Ultimately, the findings of this research not only contribute to a deeper understanding of pitch motion in semi-submersible platforms but also serve as a reference for future studies and the development of optimization techniques in the oil and gas industry. In general, future research may focus on the integration of artificial intelligence algorithms with hydrodynamic modeling to achieve improved outcomes in this field.

2- Governing Equations

A semi-submersible platform, as an offshore structure, is governed by hydrodynamic and structural equations. These equations are used to analyze the displacement behavior and platform responses to environmental forces and motions [11]. A floating structure in open waters is subjected to environmental loads resulting from wind, waves, currents, ice, and other factors [12-

13]. Figure 3 illustrates the effects of wind, current, and waves. These forces are among the most significant environmental parameters that influence the motion of the floating structure. The mooring system is designed to provide control over the structure in response to these external and internal forces.

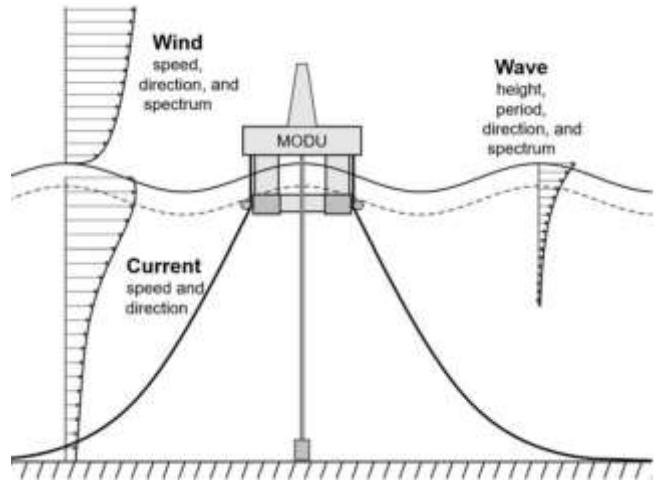


Figure 3. Wind, wave and current forces on a floating platform [1]

2-1- Motion Equation for a Semi-Submersible Platform

The motion equation for a floating vessel consists of three rotations (roll, pitch, and yaw) and three translations (surge, sway, and heave) along the x, y, and z axes. For analyzing and modeling motion for a semi-submersible vessel under different forces, the motion equation is given as:

$$M(p, a) + C(p, v) + K(p) = F(p, v, t) \quad (1)$$

Where:

M is the inertia matrix of the structure

C is the damping matrix

K is the restoring force matrix

F is the external force vector acting on the structure

p, v, a, and t are the vectors for position, velocity, acceleration, and time, respectively

2-2- Wind Load

The wind force acting on a semi-submersible platform can be calculated using the following equation [1]:

$$F = \frac{1}{2} \rho V_p^2 C_D A \quad (2)$$

Where:

ρ is the air density

V_p is the wind speed

C_D is the drag coefficient of the platform's surface

A is the projected area of the platform exposed to wind

2-3- Hydrodynamic Forces

The hydrodynamic forces exerted on floating structures can be divided into categories according to wave frequency:

- Sustained wave-frequency forces, which are always present and have a magnitude and direction that does not change over an amount of time and lead to wave drift forces. Such fixed loads cause the floating object to be pushed in one direction and are counteracted by the restoring force from moorings [1].
- Oscillating wave-frequency forces, whose periods average from 5 up to 30 seconds. Such forces cause periodic stresses within the structure, which give rise to maximum mooring line tensions and fatigue damage accumulation within the mooring system. Anchors and risers in some conditions exert extra damping in the floating body's movements, including surge, sway, and roll motions [13].
- Low-frequency wave loads affect floating platform components such as the mooring system, typically within the time range of 180 to 600 seconds [14].

The maximum wave load on marine structures occurs at the wave frequency, causing the floating structure to oscillate at that frequency. To avoid large resonance effects, marine structures and their mooring systems are generally designed such that their resonance frequencies lie well outside the structure's natural frequency range. Wave-induced loads can trigger high-frequency elastic responses, and due to nonlinear load effects, some responses may still occur at natural frequencies [15].

Hydrodynamic loads were calculated using the classical Morison equation, in which ρ is the water density, C_D the drag coefficient, C_M the inertia coefficient, R^* the dimension of the element (diameter for a cylindrical section, width or length for a rectangular section), u the water particle velocity, a the particle acceleration, x the displacement of the member, and z the vertical coordinate of the node.

$$F_{hydro}(z) = \rho C_d R |u - \dot{x}|(u - \dot{x}) + \pi \rho R^2 a + (C_M - 1) \pi \rho R^2 (a - \ddot{x}) \quad (3)$$

2-4- Damping

Damping effects were considered using classical Rayleigh damping as defined in Equation (4). Rayleigh damping is a linear combination of mass and stiffness. Here, the damping matrix C is defined as:

$$C = \mu M + \lambda K \quad (4)$$

In Equation (4), M and K are the mass and stiffness matrices, respectively, and μ and λ are proportionality constants. Figure 4 shows how the damping ratio varies with frequency. This graph demonstrates the contribution of mass and stiffness damping to the total damping ratio.

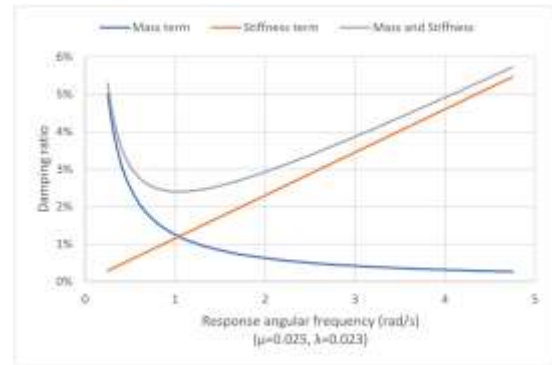


Figure 4. Change in damping ratio [16]

Rayleigh damping coefficients must be carefully selected to avoid the excessive damping of low-frequency responses caused by the mass-proportional damping component. It is also important to note that mass damping can induce damping due to the rigid-body motions of the floating structure. Therefore, mass-proportional damping is generally neglected. In other words, for such systems, the use of stiffness-

proportional damping (upper red curve) is recommended [16].

Natural frequencies and critical damping are essential parameters for analyzing floating body motions. Resonance occurs when the period of an external excitation force approaches the natural period of the floating system. The natural frequency f and the critical damping BC of a floating system, as functions of total mass ($M + M_a$) and stiffness K in six degrees of freedom, are defined as follows:

$$\text{Natural frequency: } f = \sqrt{\frac{K}{M + M_a}} \quad (5)$$

$$\text{Critical damping: } B_c = 2\sqrt{(M + M_a)K} \quad (6)$$

2-5- Mooring Lines Governing Equations

Figure 5 illustrates a small element of the mooring line in a two-dimensional plane (x - z coordinate system). In the free-body diagram shown, P represents the submerged weight per unit length, T the effective tension, dl the length element, AE the axial stiffness, $d\psi$ the normal displacement, and $d\phi$ the tangential displacement of the mooring line.

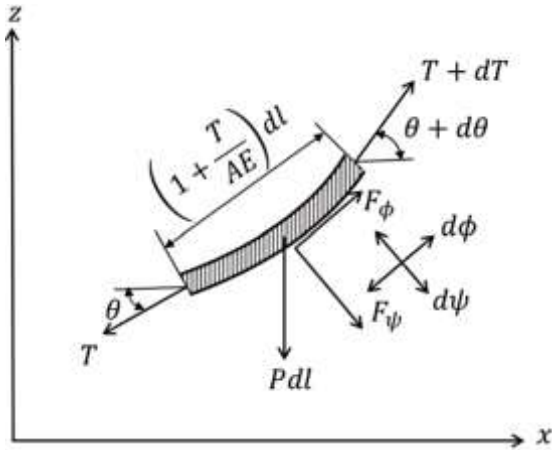


Figure 5. Force and displacement on an element of the mooring line [1]

In mooring line design, it is assumed that the bending and torsional stiffness of the line are negligible—an assumption considered valid for chains and for wire or polyester ropes with a large curvature radius and broadly accepted in the industry [17]. The effects of the hydrodynamic forces F_ϕ and F_ψ on the mooring are calculated using Morison's equation. The governing

differential equations for computing the forces on the mooring lines take into account both dynamic and elastic effects. These equations are nonlinear and require numerical simulations for accurate solutions [18-19].

2-5-1- Static Mooring Equations

The static equations of mooring lines were first formulated by Leibniz, Huygens, and Bernoulli in 1691 [20-21]. The solution to the catenary equation has a hyperbolic cosine function form. In dynamic load calculations on mooring lines, damping and inertial forces are neglected due to their small magnitude. It is assumed that the mean horizontal environmental force (due to wind, wave, and current) applied at the mooring connection point is T_0 . The reference frame origin (x_0, z_0) is placed at the seabed contact point of the mooring line, where the line's slope is zero, as shown in Figure 6. Here, l_s is the suspended length (arc length) of the mooring line, l_t the total mooring length, and h the vertical distance from the starting point to the seabed.

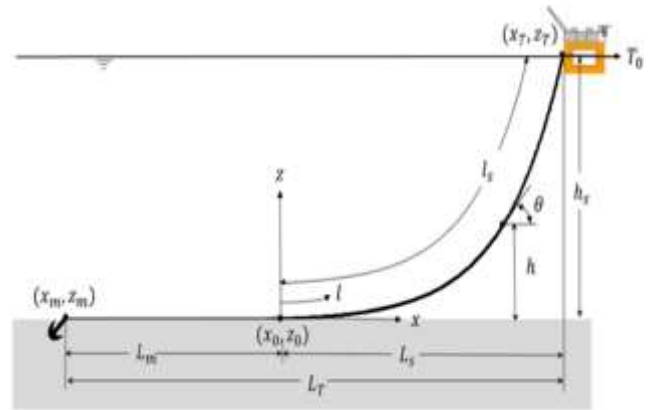


Figure 6. Geometric characteristics of the catenary line [1]

For simplicity in calculation, mooring elements are assumed inelastic; i.e., for a homogeneous catenary mooring line, $AE = \infty$, which gives:

$$dT - P \sin\theta \, dl = 0 \quad (7)$$

$$T \, d\theta - p \cos\theta \, dl = 0 \quad (8)$$

These equations are derived from the above relations when seabed boundary conditions are applied:

$$l(x) = \frac{T_0}{P} \sinh\left(\frac{P}{T_0} x\right) \quad (9)$$

$$h(x) = \frac{T_0}{P} \cosh\left(\frac{P}{T_0} x\right) - \frac{T_0}{p} \quad (10)$$

From Equations (9) and (10), for a given horizontal tension T_0 , we can plot the mooring line configuration.

Within the suspended range, for which $0 < l < l_s$, we have:

$$l = \sqrt{h\left(h + 2\frac{T_0}{P}\right)} \quad (11)$$

To calculate tension along this section, we use the following relation:

$$T(l) = T_0 + P h \quad (12)$$

For a chain-type catenary mooring line, Equation 12 shows that static chain tension along the fairlead increases linearly with environmental force and is equal to the horizontal force plus the weight of the chain when submerged. For moorings that are taut and do not have load-bearing capacity in the direction of elevation, an estimate of the minimum required length for moorings to prevent uplift is essential, which can be derived from the following relation between total length l and total tension T .

$$l = h \sqrt{\left(2\frac{T}{Ph} - 1\right)} \quad (13)$$

Based on Equations (9) and (10), the preferred approach for force resistance is with inelastic catenary lines. Next, including elastic stretch in them, one can find quasi-static solutions for multi-material catenary lines [22-23].

2-5-2- Mooring line stiffness

A mooring line exerts horizontal and vertical forces, denoted by T_H and T_v respectively, on the floating structure, as defined in Equations (14) and (15).

$$T_H = (T_H)_M + k_{11}\eta_1 \quad (14)$$

$$T_v = (T_v)_M + k_{33}\eta_3 \quad (15)$$

In Equations (14) and (15), η_1 and η_3 represent motions, while k_{11} and k_{33} denote the stiffness in the horizontal and vertical directions, respectively. Both T_H and T_v are related to the offset of the floating structure. The greater the displacement of the structure from its equilibrium position, the greater the reaction force T_H will be. Similar to a simple spring system, this relationship between the structure's offset and the mooring line's reaction force is referred to as mooring stiffness. Mooring stiffness represents a proportional relationship between force and displacement. When the line tension increases significantly, the mooring line experiences both axial elongation and overall geometric deformation. Therefore, mooring stiffness consists of both axial stiffness (AE) and geometric stiffness components [24].

2-5-3- Mooring Line Dynamics

Equation (16) describes the tension in a mooring line resulting from wave-frequency (WF) motion:

$$M \frac{d^2 r}{dt^2} + B \frac{dr}{dt} + K r = F(r, t) \quad (16)$$

In Equation (16), M is the added mass, B is damping, K is the stiffness matrix, F is an external excitation force, and $r = (x, y, z)$ is the displacement vector from the equilibrium position. The dynamic analysis, which includes added mass, damping, and stiffness, is illustrated in Figure 7.

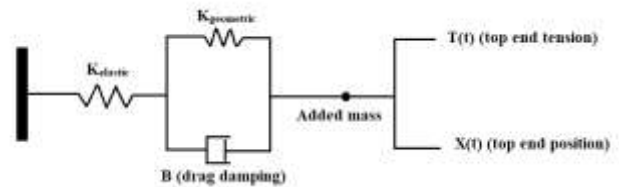


Figure 7. Illustration of a dynamic analysis for a catenary mooring line

2-5-4- Mooring Systems General Design

As shown in Figure 8, a mooring system is connected to a semi-submersible structure using multiple lines.

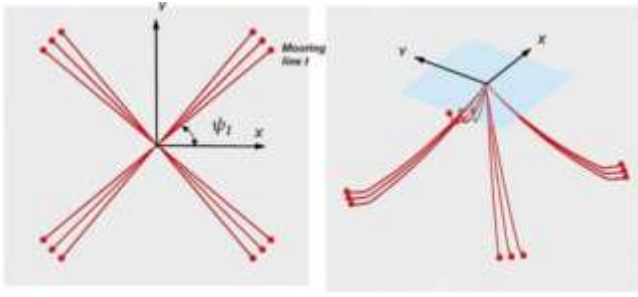


Figure 8. Multiple-line mooring system [1]

The motion of the floating structure can be described using the equations of motion in six degrees of freedom:

$$\sum_{j=1}^6 \left[(M_{ij} + M_{aij}) \frac{d^2 \eta_j}{dt^2} + B_{Lij} \frac{d\eta_j}{dt} + B_{Qij} \left| \frac{d\eta_j}{dt} \right| \frac{d\eta_j}{dt} + K_{ij} \eta_j \right] = F_i \quad (17)$$

In Equation (17), the indices i and j denote the direction of hydrodynamic force and the mode of motion, respectively. $i = 1-2-3-4-5-6$ correspond to surge, sway, heave, roll, pitch, and yaw. B_L and B_Q represent linear and quadratic damping coefficients, respectively. The right-hand side of Equation (17) includes environmental forces (mean wind, wave, and current forces) [23-25].

On the left-hand side of Equation (17), M_a represents added mass (in-phase with acceleration), along with the damping and stiffness contributions of the mooring lines. For the stiffness matrix K and damping matrix B , the total contribution from mooring lines is the sum of all individual lines. For instance, the surge-direction contribution can be calculated using the following relation:

$$\text{Surge: } K_{11} = \sum_{l=1}^n k_l \cos^2 \psi_l \quad (18)$$

$$\text{Sway: } K_{22} = \sum_{l=1}^n k_l \sin^2 \psi_l \quad (19)$$

2-6- Genetic Algorithm

The genetic algorithm is a specific type of evolutionary algorithm that utilizes evolutionary biology techniques

such as inheritance, biological mutation, and Darwinian principles of selection to find an optimal formula for prediction or pattern matching. Genetic algorithms are often a good option for regression-based prediction techniques. As illustrated in Figure 9, genetic evolution is used as a problem-solving model in genetic algorithm modeling [8]. The problem to be solved has inputs that are transformed into solutions through a process modeled on genetic evolution. These solutions are then evaluated as candidates using a fitness function. If the termination condition is met, the algorithm stops. In general, the genetic algorithm is an iterative algorithm in which many of the components are selected via stochastic processes [26].

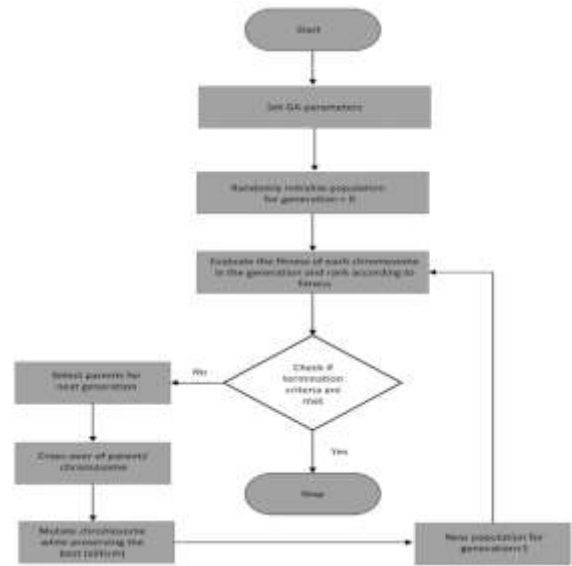


Figure 9. Flowchart of the steps of the genetic algorithm [8]

3- Simulation

Simulation, as a powerful tool in engineering sciences, allows us to model and analyze the behavior and performance of systems and processes under actual or desired conditions. Through simulation, we can enhance the predictive capability and performance optimization of a system without the need for costly and time-consuming experiments. Numerical simulation enables us to perform a wide range of analyses related to mooring lines and floating platforms within a simulated environment. Finite element simulation is used for analyzing moorings and dynamic analysis within the OrcaFlex software [27]. Mooring analysis is performed by dividing the mass of the system into discrete nodes, treated as point masses connected by springs [28-29]. Initially, the geometry of

the structure and moorings is modeled in a three-dimensional environment. Then, the model is divided into smaller linear elements (for moorings) and surface elements (for the platform). For each element, material properties, boundary conditions, and other required parameters are defined. Using the governing equations for linear and surface elements, the response of each element at every time step is computed. The results of individual elements are then combined to obtain the overall structural response.

The structure considered in this paper is the Amirkabir semi-submersible platform, which was developed from the GVA-4000 basic design and is positioned 250 km off Neka Port, Iran, in the Caspian Sea. The overall shape and structural parameters of the Amirkabir platform are depicted in Figure 10 and Table 1.



Figure 10. AmirKabir Semi-submersible platform

Table 1. Geometrical specifications of the Amirkabir semi-submersible platform [30-31].

Description	Value	Description	Value
Width (m)	78.84	Length (m)	98.6
Pantone length (m)	80.56	Height to deck floor (m)	28.5
Pantone width (m)	18.68	Height to deck ceiling (m)	36.5
Brace diameter (m)	2	Column diameter (m)	12.9
Draught (m)	19.5	Distance between columns (m)	54.72
Operating weight	28,621	Fairlead height (m)	11.2

The Amirkabir semi-submersible platform is designed with eight mooring lines, each three kilometers in length (two mooring lines at each corner of the

platform). This involves the use of long and complex mooring systems, which can result in challenges such as high costs, complexity of installation, maintenance difficulties under varying weather conditions, and technical and physical constraints. The mooring specifications are presented in Figure 11 and Table 2.

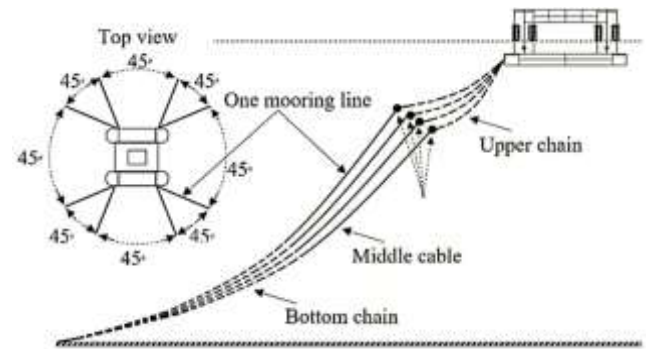


Figure 11. AmirKabir semi-submersible platform mooring specifications [32]

Table 2. Specifications of a mooring for the Amirkabir semi-submersible platform [33]

Fracture strength KN	Quality	Length (m)	Diameter (mm)	Type	Section
MBL5454	NV-R3S	900	76	Chain	Top
MBL5100	IWRS37*6	1000	86	Cable	Middle
MBL5454	NV-R3S	1100	76	chain	Bottom

3-1- Environmental Data Collection

For modeling the semi-submersible platform and calculating the forces, accurate and consistent environmental data must be used (data presented in this section were collected by the consulting company Owj Pajooohesh Sanat'e Iran). The air density is taken as 0.0013 te/m^3 , and the kinematic viscosity of air used for Reynolds number calculations is considered as $15 \times 10^{-6} \text{ m}^2/\text{s}$. The seabed is assumed to be smooth and elastic, with a design depth of 500 meters for this platform. The specifications of environmental forces (wave, wind, and current) used in the software are listed in Table 3 [32-34].

Table 3. Environmental forces of the Caspian Sea [32-33]

Type	Value		Angle	Description
JONSWAP	T _z	H _s	180	Wave
	12.8 s	9.5 m		
NPD	22 m/s		180	Wind

Interpolated	0.86 m/s	180	Curent
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3-2- Model Validation

Following the geometric modeling and definition of environmental conditions and applied forces, the software's validity is evaluated. In the context of floating structure design, the Response Amplitude Operator (RAO) is an engineering statistic used to determine the probable behavior of a floating body when subjected to sea forces. RAOs, typically derived from tested models in wave tanks or from specialized computational CFD software (such as ANSYS), represent how a structure responds to incoming wave energy at various frequencies.

As shown in Figure 12, in this context, RAO results obtained from existing ANSYS simulations of the Amirkabir platform in six degrees of motion from three angles are carefully recorded.

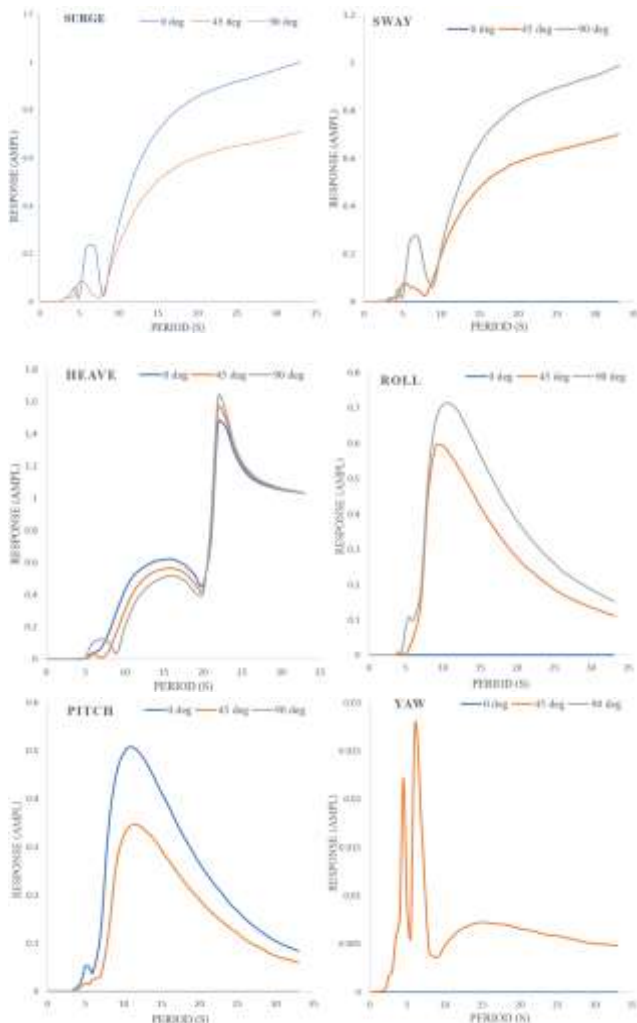


Figure 12. Response spectrum range of the Amirkabir semi-submersible platform

Interpolation techniques were used to compute the remaining angles. Then, the forces are input, and the Amirkabir semi-submersible platform is modeled in OrcaFlex software. To ensure that the RAOs from ANSYS align with those of the simulated platform and input forces, the output spectral RAOs from OrcaFlex are then compared with previously obtained data. The validation steps are as follows:

1. Input of existing RAOs
2. Modeling of platform and moorings
3. Input of environmental forces
4. Examination of output RAOs
5. If matched, validation is confirmed; otherwise, model parameters are adjusted accordingly

In OrcaFlex, the input RAOs, platform specifications, mooring lines, and environmental forces are fixed and unchangeable; however, the output RAOs vary depending on all the aforementioned fixed parameters. In cases of discrepancy, to minimize differences between input and output RAOs, model-level variables such as connectors and similar details (without altering the main form of the platform, moorings, or environmental forces) are adjusted through trial and error. As shown in Figure 12, the RAOs of the simulated platform are presented. Thus, by disregarding minor errors, the results in Figures 12 and 13 are considered acceptable and largely consistent.

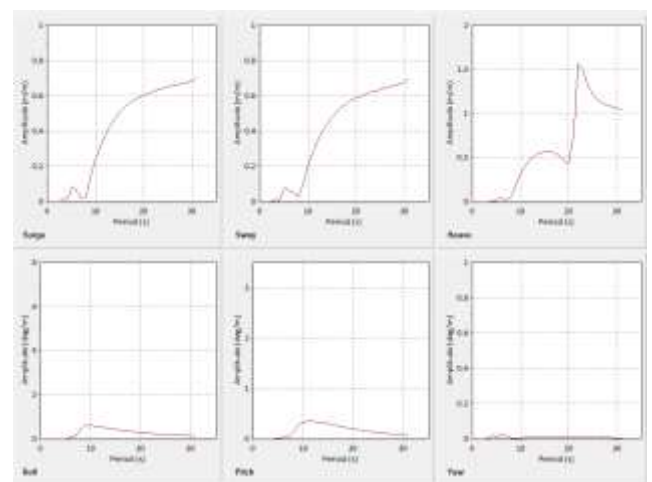


Figure 13. Response spectrum amplitude at 45 degree angle

The similarity between the two graphs can be further increased by maintaining modeling accuracy and

continuously improving simulation criteria in OrcaFlex.

3-3- Modeling

3-3-1- Numerical Modeling

Various configurations of the Amirkabir semi-submersible platform with different numbers of mooring lines (4, 8, 12, and 16) are examined in this section.

As shown in Figure 14, the initial model assumes the platform with eight mooring lines (two per corner) as the baseline. Subsequently, by changing the length and placement of the moorings, alternative models of the Amirkabir platform are created.

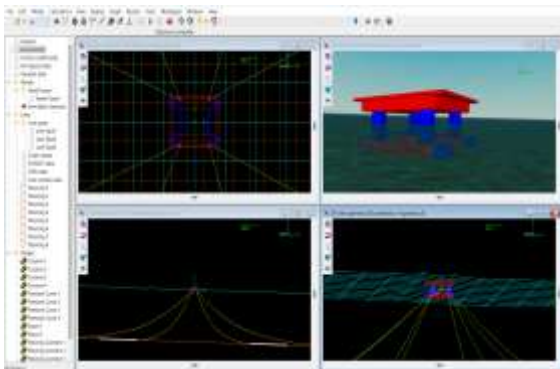


Figure 14. Model of the Amir Kabir semi-submersible platform with Orcaflex software

After running each model, time-displacement graphs are extracted to analyze the platform's pitch motion. Then, using Fast Fourier Transform (FFT), the time-displacement data are converted into dimensionless RAO amplitude spectra graphs. These graphs illustrate the platform's displacement over time, and pitch angles are used to analyze these graphs.

Given that each of the Amirkabir platform's mooring lines consists of three segments (catenary – taut – catenary), in the conducted models, each mooring is modeled using a single material and simplified as a one-piece element (either catenary or taut). The pretension forces of the moorings are determined based on relevant standards and the specific requirements of the Amirkabir platform.

The following modifications were applied in the numerical modeling to improve the mooring performance:

- Reducing taut mooring length
- Reducing vertical connection angle
- Reducing catenary length
- Optimizing anchor location
- Altering horizontal angles

Using OrcaFlex, a total of 30 different mooring configurations were tested on the Amirkabir platform. The catenary mooring length was set to 2000 meters and the taut section to 700 meters. The number of moorings varied from one to four per column of the semi-submersible platform.

The 30 initial models included:

1. Two 4-mooring (4×1) configurations
2. Four 8-mooring (4×2) configurations
3. Eight 12-mooring (4×3) configurations
4. Twelve 16-mooring (4×4) configurations

Each model was created in OrcaFlex and the respective time-displacement graphs were extracted. Figure 15 presents the pitch motion response graphs of the 30 configurations.

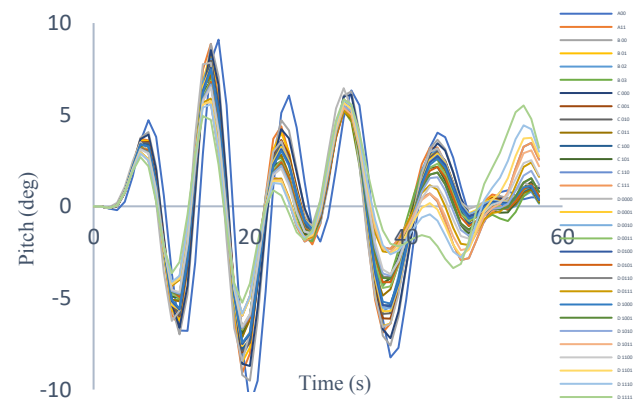


Figure 15. Time-displacement diagrams of 30 numerical models at the pitch movement angle

3-3-2- Modeling Using Genetic Algorithm

Following the numerical modeling and corresponding outputs, the genetic algorithm was employed to further improve the pitch motion of the platform. Initially, the pitch motion outputs of the 30 numerical models described previously were encoded using a neural network based on the mooring specifications of each

platform. The specifications of the neural network are presented in Tables 4 and 5.

Table 4. Neural network specifications

Data Division	Random (dividerand)
Training	Levenberg-Marquardt (trainlm)
Performance	Mean Squared Error (mse)
Calculations	MEX

The output of this neural network served as the initial fitness function in the genetic algorithm's coding. In this implementation, the optimization was prioritized based on the degree of rotational motion in the pitch direction. In other words, parent models that exhibited less pitch motion were prioritized and their traits were passed on to the next generation. Given that the operation of the genetic algorithm is based on random selection, two output iterations were generated for a more robust evaluation. Each output iteration proposed a significant number of semi-submersible platforms with different mooring configurations. Figures 16 and 17, along with Table 5, illustrate the neural network regression and genetic algorithm parameters for the two output iterations.

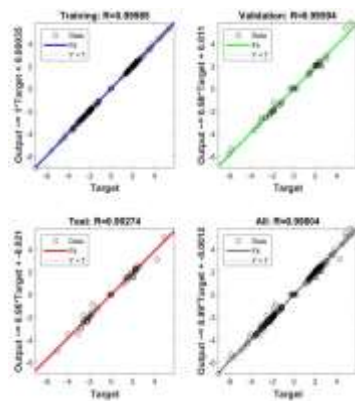


Figure 16. Neural Network Regression Run1

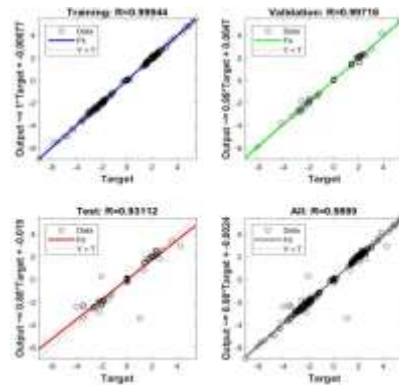


Figure 17. Run2 neural network regression

As regulated by the genetic algorithm, the optimization paths for each of the two iterations are manifested in Figure 18. As can be noticed, in both iterations, the objective function improved from a higher to a lower value and dropped from approximately 7–8 to values near 5–6. As regulated by the genetic algorithm, the optimization paths for each of the two iterations are manifested in Figure 18. As can be noticed, in both iterations, the objective function improved from a higher to a lower value and dropped from approximately 7–8 to values near 5–6.

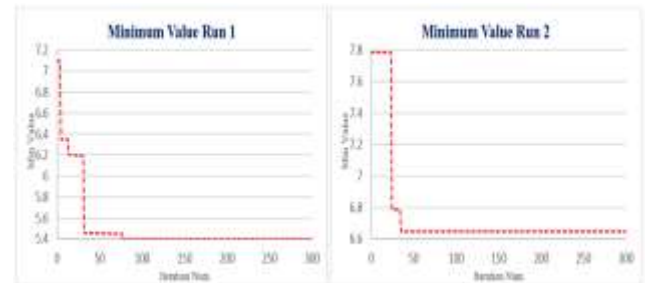


Figure 18. Minimize diagram of two-period genetic algorithm

According to the objective function in Figure 18, each output of the genetic algorithm generated 2,000 mooring configuration models for the semi-submersible platform. From each set, six models with better pitch motion performance were selected based on the number of moorings, resulting in a total of twelve selected models. Each of these models was subsequently simulated under defined conditions, and the pitch motion outputs were analyzed for the configurations proposed by the genetic algorithm.

Table 5. Characteristics of the four-output neural network of the genetic algorithm

	Unit	Epoch	Performance	Gradient	Mu	Validation Checks
Run 1	Initial Value	0	1.4	2.15	0.001	0

Run 2	Stopped Value	47	0.000644	0.00491	1.00E-05	6
	Target Value	1000	1.00E-07	1.00E+10	6	6
	Initial Value	0	1.67	2.63	0.001	0
	Stopped Value	12	0.000869	0.00366	1.00E-05	6
	Target Value	1000	0	1.00E-07	1.00E+10	6

line 3	Taut	522	700	50
line 4	Catenary	184	200	60
		7	0	

4- Results

4-1- Numerical Modeling Results

In the initial stage of numerical modeling, by applying static and dynamic loads, the platform reached an equilibrium state and displacements were reduced. However, over time, amplification in the platform's motion fluctuations was observed. Based on minimum displacement, four out of the thirty numerically modeled platforms simulated in OrcaFlex were selected, as listed in Table 6. Their response amplitudes were identified and compared to the original Amirkabir semi-submersible platform. The mooring characteristics of these four optimized models are also described in Table 6. For simplicity and better comprehension, all tables describing mooring specifications only include the moorings connected to one column located in the first quadrant of the four-column configuration.

Table 6. Characteristics of the restraints of the selected models in numerical modeling

Model name	Specifications moorings					
	Number of mooring lines	Type	Radius	Length	Azimuth angle	
C 110	3	line 1	Taut	521	700	22.5
		line 2	Taut	521	700	45
		line 3	Catenary	1860	2000	67.5
D 0111	4	line 1	Catenary	1848	2000	30
		line 2	Taut	519	700	40
		line 3	Taut	519	700	50
		line 4	Taut	519	700	60
D 1101	4	line 1	Taut	520	700	30
		line 2	Taut	520	700	40
		line 3	Catenary	1848	2000	50
		line 4	Taut	520	700	60
D 1110	4	line 1	Taut	522	700	30
		line 2	Taut	522	700	40

Using Fourier series, the time-displacement graphs of the models were converted into Response Amplitude Operator (RAO) graphs. In offshore platforms, three directions are of particular importance: surge, heave, and pitch. Figure 19 shows the pitch RAO spectra of the four numerical models alongside the pitch RAO spectrum of the Amirkabir semi-submersible platform.

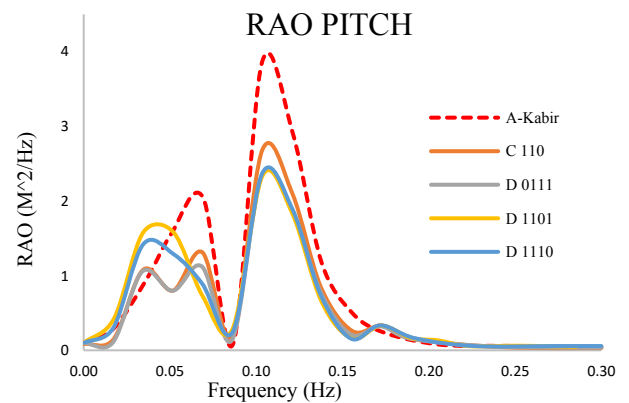


Figure 19. Comparison chart and examination of the response amplitude spectrum of the screw movement of numerical models

A considerable reduction in pitch motion was proven through the graphs, which verified acceptable and favorable optimization. However, for optimizing the models further, one of the best-suited optimization algorithms, (the genetic algorithm), was utilized in the following step.

4-2- Genetic Algorithm Modeling Results

This section analyzes the performance of the twelve models given by the genetic algorithm, previously described. Based on two groups of outputs and comparison between motion graphs derived from simulations made in OrcaFlex, three superior models were identified. The mooring specifications of these

chosen models from the genetic algorithm are given in Table 7. The pre-tension and mean tensile forces for all three catenary and taut moorings are further given in Figure 20.

Table 7. Characteristics of the constraints of the genetic algorithm output models

Models	Num Line	Catenary %	Taut %	L Catenary (m)	L Taut (m)	Azimuth			
						C1	T1	T2	T3
D1-1	4	25%	75%	1,742	551	68	68	55	69
C1-2	3	33%	67%	1,683	522	43	21	28	-
D1-2	4	25%	75%	1,757	560	40	41	42	44

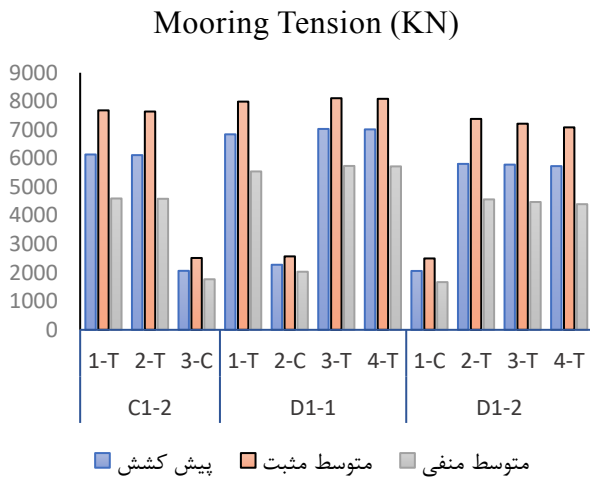


Figure 20. Restraint force of the final optimal motion models

Figure 20 displays the forces on the moorings on one side of the four-sided platform, with the taut moorings labeled as T and the catenary moorings as C. By modeling the configurations proposed by the genetic algorithm in OrcaFlex, their time-displacement graphs were obtained. These were then converted into RAO graphs and compared with the best numerical model. Figure 21 presents comparative RAO pitch motion spectra of the best genetic algorithm-based models. These graphs include the numerical model D0111 (the optimal numerical model) and the genetic algorithm-based models C1-2, D1-1, and D1-2.

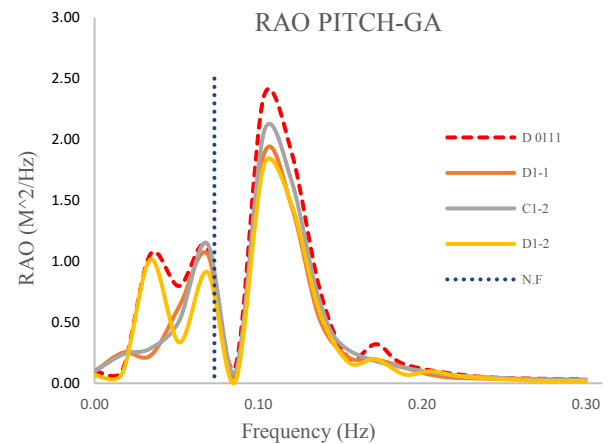


Figure 21. Comparison chart and examination of the response amplitude spectrum of the screw movement of genetic algorithm models

As seen in the figure, all genetic algorithm models outperform the optimal numerical model in terms of pitch motion. By comparing and analyzing the RAO spectra of the optimized and initial models, and considering the significance of the peak response location relative to the natural frequency due to the risk of resonance, the critical role of mooring optimization on platform behavior becomes clearer. According to Figure 21, the peak RAO responses lie within a favorable frequency range relative to the natural frequency.

4-3- Two Modeling Methods Comparison

The results of platform motion variations due to different mooring configurations were evaluated under both numerical and genetic algorithm-based modeling. In this section, for each model, mooring variations and their relation to platform displacements over time were analyzed, with a focus on catenary and taut moorings. Based on the modeling described earlier, four numerical and three genetic algorithm-based models were ultimately selected. Their mooring configurations were compared to the Amirkabir semi-submersible platform in Table 8.

Table 8. Percentage reduction in anchorage length and operating radius of anchorages of numerical models and genetic algorithm compared to the Amirkabir semi-submersible platform

Manual Models	Percentage reduction		GA Models	Percentage reduction	
	Mooring length	Operating radius		Mooring length	Operating radius
C 110	41%	36%	D1-1	43%	44%
D 0111	32%	36%	C1-2	55%	47%
D 1101	32%	36%	D1-2	43%	44%
D 1110	32%	36%			

The results from modeling demonstrate that adjustments in mooring number and position have a considerable impact on the pitch motion characteristics of the semi-submersible platform. An increase in mooring number lessened platform displacement while maximizing its stiffness and stability.

These results, as displayed in Table 9, further illustrate that mooring configurations vary the stability and strength of the platform in all directions. The percentage reduction in pitch motion for genetic algorithm-based models relative to the best numerical model is given in Table 9.

Table 9. Percentage improvement in motion changes of genetic algorithm models compared to the best numerical model (D0111)

Method	Models	Pitch
Genetic Algorithm	D1-1	32%
Genetic Algorithm	C1-2	28%
Genetic Algorithm	D1-2	31%

As seen, D1-1 proved to perform optimally in relation to platform displacement. This model, which was proposed by the genetic algorithm, has 16 moorings

(twelve taut and four catenary). The changes made in moorings greatly enhanced motion behavior of the platform compared to the original one. The mooring changes resulted in a remarkable reduction in motion behavior in terms of the platform's pitch motion.

5- Conclusion

From modeling and displacement analyses, we can see clearly that changes in mooring number, length, and position relative to the original design model have a direct bearing upon the behavior and displacement of the platform.

One of the main changes applied in the models was the adjustment, enhancement, and reduction of moorings. The findings indicate that utilizing a single type of mooring (either catenary or taut) yields better platform motion performance than using a combination of both. This design strategy enhances the platform's strength and stability when faced with harsh marine environmental conditions. In summary, mooring modifications significantly improved the platform's performance and stability. Utilizing these optimized models minimizes the risk of unwanted vibrations and oscillations in the platform. These improvements in the semi-submersible platform's motion enhance its strength and stability during operation.

Moreover, analyzing the time-displacement graphs can reveal how displacements evolve over time, which can aid in improving the platform design and enhancing its safety. The modeling of the Amirkabir semi-submersible platform with various mooring configurations using the genetic algorithm clearly demonstrated the direct influence of mooring type and position on platform behavior and displacement. Given the responsiveness of optimization algorithms in the offshore industry, their application can lead to meaningful advancements in the design and optimization of semi-submersible platforms. The mooring optimization conducted here resulted in significant improvements in platform performance and structural integrity.

For future research, other salient parameters influencing semi-submersible platform motion, specifically for moorings, can be explored—e.g., different depths, column geometry, and pontoons. Further accuracy can be achieved through refining

modeling and analysis procedures, as well as pursuing an exploration of the remaining five degrees of motion.

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Artificial Neural Networks for Identifying minor Damage on Jacket Platforms

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ABSTRACT

In the field of structural engineering, neural networks are utilized to detect damage in offshore jacket platforms using a combination of modal analysis results. By analyzing the shape of natural frequencies and utilizing information from five modal results, damage identification indices are developed. This study investigates Structural Health Monitoring (SHM) strategies utilizing mode shape analysis and neural networks to detect failures within a multi-story structure. Various failure scenarios, including corrosion-induced damage and collisions, were analyzed across 52 structural members, with induced damage ranging from 0% to 20%. Results reveal the critical importance of floor levels: the fourth floor exhibited heightened accuracy in failure detection, particularly in columns and wind braces, crucial for corrosion protection. Notably, secondary beams consistently displayed higher precision in identifying failures compared to main beams. The neural network performance peaked at a mean squared error of 0.039206, validating its efficiency in detecting and allocating damage across different structural elements. Subsequent scenarios involving two members of the fourth floor demonstrated the adaptability of the approach in addressing diverse failure rates. This research underscores the efficacy of combining mode shape analysis and neural networks for robust SHM. It emphasizes the significance of floor levels and specific structural elements in enhancing failure detection accuracy, offering valuable insights for proactive maintenance and structural integrity preservation.

1. Introduction

Monitoring the health of structures and identifying damage early on is a crucial and essential task. One of the newer methods for identifying damage in structures is using dynamic responses of systems, which is a non-destructive and cost-effective approach. The failure to repair damage can lead to the spread and eventual collapse of the structure. Therefore, it is crucial to detect the location and extent of damage in the structure in order to take the necessary steps to prevent further damage and increase the structure's lifespan. One method that utilizes the changes in dynamic characteristics of the structure is based on changes in mode shapes. [1] [2]

Structures in the industrial sector require regular monitoring to maintain their condition and gather

information on their status. This is particularly important for marine structures, which are constantly exposed to environmental forces and can accumulate damage over time. Offshore jacket structures are a prevalent type of marine structure in shallow and medium depths and play a key role in the oil and gas industry and as infrastructure for offshore wind turbines. [1] [2]

Identifying potential damage in jacket structures is vital for safety but can be challenging due to the difficulty of conducting maintenance tests under harsh environmental conditions. Therefore, developing robust and effective methods for identifying structural damage is crucial in avoiding failure. Artificial Intelligence (AI) techniques, such as machine learning and artificial neural networks (ANN), have been used to select features for condition assessment of

mechanical systems. Machine learning is particularly useful as it can learn from large, multi-faceted uncertainties in data. ANNs are a type of algorithm used in machine learning to model data and have been used as a novel approach in structural health monitoring. [1] [2]

There are two main types of ANNs: shallow neural networks and deep neural networks. There are also two types of mechanical system data sets: artificial data sets, which can be generated manually using machining devices or virtual models, and real data sets, which are generated according to a data-driven algorithm. Data-driven methods have been shown to be effective in detecting mechanical damage and many data-driven methods are based on AI algorithms.

The way in which a material reacts to certain forces can indicate if there is any structural damage present, as was observed by rotima [1] in his research.

In addition to identifying damage through analyzing how a material responds to dynamic forces, many researchers are also exploring methods for identifying damage by making updates to a material's finite element model.

Li [2] proposed a method for updating a material's model that combines cross-modal analysis with a Guyan reduction scheme.

Weber [3] suggests that, in order to prevent measurement errors from leading to inaccurate results, nonlinear model updates should be made on a regular basis when assessing damage to a material.

Link[4] evaluated the effectiveness of two different techniques for updating a material's model.

Reynders[5] suggested using an OMAX approach to address issues that arise when trying to identify the status of a material.

Xia [6]proposed an infrastructure method that involves extracting dynamic plasticity matrices from the natural vibration modes of the overall structure, and then updating these matrices directly using current model updating techniques.

Fang [7]developed a modification to a finite element model updating method that uses response surfaces to identify damage.

Xu [8]suggested using a probabilistic approach to detect damage.

Simoen [9]researchers studied the use of model updates to assess damage, taking into account uncertainty in the process.

Waeytens [10]suggested using a Bayesian method to enhance the updating technique.

Altun,şık [11]proposed an automated method for updating model parameters which accounts for the effects of multiple cracks

Pedram [12]used power spectral density in the context of updated damage models.

Nozari [13] studied how environmental vibration measurements affect model updating and failure analysis.

Lu [14]proposed using a sensitivity-based finite element model updating method to identify local defects in axially functionally graded beams.

Behmanesh [15]suggested a method to reduce the impact of modeling errors when updating a material's model. Pérez[16] proposed a technique for identifying damage by using damage submatrices.

Haeri [17] proposed a new method for structural health monitoring (SHM) of offshore jacket platforms.

Overall, identifying damage in a structure is a reverse problem that requires determining structural parameters based on the structure's response. Artificial neural networks (ANNs) have been used in a variety of applications because they can solve inverse problems that cannot be expressed using mathematical equations. Guo[18]utilized a back-propagation network to study the updating model of a suspended dome. They developed a method to improve the accuracy of the back-propagation network.

Mangalathu [19] proposed a multiparameter fragility methodology using an artificial neural network to create fragility curves specific to bridges without classifying bridges into categories.

Wang et al. [20] developed an Artificial Neural Network (ANN) to enhance the computational efficiency of structural collapse calculation.

Artificial neural networks can also be used for damage identification. Adams.[21] was the first to demonstrate the use of back propagation (BP) neural networks for damage detection in the 1970s.

Later, Tsou [22]used the absolute eigenvalues of a spring-mass system in neural networks and demonstrated the effectiveness of using neural networks for injury detection.

Sahin [23]applied neural networks to locate the damage position by analyzing changes in frequency and mode shape.

Lee [24]used back propagation neural networks to assess the difference between the model's behavior before and after structural damage in terms of parameter error in the model.

Pathirage [25]suggested a method that uses an autoencoder framework to support deep neural networks for damage identification.

Tan[26]proposed a vibration-based method for predicting damage and its location, using only the first vibration mode.

Ye [27]used artificial neural networks (ANNs) to analyze a large amount of training data (damage cases) to establish the relationship between the amount of training data and the accuracy of damage location.

Padil [28] suggested using non-probabilistic artificial neural networks (ANNs) to handle uncertainty in vibration-based damage detection.

Artificial neural networks (ANNs) have also been used in other research areas such as [29][30][31].

Structural health monitoring (SHM) methods can be used to identify damage in structures, but they are often

applied to onshore structures such as bridges and buildings, and the overall modal results of the structure are used as indicators of damage. Obtaining overall modal results from partially submerged offshore structures is difficult due to a limited range of sensor measurements. Therefore, it is desirable to predict structural damage based on sparse sensor measurements. This paper presents a method for detecting damage in offshore steel platforms.

Research breakthroughs introduce several innovations. Among them are a 3D model of a steel platform enabling thorough assessment of potential failures. Additionally, there's a technique capable of pinpointing failure extent and location, even at low levels like 5%, distinguishing itself from methods that merely note a component's failure. This approach is adaptable, applicable to similar steel platforms, and accompanied by a straightforward algorithm for easy development and implementation.

The proposed damage identification index and artificial neural network (ANN) method for damage identification are discussed in Section 2, and the process for recognizing damage in offshore structures is described in Section 3. The proposed method is used to recognize damage on a jacket platform with actual damage, and the research is concluded in the last section.

2. Material and methods

2.1. Damage Identification Index

For an n-dimensional arrangement collected of mass, spring, and damper, the dynamic behavior of the arrangement can be uttered as[32]:

$$M\ddot{x}(t) + C\dot{x} + Kx(t) = f(t) = B_1 u(t) \quad 1$$

Where $x(t)$ is the displacement at incessant time t ; M , C , and K are the mass, damping, and stiffness matrices, individually; $f(t)$ is the external force. The output vector $y(t)$ can be defined as[32]:

$$y(t) = C_a \ddot{x}(t) + C_v \dot{x} + C_d x(t) \quad 2$$

Where C_a , C_v , and C_d are the output matrices of acceleration, velocity, and displacement, $y(t)$ can be further expressed as[32]:

$$y(t) = Cs(t) + Du(t) \quad 3$$

Where $S(t) = \begin{pmatrix} x(t) \\ \dot{x} \end{pmatrix}$, $C = [C_d - C_a M^{-1} \quad C_v - C_a M^{-1} C_1]$

Is the production matrix, $D = C_a M^{-1} B_1$ is the direct transmission matrix. Equations (2) and (3) are rewritten to show the discrete-time state model as [32]:

$$S_{k+1} = A S_k + B u_k \quad 4$$

$$Y_k = C S_k + D u_k \quad 5$$

Where A is the discrete state matrix; B is the discrete input matrix; $s_k = s(kdt)$ is the discrete-time state vector; dt is the time interval; k is an integer.

The equation (4) presents a clear representation of a deterministic model, in which the input and output can be accurately determined. When taking into account the presence of noise, it is possible to demonstrate a combination of a discrete-time state-space model that encompasses both determinism and stochasticity[32].

$$S_{k+1} = A S_k + B u_k + w_k \quad 6$$

$$y_k = C S_k + D u_k + v_k \quad 7$$

Where w_k is the process noise produced by modeling error; v_k is the measurement noise caused by sensor error.

2.2. Damage ID Process

Artificial Neural Networks (ANNs) are highly proficient in identifying and understanding complex nonlinear relationships between multiple inputs and outputs. The fundamental design of a neuron is illustrated in Figure 1.

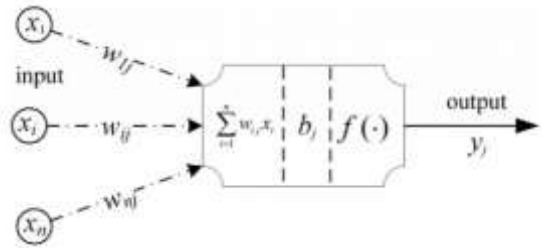


Figure 1: Schematic of the basic structure of a neuron. [31]

In Figure 1, x_n is the n th input signal, w_{nj} is the joining weight, b_j is the threshold value of the i th neuron, and y_j is the output signal of the i th neuron. The neuron output signal y_j is calculated by the activation function as follows:

$$y_i = f(\sum_{i=1}^n (w_{ij} x_i) - b_j) \quad 8$$

In a structural health monitoring (SHM) process, the system signals can serve as indicators of damage and the output signals can be the damage sustained by mechanical components. In this study, damage is applied to specific members to create distinct categories of damage. The damage inflicted on each member is the reduction of its cross-sectional area, simulating the corrosion commonly found on oil platforms in the Persian Gulf. The level of failure is determined based on specific intervals established for each member. The research aims to detect failure at levels 1 to 4 using this criterion. The BP neural network used is a multi-layer feed-forward network, and its basic structure is depicted in Figure 2.

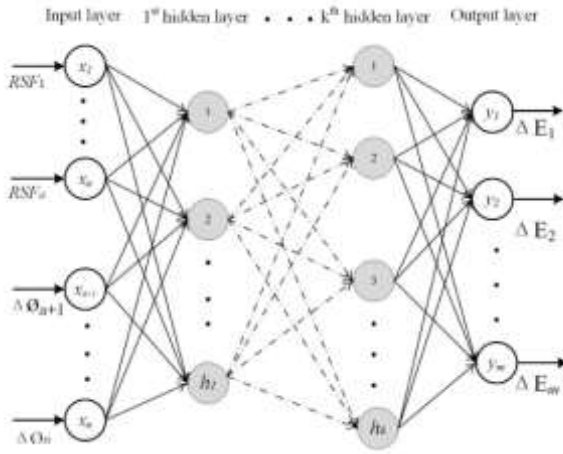


Figure 2: Structure of the BP network.[31]

The amount of nerve cell (n, m) and the hidden layer (k) are resolute based on the engineering tricky of attention. In our situation, the total number of injured elements and the total number of injury indices are known. The total number of units in the i th hidden layer (x_i) is determined by the following function:

$$X_i = N - 1 \quad 9$$

The initial values of the joining weights (w_{ij}) and thresholds (b_j) are set arbitrarily between -1 and +1. The training process involves repeatedly adjusting the w_{ij} and b_j based on the difference between the network's output and the desired output until the error falls within a certain threshold. One of the key features of Artificial Neural Networks (ANNs) is their ability to learn and adapt to problems through training. After sufficient training, the network can then solve similar problems it has not encountered before. This ability allows us to use the trained network to identify the primary damage based on the measurement results.

2.3. damage ID procedure

This research proposes a general procedure for identifying damage. The method is outlined in Figure 3, and it includes four main steps: finite element modeling, creation of training samples, training of neural networks, and prediction of structural damage. The first step involves creating detailed finite element models of offshore structures for specific projects. It is also necessary to determine the number of samples and the prediction precision (ϵ) in this step. In the second step, training samples are produced using the updated damaged model. As previously discussed in sections 2.1 and 2.2, the normalized mode shape can serve as a damage indicator (ΔU) and the training data is obtained from the modal analysis of the finite element model. The third step involves setting up neural networks using the training data and training them with the samples.

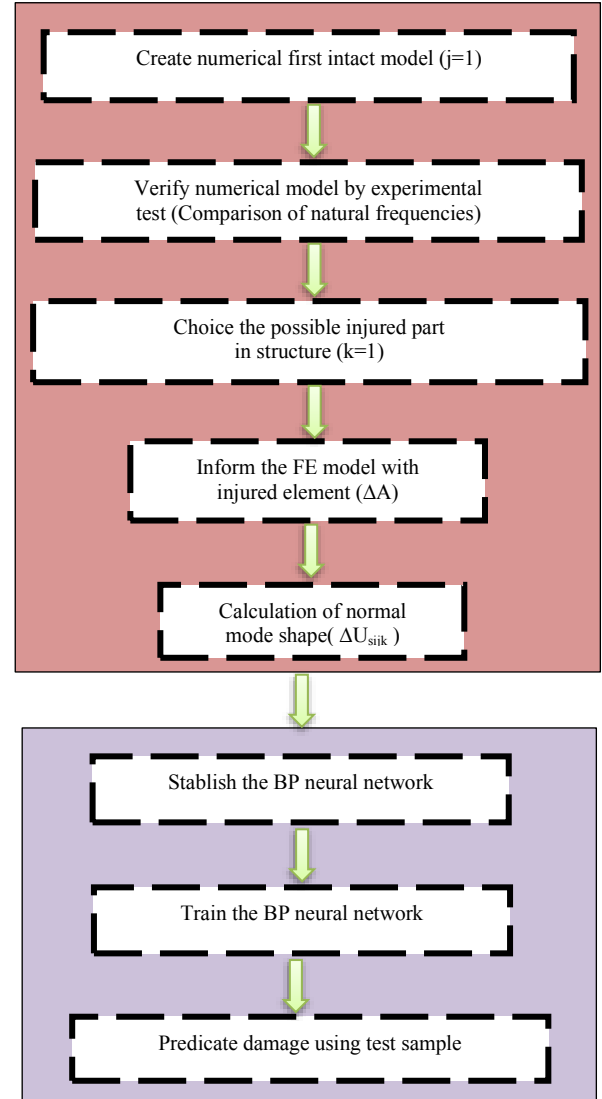


Figure 3: Analysis flowchart

2.4. Modal validation Modeling

A lab-scale model of an offshore jacket structure (referred to as the "lab-scale offshore jacket model" in this study) was used for the experimental portion of the research, as seen in Figure 4. The model was designed and set up in the Vibration and Modal Analysis Research Lab at the University of Tabriz [33]. The structure being studied is a jacket-type offshore platform model, as illustrated in Figure 4. The platform model is a welded-steel space frame with four main legs, reinforced with horizontal and diagonal members. All members are made of steel pipes, except for the top deck which is a steel plate. The following table lists the essential geometrical and material properties of the frame structure: Young's modulus (E) is a constant equal to 2.07×10^{11} Pa for all members. The main legs of the first story of the model have a diameter of 18mm with a pipe thickness of 2.5mm. The main legs of the other three stories of the model have a diameter of 14mm with a pipe thickness of 2.5mm. All the

horizontal braces have a diameter of 10mm(thickness of 2mm). All the diagonal braces in the vertical plane have a diameter of 8mm (thickness of 1.5mm). All the diagonal braces in horizontal planes are solid bars with a diameter of 10mm. The deck is a steel plate of 20mm thickness.

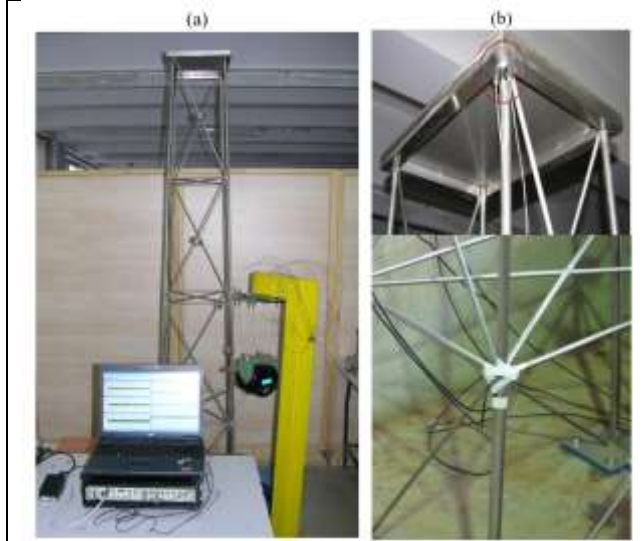


Figure 4:(a) modal testing and tested three-dimensional, (b) Installed accelerometers and sensor position

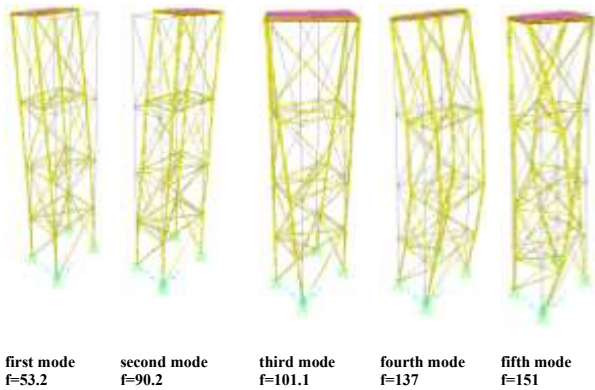


Figure 5:modal analysis results

Given the minimal distortion and linear behavior of the system, an initial 3D Finite Element (FE) model of the offshore steel jacket structure (referred to as the "FE offshore jacket model" in this article) was developed using the software SAP2000. The resulting FE offshore jacket model, in its undamaged state, is shown in Figure 6

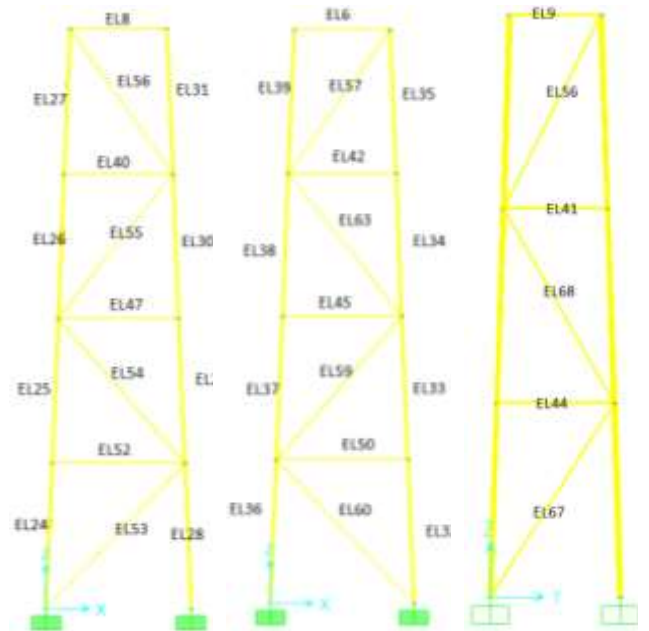


Figure 6: Naming the elements of the simulated platform

The material properties for all members are detailed in Table 1. The joint connections are assumed to be rigid. The clamp boundary condition is applied to the bottom of the structure. All model members were meshed with two-node linear beam elements (type B31) to account for transverse shear distortion. Table 2 compares the four main frequencies of the constructed numerical model with the numerical modes obtained from the laboratory model. The results have an error of less than 10%.

Table 1: Material characteristics considered in the numerical model		
No.	property	value
1	E	200 GPa
2	poisson ratio	0.3
3	density	7800 kg/m ³
4	modal damping ratio	0.01

Table 2: the first five natural frequencies			
Model no.	Natural frequencies(Hz)		Difference(%)
	Numerical Analysis	Experimental Result	
1	53.2	58.34	8.81
2	90.2	94.13	4.17
3	101.1	106.21	4.81
4	137	130.28	5.15

2.5. Failure factors

A variety of factors such as corrosion, ship impact, damage caused by severe storms and earthquakes, fire, explosions and terrorist attacks can cause damage to offshore platforms. Among these, corrosion is the most significant and ongoing issue that affects all marine platforms. It is the primary factor that alters the structural characteristics and behavior of platforms that have been in operation for an extended period.

3. Result and discussion

3.1. Damage scenario

As shown in Figure 5, the structure consists of 52 members which are located on four different floors. These members include 16 columns, 16 main beams, 4 secondary beams and 16 wind braces. The study creates damage scenarios based on two cases of damage, one where a single member is affected, another where two or more members are damaged in different ways.

3.2. Failure of a single member

The first scenario considered is the individual failure of a member, which can be caused by corrosion, ship collision or other factors. It was assumed that each of the 52 members of the structure lost between 0 and 20% of their area, one by one. In this scenario, the mode and mode shape analyses were calculated for the first five modes of the structure.

The number of mode shapes used for Structural Health Monitoring (SHM) depends on several factors, including the size and complexity of the structure, the type and location of potential damage, and the accuracy and resolution of the measurement system.

In general, a larger number of mode shapes can provide more detailed information about the structure and may improve the accuracy of damage detection. However, using too many mode shapes can increase the complexity and computational cost of the analysis, as well as the potential for noise and measurement errors [27] [28][29][30][31].

Therefore, the optimal number of mode shapes for SHM depends on a trade-off between the level of detail required and the practical limitations of the measurement and analysis system. Typically, a small number of mode shapes, such as the first 1-10, may be sufficient for most practical SHM applications. However, this number can vary depending on the specific structure and the intended purpose of the monitoring.

In general, the first few mode shapes of a structure are considered to have a greater impact on the overall behavior of the structure compared to the higher mode shapes. This is because the lower modes typically correspond to the dominant vibration patterns and have higher participation factors, meaning that more of the mass of the structure is involved in the mode shape.

The first mode shape, also known as the fundamental mode, typically has the largest amplitude and is the mode with the lowest frequency. This mode corresponds to the overall motion of the structure as a whole, and any changes in this mode shape can indicate significant damage or degradation of the structure.

For each member in the failure scenario, 20 analyses were performed, with 16 analyses used for network training and 4 analyses for testing. This resulted in a total of 1200 analyses performed in this section. The members then entered the training process for further validation, with comparisons ranging from 4 members to 16 members to reduce errors.

Error! Reference source not found.-a compares the first and second-floor braces included in a training process. As it is known, with an average error of 15%, the damaged member was identified. **Error! Reference source not found.-b** is also all the wind brace types located on the third and fourth floors. Due to the proximity to the water level and the surf zone, these members have a high probability of failure and only 5% error in identifying their location. **Error! Reference source not found.-c** shows a combination of windbreaks from different floors. The identification error rate in these classes is reported to be 30%. **Error! Reference source not found.-d** shows four columns in the same direction and on different floors. The accuracy of failure detection in these members was 90%. **Error! Reference source not found.-e** examines four sub-beams of four different floors. These sub-beams are each placed as a stiffener on one floor of the platform structure. The accuracy of detecting the failure location in this analysis was 70%. In Figure 7-a, the columns of the fourth floor have been examined, and 100% detection has been done. The fourth floor is the most important part in protecting against corrosion due to its location outside the water area. Also, in Figure 7-b, all the windbreaks of the fourth floor have entered the training process, and 100% recognition accuracy has been obtained performance diagrams for the injured neural network are obtainable in Figure 8. The performance limitation monitored is the mean squared error, which is 0.039206 at the best network.

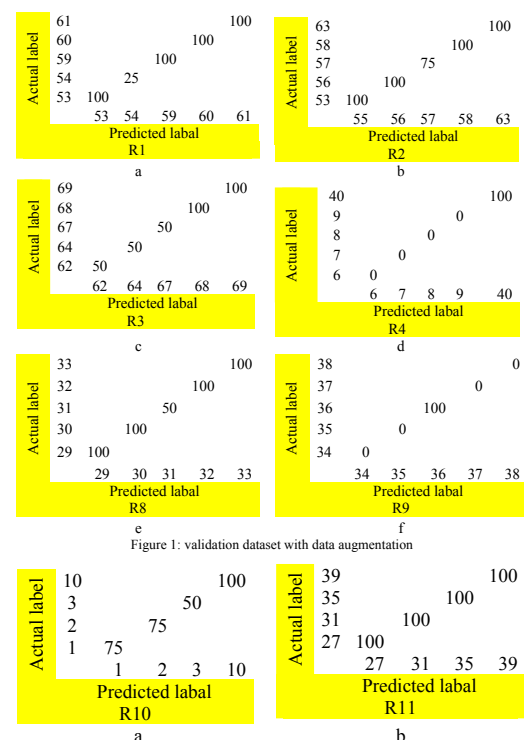


Figure 7: validation dataset with data augmentation

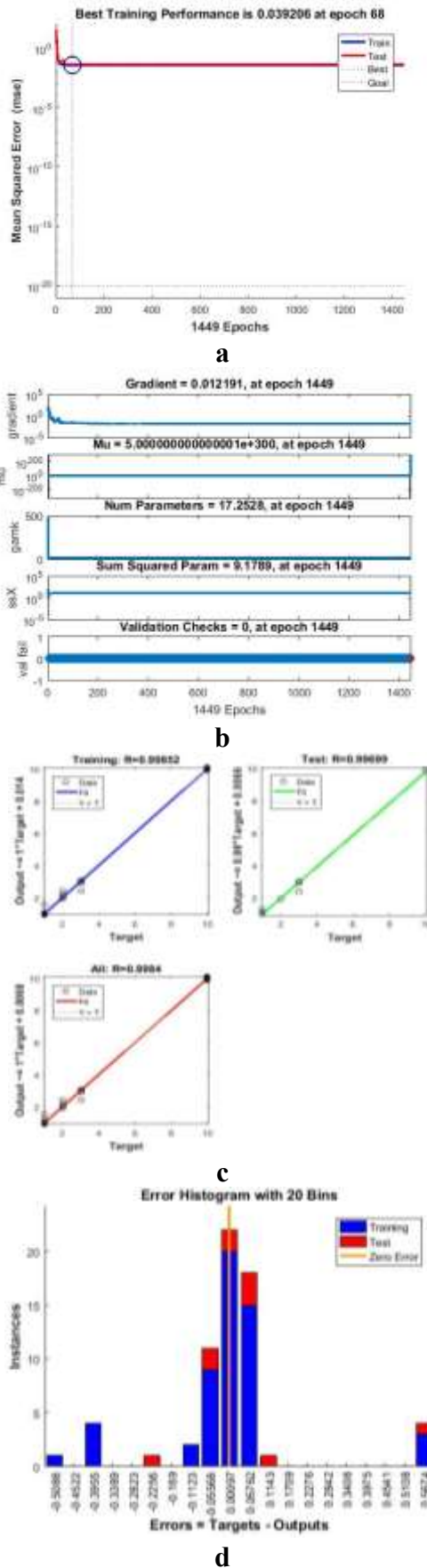


Figure 8 -Performance graph of damage localization

Figure 9 compares the effect of floor and member on failure detection accuracy. As it is apparent in the figure, the secondary beams have the most accuracy in

detecting failure, and the main beams have the least accuracy in detecting failure. Also, the difference in failure detection in different classes is not high.

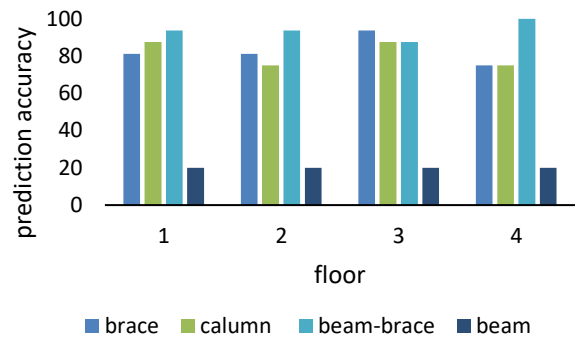


Figure 9: Comparison of average failure detection in different members

Figure 10 compares members for the fourth floor, which is very important. As it is known, the columns have the most accuracy in damage allocation, followed by wind braces. The main beams of the structure have also entered this process with very little precision.

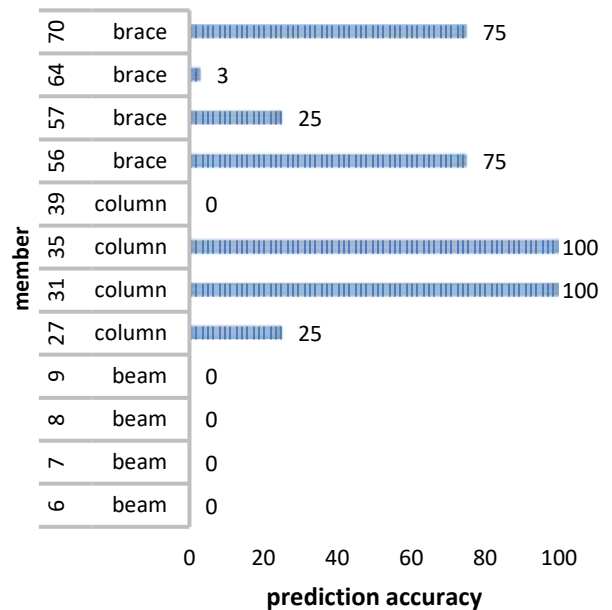


Figure 10 Comparison of all components of the fourth floor

3.3.Failure in two members at the same time

In another scenario, we create failure in two members of the fourth floor, and according to the previous section, we randomly create 20 accidental failure rates between 20% and 0% for each sample and then perform the relevant analysis. In this research, the following element numbers have been selected as samples, as shown in f and Figure 12

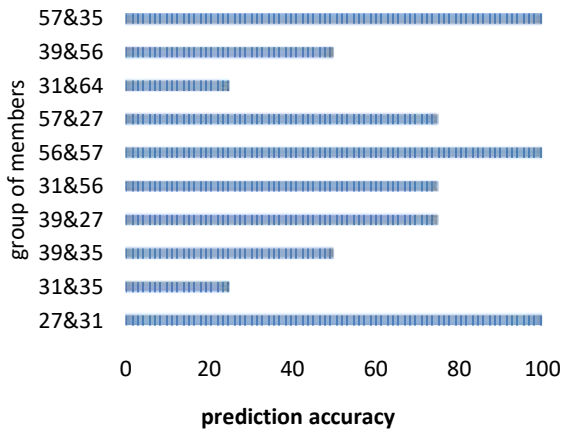


Figure 11: Comparison of average failure detection in different members-two member

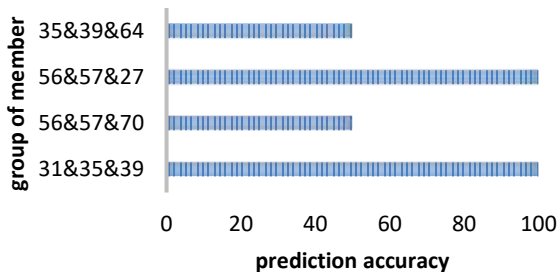


Figure 12: Comparison of average failure detection in different members-three member

4. Conclusion

This research focuses on the use of Artificial Neural Networks (ANNs) for modal-based damage identification in offshore structures. The damage identification approach is based on modal shape and utilizes AI methods and principal component analysis for feature extraction. Numerical studies were conducted on simplified prototypes of offshore structures to evaluate the proposed damage identification procedures. The study considered challenging conditions with a limited number of sensors. The research provides a damage identification process suitable for jacket-type offshore platforms. The main conclusions of this research are:

(1) A neural network-based quantitative structural damage identification method is proposed, and the case study of a jacket-type offshore platform shows that this technique can effectively identify physical damages of different components.

(2) The new method presented in this research can determine the location and approximate extent of the failure through the first five modes, which can be obtained in various ways. This method is effective in detecting local losses and can detect small and localized damages before they cause further damage, in contrast to traditional methods which can only predict complete removal of a member.

(3) The results show that the proposed method has a high accuracy for identifying failures in columns on different floors, secondary beams, and windbreaks. However, due to the small effect of main beam failures on the stiffness of the offshore structure, the method did not yield satisfactory results. It is worth noting that using structural frequency instead of modal shape and deep learning methods instead of traditional methods would be more suitable for identifying main beam failures.

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Identification and Ranking of Factors Affecting Government Investment in Iranian Ports within the Framework of the Blue Economy: A Fuzzy Delphi Approach

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ABSTRACT

Government investment in ports, as one of the main pillars of maritime transport infrastructure development, plays a vital role in strengthening economic growth and enhancing the country's position in the blue economy. The aim of this study is to identify and prioritize the factors influencing government investment in Iranian ports within the framework of the blue economy. To this end, the Fuzzy Delphi method was employed, and data were collected and analyzed based on the opinions of experts in the fields of economics and maritime transport. The results revealed ten key factors influencing government investment in ports, among which "government revenue status" and "its financial capacity with an emphasis on dependence on oil and tax resources" play the most critical roles. Other influential factors include the volume of maritime trade and global demand, the quality and extent of domestic transport infrastructure, government economic policies, the geographical location of ports, the intensity of regional competition, the level of technology and automation, security and safety requirements, the level of foreign investment attraction, and attention to environmental sustainability. The findings indicate that government investment in ports, in addition to macroeconomic variables, is also affected by institutional, regional, and environmental factors. Accordingly, strengthening the government's financial sustainability, developing transport networks, leveraging geopolitical advantages, and enhancing technological capabilities can pave the way for the sustainable development of Iranian ports and their more effective contribution to the realization of blue economy objectives.

1. Introduction

Seas and coastal areas have always been recognized as one of the most important foundations of economic, social, and environmental development worldwide. International statistics indicate that today more than one-third of the world's population lives within 60 kilometers of the coasts, and over two-thirds of the world's major cities are located in coastal regions. In

addition, more than one percent of the global active population is directly employed, and about three percent are indirectly engaged in sea-related economic sectors. The contribution of the ocean economy to global GDP is estimated at about 2.5 percent, while nearly 80 percent of international trade is carried out through maritime routes. These figures clearly demonstrate that the sea functions as a driving engine of the global economy, playing a key role in growth,

job creation, and international economic interactions [1].

Iran, with over 5,800 kilometers of coastline along the Persian Gulf, the Sea of Oman, and the Caspian Sea, possesses enormous potential in the field of the blue economy. Despite this unique geopolitical position—which makes Iran a strategic bridge between Asia and Europe and a central passageway for international North–South and East–West corridors—the country’s share of the maritime economy remains far below its potential. While more than 90 percent of Iran’s foreign trade is conducted by sea, only about 10 percent of its population resides in coastal areas. In leading maritime economies such as China and Vietnam, the share of the marine-based economy in GDP ranges between 20 and 50 percent, whereas in Iran this share is estimated at only around 10 percent. According to available statistics, Iran accounts for roughly 1 percent of the global maritime economy excluding oil and gas resources, and about 2.5 percent when these resources are included. These figures clearly indicate that the vast majority of Iran’s aquatic and marine capacities have yet to be utilized [2].

Beyond trade and transport, the blue economy encompasses diverse dimensions such as fisheries, marine tourism, renewable energy, aquaculture, the use of saline water in agriculture, and seawater desalination. Estimates in the European Union show that in 2014 alone, more than 3.36 million people were employed in these sectors. Moreover, each direct job created in the blue economy generates, on average, four additional indirect jobs in other sectors. This enormous potential for employment and value creation has made the blue economy one of the key drivers of sustainable development across the world. In Iran, however, coastal exploitation has been largely limited to port and military facilities, leaving a significant portion of coastal capacities—about 95 percent—underutilized [3].

At the same time, Iran is located within the global arid belt and faces severe freshwater resource limitations. Under such conditions, the use of seawater for agriculture, the cultivation of salt-tolerant plants, and the development of marine-based industries can serve as fundamental strategies for employment generation, food security, and diversification of the national economy. In many countries, seawater desalination as well as the cultivation of algae and halophytes have already become important sources of exports. Thus, a stronger focus on the blue economy could help Iran

transition away from a single-product, oil-dependent economy [2].

Despite these capacities, multiple challenges hinder the development of Iran’s maritime economy. The shortage of modern port infrastructure, the aging of the maritime transport fleet, the lack of advanced logistics technologies, and intensifying regional competition are among the most significant obstacles. In this context, government investment in ports emerges as one of the most effective tools to overcome these challenges and leverage existing opportunities. Such investments not only enhance transport infrastructure and port facilities but also create the necessary conditions for attracting private and foreign investment, thereby paving the way for sustainable development and strengthening Iran’s position in the global blue economy [2].

Accordingly, this study employs the Fuzzy Delphi method to identify and prioritize the factors influencing government investment in Iranian ports, aiming to provide a comprehensive picture of the economic, institutional, technological, regional, and environmental elements that determine such investments, and to propose policy recommendations for improvement in this domain.

2. Theoretical Framework and Literature Review

2.1. Theoretical Framework

2.1.1. History and Concepts of the Blue Economy

The concept of the blue economy emerged in the 1990s in response to global concerns about sustainable development. Its turning point was the United Nations Conference on Environment and Development in 1992, which emphasized the protection of marine resources. In subsequent decades, meetings such as the Johannesburg Summit (2002) and the Rio+20 Conference (2012) highlighted the role of ocean-based economies in poverty reduction and environmental protection. Since 2009, the concept has been incorporated into policy discussions and gradually attracted the attention of institutions such as the U.S. Congress, the World Bank, and the United Nations. Gunter Pauli played a significant role in developing this idea through his book *The Blue Economy: 10 Years, 100 Innovations, 100 Million Jobs*. Furthermore, Goal 14 of the United Nations Sustainable Development Goals (SDGs) is specifically dedicated to the sustainable use of oceans. In recent years, the European Union, the African Union, and small island developing states have embraced the blue economy as a key

strategy for resilience and economic growth [4, 5, 6, 7, 8].

Throughout history, the sea has always been one of the fundamental pillars of human civilization's economic activities—both as a rich source of food supply and as a strategic route for the transport of goods and intercontinental trade. This vital and enduring role is evident across all historical periods and provides the foundation for the emergence of modern concepts such as the blue economy. In recent years, the term has gained a central position in global policymaking and has evolved into a concept associated with the sustainable exploitation of marine resources, grounded in the protection of oceans and coastal areas within the framework of sustainable development goals. The main objective of this approach is to achieve economic growth, improve quality of life, strengthen social inclusion, and generate employment without compromising the environmental sustainability of marine resources. Since these resources are limited and vulnerable to degradation due to human activities, scientific research into the blue economy often requires attention to overlapping and related concepts. Lee et al. (2020) note that “the blue economy has been interpreted in various ways and is often used interchangeably with terms such as ‘ocean economy’ or ‘marine economy’ without clear distinctions.” Other studies also demonstrate that terms such as Ocean Economy (OE), Marine Economy (ME), and Blue Growth (BG) have been used synonymously or complementarily [9].

2.1.2. Dimensions of the Blue Economy

In contemporary research, the blue economy is generally considered a multidimensional concept encompassing six main dimensions. Each dimension is based on principles and practices aimed at ensuring the sustainable use of ocean resources for the benefit of both present and future generations [10, 11].

- **Economic Dimension**

The economic dimension of the blue economy addresses economic growth and development within the framework of sustainability. It covers a wide range of activities, including fisheries, aquaculture, marine biotechnology, coastal and marine tourism, maritime transport, and renewable energy. The principles of this dimension focus on creating value from marine resources, fostering innovation, and developing sustainable

business models that support local communities.

- **Social Dimension**

The social dimension ensures the equitable distribution of benefits derived from marine resources among all stakeholders. It encompasses issues such as human rights, labor standards, gender equality, and community development. Its principles emphasize participation, engagement with local communities, and consideration of the social impacts of economic activities.

- **Environmental Dimension**

The environmental dimension addresses the protection of the health and integrity of marine ecosystems. It includes biodiversity conservation, climate change mitigation and adaptation, pollution prevention, and ecosystem-based management. Its principles ensure that economic activities do not undermine the ecological sustainability of marine resources.

- **Technological Dimension**

This dimension focuses on the development and application of innovative technologies to support sustainable ocean-based economic activities. It spans areas such as marine robotics, sensors, artificial intelligence, renewable energy technologies, and biotechnology. The principles emphasize innovation, technology transfer and dissemination, and the responsible use of emerging technologies.

- **Cultural Dimension**

The cultural dimension highlights the recognition and preservation of cultural heritage and traditional knowledge related to ocean resources. It covers activities such as traditional fishing, seafaring, storytelling, and cultural tourism. Its principles focus on respecting cultural diversity, acknowledging cultural aspects of marine resources, and promoting cultural exchange and cooperation.

- **Governance Dimension**

The governance dimension concerns the establishment of effective governance

mechanisms for the sustainable management of ocean resources. It involves institutional frameworks, policy coordination, and stakeholder participation. The principles emphasize transparent, participatory, and accountable governance structures that support the sustainable use of ocean resources.

3.1.2. The Role of the Blue Economy in the Global Economy

According to the UNCTAD (2024) report, ocean-related economic activities have grown at a faster pace than other sectors globally. The Ocean Economy Index increased by approximately 2.5 times between 1995 and 2020, surpassing the global average growth rate. This expansion has been primarily driven by the development of trade and innovation in this domain.

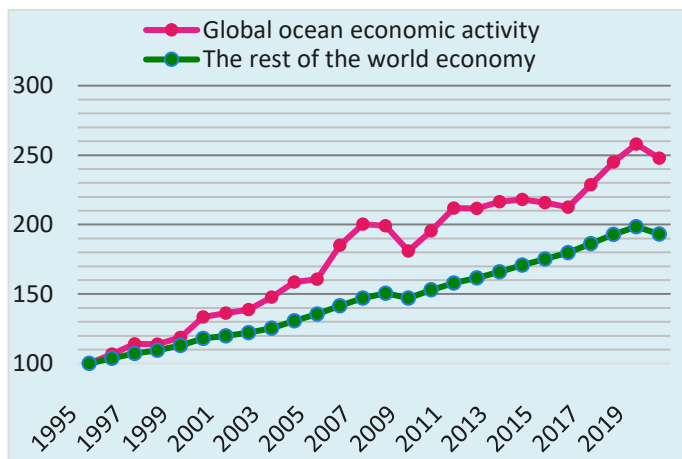


Chart 1. Growth of the Ocean Economy Compared to the Global Economy (1995–2020) [12]

In 2023, the volume of global trade in marine goods and services reached record levels of USD 899 billion and USD 1.3 trillion, respectively, highlighting the growing importance of ocean-related activities for coastal and island nations. The fisheries sector alone currently supports the livelihoods of about 600 million people, predominantly in developing countries.

Despite this remarkable economic growth, the blue economy also faces significant environmental challenges, some of the most critical of which include [13]:

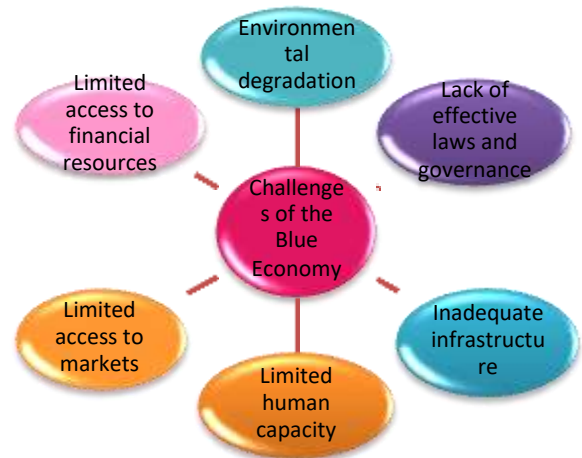


Figure 1. Challenges of the Blue Economy [13]



4-1-2. The Blue Economy within the Framework of Sustainable Development

The importance of oceans for sustainable development has been widely emphasized by the international community through instruments such as Agenda 21, the Johannesburg Plan of Implementation, the Rio+20 Outcome Documents, and the 2030 Sustainable Development Goals (SDGs). Among these, the United Nations Convention on the Law of the Sea (UNCLOS) of 1982 and its implementing agreements have established the international legal framework governing ocean-related activities, playing a strategic role in fostering global cooperation. In global literature, the Blue Economy has been introduced as a novel framework for sustainable economic development that integrates three main pillars: economic growth, environmental protection, and social equity [14].

This concept emphasizes high efficiency, low carbon emissions, and ecological cleanliness, focusing on the optimal use of marine natural resources within ecological limits and seeking to decouple development from environmental degradation. The Blue Economy

refers to resource-based development that aims to enhance human well-being and achieve social justice while simultaneously reducing poverty, environmental risks, and ecological constraints. It is closely aligned with the principles of the Green Economy and traces its origins to the United Nations Conference on Sustainable Development, where the idea of an “ocean economy” or “blue economy” was first articulated as a means to decouple socio-economic growth from environmental harm [15].

Broadly, the Blue Economy highlights the sustainable use of oceans and related resources for economic development while preserving ecosystems. It is defined as an ocean-based economic model that leverages green infrastructure, advanced technology, innovative financial mechanisms, and enabling institutional regulations to achieve ocean and coastal conservation goals while enhancing their contribution to sustainable development. These contributions include improving human well-being, reducing environmental risks, and addressing ecological deficits [16].

The Blue Economy has been explicitly recognized as the core subject of Sustainable Development Goal 14 (SDG 14) — “Life Below Water”, which calls on countries to conserve, sustainably use, and develop marine and ocean resources. Furthermore, it is directly or indirectly linked to at least ten other SDGs out of the seventeen, which are listed below.

Figure 2. Sustainable Development Goals Related to the Blue Economy

In a more comprehensive report by the United Nations, the potential linkage between the Blue Economy, sustainable development, and economic growth has also been recognized within the framework of the UN 2030 Agenda for Sustainable Development. In particular, the concepts of “Blue Growth” and a “Green Economy in a Blue World” are aligned and mutually reinforcing, strengthening the achievement of one of the United Nations Sustainable Development Goals — SDG 14, which focuses on the conservation and sustainable use of oceans and marine resources for sustainable development.

5-1-2. Government Investment in Ports

Government investment refers to the allocation of financial resources by the state for the creation, development, and operation of public infrastructure, which directly or indirectly contributes to economic growth [17]. In the port sector, government investment includes the construction and improvement of port infrastructure, development of terminals,

transportation equipment, and enhancement of logistics systems [1⁸]. Investment in economic infrastructure, particularly ports, has been identified as a key driver of economic growth. According to endogenous growth theory, investment in infrastructure that increases productivity can lead to sustainable economic growth because such investments generate positive externalities that improve the efficiency of the overall economy [1⁹].

Aschauer, in his theory of public infrastructure, also demonstrates that government investment in physical infrastructure — including maritime transport and ports — plays a significant role in boosting productivity and GDP [1⁹]. Ports, as critical nodes in global supply chains and international trade, facilitate the flow of goods, reduce transportation costs, and attract private investment [1⁹]. Therefore, government investment in ports, especially in developing economies, can indirectly stimulate exports, improve the trade balance, and ultimately support economic growth [1⁹].

Economic literature emphasizes the critical role of transportation. Adam Smith (1776) argued that: “Through waterborne transport, a broader market (compared to land-based transport alone) is opened to all types of industries, allowing industries to grow and develop by leveraging navigable rivers and coasts.” Button (2010) notes that classical economists believed transportation has a positive effect on economic development, whereby increased production can be directly linked to improved transport systems. Rosenstein-Rodan (1943) highlighted that investment in transport infrastructure is one of the main avenues for realizing the Big Push theory. A broader perspective by Anderson and Sturmquist claims that all major transitions in European economic systems began with, or were at least accompanied by, changes in transportation and communication infrastructure. Efficient transport lowers movement costs, enabling many activities to access wider markets and benefit from economies of scale. Similarly, Owen (1964) argued that expanding domestic markets through advanced transport services is a prerequisite for national economic development. Moreover, most developed countries are reliant on international trade due to geographic, economic, and historical reasons, making the improvement of trade a necessary condition for growth. From this viewpoint, providing efficient port facilities can contribute significantly to development.

The impact of a port as a critical transport infrastructure on regional economic growth can be analyzed from two perspectives. The first considers the various effects of

a port on the regional economy during different stages, from construction to full operation. The second examines potential interactions between the port and the regional economy from a macro perspective. Specifically, from the first perspective, transport infrastructure can have different effects at different operational stages. Button (2010) categorizes these effects into four types:

- **Primary effect:** The initial additive effect stems from income generated during the construction of facilities and has a multiplicative nature. Its magnitude depends on the proportion of this income absorbed by the local economy.
- **Secondary effect:** Once a transport infrastructure becomes operational, income is injected into the local economy through directly employed staff and activities utilizing the facilities. This income subsequently generates multiplier effects on the regional economy.
- **Tertiary effect:** The third additive effect, often highlighted in development economics, relates to economic activity attracted to the region due to the infrastructure, as well as successive ripple effects resulting from income injection. These regional economic effects can be sustainable.
- **Final effect:** While the tertiary effect is frequently emphasized, an efficient infrastructure can substantially shift the regional production function upward, fundamentally transforming the regional economy. For example, islands in the Caribbean and Mediterranean, whose economies were traditionally based on fishing and agriculture, have fully transitioned to tourism-driven economies following the construction of major airports [۲۲].

In Iran, given its strategic geographical position along international corridors, port investment can act as a driver of economic growth [۲۳]. Ports, as gateways for the import and export of goods and passengers, play a crucial role in developing a sea-based economy. Their efficiency and productivity are directly linked to the quality of equipment and infrastructure. Ports facilitate trade, reduce transport costs, boost exports and imports, and create employment.

Governments typically invest in areas where the private sector shows less inclination due to high costs or low returns. In Iran, the government has played a significant role in port development by financing port infrastructure and providing facilities to the private sector [۲۴]. Such investments not only support international trade but also generate employment, attract foreign investment, and increase foreign exchange earnings [۲۵]. In recent years, the Iranian government has developed multiple plans for port development; for instance, the expansion of Shahid Rajaei Port through public investment and private sector participation represents a key project in this area [۲۶]. However, challenges such as economic sanctions, limited financial resources, and managerial weaknesses have negatively affected the effectiveness of these investments.

2-2. Literature Review

In this section, domestic studies are first reviewed, followed by international research, to provide a comprehensive overview of previous scholarly efforts.

• Domestic Studies

Salarvand et al. (2024) conducted a study titled “Factors Affecting the Components of the Blue Economy and Their Impact on Sustainable Economic Growth” using the ARDL model. They found that key components of the blue economy, including total fisheries production, agricultural value-added, forestry and fisheries, coastal tourism, maritime transport, and trade value-added, have a significant positive impact on Iran’s economic growth. In contrast, government investment in ports did not show a significant effect, likely due to insufficient efficiency or the delayed return on such investments [۲۴].

Bik-Mohammadi, Bazzazan, and Khoshdil (2024), in the article “Conceptual Framework of Marine Advancement,” defined the concept of *marine advancement* across five main dimensions: economic, socio-cultural, environmental, scientific-technological, and security, based on sea-centered governance. The study emphasized the role of this discourse in guiding national policymaking in maritime affairs [۲۵].

Hasanvand and Salarvand (2024), in a research titled “A Review of the Role of the Marine Economy in the Development of Selected Countries,” examined the experiences of leading countries such as Norway, China, the European Union, Australia, the United States, and small island nations. They explored challenges arising from climate change, environmental

pollution, and financial constraints. Their findings indicate that despite serious challenges, significant opportunities exist in the development of marine renewable energy, sustainable fisheries, and marine tourism, which can serve as tools for sustainable economic growth [٢٦].

Khamr and Khodestan (2024), in a study titled “Sea-Oriented Economy of Bandar Abbas Coastal Areas,” demonstrated that a sea-based economy, by diversifying economic activities, can strengthen regional growth and reduce dependency on oil-based economic activities. Additionally, the study highlighted that neglecting the culture of maritime utilization poses a significant barrier to sustainable development [٢٧].

Elmi et al. (2023) investigated the impact of port development on the economic growth of host regions using data from six provinces — Sistan and Baluchestan, Khuzestan, Bushehr, Hormozgan, Gilan, and Mazandaran — for the period 2005–2017. The results showed that port operational capacity, human development, initial economic growth rate, employment, government investment in ports, government current budget, wages, technology, production structure, and urbanization had significant positive effects, whereas transportation costs had a significant negative impact on provincial economic output [٢٨].

Hoseinpour and Tabaeizadeh (2022), in their study “Examining the Causal and Structural Relationship between Port Development and Economic Growth: A Cross-Country Study,” addressed the debate on the diminishing role of ports in economic development. They analyzed the impact of ports on production and economic growth across 122 countries from 2004 to 2021. The study employed Dumitrescu-Hurlin causality tests for heterogeneous panels, along with various panel regression estimations. The liner shipping connectivity index was used as a measure of port development. Results indicate that a bidirectional causal relationship between port development and economic growth cannot be rejected. Regression analyses further revealed that port development continues to have a significant impact on countries’ economic growth [٢٩].

In another study, Hoseinpour (2022) in “Measuring the Spillover Effects of Ports on Economic Growth in Iran: A Spatial Econometric Analysis” measured the spillover effects of ports on economic growth in Iran using spatial econometrics for 23 non-coastal and 7 coastal provinces during 2005–2013. The results

showed that over the nine-year period, port performance positively affected the GDP of coastal provinces; however, spillover effects on non-coastal areas were negative, indicating that an increase in port performance in a specific region tends to reduce GDP in other regions [٣٠].

Saidi and Moradpour (2013) examined the role of ports in the country’s economic development process. They argued that Iranian ports have the potential to shift from a warehouse-based system to an order-based system, in which ports play a more active role in the transportation chain. Additionally, Ehsanifar (2015) investigated the impact of implementing a transit enhancement strategy via Chabahar Port on local development. The study found a significant positive relationship between employment generation, social security, and transit activities [٣١].

• International Studies

A study conducted by Danio et al. (2025) examined the role of the blue economy in strengthening Indonesia’s economic growth, emphasizing the importance of sustainable management of marine resources. The research particularly focused on sectors of the blue economy with high potential for innovation and economic growth, including marine biotechnology, which contributes to the development of new products and technologies. Additionally, environmentally friendly maritime transport helps reduce the ecological impacts of shipping and supports broader sustainability goals. The study underscores the need to integrate sustainable practices across different marine sectors to balance economic growth with environmental conservation [٣٢].

He et al. (2025), in the article “The Role of the Blue Economy and Green Economy in Economic Growth: Evidence from Pakistan,” empirically examined the impact of blue economy and green economy factors on Pakistan’s economic growth during 1990–2019. The findings indicate that both blue economy and green economy components have significant positive effects on Pakistan’s economic growth. These results highlight the importance of leveraging marine resources and renewable capacities in macroeconomic policymaking, providing empirical support for enhancing Pakistan’s economic performance through sustainable development [٣٣].

Khan and Iman (2024), in the article “Systematic Assessment of Blue Economy Potential: Strategies for Developing International Trade in Bangladesh within the Indo-Pacific Region,” analyzed the structural

capacities, key stakeholders, policies, technological advancements, investment trends, and trade in various blue economy sectors in Bangladesh. The study concluded that the blue economy offers substantial potential for economic growth, social progress, and environmental sustainability in the region; however, challenges such as regulatory complexities, inadequate infrastructure, and environmental damages require serious attention and coordinated actions among governments, private sectors, and development organizations [۳۴].

Sarker et al. (2018) investigated the realization of blue economy development in Bangladesh by examining economic value as well as opportunities and challenges faced by the country's marine areas. They collected data and engaged in discussions with stakeholders in an exploratory study aimed at achieving sustainable water-based economic development [۳۵].

Rahman (2017) studied the blue economy in the Bay of Bengal and identified the Bay as a strategic and economic actor for Bangladesh. The research suggests that, through effective regional and oceanic development efforts, the Bay can generate significant economic, security, and environmental benefits for the country [۳۶].

Park and Seo (2016) examined the impact of ports on regional economies in South Korea. Their estimates indicated that the depreciation rate had no significant effect on port performance or GDP; however, physical capital had a significant positive effect. Specifically, a 1% increase in the ratio of physical capital to revenue resulted in a 0.1185% increase in port output [۳۷].

Shan et al. (2014) explored the economic effects of port cities, finding that port activities had a significant positive impact on urban economic growth. A 1% increase in port activity was associated with a 0.065% increase in the city's economic growth [۳۸].

Bottasso et al. (2014) studied the impact of port activities on local development. Their results indicated a direct effect (the impact of a port's performance on the GDP of the same port) of 0.003, meaning that a 10% increase in port performance led to an average 0.03% increase in the port's GDP [۳۹].

3. Research Methodology

In this section, the data analysis approach is presented according to the mixed-method research design, distinguishing between the qualitative and quantitative components. In the first phase, the qualitative section

utilized content analysis with the aid of Atlas.ti software. Using an open coding approach, interviews conducted with experts were analyzed to identify the factors influencing government investment in ports. In the second phase, the fuzzy Delphi method was employed to achieve consensus on the identified factors.

3-1. Fuzzy Delphi Approach

The fuzzy Delphi method, an extension of the classical Delphi in management science, was first proposed by Kaufman and Gupta [۴۰]. The Delphi method is one of the most effective techniques for converging expert opinions. Through a structured, multi-stage process using questionnaires, the method collects expert opinions, provides feedback, and iteratively repeats the process until consensus is reached. This method is particularly valuable for decision-making and achieving consensus on objectives or parameters that are not clearly defined. A key feature of this method is that it provides a flexible framework, addressing many challenges related to lack of precision or clarity. In essence, Delphi is a systematic approach for eliciting expert opinions on a specific topic or question [۴۱].

The fuzzy Delphi method represents a robust, group-based process. It is particularly applied when complete or certain knowledge is unavailable, aiming to achieve group consensus among experts. In this method, experts' opinions are expressed as precise numbers, while they rely on subjective judgment, reflecting the inherent uncertainty of the situation. The probabilistic nature of this uncertainty aligns with fuzzy sets; therefore, it is preferable to collect data in natural language from experts and analyze them using fuzzy sets [۴۲]. Consequently, the integration of the traditional Delphi approach with fuzzy set theory was proposed. In this method, membership functions are used to represent experts' opinions. In practice, the fuzzy Delphi method structures group communication in such a way that participants can challenge the issue at hand. Implementing this structured communication requires feedback on individuals, evaluation of group judgment, opportunities for revising viewpoints, and a degree of anonymity [۴۳]. The main objective of the fuzzy Delphi method is to achieve the most reliable group consensus among experts on a specific topic, which is accomplished through repeated questionnaires and feedback [۴۴]. The implementation stages of this approach are illustrated in Figure 3.

Figure 3. Implementation Algorithm of the Fuzzy Delphi Approach [۴۵]

The main advantage of the Fuzzy Delphi method compared to the traditional Delphi is that it allows for a stage dedicated to summarizing and screening variables within the indicator screening process. Therefore, the steps of the Delphi method are as follows:

- Identifying an appropriate range for fuzzification of verbal expressions
- Fuzzy aggregation of the fuzzified values
- Defuzzification of the values
- Selecting the threshold intensity and screening the criteria

In implementing the Fuzzy Delphi method for screening, it is first necessary to develop a suitable fuzzy scale for fuzzifying respondents' verbal expressions. Methods for developing fuzzy scales can be applied for this purpose, or common fuzzy scales can be used. For example, a triangular fuzzy scale for a five-point Likert scale to indicate the importance of indicators is as follows:

Table 1: Triangular fuzzy numbers equivalent to a 5 degree Likert spectrum

very much	Much	medium	little	very little
(0, 0, 0.25)	(0, 0.25, 0.5)	(0.25, 0.5, 0.75)	(0.5, 0.75, 1)	(0.75, 1, 1)

Since in the fuzzy Delphi method, the diverse characteristics of individuals influence their subjective interpretations of qualitative variables, defining the

range of these qualitative variables ensures that experts respond to the questions with a shared mindset. These variables are defined as triangular fuzzy numbers, as shown in the figure below.

Figure 4: Triangular fuzzy numbers equivalent to a 5 degree Likert spectrum

After selecting or developing an appropriate fuzzy scale, the experts' opinions are collected and recorded in fuzzy form. In the second step, these expert opinions must be aggregated. Various methods have been proposed for the fuzzy aggregation of expert opinions. If each expert's viewpoint is represented as a triangular fuzzy number (β, m, α) , the fuzzy average of n triangular fuzzy numbers is calculated as follows:

$$F_{AVE} = \frac{\sum \beta}{n} \quad \frac{\sum m}{n} \quad \frac{\sum \alpha}{n} \quad (1)$$

Other methods have also been employed for aggregating expert opinions instead of using the fuzzy average. In fact, these aggregation methods are empirical approaches proposed by various researchers [46].

4. Research Findings

4-1. Data Analysis Process Using the Fuzzy Delphi Approach

The influential factors identified through interviews and literature review were presented to the experts in the form of a questionnaire. Based on the defined linguistic variables and the provided options, the responses collected in the questionnaire were analyzed to obtain the fuzzy mean. The following formulas are used to calculate the fuzzy mean.

$$A_i = (a_1^{(i)}, a_2^{(i)}, a_3^{(i)}), i = 1, 2, 3, \dots, n$$

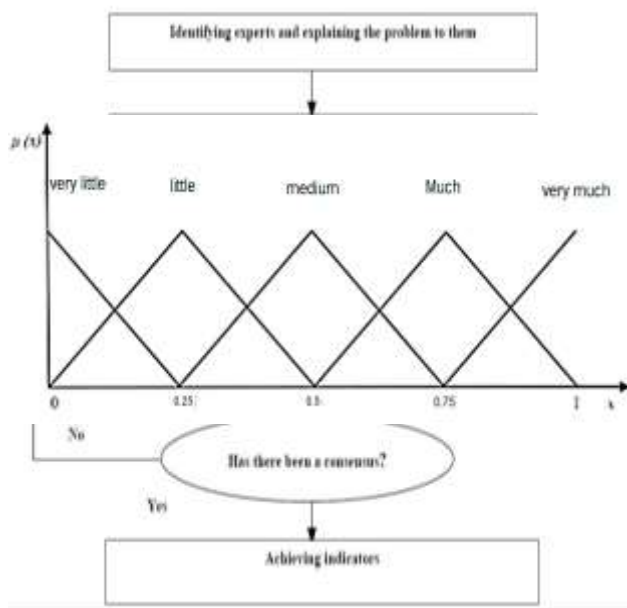
$$A_{ave} = (m_1, m_2, m_3) = \left(\frac{1}{n} \sum_{i=1}^n a_1^{(i)}, \frac{1}{n} \sum_{i=1}^n a_2^{(i)}, \frac{1}{n} \sum_{i=1}^n a_3^{(i)} \right) \quad (2)$$

In this relation, A_i represents the viewpoint of the i -th expert, and A_{ave} represents the mean of the experts' viewpoints.

After calculating the triangular fuzzy mean using the Minkowski formula, the defuzzified crisp numbers for each solution are computed.

Minkowski formula:

$$x = m + \frac{\beta - \alpha}{4} \quad (3)$$



In the fuzzy Delphi approach, since the questionnaire must be distributed to the experts at least twice, after analyzing the first-round questionnaire, it is redistributed for a second round among the experts and analyzed using the above formulas. After calculating the fuzzy mean in the second round, if the difference between the fuzzy means of the two rounds is less than 0.1, it indicates that the experts have reached a consensus on the factors.

For prioritizing the factors, the fuzzy mean from the second round is used, such that any factor with a higher fuzzy mean is assigned a higher priority.

In this context, to identify and determine the factors affecting government investment in ports, the experts on the research topic—whose descriptive statistics are presented in Table 2—were consulted for interviews and subsequently for completing the questionnaire.

Table 2. Frequency of respondents' type of relationship with the component

Type of Respondents' Relationship	Number (persons)
Active in the related component	9
Academic experts	14
Officials of relevant organizations	12
Total	35

Table 3. Frequency of respondents' education level regarding the component

Education Level	Number (persons)
Bachelor's degree	4
Master's degree	15
PhD	16
Total	35

Table 2, 3 illustrates the composition of experts who participated in the fuzzy Delphi process. In total, 35 experts with relevant expertise or experience in the component of government investment in ports were involved. The diversity in their educational background (from bachelor's to doctoral level) and the nature of their connection with the component (executive authorities, academic experts, and field practitioners) reflects a comprehensive approach in selecting the participants. This balanced composition provided the necessary foundation for achieving professional consensus and conducting an in-depth analysis of the factors influencing the component.

Following the semi-structured interviews with the experts and the coding of the obtained results, 10 key factors influencing government investment in ports were identified.

Table 4. Factors Identified as Influencing Government Investment in Ports through Interviews and

Volume of maritime trade and global demand	Government economic policies
Government revenue status	Port security and safety
Port technology and automation	Domestic transportation infrastructure
Attraction of foreign investment	Geographical location of the port
Regional competition	Environmental sustainability

After identifying the factors influencing government investment in ports, a fuzzy Delphi questionnaire was developed to reach theoretical consensus. In line with the rules of the fuzzy Delphi approach, the questionnaires were distributed in two rounds. Tables 5 and 6 present the results of the first-round distribution, while Tables 7 and 8 display the results of the second-round distribution.

Table 5. Results of the First-Round Survey Responses on the Component of Government Investment in Ports

Variables	Very High	High	Medium	Low	Very Low
Volume of maritime trade and global demand	21	10	4	0	0
Government revenue status	22	11	2	0	0
Port technology and automation	20	8	4	3	0
Attraction of foreign investment	20	4	10	1	0
Regional competition	19	10	3	2	1
Government economic policies	22	7	4	2	0
Port security and safety	20	8	4	2	1
Domestic transportation infrastructure	20	10	5	0	0
Geographical location of the port	21	8	3	2	1
Environmental sustainability	20	8	2	3	2

Table 6. Experts' Average Views from the First-Round Survey on the Component

Variables	Defuzzified Average			Defuzzification
	α	m	β	
Volume of maritime trade and global demand	0.621	0.871	0.971	0.646
Government revenue status	0.643	0.893	0.986	0.666

Port technology and automation	0.571	0.821	0.929	0.598
Attraction of foreign investment	0.557	0.807	0.914	0.584
Regional competition	0.571	0.814	0.929	0.600
Government economic policies	0.600	0.850	0.943	0.623
Port security and safety	0.571	0.814	0.921	0.598
Domestic transportation infrastructure	0.607	0.857	0.964	0.634
Geographical location of the port	0.586	0.829	0.929	0.611
Environmental sustainability	0.557	0.793	0.900	0.584

Table 7. Results of the Second-Round Survey Responses

Variables	Very High	High	Medium	Low	Very Low
Volume of maritime trade and global demand	21	11	3	0	0
Government revenue status	22	11	2	0	0
Port technology and automation	20	8	5	2	0
Attraction of foreign investment	20	4	11	0	0
Regional competition	19	10	4	2	0
Government economic policies	22	7	5	1	0
Port security and safety	20	8	4	3	0
Domestic transportation infrastructure	20	10	5	0	0
Geographical location of the port	21	8	3	3	0
Environmental sustainability	20	8	3	3	1

Table 8. Experts' Average Opinions from the Second-Round Survey

Variables	Defuzzified Average			Defuzzification
	α	m	β	
Volume of maritime trade and global demand	0.629	0.879	0.979	0.654
Government revenue status	0.643	0.893	0.986	0.666
Port technology and automation	0.579	0.829	0.936	0.605
Attraction of foreign investment	0.564	0.814	0.921	0.591
Regional competition	0.579	0.829	0.943	0.607
Government economic policies	0.607	0.857	0.950	0.630
Port security and safety	0.571	0.821	0.929	0.598
Domestic transportation infrastructure	0.607	0.857	0.964	0.634
Geographical location of the port	0.586	0.836	0.936	0.611
Environmental sustainability	0.564	0.807	0.914	0.591

Based on the opinions provided in the first round and comparing them with the results of the second round, if the difference between the defuzzified fuzzy means in the two rounds is less than 0.1, the survey process is considered complete. The table below presents the differences between the results of the first and second rounds.

Table 9. Differences in Experts' Opinions between the First and Second Round Surveys

Variables	Defuzzified Fuzzy Mean – Round 2	Defuzzified Fuzzy Mean – Round 1	Difference between Round 1 & 2
Volume of maritime trade and global demand	0.654	0.646	0.007
Government revenue status	0.666	0.666	0.000
Port technology and automation	0.605	0.598	0.007
Attraction of foreign investment	0.591	0.584	0.007
Regional competition	0.607	0.600	0.007
Government economic policies	0.630	0.623	0.007
Port security and safety	0.598	0.598	0.000
Internal transportation infrastructure	0.634	0.634	0.000
Port geographical location	0.611	0.611	0.000
Environmental sustainability	0.591	0.584	0.007

To prioritize the factors affecting the component under study, the defuzzified fuzzy means from the second (final) round were used. Each factor with a higher defuzzified fuzzy mean is assigned a higher priority.

Table 10. Prioritization of Factors Affecting Public Investment in Ports

Influential Factors	Priority
Government Revenue Status	1
Volume of Maritime Trade and Global Demand	2
Internal Transportation Infrastructure	3
Government Economic Policies	4
Port Geographical Location	5
Regional Competition	6
Port Technology and Automation	7
Port Security and Safety	8
Attraction of Foreign Investment	9
Environmental Sustainability	10

The findings from applying the fuzzy Delphi method for the public investment in ports component indicate that 10 main factors, from the experts' perspective, are

influential in shaping, reinforcing, or constraining such investments. The analysis of these priorities shows that government investment in port infrastructure depends not only on the macroeconomic conditions of the country but also on regional, institutional, and even environmental factors.

At the top of the table, the government revenue status is identified as the most critical factor affecting public investment in ports. This highlights that the government's capacity to invest in port infrastructure heavily relies on public financial resources, including revenues from oil, taxes, and exports. In situations where the government faces budget deficits and declining sustainable revenues, the maritime transport and port sectors are deprioritized, and development projects are either halted or left incomplete.

Ranked second is the volume of maritime trade and global demand. Analysis of this factor indicates that governments often decide on investment based on the activity levels of ports and the volume of incoming and outgoing goods. When global demand for Iranian exports decreases or international trade restrictions intensify, the government's incentive to allocate financial resources to port development diminishes.

The third factor, internal transportation infrastructure, reflects the close linkage between port development and the efficiency of domestic transport networks. Poor connectivity of ports to roads, railways, industrial centers, or domestic consumption hubs reduces the effectiveness of any port investment, leading to lower government willingness to allocate funds to such ports.

Government economic policies rank fourth. Governments that strategically prioritize the development of a maritime-based economy allocate more investment to ports. However, in situations of policy instability, frequent legal changes, lack of medium- and long-term planning, and poor coordination among economic institutions, the level of investment declines, and port projects often become victims of inconsistent decision-making.

Fifth is the geographical location of the port, emphasizing that ports situated in strategic positions—close to regional markets or international corridors—

receive more government investment. For example, Chabahar Port, located along the East-West corridor and capable of competing with southern Pakistani ports, enjoys higher priority.

Regional competition ranks sixth, highlighting competitive pressures from neighboring countries' ports such as those in the UAE, Oman, and Turkey, which, through substantial investment and advanced technology utilization, capture a larger share of regional maritime transport. This factor indicates that the government must increase investment in key ports to maintain its regional position and prevent monopoly by competitors.

The seventh factor, port technology and automation, points out that ports with lower technological levels typically require government support and investment for upgrades. While private sector participation in advanced technologies may face hesitations, the government's role in modernizing hardware and software infrastructure becomes more pronounced.

Port security and safety is ranked eighth. Ports lacking proper safety equipment, crisis management, maritime incident response, cargo and passenger security, and monitoring systems require governmental interventions to improve safety indicators. Poor security in ports can reduce the trust of traders and shipping companies, in addition to causing financial losses and public dissatisfaction.

Foreign investment attraction ranks ninth, showing that while this factor is complementary, it strengthens public investment in ports. Although it has a lower rank, in contexts of sanctions and restrictions on technology transfer and financial resources, the government's role in creating an enabling environment for international investment becomes increasingly important.

Finally, environmental sustainability ranks tenth. This relatively lower rank indicates that environmental concerns are not yet adequately considered in government financial decision-making for ports. While sustainable port development requires attention to environmental impacts, project assessments, and adherence to international standards, this component

still appears to be distant from the primary priorities of public investment in Iran's ports.

5. Conclusion

This study aimed to identify and prioritize the factors influencing public investment in ports in Iran. Using expert surveys and fuzzy analysis, the study identified and ranked the factors affecting public investment in port infrastructure.

The results of applying the fuzzy Delphi method indicate that government investment in ports is a multidimensional process influenced by a diverse range of economic, institutional, technological, regional, and environmental factors. The prioritization of these factors revealed that government revenue status ranks first, having the greatest impact on decisions regarding investment in port infrastructure. This finding highlights that, in an economy dependent on oil and tax revenues, financial stability and the government's ability to secure sustainable budgetary resources are prerequisites for any port investment. In other words, macroeconomic policies and the government's financial situation remain the main determinants of resource allocation to maritime transport, and without budgetary reforms and diversification of financial resources, sustainable port development cannot be expected.

Next in importance is the volume of maritime trade and global demand. This indicates that public investment is not only reliant on domestic capacities but also dependent on international trade conditions and the position of ports within the global supply chain. When exports decline or international trade restrictions or sanctions increase, the government's motivation and ability to allocate financial resources decrease. Conversely, when ports experience commercial growth, the pressure to upgrade capacities and expand infrastructure rises, making government investment more justifiable.

Another key finding is the ranking of domestic transportation infrastructure as the third most important factor. This underscores that ports alone cannot play a central role in development unless they are connected to efficient rail, road, and industrial networks. Weak

hinterland connectivity limits the return on port investments and reduces their economic and strategic justification from the government's perspective. Therefore, port development must proceed in tandem with improvements in domestic transport networks.

The fourth factor, government economic policies, also demonstrated that the degree of commitment and consistency in macroeconomic policymaking significantly shapes investment patterns. Governments that prioritize a maritime-based economy and implement coherent medium- and long-term plans have achieved more effective investments in ports. Conversely, frequent legal changes, institutional coordination failures, and policy instability have led to failed or halted investments.

Geographical and regional factors, such as port location and regional competition (ranked fifth and sixth), indicate that governments are strongly influenced by the geopolitical and commercial positioning of their ports. Ports like Chabahar, due to strategic location and competition with neighboring countries' ports, have received higher investment priority. These findings show that, in addition to domestic requirements, governments must respond to regional competitive pressures by increasing investment in key ports to secure their international standing.

From a technological perspective, port technology and automation (seventh) emerged as important. This shows that Iranian ports must modernize hardware and software to keep pace with global trends. With the private sector facing limitations and risks in this domain, the government's role in financing and guiding investments becomes more prominent, particularly in areas like automation, digitalization, and advanced equipment development.

Port safety and security (eighth) and foreign investment attraction (ninth) were also identified. These findings emphasize that the government should not only enhance safety indicators and build trust in ports but also provide the necessary environment for foreign investors. While foreign investment currently ranks lower, in the long term it can complement public investments and reduce financial pressure on the government.

Finally, environmental sustainability ranks tenth, indicating a gap between current policymaking and the requirements of sustainable development. Although environmental concerns are not yet a top government priority, neglecting this factor can have long-term negative consequences for ports and the blue economy. Integrating environmental considerations into port investment decisions is therefore essential.

Overall, the study shows that public investment in ports is not a simple financial decision but a complex process influenced by an intertwined set of factors. Macroeconomic conditions and government revenues, as well as geographical location, regional competition, technology levels, and environmental considerations, all directly or indirectly affect the scale and direction of investment. To achieve sustainable development in Iran's ports, a comprehensive, cross-sectoral approach is necessary, integrating economic policies, transport infrastructure, technological requirements, and environmental standards simultaneously.

From a practical perspective, this research provides guidance for policymakers, economic managers, and maritime transport planners. By identifying key factors and considering the prioritized list, they can design and implement more efficient and effective port investments. Attention to these factors can not only ensure the development of port infrastructure but also enhance Iran's position in the blue economy and global value chains.

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Evaluating the Integrity of Marine Composite Panels Using LSTM Networks

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ABSTRACT

Structural health monitoring (SHM) is critical for ensuring the integrity and safety of composite structures subjected to dynamic loading conditions. Traditional damage detection methods are often limited in real-time applications, necessitating advanced data-driven approaches. This study investigates the use of Long Short-Term Memory (LSTM) networks for damage detection in composite panels under varying boundary conditions (fixed and pinned) and applied weights to assess their impact on vibrational characteristics. Time-series vibration data, including velocity, acceleration, and displacement, were collected under controlled conditions using a shaker-induced excitation. The LSTM model was trained to classify panels as intact or damaged, leveraging its ability to capture long-term dependencies in sequential data. The results show that the LSTM model effectively distinguishes between damaged and undamaged states, achieving high classification accuracy while adapting to variations in loading and boundary constraints. The model performed better under fixed boundary conditions, suggesting that structural stiffness enhances classification effectiveness by producing clearer vibrational patterns. To further evaluate performance, Precision-Recall curves and confusion matrices were analyzed, demonstrating the model's ability to balance false positives and false negatives. Additionally, a robustness analysis was conducted by introducing Gaussian noise (0.1, 0.2, and 0.3) into the dataset, confirming that the model maintains stable accuracy despite increasing noise levels, making it reliable for real-world applications. These findings highlight the potential of LSTM-based SHM systems for real-time damage detection in composite structures, with promising applications in aerospace, marine, and civil engineering.

1. Introduction

Composite materials particularly fiber-reinforced polymers (FRP) have gained significant traction in marine engineering due to their superior strength-to-weight ratio, resistance to corrosion and overall durability in harsh marine environments. These materials offer an ideal solution for applications in coastal and offshore structures. Composite panels are increasingly being used in the construction of offshore platforms, ships, boats and coastal infrastructures like piers, jetties and seawalls due to their lightweight nature and resistance to the aggressive effects of seawater [1,2]. Unlike traditional materials such as steel or concrete which are vulnerable to corrosion

from saltwater exposure, composite materials can maintain their structural integrity for longer periods without requiring frequent maintenance or costly repairs [3]. In offshore platforms where weight reduction is critical to optimize stability and reduce operational costs composite panels provide an excellent alternative to conventional construction materials by significantly lowering weight without compromising strength or safety [4]. Additionally, these materials exhibit high resistance to impact, fatigue and environmental degradation making them well-suited for the dynamic and often extreme conditions present in marine environments [5]. Furthermore, composite panels are integral to the development of sustainable

marine structures such as floating platforms for aquaculture and renewable energy generation [6]. As marine industries continue to push for more resilient, sustainable and efficient structures the role of composite panels in reducing costs, enhancing performance and extending the service life of marine infrastructures will only become more crucial [7]. However, composites pose unique challenges in SHM due to their heterogeneous nature, complex internal structures and susceptibility to damage modes like delamination, matrix cracking and fiber breakage [8]. Structural Health Monitoring (SHM) refers to the use of integrated systems for the continuous or periodic assessment of a structure's condition aiming to detect damage or degradation over time [9]. In engineering applications, SHM plays a critical role in ensuring the safety, reliability and longevity of structures. Traditionally, SHM has relied on visual inspections and periodic maintenance but these methods are often insufficient for detecting hidden or early-stage damages [10]. The advent of advanced sensing technologies and data-driven approaches such as machine learning and artificial intelligence, has revolutionized SHM by enabling real-time, automated damage detection and prognosis [11]. Among the most promising materials in modern engineering are composite materials. In particular, damage in composites is often difficult to detect with traditional methods making the integration of advanced monitoring techniques imperative [12]. Recent advances in data-driven methodologies such as the use of machine learning and artificial intelligence-based methods, have shown potential for capturing subtle patterns in time-series data generated from dynamic and static loading conditions [13]. These techniques offer a promising pathway to more effective and precise damage detection in composite materials, enabling earlier interventions and improving the overall safety and cost-effectiveness of engineered systems [14]. Damage detection in composite panels poses a significant challenge due to the inherent complexity of these materials [15]. the traditional methods of damage detection can be expensive, time-consuming and require significant manual intervention which limits their effectiveness for large-scale monitoring or real-time assessments [16]. A significant limitation of current damage detection methods is their inability to provide continuous monitoring [17]. For example, non-destructive testing (NDT) methods such as ultrasonic or X-ray imaging are typically performed at discrete intervals and require the structure to be taken offline, making them impractical for continuous or real-time health monitoring [18]. Additionally, these methods often struggle to detect early-stage damage or to assess the damage severity accurately [19]. For instance, minor damages or matrix cracks may be missed in the early stages leading to undetected deterioration that compromises the structural integrity

over time [20]. The dynamic nature of composite materials also complicates damage detection further. Under varying loading conditions such as vibrations or impacts, composites exhibit nonlinear and complex behavior making it challenging to distinguish between normal operational variations and damage-induced changes [21]. These challenges underscore the need for more advanced, automated and real-time methods of damage detection that can monitor the health of composite structures continuously, identify damage at its earliest stages and accurately assess its impact on performance [22]. With the rise of machine learning and deep learning techniques, the possibility of addressing these challenges has become more feasible by enabling the analysis of time-series data from dynamic and static loading conditions, offering the potential for more effective and reliable monitoring of composite materials. The integration of such technologies represents a significant advancement over traditional methods, paving the way for smarter, more efficient SHM systems. Dhiraj et al. discussed the integration of machine learning (ML) for the detection, localization, and quantification of damage in structural materials to help extend the service life of structures. They utilized a supervised learning model that analyzes sensor data, such as vibration signals, to identify and assess damage in materials, particularly composite structures. Their results demonstrated that the ML model was able to effectively detect and localize damage, offering a more automated and efficient alternative to traditional manual inspection methods. However, the authors noted that further optimization of the algorithms is required, and more complex structures need to be tested before the model can be fully integrated into real-world structural health monitoring (SHM) systems [23]. Azad and Kim proposed a multichannel wavelet-enhanced deep learning model for noise-robust damage detection in laminated composites. The model combines wavelet transforms to extract features from vibration signals and uses deep learning techniques to accurately identify damage in the composite material despite the presence of noise. The approach was applied to laminated composite structures, where traditional methods often struggle with noisy environments. The results showed that the model significantly outperformed conventional damage detection techniques by providing more accurate and reliable damage detection, even in noisy conditions. For future work, the authors suggested the need for further testing on larger-scale structures and improving the model's generalization ability to various types of composite materials, to ensure its broad applicability in real-world structural health monitoring scenarios [24]. Zhang et al. introduced a multilevel LSTM model for detecting ultrasonic lamination defects in carbon fiber composite plates. The model uses ultrasonic wave signals to identify defects at different layers of the composite material, utilizing a

multilevel LSTM architecture to capture complex temporal dependencies and detect subtle damage features. Their approach demonstrated high accuracy in detecting defects in carbon fiber composites, even in the presence of noise and varying material properties. The results indicated that the multilevel LSTM model provided superior performance compared to traditional methods, offering better sensitivity and reliability in identifying lamination defects. For future work, the authors suggested that the model could be further optimized for real-time damage monitoring and extended to other types of composite materials, aiming for broader applicability in structural health monitoring systems [25]. Tian et al. developed a two-stage residual network model for damage identification and location in stiffened composite panels using guided waves. The model employs a two-stage process: the first stage uses guided wave signals to capture the features indicative of damage, and the second stage utilizes a residual network to enhance the model's ability to detect and locate damage with high precision. Their approach was tested on stiffened composite panels, where traditional methods often struggle with complex geometries and variable damage patterns. The results showed that the two-stage residual network effectively identified and located damage in the composite panels, offering improved accuracy over conventional damage detection techniques. For future work, the authors suggested extending the model to more complex structural configurations and further refining its generalization capability for real-world applications in structural health monitoring [26]. Le-Xuan et al. proposed a novel damage detection model that combines 1D Convolutional Neural Networks (CNN) with LSTM and Residual Networks (ResNet) for analyzing signal data. This hybrid approach is designed to enhance the detection of damage by first using the 1D CNN to extract meaningful features from the signal data, followed by the LSTM to capture temporal dependencies, and finally applying the ResNet to improve the model's robustness and performance. The model was tested on damage detection tasks, demonstrating significant improvements in accuracy and efficiency compared to traditional methods. The results indicated that the combined approach was particularly effective in handling noisy and incomplete data, which is often encountered in real-world damage detection scenarios. The authors proposed further refinement of the model to expand its scalability and adaptability to a broader range of damage detection applications in structural health monitoring systems [27]. Huang et al. developed a CNN-LSTM network-based damage detection approach for copper pipelines using laser ultrasonic scanning. The model combines Convolutional Neural Networks (CNN) to extract spatial features from ultrasonic wave signals, followed by Long Short-Term Memory (LSTM) networks to capture the temporal dynamics of the damage. This

hybrid approach was applied to detect and assess damage in copper pipelines, where traditional methods often struggle with complex signal patterns and noisy data. The results demonstrated that the CNN-LSTM model provided high accuracy in detecting damage, even in the presence of noise, and was more efficient than conventional damage detection techniques. The authors suggested that future work could focus on expanding the model's application to other types of materials and refining its real-time capabilities for broader structural health monitoring [28]. Das and Guchhait proposed a hybrid GRU and LSTM-based deep learning approach for multiclass structural damage identification using dynamic acceleration data. The model integrates Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) networks to effectively process the time-series acceleration data, allowing it to identify and classify different types of structural damage. The approach was tested on structural components subjected to dynamic loading, where traditional methods often face challenges in accurately detecting and classifying various damage states. The results showed that the hybrid GRU-LSTM model outperformed conventional methods in terms of classification accuracy and robustness, especially in handling multiple damage scenarios. The authors noted that further work should focus on optimizing the model for real-time damage detection and extending its application to larger, more complex structures in structural health monitoring systems [29]. However, this remains an emerging area of study, and more work is needed to refine these techniques to address the real-world complexities. While LSTM models are designed to process time-series data, the quality of the input data plays a crucial role in the model's performance. In marine environments, where conditions are subject to harsh weather, vibrations, and other external factors, sensor data may be noisy or incomplete, making it difficult for machine learning models to accurately detect damage. Techniques such as data fusion, which combines data from multiple sensor types (e.g., accelerometers and displacement sensors), could enhance model accuracy. Additionally, preprocessing methods, such as noise filtering and feature extraction, are essential to ensure the data fed into the LSTM model accurately reflects the structural health rather than being influenced by extraneous environmental factors. The integration of LSTM-based Structural Health Monitoring (SHM) systems into large-scale marine infrastructures represents the future of damage detection in composite panels. The development of more robust, adaptive, and computationally efficient models could lead to significant advances in real-time monitoring, enabling earlier damage detection and reducing the need for costly repairs and downtime. One notable gap in recent studies is the impact of varying boundary conditions on the vibrational characteristics of composite panels in the marine domain. Most studies

have primarily focused on fixed boundary conditions, which do not capture the full range of behaviors observed in real marine structures, such as those found in offshore platforms or floating vessels. Additionally, these studies have largely concentrated on uniform loading conditions or simple damage modes, overlooking the complexities present in real-world applications. This study addresses this gap by incorporating both pinned and fixed boundary conditions, offering a more accurate reflection of real-world marine applications. The dynamic response of composite panels to weights placed at varying positions under shaker-induced vibrations is a unique and under-explored area, setting our study apart from previous researches. Moreover, while some studies have utilized LSTM networks for damage detection in composite materials, few have considered the combination of dynamic loading with sensor data from multiple sources to monitor the health of composite panels continuously. By integrating data from different sensors and accounting for real-world variations in environmental conditions, the proposed approach not only enhances damage detection accuracy but also lays the foundation for continuous real-time health monitoring systems that could operate effectively on offshore platforms or ships. This combination of loading conditions, boundary condition variations, and real-time monitoring is a novel approach that has not been fully explored in the context of marine composite panels. In this study, a novel nondestructive method is proposed for the damage detection of marine composite panels subjected to dynamic loading conditions. The experimental setup involves both contact and non-contact sensors to capture comprehensive structural responses. These sensors are used for experimental vibration analysis to understand the vibrational characteristics of the composite panels under varying weight placements. Additionally, the sensors gather data for the damage detection procedure, specifically capturing vibrational behavior under dynamic loading. The data collected from these sensors are then processed using an LSTM network, integrated with a sliding window technique for efficient time-series data processing. The damage classification results from the LSTM model are evaluated using key performance metrics such as accuracy, confusion matrices, and loss to assess the model's effectiveness in real-time damage detection. This approach not only enhances damage detection accuracy but also integrates data-driven techniques for structural health monitoring in marine environments. The ultimate goal of this work is to bridge the gap by providing a more comprehensive and real-time damage detection system that addresses the unique challenges of marine engineering.

2. Methodology

2.1. Model description

In this study, to conduct the experimental tests a 10-layer rectangular composite panel is fabricated in the Composite Laboratory of the University of Tabriz. The fabrication of the experimental model of the composite panel was carried out based on guidelines and instructions from the relevant regulations, which are specifically intended for the production of composite structures in marine environments [30]. The final design of the composite panel is illustrated in Figure 1.



Figure 1. Final design of the composite panel

The dimensions of the composite panel are provided in Table 1.

Table 1. Geometric properties of the composite panel considered for the experiment

Panel properties	Numerical values
Length (L_x)	800 [mm]
Width (L_y)	750 [mm]
Thickness (t_h)	2 [mm]

The mechanical properties of the composite panel are determined using the DNV code formulation [30], which allows for the calculation of the elasticity modulus and other key mechanical properties, as presented in Table 2.

Table 2. Characteristics of the materials and the composite panel considered for the experiment

Material	Density [g/cc]	Elasticity modulus [Gpa]	Poisson's ratio	Shear modulus [Gpa]
Glass fiber	2.5	30.1	0.2	30
Resin	1.5	3.5	0.35	2
Composite panel	1.9	25.9	0.36	2.91

The composite panel is subjected to two distinct boundary conditions to simulate different structural support scenarios: fixed and pinned. The fixed boundary condition represents a scenario where the edges of the panel are rigidly constrained, preventing

any displacement or rotation at the boundaries. This condition closely mimics structures where the panel is fully anchored, such as in offshore platforms or coastal infrastructure where stability is crucial under dynamic loading. On the other hand, the pinned boundary condition allows for rotational movement but restrains the translational displacement of the panel at the edges. This setup is used to simulate situations where the panel is supported at specific points such as in certain marine vessel hulls or modular platforms. By evaluating the vibrational responses under both boundary conditions, this study aims to understand how the structural stiffness and vibrational behavior of composite panels are influenced by different support configurations which is critical for assessing the damage detection capabilities of the LSTM model under varying loading conditions.

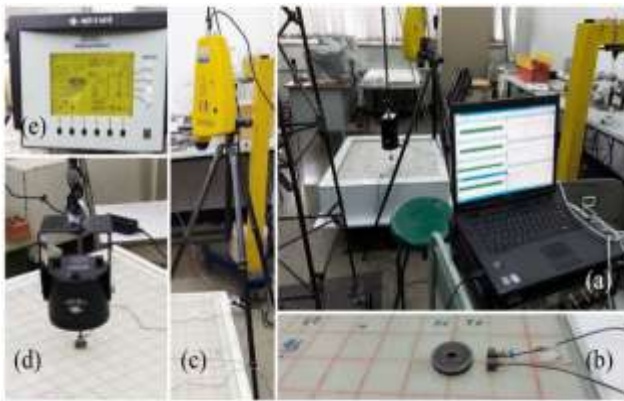


Figure 2. The layout of the vibration test: (a) Overall view of the experimental setup; (b) Attached accelerometers; (c) Laser doppler vibrometer; (d) Attached shaker; (e) Conditioning amplifier

2.2. Experimental Methodology

Vibration analysis is a crucial technique for evaluating the dynamic behavior of structures under various loading conditions. This method involves capturing vibrational responses, such as acceleration, velocity, and displacement, at different locations on the composite panel. In this study, vibration analysis is performed using a combination of contact and non-contact sensors. A Laser Doppler Vibrometer (LVD, VH3000+, Ometron Ltd), which is a non-contact sensing component, measures vibration velocity at multiple points on the panel's surface. Additionally, contact accelerometers (manufactured by Brüel & Kjær Engineering) are used to capture acceleration data. These acceleration signals are processed through a B&K conditioning amplifier, which then calculates the corresponding displacement by integrating the acceleration data. The experimental setup, including sensor placements, is depicted in Figure 2. A shaker is used to apply dynamic loading to simulate realistic vibrational environments. The use of both contact and non-contact sensors provides a comprehensive understanding of the composite panel's vibrational characteristics under varying conditions. For

excitation, a sinusoidal signal with a zero mean is applied under both pinned and fixed boundary conditions. The time histories for acceleration, velocity, and displacement are recorded at several points using both accelerometers and the LDV system. Over 20 sensors are distributed across the panel, capturing more than 40,000 data points each. The composite panel model is meshed and numbered based on the numerical model, allowing for precise identification of sensor locations and excitation points. The excitation force is applied at the center of the panel (Figure 3). Both intact and damaged models are tested under the two boundary conditions. Damage is introduced by adding mass at three locations using 100gr, 200gr, and 500gr weights, as shown in Figure 3.

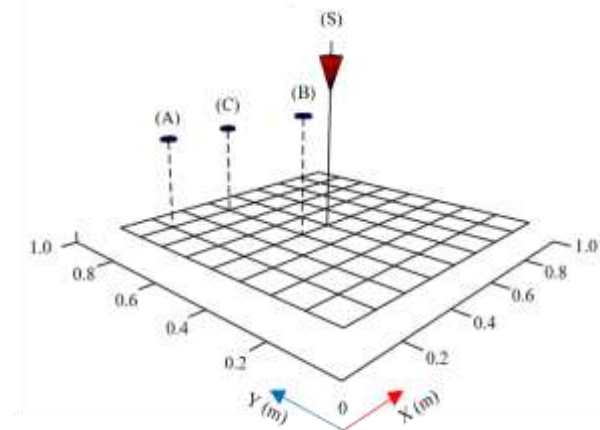


Figure 3. A schematic of the panel including: (A, B, and C) Location of the weights; (S) Shaker position

2.3. Data Preprocessing

The vibration data from a composite panel was preprocessed using the sliding window technique to prepare it for training with an LSTM model. The raw data consists of five columns: Time, Force, Velocity, Displacement, and Acceleration. The first preprocessing step involved converting the raw data into sequences to capture the time-series dynamics. The raw data was divided into sequences of N number of sequences, with each sequence containing T data points. In this study, a window size of 3 time-steps was used for each sequence. This hyperparameter was found to be the best during experimentation, as it effectively captured the history of the time-series dynamics without significantly increasing computational costs. Using the sliding window technique, compared to passing the data as a single column, showed a 3% improvement in accuracy in the experiments. The window slides one step at a time across the data, with overlap between consecutive windows. For each sequence, all features (Time, Force, Velocity, Displacement, and Acceleration) were used to capture temporal relationships and patterns for model training. The sequencing process is illustrated by the following equation:

$$X_{Seq} = [(X_1, X_2 \dots, X_T) + (X_2, X_3 \dots, X_{T+1}), \dots, (X_{N-T+1}, X_{N-T+2} \dots, X_N)] \quad (1)$$

Where X_{Seq} represents the set of sequences, each containing T time-steps, and X_i represents the raw data at the i – th time-step. In this case, $T = 3$, meaning each sequence consists of 3 consecutive time-steps. This ensures that the temporal dynamics are captured effectively within each sequence for model training. After the sliding window transformation, the data was normalized using standard scaling. The standard scaling was performed using the following equation:

$$X_{scaled} = \frac{X - \mu}{\sigma} \quad (2)$$

Where X represents the raw data, μ is the mean of the feature, and σ is the standard deviation. This normalization step improved the accuracy by 2%, as it scaled the features to a common range, making it easier for the model to understand the temporal dynamics during training.

The data was labeled based on damage detection criteria: intact data was labeled as 0 and damaged data was labeled as 1. Damage detection was based on measurements from the Velocity, Displacement, and Acceleration data. The dataset was split into 80% training, 10% validation, and 10% test sets. These splits were performed to ensure an equal distribution across different conditions such as intact vs damaged and pinned vs fixed boundary conditions. This balance ensures that the model is trained on a representative dataset and that the training process is not biased toward a single label or data subset. No additional preprocessing steps, such as handling missing values, resampling, or feature engineering, were performed, as the data was assumed to be clean and appropriately formatted.

2.3. LSTM Model

LSTM model has been widely used in sequence prediction problems, such as sequence classification and sequence-to-sequence prediction, which may differ based on the input and output sequences. LSTM is a type of recurrent neural network (RNN). It has recurrent connections that use the state of neuron activation from the previous time step to determine the output [31]. RNNs are designed for sequence prediction, for example, multi-layer perceptron adding loops. RNNs face the challenge of getting trained effectively owing to vanishing gradient problems. LSTM is designed to overcome this challenge. Moreover, LSTM can learn long-term dependencies better than an RNN [32]. LSTM uses gates that process the information contained in the incoming data sequences. The gates include a forget gate, an input gate and an output gate, each of which can be considered a neural network [33, 34, 35]. The output from an LSTM cell depends on the long-term memory

(referred to as the cell state), output from the previous time step, and data of the input sequence of the current time step. Figure 4, shows a typical example of an LSTM cell.

The forget gate determines which information of the cell state is useful based on the previous hidden state and the current input data. The previous hidden state and the current input data are fed to the forget gate, generating a vector between 0 and 1 using sigmoid activation. A value of 0 indicates that the input component is irrelevant, whereas 1 indicates the input component is relevant. In the following equations, W and W_h are the input and hidden state weights for the forget gate f , input gate i , and output gate o .

$$f_t = \sigma(x_t \times W_f + h_{t-1} \times W_{hf}) \quad (3)$$

Where x_t , h_{t-1} and f_t denote the data at time instant t , the previous hidden state, and the forget gate at t , respectively. σ is the sigmoid activation function. The input and hidden state are multiplied by the weights. The weight matrix remains the same and it does not change from one time step to another. The amount of information sent is based on this value. More information is sent when the value is closer to 1. The output from this part of the forget gate is multiplied pointwise by the previous cell state. The output of pointwise multiplication is given by Eq. (4) or Eq. (5) when f_t is 0 or 1, respectively. When it is 1, all previous cell states are sent.

$$C_{t-1} * f_t = 0 \text{ for } f_t = 0 \quad (4)$$

$$C_{t-1} * f_t = C_{t-1} \text{ for } f_t = 1 \quad (5)$$

Where C_{t-1} denotes the previous cell state. The next stage is the input gate. The input gate uses the current input and the previous hidden states to quantify the amount of new information to be retained along with the previous cell state. The equation for the input gate can be expressed as:

$$i_t = \sigma(x_t \times W_i + h_{t-1} \times W_{hi}) \quad (6)$$

Where i_t is the input gate at time instant t . Using a sigmoid function, the input gate outputs a vector ranging from 0 to 1. The new information is a function of the previous hidden state and current input data. It uses the (tanh) activation function to output the new information ranging from -1 to 1. The new information is determined as:

$$I_N = \tanh(x_t \times W_c + h_{t-1} \times W_{hc}) \quad (7)$$

The new information generated using the input gate can help to reduce the previous-state information in the cell state, if necessary. A negative value using the activation function (tanh) helps to achieve this. However, the necessity of retaining all the new input data is unknown. The output from the input gate is multiplied pointwise by the new input vector to

determine the amount of new input data that can be retained. This output is added to the cell state. The current cell state is given as:

$$C_t = C_{t-1} * f_t + I_N * i_t \quad (8)$$

The output gate is the last gate, which determines the new hidden state. It uses the current input data and previous hidden state, similar to the forget and input gates. The equation for the output gate can be expressed as:

$$o_t = \sigma(x_t \times W_o + h_{t-1} \times W_{ho}) \quad (9)$$

The new hidden state is the output of the pointwise multiplication of the value of the output gate and new cell state. The (tanh) activation function is applied to the current cell state, resulting in a new output ranging from -1 to 1. The new hidden state can be expressed as:

$$h_t = \sigma(x_t \times W_o + h_{t-1} \times W_{ho}) * \tanh(C_t) \quad (10)$$

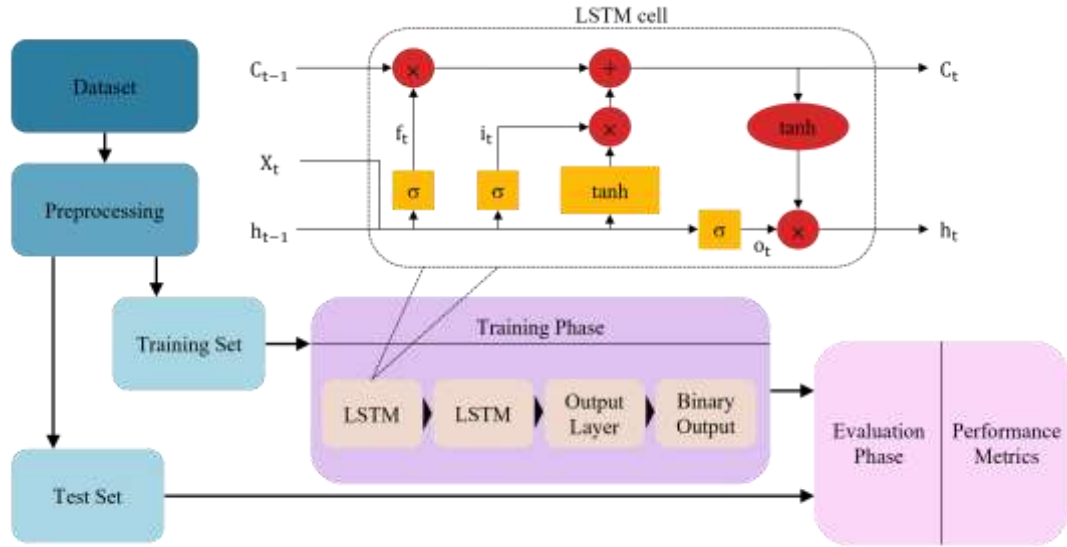


Figure 4. An optimized machine learning pipeline for time-series data using LSTM for damage detection

2.3.1. Architecture Details

The LSTM model used for damage detection in this study consists of an input layer with dimensions (3, 5), where 3 represents the number of time steps and 5 corresponds to the feature dimensions (Force, Velocity, Displacement, and Acceleration). This is followed by a first LSTM layer with 64 neurons, using the default (tanh) activation function and returning sequences for the next layer. The second LSTM layer, also with 64 neurons, processes the sequences to capture more complex temporal patterns. A fully connected dense layer then generates predictions based on the features learned by the LSTM layers, with the final output layer using a sigmoid activation function to produce a binary classification result (intact or damaged). As shown in Figure 4, the optimized machine learning pipeline outlines the process from dataset collection and preprocessing to model training, evaluation, and performance metrics, ensuring a systematic approach to damage detection using the LSTM method.

2.3.2. Training Details

The training process of the LSTM model is designed to ensure efficient learning and convergence, optimizing performance for the binary classification task of detecting structural damage. The model is built to process sequences of 3 time-steps, with 5 features (Time, Force, Velocity, Displacement, and

Acceleration) at each time-step. The ADAM (Adaptive Moment Estimation) optimizer is used to adjust the weights during training due to its efficiency in handling sparse gradients and providing fast convergence. Binary cross-entropy is employed as the loss function, appropriate for this binary classification task (intact vs. damaged). The batch size is set to 64, which is a common choice for time-series data, meaning the model processes 64 samples at a time before updating its weights. The model is trained for 2 epochs to ensure sufficient learning while avoiding overfitting. During the training process, the best model is saved after each epoch based on validation data performance, ensuring the retention of the most accurate model throughout the training. The performance of the model is evaluated using accuracy as the primary metric.

2.3.3. Model Evaluation

The model's performance is evaluated using the following metrics:

1. Precision-Recall Curves: The PR curves are used to assess the model's ability to correctly classify damaged vs intact panels, especially given the potential class imbalance in real-world damage detection tasks.
2. Confusion Matrix: To identify false positives (FP), false negatives (FN), true positives (TP), and true

negatives (TN), and better understanding of the model behavior.

3. Accuracy: Measures the overall correctness of the model (see Eq. 11).

$$\frac{TP + TN}{TP + TN + FP + FN} \quad (11)$$

4. Precision: Measures the accuracy of positive predictions (see Eq. 12).

$$\frac{TP}{TP + FP} \quad (12)$$

5. Recall: Measures the ability to correctly identify positive instances (see Eq. 13).

$$\frac{TP}{TP + FN} \quad (13)$$

6. F1-Score: The harmonic mean of precision and recall (see Eq. 14).

$$2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (14)$$

7. Robustness Analysis.

3. Results and Discussion

3.1. Overall Results

The heatmap shown in Figure 5, provides a visual representation of the classification distribution of the dataset based on different weights (100gr, 200gr, and 500gr) and boundary conditions (Fixed and Pinned). Additionally, the heatmap distinguishes between damaged and intact panel, offering insights into how the model classifies structural conditions under varying load and support configurations.

This heatmap highlights the imbalance present in the dataset, where certain categories are overrepresented while others are underrepresented. The heatmap highlights significant imbalance in the dataset, particularly in the classification of panels under different weight placement and boundary conditions.

100gr	1.83091e+06	1.7111e+06	0
200gr	1.83808e+06	1.75411e+06	0
500gr	1.53907e+06	0	0
Fixed	0	0	614401
Pinned	0	0	983040
	Damaged Fixed	Damaged Pinned	Intact

Figure 5. Heatmap showing the distribution of the damaged and undamaged dataset across different weights and boundary conditions

The overrepresentation of "Damaged" instances, especially under the Fixed boundary condition, poses a challenge for the model to generalize well. Addressing this imbalance will be critical to improving the model's performance and ensuring that it can effectively classify damage under all conditions.

3.2. Both Fixed and Pinned Boundary Conditions

As shown in Figure 6, the Precision-Recall (PR) curve illustrates the performance of the LSTM model in distinguishing between damaged and undamaged states across both fixed and pinned boundary conditions. The curve starts with a high precision (~1.0) at low recall values, indicating that when the model is highly selective, it makes very few false positive predictions. As recall increases, precision gradually decreases, reflecting the trade-off between capturing more true positives while introducing some false positives.

The model maintains high precision above 95% across a large portion of the recall range, demonstrating its effectiveness in correctly classifying damage with minimal false alarms. The gradual decline in precision, rather than an abrupt drop, indicates that the model is well-calibrated and maintains a balanced classification ability. However, at very high recall values (~0.9 - 1.0), precision drops below 85%, suggesting an increase in false positives as the model attempts to capture all instances of damage.

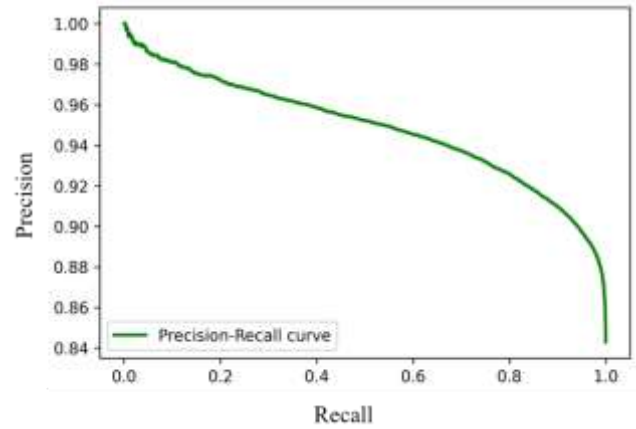


Figure 6. Precision-Recall curve for the LSTM model for both fixed and pinned boundary conditions

The confusion matrix, as shown in Figure 7, represents the overall performance of the LSTM model across both fixed and pinned boundary conditions. It illustrates the distribution of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), providing insight into the model's accuracy, precision, recall, and effectiveness in detecting damage under varying structural constraints.

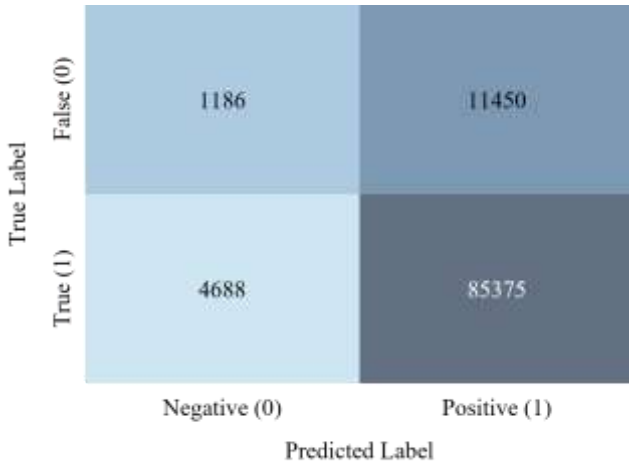


Figure 7. Overall confusion matrix for both fixed and pinned boundary conditions

The overall performance of the LSTM model across both fixed and pinned boundary conditions demonstrates its effectiveness in detecting damage with a high recall of 98.63%, indicating that the model successfully identifies most instances of actual damage. The accuracy of 87.70% reflects the model's overall correctness in classification, while the precision of 88.17% suggests that the majority of predicted damage cases are indeed accurate, minimizing false alarms. Furthermore, the F1-score of 93.11% balances precision and recall, confirming that the model maintains strong predictive power while effectively distinguishing between damaged and undamaged states.

3.2. Pinned Boundary Condition

As shown in Figure 8, the Precision-Recall (PR) curve provides an evaluation of the LSTM model's performance in classifying damaged and undamaged states under pinned boundary condition. The curve maintains a high precision near 1.0 at the beginning when recall is low, indicating that the model effectively identifies damaged cases while keeping false positives minimal in this region. As recall increases, precision gradually declines, reflecting the model's trade-off between identifying more true positives and introducing more false positives. Compared to other PR curves (Figure 6, and Figure 10), this one demonstrates a more extended stability in precision, maintaining values above 95% for most recall values. However, at high recall levels (~0.8 - 1.0), precision begins to decline more steeply, dropping below 85% as recall approaches 1.0. This suggests that while the model captures almost all damaged instances at high recall, it also classifies more undamaged cases incorrectly, leading to an increase in false positives.

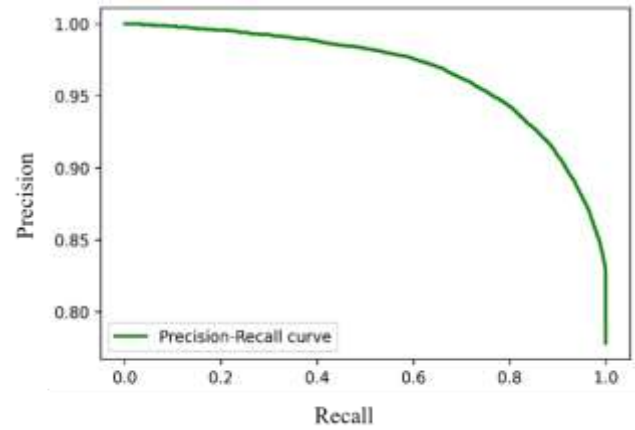


Figure 8. Precision-Recall curve for the LSTM model under the pinned boundary condition

The confusion matrix, as shown in Figure 9, represents the performance of the LSTM model under pinned boundary condition. It illustrates the distribution of true positives, true negatives, false positives, and false negatives, providing insight into the model's accuracy, precision, recall, and effectiveness in detecting damage under varying structural constraints.

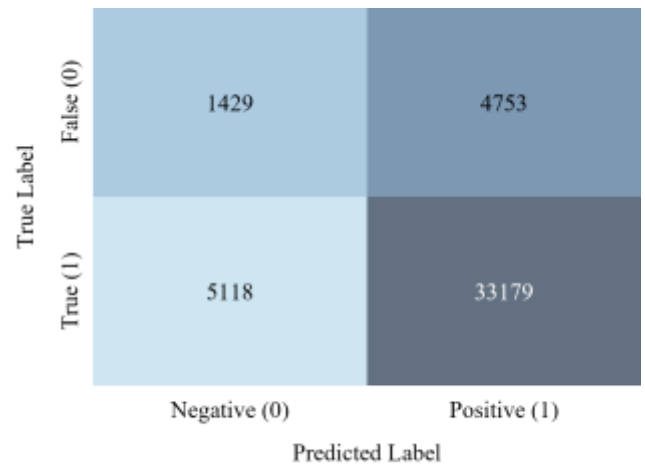


Figure 9. Confusion matrix for pinned boundary condition

The overall performance of the LSTM model under the pinned boundary condition demonstrates strong accuracy and reliability in damage detection. With an accuracy of 86.10%, the model maintains a high level of correct classifications. The recall of 95.87% indicates that the model is highly effective in identifying actual damage cases, minimizing false negatives. Precision, at 87.47%, shows that the majority of predicted damage cases are accurate, reducing the occurrence of false alarms. The F1-score of 91.48% balances precision and recall, highlighting the model's robust performance in distinguishing between damaged and undamaged states. These results confirm the effectiveness of the LSTM model in structural health monitoring under pinned boundary conditions.

3.3. Fixed Boundary Condition

As shown in Figure 10, the Precision-Recall (PR) curve provides insights into the performance of the LSTM model in classifying damaged and undamaged states under fixed boundary condition. The curve starts with

high precision near 1.0 at low recall values, indicating that the model effectively detects damage with minimal false positives when it is highly selective. As recall increases, precision gradually declines, reflecting the trade-off between capturing more true positives while introducing more false positives. Unlike an abrupt drop (see Figure 8), the precision decreases smoothly, maintaining values above 90% for most recall values, demonstrating that the model effectively balances precision and recall across a wide range of thresholds. However, at high recall levels ($\sim 0.9 - 1.0$), precision falls below 90%, indicating an increase in false positive predictions as the model attempts to classify all damaged instances.

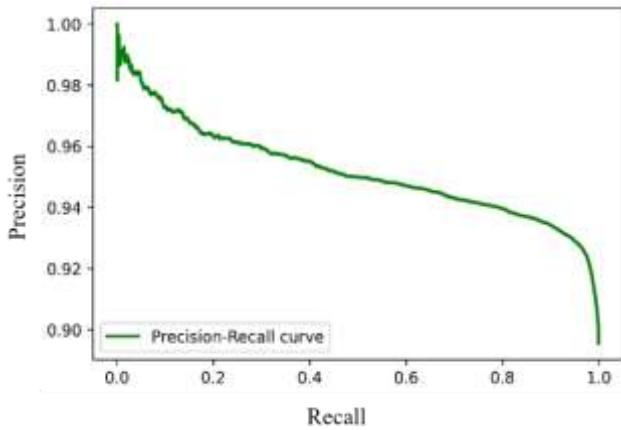


Figure 10. Precision-Recall curve for the LSTM model under the fixed boundary condition

The confusion matrix, as shown in Figure 11, represents the performance of the LSTM model under fixed boundary condition. It illustrates the distribution of true positives, true negatives, false positives, and false negatives, providing insight into the model's accuracy, precision, recall, and effectiveness in detecting damage under varying structural constraints.

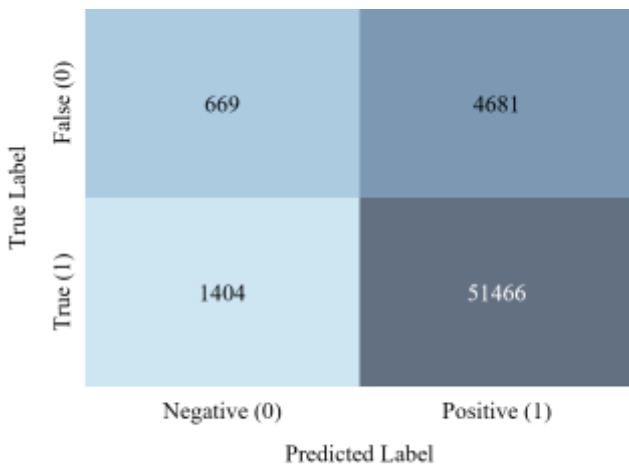


Figure 11. Confusion matrix for fixed boundary condition

The overall performance of the LSTM model under the fixed boundary condition demonstrates impressive results in damage detection. With an accuracy of 90.76%, the model effectively classifies both damaged

and undamaged panels. The recall of 98.66% indicates that the model successfully identifies nearly all actual damage cases, minimizing false negatives. Precision, at 91.66%, shows that most of the predicted damage instances are correct, reducing false alarms. The F1-score of 95.03% reflects a strong balance between precision and recall, highlighting the model's effectiveness in distinguishing between damaged and undamaged panels under fixed boundary conditions.

3.4. Robustness Analysis

In real-world applications, structural health monitoring systems often encounter noisy data due to environmental disturbances, sensor inaccuracies, and external vibrations. To assess the robustness of the LSTM model under such conditions, Gaussian noise was introduced into the dataset at three different levels (0.1, 0.2, and 0.3) to evaluate its impact on validation accuracy over multiple training epochs. This analysis helps determine how well the model generalizes when subjected to increasing noise levels.

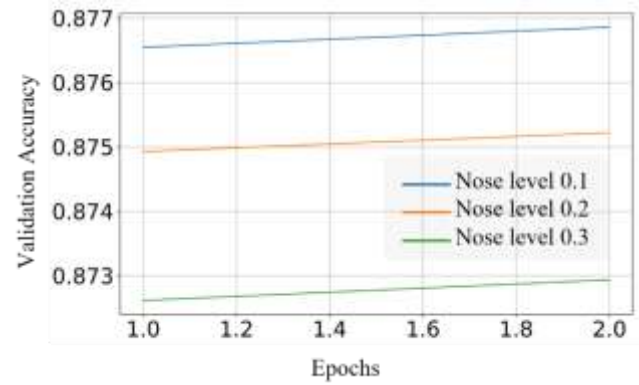


Figure 12: Validation accuracy of the LSTM model across training epochs under different noise levels

Figure 12, presents the validation accuracy trends across training epochs for each noise level. The results indicate that despite the presence of noise, the model maintains a relatively stable validation accuracy, with only minor variations observed between different noise levels. The highest accuracy is achieved under the lowest noise condition, while a slight decline is observed as noise levels increase. However, the overall upward trend suggests that the model continues to learn and adapt even in noisy conditions. These findings highlight the model's robustness to moderate noise, demonstrating its ability to generalize effectively despite minor performance degradation.

4. Conclusions

This study presented a novel approach for damage detection in marine composite panels subjected to dynamic loading conditions using an LSTM-based structural health monitoring (SHM) system. The experimental setup incorporated both fixed and pinned boundary conditions, providing a more comprehensive analysis of how vibrational characteristics vary under different structural constraints. The LSTM model

effectively classified intact and damaged states by analyzing time-series data, demonstrating strong performance in distinguishing damage states across varying weight placements and boundary conditions. The relevance results of the research could be summarized as follows:

- The overall evaluation metrics, including accuracy (87.70%), precision (88.17%), recall (98.63%), and F1-score (93.11%), confirmed the model's high reliability in damage detection, regardless of boundary conditions. However, when analyzing the model's performance separately for fixed and pinned boundary conditions, the results indicate that the model performed better under fixed boundary conditions, achieving higher precision (91.66%) and recall (98.66%), compared to the pinned boundary condition where the precision and recall were slightly lower. This suggests that fixed boundary conditions provide a more stable vibrational response, allowing the LSTM model to make more accurate classifications.
- Precision-Recall curves highlighted the model's ability to balance false positives and false negatives effectively, while the confusion matrices provided insight into classification performance across both boundary conditions.
- The LSTM model demonstrated strong efficiency in handling the imbalanced dataset, achieving high recall for damage detection while slightly compromising precision, indicating a tendency toward false positives.
- A robustness analysis was conducted by introducing Gaussian noise (0.1, 0.2, 0.3) into the dataset, demonstrating that the model maintains a stable validation accuracy despite increasing noise levels.

The findings of this study emphasize the potential applications of LSTM-based SHM systems in marine and offshore engineering, where composite materials are widely used. The integration of deep learning models with real-time monitoring systems can significantly improve structural safety, maintenance efficiency, and cost-effectiveness.

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Estimation of Alongshore Sediment Transport Rate -A Comparison among Semi-Empirical Formulas and an Artificial Neural Network model (ANN)

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ABSTRACT

The rate of alongshore sediment transport in the surf zone is depend on the product of the local wave height and mean alongshore current speed. In this study, measurement of alongshore sediment transport rate had carried out in the surf zone of Noor coastal area, in the southern part of the Caspian Sea during September to June 2012. Further, alongshore sediment transport rate had estimated by different famous semi-empirical formulas. Further, an Artificial Neural Network (ANN) model is trained using three dominant parameters of sediment transport formulas including wave breaking height (H_b), surf zone width (W), and alongshore current velocity (V). ANN models are able to show hidden laws of natural phenomena such as sediment transport process. The results of ANN and some sediment transport rate formulas were compared with mean variables which can be used in developing sediment transport rate formulas. The Results show that, the estimated value of alongshore sediment transport rate by C.E.R.C, Walton and Bruno (W.B) and Kamphuis (K) formulas and ANN model was $737.8 \left(\frac{m^3}{day}\right)$, $670.3 \left(\frac{m^3}{day}\right)$ and $593.3 \left(\frac{m^3}{day}\right)$ and $592.4 \left(\frac{m^3}{day}\right)$ Respectively. Also according to the results, the calculated R^2 values in estimation of alongshore sediment transport rate for ANN method and C.E.R.C, W.B, and K, were 0.99, 0.98, 0.75, and 0.84 and RMSE 4.7×10^{-4} , 8.4×10^{-4} , 9.1×10^{-2} , and 1.4×10^{-3} , respectively. The results, the Study also show that the formulas based on physical laws of sediment transport rate, such as C.E.R.C, W.B, and K formulas that were developed based on power concept, are more accurate than Galvin and Van Deer Meer formulas for estimating sediment transport rate in the Caspian Sea coastal areas.

1. Introduction

The total alongshore sediment transport rate (LSTR) is one of the most commonly required quantities in coastal engineering needed in problems such as infilling of dredged channels, dispersion of beach fills and placed dredged material, and the morphodynamic response of coastal areas to engineering works [2].

Measurement of the LSTR in the surf zone is one of the great challenges in coastal engineering and sciences. Transport rate data collected with along with the waves and currents that caused the transport are needed to improve basic understanding of sand movement also to develop engineering predictive techniques for estimating transport rates beach evolution [18].

For these purposes, it is desirable to make simultaneous measurements of the transport rate at a point across the surf zone to get its cross-shore or lateral distribution. Point measurements are needed, because the transport rate are depending up on the characteristics of the local waves, currents, also bottom material, and beach morphology. the lateral and vertical distributions of the long shore sand transport rate are needed for relating changes in the beach morphology to the imposed hydraulic forces, and for designing structures this may intercept sand transported alongshore. Total longshore transport is easily computed from the lateral distribution by integration over the active zone of transport [2]. many formulae were proposed for to predict LSTR, in which normally represented in term of the incident wave climate and beach characteristics [34].

The most widely formula for estimation of LSTR is commonly known as the C.E.R.C Equation [30]. This method is based on the principle the LSTR, including bed load and suspended load that is a proportional to alongshore wave power P per unit length of beach; $LSTR = K P$, with K =calibration coefficient. The C.E.R.C formula was calibrated using field data from sand beaches. The effects of particle diameter and bed slope were studied systematically by Kamphuis (1991), resulting in a more refined equation for LSTR. The last equation was found to be in best agreement between computed and measured transport rates. Equations (C.E.R.C and Kamphuis) were used in the present study as well [26].

Transported sediment rate sometimes only results in local rearrangement of sand into bars and troughs, or into a series of rhythmic embayment cut into the beach [10]. Littoral transport is to move sedimentary material in the littoral zone, which is, the zone close to the shoreline. Littoral transport is classified as cross-shore

transport or as alongshore transport. It may result from to interact winds, waves, currents, tides, sediments and other phenomena in the littoral zone. Transport can be described by the product of instantaneous concentration and the instantaneous velocity [14].

To place the role of the streamer trap in perspective, a review is first given of methods usually employed to measure the LSTR in the surf zone. The advantages and disadvantages of each method are looked. The streamer trap is described in detail and sample field results are given. The paper concludes by describing some applications of the trap made in environments except the surf zone, and plans for further testing and development [19].

A few predicting model such as Artificial Neural Networks (ANNs) were previously applied to coastal studies [6], wave prediction [15, 22], ripple and beach bar behavior and location [29, 36], coastal water level prediction [8, 12, 23, 27], wind-wave analysis [5, 11], head-bay geometry [13], tidal prediction [24], breakwater design [28, 35] and estimation of suspended sediment concentrations [7, 31]. The streamer can be used to measure sediment transport rate when a current is present, too. Kraus et al. (1989) used similar traps to carry out 10-15 minutes daily measurement of sediment transport for a 6 days' period [19].

Bakhtyar et al., (2008) by Neural Fuzzy inference system estimate the sediment transport rate in Arge coast of India [1]. Also, Hashemi et al (2011) stated that the ANN could predict the seasonal changes in Tremadoc Bay coast profiles [9]. In another studies, Kabiri - samani et al (2011) by using of Artificial Neural Network (ANN) and Fuzzy Logic (FL) evaluated the sediment transport rate methods in coastal zone of Iran and concluded that ANN, FL and Gradient descent method have better efficiencies from the others [14]. In addition, Boveiri and Musaddad (2012) calculated the sediment transport rate in the Caspian Sea and reported that the highest transport rate was $3927.45 \text{ m}^3/\text{day}$ during cold season in Anzali port and the lowest transport rate is $122.53 \text{ m}^3/\text{day}$ during warm season in Noshahr port [4].

A trap, called the streamer trap, which was developed to allow direct point measurement of the lateral and vertical distributions of the transport rate in the near shore zone under low wave energy conditions was used in this study. Emphasis will be given to measure of the LSTR in the surf zone. The main and this study is to compare the performances of semi-empirical formulas and an artificial neural network ANN, model in predicting of LSTR in the Noor coastal area in the southern part of the Caspian Sea. For this purpose, a daily observation of alongshore sediment transport rates is performed and used as reference for evaluating the accuracy of the semi-empirical formulas and the proposed ANN model.

2. Material and methods

2.1. Study Areas

A segment of beach by 2.4 km in length at Noor's coastal area, in the southern part of the Caspian Sea, in the North of Iran, was selected for this study. The beach is straight and open and lies between $36^{\circ} 52' 5.20''$ and $37^{\circ} 17' 40.93''$ N latitudes and $50^{\circ} 32' 17.16''$ and $53^{\circ} 27' 37.18''$ E longitudes. These measurements were carried out from September to June 2012. The mentioned stations were far apart 0.6 km in distance. The 0.6km coastal stretch of Izadshahar city on the East and Royan City on the West forms the study area (Fig 1). Sediment samples were collected at 0, 5, and 10 meter depths using by grain size of shoreline of Caspian Sea.



Fig 1: An illustration of the sampling stations in the Caspian Sea shoreline

2.2. Research Method

In order to conduct the present study observation obtained parameters from September to July 2012 including: wave breaking height ($H_{(s,b)}$), wave period (T), wave breaking angle (α_b), surf zone width (W), was measured. Sediment samples collected at each trap location during September to the end of July 2012 were used for the sieve analysis to estimate the median grain size. Measurement was alongshore current velocity in the surf zone (V) by using current meter and bed slope was mathematical formula slope measuring water depth and horizontal distance between the shoreline and the depth of 1 m.

2.3. The Streamer Trap method

The streamer trap was used for measuring the sand transport rate in the surf zone. The name of the trap derives from the long rectangular bags of sieve cloth that stream out with the current and capture sediment, while letting water pass through. The streamer trap was originally designed to measure alongshore sand transport in the surf zone [20] and the present discussion will mainly focus on that application. The basic idea of streamer trap was developed during a series of field experiments in Japan [20]. It was later

learned that a similar type of portable trap, the Helley-Smith trap is used by geologists in the United States for measuring bed load transport in rivers [3].

The mentioned method does not widely known in the coastal engineering community, however. But, given the present small capability to measure sand transport in the surf zone, simple devices such as the streamer trap and Helley- Smith trap are worthy of serious consideration by coastal engineers and scientists.

The streamer is made from commercially available polyester monofilament sieve cloth. Polyester cloth does not stretch or degrade in seawater. The cloth is available from scientific distributors in square mesh sizes ranging from 0.074 to 1.68 mm (Fig 2).

A sieve cloth allows water to flow through, but captures sediment particles of nominal diameter greater than the mesh opening. Streamers in use at C.E.R.C are made of 0.105 mm mesh cloth. In the United States, the cloth can be purchased in bolts 102 cm (40 in.) wide and is bought by the linear foot (30.5 cm) [20].



Fig2: Streamer trap rack at study

2.4. Trap Design

Two streamers were made each width of cloth by setting mouth dimensions at 25 cm wide by 15 cm high (Fig2). The frame holding the streamer was made of P.V.C. The rectangular section, on to which the streamer mouth is sewn, is found 4 cm forward of the four mounting rods, to place the mouth up current and away from flow disturbance and scour created at the legs of the rack holding the streamers. The bottom-most streamer frames its can generate scour, Factors controlling scour include the long shore current speed, wave height, water depth, turbulence, grain size, and duration of sampling interval. The dependence of scour on these factors has yet to be investigated.

2.5. Trap Operation

To conduct a cycle of sampling, streamers are mounted in the rack and the trap is carried out to a mentioned location in the surf zone. At the start signal, the trap is positioned so the streamer mouths face into the alongshore current, and the rack legs are thrust into the bed. The streamers immediately unfurl to full-

length when their mouths are pointed into the current. If the current is weak or intermittent, the streamers wrap around the legs of the rack caused oscillatory water motion caused by the passage of waves.

In a reasonably steady current, however, the streamers expand fully behind the trap without tangling. The operator stands down current and shoreward of the trap to monitor the streamers and to keep the rack legs fully inserted in the bed. It is dangerous to stand seaward of a trap as a large wave may throw the operator into it. The trap is more stable under wave action than a standing human. Traps in operation in the surf zone are shown in Figure 3. The streamer trap presents a fairly small cross-sectional area to the current and waves.

The weight of the steel rack, small cross-sectional area of rack members and streamers, and the implanted legs combine to produce stability. But, it was found that if all streamers are mounted on a rack deployed in waves higher than roughly 50 cm, the trap tended to tip in to direct forward wave motion.

The tendency of tip in higher waves and deeper water is Decrease if less than the maximum possible a streamer is mounted. In this configuration the trap has acted well with one operator in breaking wave heights up to 1 m and more. At the end of the sampling interval, usual 5 to 10 minute, the trap is brought to shore and the streamers are removed from the rack. Most of the collected sediment is found to lie at the back of the streamer. Sediment clinging to the sides can be washed down to the back, either with a jet of water, or by immersing the streamer in a large bucket and gently lifting it up and down. The streamer is opened by untying the nylon cord, allowing the trapped sediment to be washed into a container.

Collected sediment was easily transferred from streamer to container. In experiments performed by C.E.R.C, sediment sample transfer and weighing operations are done on the beach. Trapped sediment is washed out of the streamer and on to a square of pre-wetted sieve cloth placed in a plastic cooking colander to allow drainage of water. The wet sediment and prepared wet cloth are weighed on a portable electronic balance. Dry weight of sediment samples consisting mainly of cohesion less sand can be accurately estimated from the weight of wet sediment in sieve cloth [10]. Selected samples are retained for further analysis in the laboratory and for calibrating between wet and dry sample weight [20].



Fig3: Photograph showing traps employed in the surf zone

2.6. Transport Rate Analysis

As opposed to instantaneous samplers, pumps, and acoustic or optical sensors which measures and concentration, the streamers measure a sand flux, i.e., the weight of sand passing through the nozzle of a certain cross-sectional area in the sampling interval. If the sampling is performed in a unidirectional flow, as was the case in these experiments, no sand is lost once it has entered the streamer, and the flux can be directly associated with the current to develop predictive empirical relations. The transport rate was calculated according to the following procedures. The flux of sand F at streamer k is given by:

$$F(k) = \frac{S(k)}{\Delta h \Delta w \Delta t} \quad (1)$$

Where; F is sand flux ($\text{kg. (m}^2\text{.sec)}^{-1}$), k is streamer number, 'raising in order from the bottom ($k = 1$) to the last streamer ($k = N$), S is dry weight of sand (kg), Δh is height of streamer nozzle (0.15 m), Δw is width of streamer nozzle (0.25 m), Δt is Sampling time interval (sec).

The flux between adjacent streamers, $F_E(k)$, can be estimated by linear interpolation using adjacent measured values:

$$F_E(k) = 0.15 [F(k) + F(k+1)] \quad (2)$$

2.7. Alongshore Sediment Transport Rate (LSTR)

The LSTR was calculated from the empirical equation relating the alongshore energy flux in the breaker zone to the alongshore transport rate (Komar and Inman, 1970). the simplest and most commonly used methods

for calculating LSTR is the Coastal Engineering Research Center (CERC) formula (Shore Protection Manual, 1984), Kamphuis (1991) and Walton & Bruno (1989) (table. 1). (refer to Appendix)

Table1.Semi-empirical formula

Name	Formula	Year
CERC	$Q_t = 2.9 \times 10^6 H_{sb}^{2.5} \sin \alpha_b$	1984
KAMPHUIS	$Q_{Lst,m} = 6.4 \times 10^4 H_{sb}^2 T_p^{1.5} m_b^{0.75} D_{50}^{-0.25} \sin^{0.6}(2\alpha_b)$	1991
Walton & Bruno	$Q = \frac{KA\rho g H_b WVC_f}{0.78(\frac{5\pi}{2})(\frac{v}{v_0})_{LH}}$	1989

2.8. Artificial Neural Network (ANN)

2.8.1. Concepts of ANN

ANNs is a fairly new nonlinear statistical technique that can be used to solve problems that are not suitable for conventional statistical methods. ANNs are based on the present understanding of the biological nervous system, which consists of some data processing parts called neurons or nodes that are grouped in layers. The input layer neurons get input data or information and send the values to the next layer of processing get across connections. This process is continued until the output layer is reached. Such network in which data flows in one direction (forward) is known as a feed-forward network. The application of ANN models was the topic of many recent literatures, (such as, Lingireddy and Brion, 2005) [25].

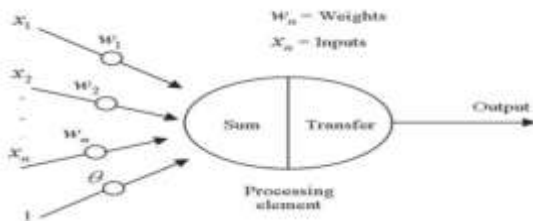


Fig 4: basic concepts of artificial neuron

Figure 4 shows the basic an artificial neuron. In this figure, various inputs to the network are represented by the symbol x_n . Another input in the figure is called a bias, θ , and it is always equal to one. Each of these inputs is multiplied by a connection weight. These weights are represented by w_n . In the simplest case, these products are simply summed, fed through a

transfer function, σ , to generate a result, and then output. In mathematical form, a neuron with n number of inputs is shown in Eq. (9).

$$Output = \sigma(\sum_{i=1}^n w_i \times x_i + \theta) \quad (9)$$

2.8.2. Training of ANN

Determining ANN weights is called learning or training, and is similar to calibrating a mathematical model. The ANNs are trained with a training an input data and known output data. At the beginning of training, the weights are initialized either with a random values or based on previous experiences. Next, the weights are systematically changed by the learning algorithm such that for a given input the difference between the ANN output and output is lowered.

Many learning examples are repeatedly presented to the network, and the process is ended when output and observed value difference is less than a specified value. This process requires that the neural network computes the error derivative of the weights (EW). In other words, it must calculate how the error changes as each weight is resin or decreased slightly. The back propagation algorithm is the most widely used method for determining the EW. The algorithm involves calculating the derivatives of the network training error about the weights by the application of chain rule and gradient descent optimization to adjust the weights to lower the error. The equations on this algorithm are available in ANN text books (such as. Lingireddy, Brion 2005) [25].

In ANNs modeling process, large attribute values might cause numerical problems because the neurons in ANN are combined sigmoid function as excitation function. There are two main advantages to normalize features before applying ANN to prediction. One advantage is to avoid attributes in greater numeric ranges dominating those in smaller numeric ranges, and another advantage is to avoid numerical difficulties during the calculation. It is recommended to linearly

scale each attribute to the range [0.1, 0.9], $[-1, +1]$ or [0, 1]. In the modeling process, the data sets of alongshore current velocity, surf zone width, breaking wave height and sediment transport rate were standardized to the range between 0 and 1 as follow:

$$N_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (10)$$

Where N_i is the normalized value, x_i is the original data, and x_{min} , x_{max} are the minimum and maximum of the original data, respectively.

2.8.3. Performance evaluation

Four different types of standard statistical criterion were considered as statistical performance evaluation. The root mean squared error (*RMSE*), efficiency coefficients (*CE*), mean absolute error (*MAE*) and mean relative error (*MRE*) was used. The four performance evaluation criteria used in this study can be calculated utilizing Eqs.11 to 14.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_i - O_i)^2} \quad (11)$$

$$CE = 1 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (O_i - \bar{O}_m)^2} \quad (12)$$

$$MAE = \frac{1}{n} |P_i - O_i| \quad (13)$$

$$MRE = \frac{1}{n} \sum_{i=1}^n \left| \frac{P_i - O_i}{\bar{O}_m} \right| \times 100 \quad (14)$$

Where O_i and P_i are, respectively the observed and the predicted sediment transport rate, $\bar{O}_m$ is the average observed sediment transport rate and n is the number of observations.

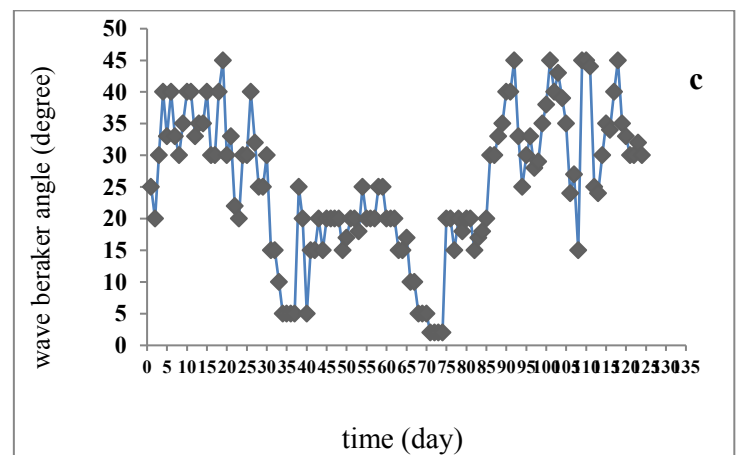
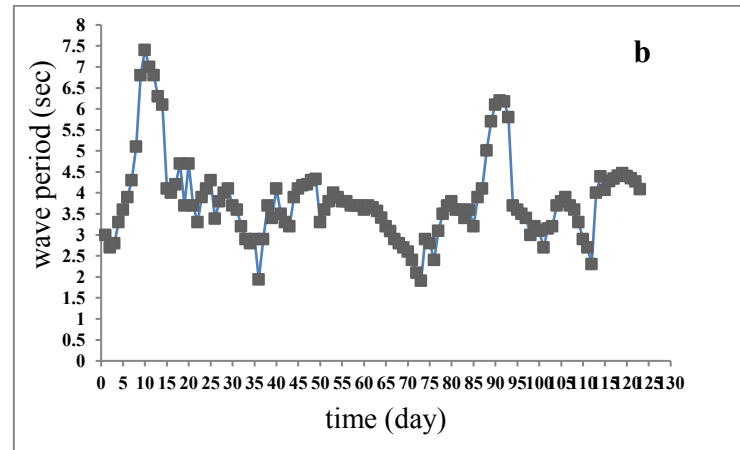
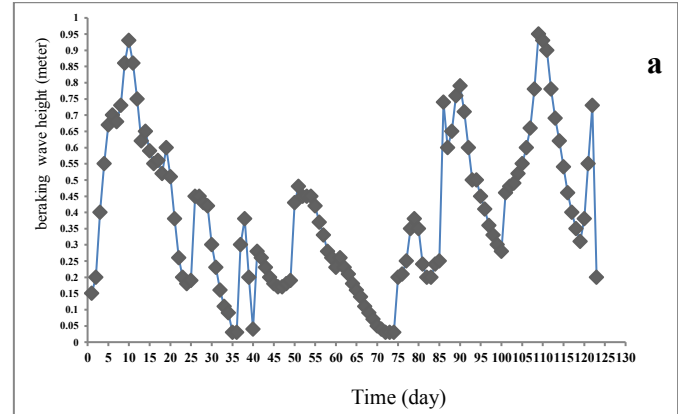
1. Results and discussions

1.1. Breaker characteristics

The daily variations of breaking significant wave height, wave period, and breaker angle calculated from the wave measurements along are shown in Fig. 5. The breaking wave height varied from 0.01 to 1.8 m with an average value of 0.47 m during September to June 2012. The wave period mostly varied from 1.91 to 7.4 with an average value of 4.65 s, and the average wave-breaking angle was 27.8 degree. The breaking waves

approached the coast predominantly from the south (positive values). The average surf zone width was about 84 m. The daily statistical variables of wave characteristics (height, period and angle), surf zone width, alongshore current velocity, beach slope, and grain size data are shown in Table 1.

Table 1.



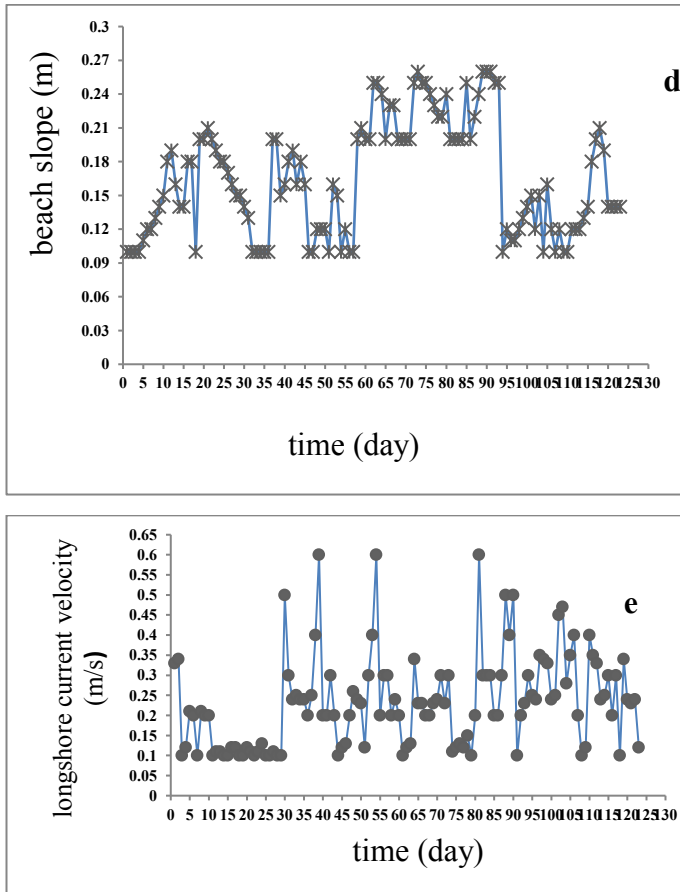


Fig 5: Variation of (a) breaker height, (b) breaker period, (c) breaker angle, (d) beach slope, and (e) alongshore current velocity from September to June 2012.

Table 1. The daily statistical variables of the observation data in the study area

Parameter	N	Max	Min	Mean	Sta.dev	C.V
H(m)	123	0.87	0.01	0.3	0.18	0.6
T(sec)	123	7	2.3	4.6	0.9	0.2
(degree) α	123	45	5	27.8	11.5	0.41
W(m)	123	170	30	83.3	31.6	0.38
V(m/s)	123	0.5	0.1	0.2	0.09	0.45
m	123	0.26	0.08	0.14	0.045	0.32
D(ϕ)	123	5.12	0.2	1.22	1.25	1.02

3.2.Sediment size distribution

The variations of median size (d_{50}) and d_{90} of the sediment at each trap location are shown in Table2. As an expected, d_{50} increased from the water surface to the seabed at each trap location. In general, the

sediments consist of fine sand ($d_{50}=0.12$ to 0.2 mm) to medium sand ($d_{50}=0.2$ to 0.25 mm).

Table2. Sediment size article of the observation data in the study area

Deep(m)	$d_{10}(\mu m)$	$d_{50}(\mu m)$	$d_{90}(\mu m)$
0	154.3	219.2	590.3
5	92.15	173.7	283.6
10	60.02	117.0	577.0

1.1.Longshore Sediment Transport Rates Measured by Streamer Traps

The measured LSTRs123 observation in this study by the streamer traps and the rates predicted by the employed formulas are compared in Table 3. The ACES (Automated Coastal Engineering System; LEENKNECHT et al., 1992) prediction applies the same C.E.R.C-formula except that the wave group velocity is calculated by solitary wave theory instead of linear wave theory. The use of solitary approximation results in a prediction that is 25% greater than the C.E.R.C prediction and is not considered appropriate by Bodge and Kraus (1991). Conclusions from streamer trap are summarized in figure 6:

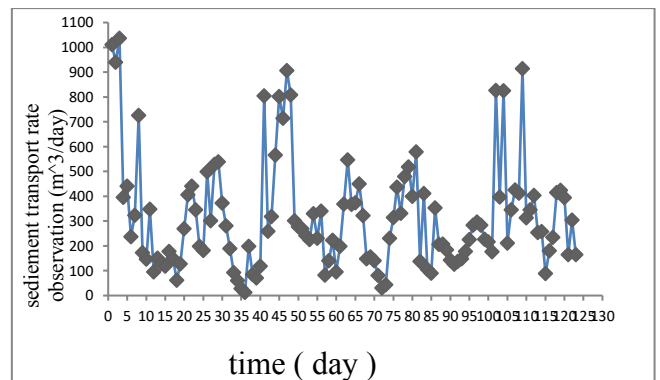


Fig6: collected sediment transport data in Noor coastal zone by streamer traps

Tabel3: The estimated value sediment transport rates by the observation method

Name	Q(kg.(year) ⁻¹)	Q(kg.(day) ⁻¹)
Sediment transport rate	334340	916

3.4. Prediction of longshore sediment transport rate

To determine the LSTR in the study area; the long-term observations of shoreline changes, sediment properties, wave characterizes measurement campaigns were performed. The LSTRs are obtained from three different methods (e.g. C.E.R.C (USACE, 1984) Formula, Kamphuis (1991) Formula, Walton and Bruno (1989) Formula).

According to the calculations for the research area, the gross and the net LSTRs were obtained as shown in Table 4 statistical evolution reuse C.E.R.C, W.B and Kamphuis formulas are shown in Table 5.

Table 4: The daily and yearly alongshore sediment transport rates predicted by different methods

Formula	$Q(m^3 \cdot (year)^{-1})$	$Q(m^3 \cdot (day)^{-1})$
C.E.R.C (USACE, 1984)	350400	960
Kamphuis (1991)	359890	986
Walton and Bruno, 1989	315360	864

For the current study, C.E.R.C formula used to be the most frequently applied expression which yields to the new models that include more coastal parameters. It is recommended that to use C.E.R.C formula in storm conditions where the wave heights exceed 4 m [34]. But, in Noor coastal region according to the wave climate studies, the average wave height was 0.3 m. Thus, C.E.R.C equation overestimates LSTRs obtained from Kamphuis (1991), W. B, and ANN by factor of 0.97 and 1.1, and 0.98 respectively. It is recommended to use Kamphuis (1991) formula in low-wave energy conditions with breaker heights of less than 1 m [34]. The recommended value corresponds to the study area's wave condition. Thus,

Kamphuis (1991) equation overestimates LSTRs obtained from C.E.R.C, W.B, and ANN by factor of 1.03 and 1.14, and 1.01, respectively.

3.5. Application of ANN for estimation of alongshore sediment transport rate

3.5.1. Data used in training the ANN model

Important parameters in most sediment transport formulas area alongshore current velocity (V), surf zone width (W) and breaking wave height (H_b) in this study, observed data by obtained from streamer trap was used. Measured V , W , H_b values were used as an input data to the model and sediment transport rate (Q_s) as an output of model. A total of 123 samples were used for training the model and 87 samples, 36 samples of total measured data randomly selected to validation and testing the model.

3.5.2 ANN model development

To choose the best network for forecasting, different models were built with various nodes and middle layers. In Learn Rate Control (LRC) feature, 0.001 and 0.15 were used as the minimum and maximum limit for auto control of learning rate. The input combinations to estimate total sediment load are: 1) H , W and V 2) H and α ; and 3) H , T , α , D_{50} and m . The first combination includes breaking wave height, long shore current velocity and surf zone width most of sediment transport rate using W.B formula. Other two combinations include parameter used C.E.R.C and Kamphuis formulas. After try-and-error tests, the best network found in this study is the one with 3 layers including one input layer, one middle layer, and one output layer. The best model consists of 3 input including H , W and V , 14 middle nodes, and an output node which should have a sigmoid transfer function. The sigmoid function represented by $1/(1+e^{-x})$ and set the output single strength between 0 and 1. The correlation coefficient and RMSE of this model

were 0.98 and 0.017 for the training data set and 0.96 and 0.015 for the test data set, respectively. The final architecture of the ANN model is given in Table 6.

The ANN model (3-14-1) which was trained using three important parameters of sediment transport rate formulas has slightly more accurate results than other models with four inputs. The accuracy of the chosen ANN model (3-14-1) in comparison with other models of 3 inputs, especially those ones with more than one hidden layer, has insignificant difference. According to the intricacy and longer time needed for training of models with more than one hidden layer, the selection of ANN model (3-14-1) is reasonable. The comparison of the measured data and estimated total sediment load using ANN for training and testing procedures are shown in Figs. 7.

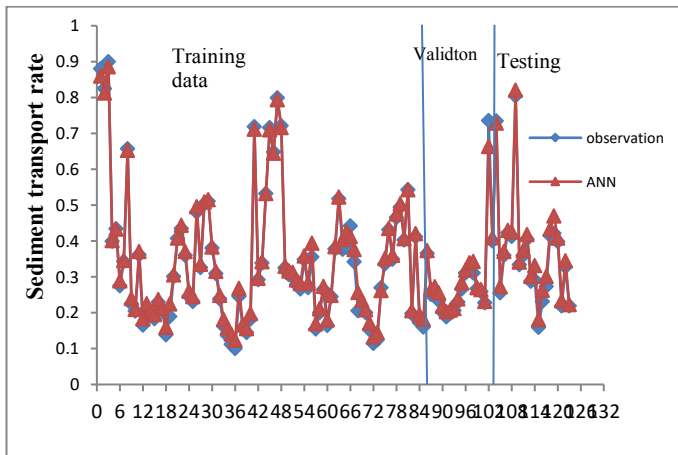


Fig 7: Comparison of observed and simulated sediment transport rate form ANN (3-14-1)

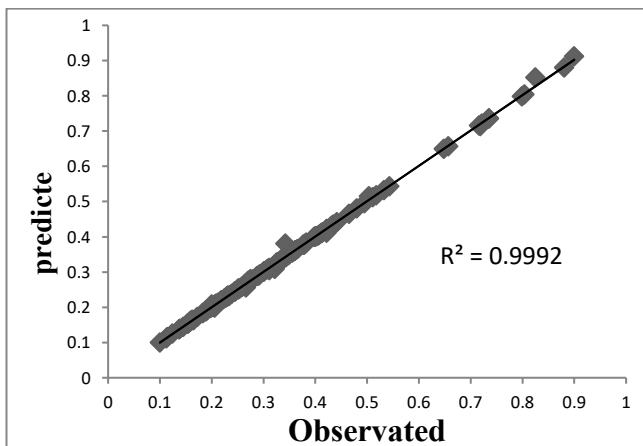


Fig 8: The scatter plot of observed and predicted sediment transport rates forecasts of the ANN (3-14-1)

The daily statistical variables of the breaking wave height (H), wave period (T), wave breaker angle (α), surf zone width (W), long shore current (V), beach slope (m), grain size (D), sediment transport rate observation ($Q_{\text{observation}}$), and sediment transport rate forecast ANN (Q_{ANN}) data. Table.7. In this table, S_x , C_v and C_{sx} denote the standard deviation, variation and skewness coefficients, respectively.

4.Comparison the results of ANN and sediment transport rate formulas

123 sets of observed data with accurate wave properties, surf zone width and alongshore current velocity information, not used in the training and verification of Ann in previous section, are used to compare the results of Ann model and sediment transport formulas. Field data including breaking wave height, period wave, breaker wave angle, surf zone width, long shore current velocity, sediment particle size distribution, beach slope and sediment transport rate. These data were measured by observation filed using streamer trap.

Figure 9 shows the comparisons between computed results from three sediment transport rate formulas and the computed results from the Ann.

In summary, the ANN model was trained using three important parameters H , W , and V which can be further used to estimate sediment transport rate in Caspian Sea data. But, the accuracy of an ANN model is data sensitive, and should not be applied to the conditions outside the data range used in training the ANN model without verification.

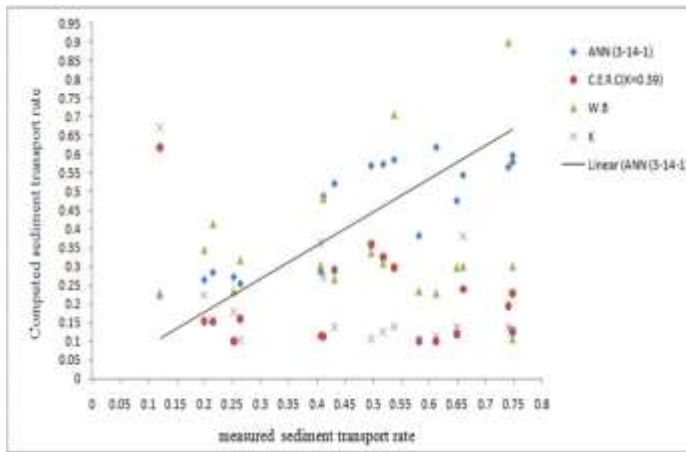


Fig 9: Comparison of ANN the formulas results with observed data

Fig. 10 shows the predicted Q_p compared with observed Q_s using C.E.R.C, Kamphuis, W.B formulas, and ANN method. The R^2 , $RMSE$, CE , MRE and MAE statistical criteria were used to calculation the results of the different models (Table 8).

5.CONCLUSIONS

In the presented study, the accuracy of empirical formula and ANN was evaluated in prediction of daily sediment transport rate. The LSTRs measured by the streamer sediment traps along the low-wave energy coast are lower than the rates predicted by the various empirical formulas. The commonly used C.E.R.C-formula, Kamphuis Formula, W.B predictions are unrealistically high for the studied low-energy settings. The linear relationship between the energy flux factor and LSTR contained 0n the C.E.R.C formula is supported by the streamer trap measurements. But, an order-of-extent lower empirical coefficient, 0.08 rather than 0.78 recommended by Shore Protection Manual (1984), is suggested by the trap data for low-energy coast.

The LSTR predicted by the Kamphuis (1991) formula was 3 times lower than the C.E.R.C prediction and closer to the measured values. The relationships between LSTR with the wave period, beach slope, and sediment grain size established in the Kamphuis (1991) formula are approved by the present study. It is

essential to reconcile the different measurement techniques of, sampling. Further studies on the comparability of the field techniques are recommended. Relationship among the different key measurements (Table 3) needs to be explored to further under-stand their compatibility ANN model is used for estimating sediment transport rate in sea in this study. 87 samples were used for training the ANN model and 36 samples were used to verify the model. Inputs for training the model include breaking wave height (H), surf zone width (W) and alongshore current (V). The results showed that the artificial neural network alongshore sediment transport rate in Noor coastal zone calculate. It is obvious R^2 , RMSE, MAE, CE and MRE form ANN method, 0.96, 0.015, 1.7×10^{-4} , 0.93, and 3.5×10^{-2} respectively.

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