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A hybrid framework for evaluating the performance of port container terminal operations: Moroccan case study

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ABSTRACT

This work intends to integrate artificial neural network (ANN) and data envelopment analysis (DEA) in a single framework to evaluate the performance of operations in the container terminal. The proposed framework is based on three steps. In the first step, a proposed identify the performance measures objectives and the indicators affecting the system. In the second step, the efficiency scores of the system are computed by using the Charnes Cooper and Rhodes (CCR) model (oriented inputs). In the last step, the Moth Search Algorithm (MSA) is employed as a new method for training the Feedforward Neural Network (FNN) to determine the efficiency scores. To demonstrate the efficacy of the proposed framework, two container terminals of Tangier and Casablanca are adopted to evaluate the performance.

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1 Introduction

The container terminals have great importance in the international logistics chain. Their role has continuously evolved from the first generation of port terminals to the present. United Nations Conference on Trade and Development [1] defines the fourth generation of port terminals as geographically separated areas, which have common or administratively centralized operators. Currently, some authors define the beginning of the fifth generation of the port as customer-centric and community focused ports, with service deliverables related to port users' multifaceted business requirements, while also taking care of community stakeholder requirements. In the same direction as the fifth generation, some other authors introduce the smart side to port [2].

In [3], the evolution was based on the multiplication of goods transported via the port terminal, which is the weakest link in the logistics chain. Generally, port terminals are complex environments with many aspects: social, economic, political and cultural where different organizations, institutions, and functions interact at different levels. One of the challenging tasks is to managing separate

spaces in the port's terminals which is responsible for 90% of global trade goods. Due to this complexity, many performance measurement systems at port terminals or the whole dry port-sea port system have been developed. As introduced in [4], the state of the art of different models developing in the whole dry port-sea port system was presented. In 2016, a MACBETH multi-criteria approach was used to evaluate the performance indicators of the whole dry port-sea port system [5].

Despite the value-added of the mentioned work, the challenge is the lack of effective performance measurement systems in the ports. Thus, this paper aims to develop a performance measurement system from the maritime perspective, which is based on three main ideas:

- (1) A third-level horizontal interaction model; the first level aims to evaluate the overall performance, the second aims to evaluate the various objectives of the container terminal when the third level determines the performance indicators.
- (2) An overall evaluation resulting from all objectives of the evaluated organization.

(3) The non-obligation to define the weight of each indicator. It is sufficient to determine the interaction between the levels of each indicator and the interaction between the different indicators.

In recent years, the data envelopment analysis (DEA) and artificial neural network (ANN) have been widely used as a non-parametric tool for evaluating the performance of operations in a container terminal. The first combination of the neural networks (NNs) and DEA was first proposed in [6] for forecasting the number of employees in the health care industry. In the proposed model, they considered the DEA as a preprocessing methodology for training steps, while the ANN is then trained on a selecting sample as a non-linear forecasting model. As stated in [7], the ANNs with corrected ordinary least squares (COLS) and DEA were compared. The proposed approach is applied to the London underground efficiency analysis. Their results indicate that the ANNs find reveal results than (COLS) and DEA regarding the decision making about the impact of constant vs. variable returns to scale or congestion areas. In [7], the treatment of DEA as a reprocessing methodology to create two sub-training datasets which is used in ANN. Based on the results of DEA efficiency, the 50 highest ranking efficiency scores are called "efficient" set and the other set is called "inefficient. As two nonparametric models, there are many similarities between ANNs and DEA models [6] such as:

- (1) Neither DEA nor ANNs makes assumptions about the functional form that links its inputs to outputs.
- (2) DEA seeks a set of weights to maximize the technical efficiency, whereas ANNs seek a set of weights to derive the best possible fit through observations of the training dataset.

The main scope of DEA is to provide an estimation of efficiency surfaces by solving mathematical programming model. However, a major problem faced by DEA is that the derived frontier may be warped if the data is affected by statistical noises [8]. The artificial neural network (ANN) has been widely used as a good alternative tool to estimate the efficiency frontiers for decision-makers [9]. One of the most important problems faced by neural networks is the training process. In general, training algorithms can be classified into two groups: gradient-based algorithms versus stochastic search algorithms. The most widely applied gradient-based training algorithm is the backpropagation (BP) algorithm in [10]. However, this method has some drawbacks such as the slow speed of convergence and getting trapped in local minima. On the other hand, the nature-inspired metaheuristic algorithms as an alternative trainer are proved more efficient in escaping from local minima for optimization problems.

In the literature, several metaheuristic methods have been used as a trainer for FNNs. In [11], a hybrid method has been proposed based on particle swarm optimization (PSO) and gravitational search algorithm (GSA) to train FNNs. The reported numerical results show that the accuracy of PSO-GSA in terms of converging speed, avoiding the local optima training process is better than both PSO

and GSA. Recently, several other metaheuristic algorithms have been proposed as a new trainer of NNs. In [12], the biogeography-based optimizer is to train FNNs. The reported numerical results show that the accuracy of BBO in terms of converging speed, avoiding local optima training process is better than compared algorithms. In 2016, the krill herd algorithm (KHA) is introduced as a trainer of FNNs for data classification [13]. In 2016, a recently proposed nature-inspired algorithm called multiverse optimizer (MVO) was utilized in [14] for training the FNNs. The reported numerical results show that MVO is very competitive and outperforms other training algorithms in the majority of the dataset.

To the best of the knowledge, there are no previous work attempts to dealing with the performance of operations in container terminals using ANNs and DEA. This paper presents a hybrid framework to evaluate the performance of operations in a container terminal. The proposed framework is based on three steps. The first step is to set performance measurement targets and indicators affecting the system. The second step is to calculate the efficiency scores using the CCR (orientated-input). In the last step, the Moth Search Algorithm (MSA) is employed as a new method for training FNNs to determine the efficiency scores.

The rest of the paper is organized as follows. Section 2 provides the performance measurement system. Section 3 provides the methodologies utilized in this paper. Section 4 reports the numerical results and discussion. Finally, the conclusion and future work are presented in Section 5.

2 Performance measurement system

Today, evaluating the performance of operations in a container terminal is one of the important tasks for ports' managers. As presented in [15], it is difficult to assess the performance of an organization when there are several performance measures related to a system or operation, including several organizations in the case of container terminals. Whereas the growing competitiveness in the container terminals needs a higher level of performance. Over the past decades, many researchers have been studying the evaluation of the efficiency and performance of container terminals, particularly those of ports containers and terminals.

The indicators in the performance measurement system mainly depend on the overall aims of the company [16], which requires us to first determine the aims of the container terminals. Most companies give more importance to financial performance since the objective of each organization is to create profits, which explains the existence of financial performance in all the performance measures proposed by the container terminals and the international organizations. But, surprisingly, container terminals managers continue to neglect operational and logistical performance. In [17], the approaches adopted by container terminals and researchers who neglect the logistic side despite the primary role of the container terminals in the global logistic chain is criticized. While in [18], the operations

in container terminals are considered very important; this is why it is judicious to focus on operational and logistical performance. Several organizations classify container terminals according to their size, in particular the surface area of container terminals, lengths and platform infrastructure. The physical performance contributes to 51.23% of total performance [19]; which explains the significance of the physical performance to overall performance In addition to

those objectives, there is a need to improve trade performance, as shipping which is correlated with the economic developments and the performance in international trade.

This work presents the aimed objectives to have a global container terminal performance, as well as the involved performance indicators. Fig. 1 shows the overall steps. Based on identifying the performance indicators mentioned in the literature, the organizations (ESPO,

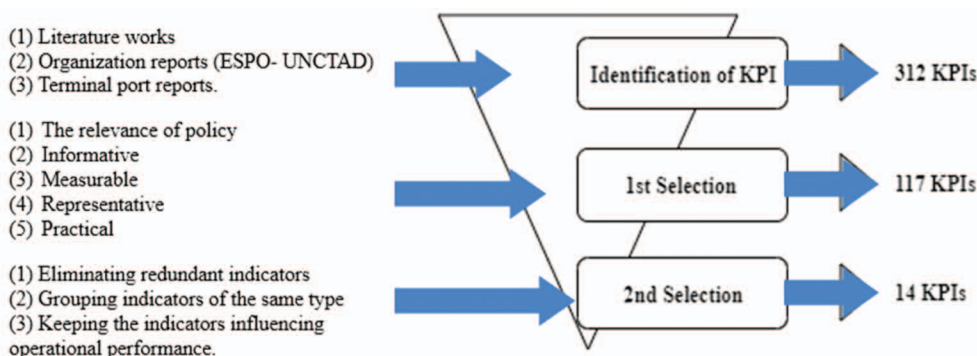


Fig. 1 Steps to identify the objectives and indicators.

Source: Authors

Table 1 List of criterions and its description.

Criteria	Description
The relevance of policy	Monitor the strategy and progress of the activity
Informative	Provide relevant information to the activity
Measurable	Measure following a reliable procedure
Representative	Gives information simply to interpret
Practical	Simple to monitor

Source: Authors

Table 2 Global performance.

Aims of the Performance Measurement System	Key driver
Operational and Logistic Performance	• Administrative Management (AM)
	• Management of Ship Services (MSS)
	• Management of Quay Operations (MQO)
	• Yard Operations (YO)
	• Employee Performance (EP)
Financial Performance	• Financial Wealth (FW)
	• Financial Health (FH)
	• Investment (I)
Physical Performance	• Port Sizes (PS)
	• Port Equipment (PE)
	• Exploitation of Technology (ET)
Commercial Performance	• Services and Organizations (SO)
	• Competitive Position (CP)
	• Safety and Security (SS)

Source: Authors

UNCTAD ...) and the reports of the container terminals, 312 indicators were set. In the first step, a selection is made based on the five criteria provided by the work of the literature illustrated in Table 1. In the second step, the critical study on each indicator is done by:

- (1) Eliminating redundant indicators
- (2) Grouping indicators of the same type
- (3) Keeping the indicators influencing operational performance.

In the last stage, the list of performance indicators has been limited to 14 indicators. Table 2 presents the overall performance measurement system containing all system performance indicators.

3 Hybrid framework

In this section, the framework for assessing the performance of container terminal is described as follows:

3.1 Data Envelopment Analysis (DEA)

Measuring and improving efficiency are two challenging tasks for all companies. Data envelopment analysis (DEA) is a nonparametric tool based on linear programming proposed in [20] to measure the relative efficiency of a decision making unit (DMU) and provide DMUs with relative performance assessment on multiple inputs and outputs.

DEA models may have two different orientations, input-oriented and output-oriented modes. Input-oriented models are centered on the utilization of minimum inputs while having a constant level of output. Contrary, output-oriented models are concentrated on maximizing outputs within a constant input. In general, the selection of the model depends on the nature of the problems to solve. In this paper, an input-oriented model CCR is used to evaluate the efficiency of the terminal port. In the CCR model, the efficiency of an evaluated entity is obtained as a ratio of its weighted output to its weighted input; subject to the condition that the ratio for each entity is not greater than 1.

Let us suppose that there are n DMUs, m inputs, and s outputs. Suppose x_{ij} ($i = 1, \dots, m; j = 1, \dots, n$) is a quantity of input i consumed by DM and y_{rj} ($r = 1, \dots, s; j = 1, \dots, n$) is the quantity of output r produced by DM, u_r the weight of r_{th} output elements, v_i the weight i_{th} input item. As suggested by the CCR model, the efficiency of DM denoted as P_k can be measured by solving the linear equations (Eqs. 1-4) [20]:

$$\begin{cases} \max P_k = \sum_{r \in S} u_r * y_{r,k} & (1) \\ \text{Subject to:} \\ \sum_{i \in M} v_i * x_{i,k} = 1 & (2) \\ \sum_{r \in S} u_r * y_{r,j} - \sum_{i \in M} v_i * x_{i,k} \leq 0, \quad \forall j \quad (j = 1, 2 \dots n) & (3) \\ u_r, v_i \geq 0, \quad \forall r, i \quad (r = 1, 2 \dots s), (i = 1, 2 \dots m) & (4) \end{cases}$$

3.2 Feedforward Neural Network (FNN)

In the artificial neural network, the feedforward neural network (FNN) was the simplest type that consists of a processing elements' set called "neurons". In this network, the information moves in only one direction, forward, from the input layer, through the hidden layer, and to the output layer. There are no cycles or loops in the network. An example of a simple FNN is shown in Fig. 2. The presented example has a single hidden layer, input and one output O, each neuron computes the sum of the weight of the inputs at the presence of bias and passes this sum through an activation function (like a sigmoid function) so that the output is obtained. This process can be expressed as (Eqs. 5-7).

$$H_j = \sum_{i=1}^R iw_{j,i}I_j + hb_j \tag{5}$$

Where iw_{ji} is the weight connected between neurons $i = (1, 2, \dots, R)$ and $j = (1, 2, \dots, N)$, hb_j is a bias in hidden layers, R is the total number of neurons in input layers, and I_j are the corresponding input data.

Here, the S-shaped curved sigmoid function is used as the activation function, which is shown in

$$ho_j = f_j(h_j) = \frac{1}{1 + e^{-h_j}} \tag{6}$$

where ho_j the output of the neuron in the hidden layer. In the output layer, the output of the neuron is shown in

$$y_k = f_k \left(\sum_{j=1}^N hw_{k,j}ho_j + ob_k \right) \tag{7}$$

Where hw_{kj} is the weight connected between neurons $j = (1, 2, \dots, N)$ and $k = (1, 2, \dots, S)$, ob_k is a bias in output layers, N is the total number of neurons in hidden layers, and S is the total number of neurons in the output layer.

The training process is carried out to adjust the weights and bias until some error criterion is met. Above all, one problem is to select a proper training algorithm. Besides, it is very complex to design the neural network because many elements affect the performance of training, such as the number of neurons in hidden layers, the interconnection between neurons and layer, error function and activation function.

3.2 Moth Search Algorithm (MSA)

Recently, the moth search algorithm (MSA) has been proposed as a new swarm algorithm [21], through simulating the behavior of moths in nature where the moths are a family insect coupled with the butterflies are belonging to the order Lepidoptera. The simulation is performed through using the phototaxis and Levy flights. Where the phototaxis is considered as one of the most features of moths which are used to represent the movement of moth towards or away from the light source. Also, it has

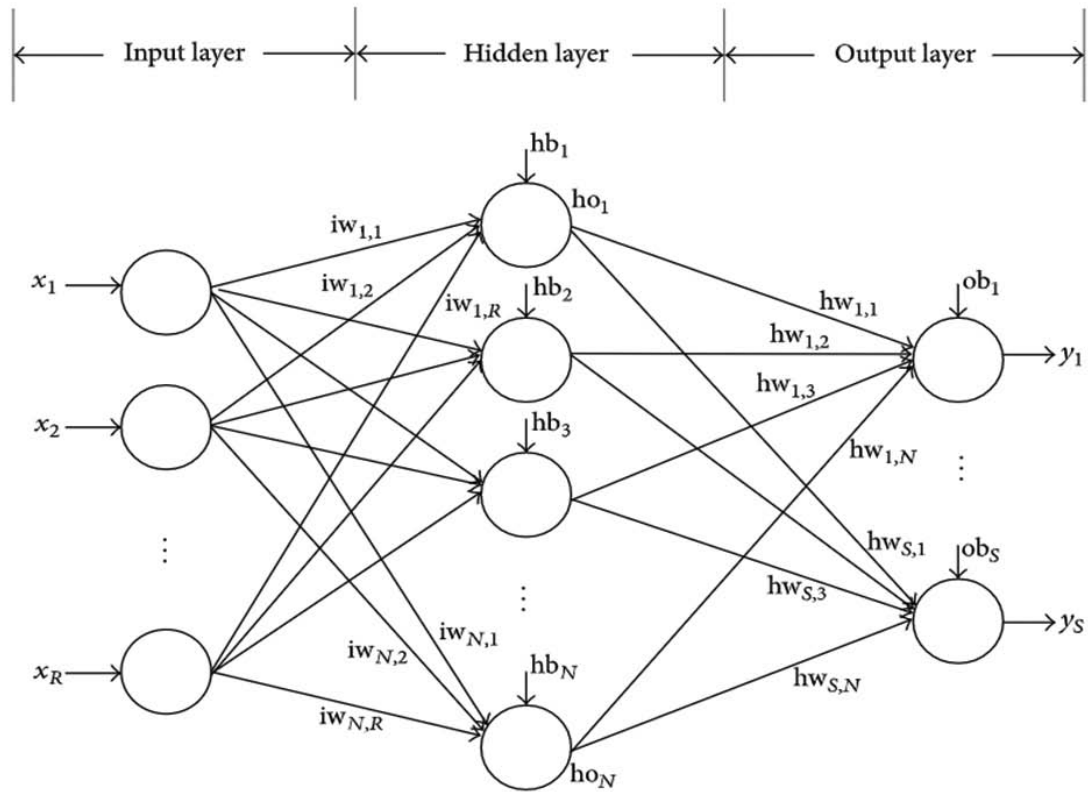


Fig. 2 Example of ANN architecture. [14]

been perceived that the characteristics of moths follow Levy flights [21]. In general, the light source represents the best moth (solution) inside the population, also, the moths which close to the best moth are fly around their positions using the Levy flights. On the other hand, those moths which are far from the best moth will fly toward it directly in a straight line and this is the result of the phototaxis. The previous features of the moths are representing the exploration and exploitation abilities of moth search algorithm as a swarm algorithm. The mathematical model of the moth search algorithm (MSA) [21] is given in this section. Where the MSA simulates the behavior of the moths in natural by using the phototaxis and Levy flights which represent the exploration and exploitation of the algorithm, respectively. The MSA starts by generating a random population of moths (solutions) and then evaluate the quality of each moth using the fitness function. The moths that are nearest to the best moth with fly around it through using the Levy flights as in the following equation [21]:

$$x_i^{t+1} = x_i^t + \frac{S_{max}}{t^2} L(s) \tag{8}$$

where x_i^{t+1} and x_i^t represents the updated and the current position of the i_{th} moth at iteration t . While S_{max} represents the maximum walk step and $L(s)$ represents the step drawn from Levy flights, using parameter s , that is defined using the gamma function $\Gamma(x)$ as Eq. 9:

$$L(s) = \frac{(1 - \beta)\Gamma(\beta - 1) \sin\left(\frac{\pi * (\beta - 1)}{2}\right)}{\pi s^\beta}, s \geq 0 \tag{9}$$

where $\beta = 1.5$ represents the parameter of Levy distribution [9]. Moreover, the moths that are far away from the source of the light they will fly in line towards this source or towards the final position that is beyond that source according to probability ($Prob_s$).

$$x_i^{t+1} = \begin{cases} \lambda * (x_i^t + \phi * (x_b - x_i^t)), & \text{if } Prob_s \leq 0.5 \\ \lambda * \left(x_i^t + \frac{1}{\phi} * (x_b - x_i^t)\right), & \text{Otherwise} \end{cases} \tag{10}$$

where x_b represents the best moth position, while λ and ϕ are the scale and acceleration factor respectively.

Algorithm 1: Moth Search Algorithm [21]

- 1: Input: The number of solutions N , maximum number of iterations t_{max} the dimension dim
- 2: Output: The best solution x_b
- 3: Initialize the maximum of walk S_{max} , the index β , acceleration factor \emptyset
- 4: Generate a random population X with N size and dimension dim
- 5: Compute the fitness of each solution $x_i \in X, i = 1, 2, \dots, N$
- 6: **while** ($t < t_{max}$) **do**
- 7: Sort the moths based on the fitness function values
- 8: **for** $k = 1$ to $N/2$ **do**
- 9: Update x_i using Levy flights as in Equation (8)
- 10: Compute the fitness function of x_i
- 11: **end for**
- 12: **for** $k = N/2 + 1$ to N **do**
- 13: Update x_i using Equation (10).
- 14: Compute the fitness function of x_i
- 15: **end for**
- 16: Update $t = t + 1$
- 17: **end while**

3.3 MSA for Train FNNs

3.3.1 The Feedforward Neural Networks Architecture

When implementing a neural network, it is necessary to determine the structure based on the number of layers and the number of neurons in the layers. The larger the number of hidden layers and nodes, the more complex the network will be. In this work, the number of input and output neurons in MLP network is a problem-dependent, and the number of hidden nodes is computed based on Kolmogorov theorem [22] throw the equation (11) :

$$Hidden = 2 * Inputs + 1 \tag{11}$$

When using MSA to optimize the weights and bias in the network. The dimension of each organism is considered as D , as follows:

$$D = (I * H) + (H * O) + H_{bias} + O_{bias} \tag{12}$$

where I, H and O refer to the number of inputs, hidden, and output neurons of FNN, respectively. Also, H_{bias} and O_{bias} are the number of biases in hidden and output layers.

3.3.2 Method evaluation

In MSA, every organism is evaluated according to its status (fitness). This evaluation is done by passing the vector of weights and biases to FNNs, then the mean squared error (MSE) criterion is calculated based on the prediction of the neural network using the training dataset. Through continuous iterations, the optimal solution is finally achieved, which is regarded as the weights and biases of a neural network. The MSE criterion is given in Eq. 13 where y and \hat{y} are the actual and the estimated values based on the proposed model and R is the number of samples in the training dataset.

$$MSE = \frac{1}{R} \sum_{i=1}^R (y - \hat{y})^2 \tag{13}$$

3.3.3 Encoding Strategy x

In [23], the weights and biases of FNNs for every agent in evolutionary algorithms can be encoded and represented in the form of a vector, matrix, or binary. In this work, the vector encoding method is utilized. An example of the vector encoding method for FNN is provided as shown in Fig. 3. Each moth represents a complete set of FNN weights and biases, which is converted into a single vector of the real number.

3.3.4 The proposed Hybrid Algorithm

The proposed framework is based on three steps. The first step identifies the focus and the indicators of measuring performance, in addition to the sub-indicators affecting the system. The second step computes the efficiency scores by the CCR model (oriented inputs). In the last step, the Moth Search Algorithm (MSA) is employed as a new method for training FNNs to determine the efficiency scores. Fig. 4 describes the hybrid framework algorithm.

4 Numerical results

This section investigates the efficiency of the proposed hybrid framework evaluating the performance of operations in a container terminal. The experiments were done

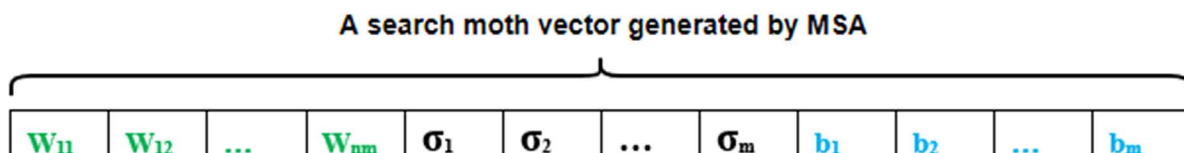


Fig. 3 Solution representation. [24]

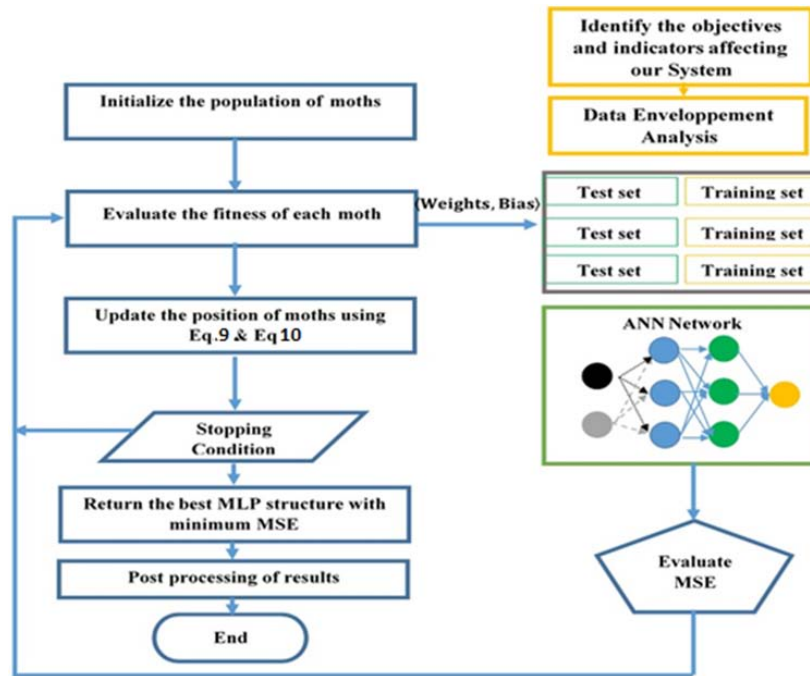


Fig. 4 Proposed hybrid framework algorithm.

Source: Authors

Table 3 Input and output of datasets

Input	Key driver	Input	Key driver	Output	Key driver
I1	AM	I7	FH	O1	CP
I2	MSS	I8	I	O2	SS
I3	MQO	I9	PS		
I4	YO	I10	PE		
I5	EP	I11	ET		
I6	FW	I12	SO		

Source: Authors

Table 4 Set of parameters

	Pop_{size}	50
	Max_{GEN}	300
MSA	β	1.5
	S_{max}	1
	Acceleration factor	0.68
	Keep	2

Source: Authors

using a PC with a 3.30 GHz Intel(R) Core (TM) i5 processor, 4 GB of memory. The entire algorithms were programmed in MATLAB R2014a. All experiments are executed for 20 different runs and a given set of parameters presented in Table 4; the other algorithms' parameters such as BBO, PSO and GA are taken the same as [12]. The dataset of container terminals which visualized in Fig. 5 are collected based on

brainstorming. Due to confidential issues, the initial data was modified with a uniform random variable between [0.15 -1] and partitioned based on DEA into 66% for training and 34% for testing. The column name of the dataset is the Key driver of the performance measurement system is displayed in Table 2 and the efficiency (eff) issued from applying DEA CCR model to the key driver. In order to compute the efficiency, the key driver is split to Input (from I1 to I12) and output (O1 and O2) as shown in table 3.

For all benchmarks, the average (AVE) and standard deviation (STD) are used to compare all algorithms. The purpose of employing these two measures is to indicate the ability of algorithms to avoid local minima.

The results are reported in Table 5. By analyzing the Table 5, the first thing that can be observed in the results is the highest performance obtained by the proposed method. This behavior is due to a great ability to avoid local optima, significantly better than other algorithms. Also,

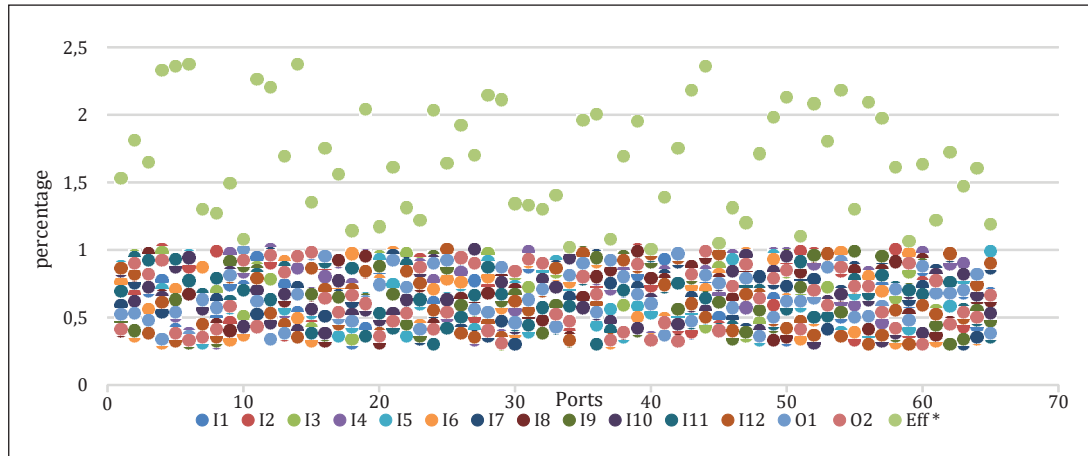


Fig. 5 Datasets visualizations

Source: Authors

Table 5 Experimental results for container terminals dataset

Algorithm	AVG ± STD	Performance - Error
MSA	3.2902 ± 1.649e - 07	0.5925
BBO [12]	3.1126 ± 0.04898	1.2210
PSO [12]	2.0106 ± 0.23041	2.8324
GA [12]	2.0096 ± 0.18295	3.8081

Source: Authors

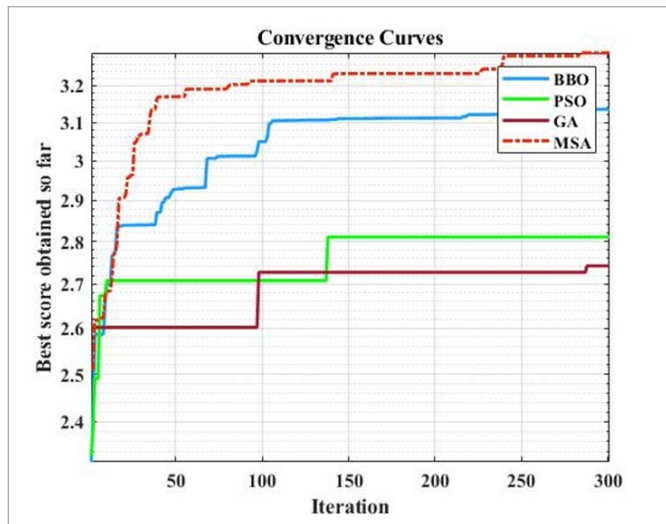


Fig. 6 Convergence curves of algorithms for the container terminals.

Source: Authors

Table 6 Moroccan case study

Ports	Target	Obtained-Performance				Rank
		BBO	PSO	GA	MSA	
Tangier	200%	155%	108%	120%	163%	1
Casablanca	200%	118%	92%	95%	126%	2

Source: Authors

a convergence comparative experiment was carried out to confirm that MSA has better convergence performance than BBO, GA and PSO. Fig. 6 shows the convergence of MSA, GA and PSO.

To validate the model, a case study is conducted based on two container terminals namely: Tangier and Casablanca. Table 6 shows the obtained results. As can be seen, all the algorithms give the same rank for considered ports. In other terms, the Tangier Port is very efficient than Casablanca Port. Moreover, the proposed algorithm gives better values than other algorithms in terms of obtained performance.

5 Conclusion

This paper presents an ANN-DEA study to evaluate the performance of operations in the container terminal. The result helps DMUs to improve their efficiency and gives them a useful strategic plan for future developments. Unlike DEA, the ANN-DEA approach guides weaker performers on how to improve their performance to different efficiency ratings for the future. The proposed framework is based on three steps. The first one identifies the performance measures objectives and the indicators affecting the system. In the second step, the efficiency scores of the system are computed by using the DEA. In the last step, the Moth Search Algorithm (MSA) is employed as a new method for training the Feedforward Neural Network (FNN) to determine the efficiency scores. To demonstrate the efficacy of the proposed framework, a performance evaluation is performed for two container terminals, namely, Tangier and Casablanca. For future work, it is essential to have a reliable methodology to measure and identify the key performance indicators. With a different method of measurement and identification, these indicators became insignificant. A deeper work is to develop in this scope to standardize the measurement methods as well as the performance indicators.

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