A DEA-ANN framework based in Improved Grey Wolf Algorithm to evaluate the performance of container terminal.

Mouhsene Fri1,2,3, Kaoutar Douaion1, Samir Tetouani1,2, Charif Mabrouki1 and El Alami Semma1

1 LMII- Faculty of Sciences and Technology, Hassan 1st University, PO Box 577, Settat, Morocco
2 CELOG-ESITH, PO Box 7731 OULFA, Casablanca, Morocco
3 Author to whom any correspondence should be addressed

frimouhsene@gmail.com

Abstract. Managing the performance of port container terminals is one of the major challenges in the supply chain management. In response to this challenge, we propose a new framework to assess managers in evaluating the global performance of operations in port container terminals. The new framework integrates the Data Envelopment Analysis (DEA) and Artificial Neural Network (ANN). The DEA is used to compute the efficient score of the system. In ANN, we use the improved grey wolf optimizer based on Levy’s flights to improve learning. In order to prove the efficiency of our model, we apply the framework in 2 ports container terminal: Tangier Med Port and Casablanca Port. The result is compared to standard algorithms and outperforms the cited algorithm in order to avoid local minima. The new trainer improved grey wolf optimizer is also evaluated using four known classification datasets and on three approximation functions datasets.

Keywords: Port Container Terminal, Performance Measurement System (PMS), Data Envelopment Analysis (DEA), Artificial Neural Network (ANN), Levy Flights.

1. Introduction

Port is the link between two geographical space; the seaside and the landside. One of the main goals of the seaport is to transport cargo from suppliers to customers in excellent conditions. In this regard, the important role of port container terminal has evolved from the first generation to the fourth generation. However, the issue of managing the performance present one of the most challenges in the port terminal container. Port performance has largely been treated by researchers [1], [2]; Bichou and Gray highlight the important role of logistics performance in Port containers [3]. On the other hand, Chul-hwan demonstrate the impact of the supply chain integration into port performance by proving that the customer integration and cost performance impact the quality performance [4]. European seaports launch a project named “Performance Indicators: Selection and Measurement Project” in order to standardize the performance indicators in all European ports [5]. Despite this, we call attention to the lack of unique performance measurement system able to reflect the global performance in order to evaluate and classify different ports. In this study, we define the performance measurement system, in addition, we developed a new framework to evaluate the global performance based on two steps. In the first step we compute the efficiency score by using DEA oriented input models and in the second step we use ANN based in improved grey wolf optimizer. Grey Wolf Optimizer is enhanced by the so-called
Levy flights.

This study is organized as follows: The first section aims to provide a performance measurement system. The second section presents the methods and algorithms used to elaborate the proposed framework. The third section contains the numerical results as well as the benchmarking of result with the known algorithms. Finally, the fourth section aims to present the conclusion and future works.

2. Performance Measurement System

Globalization and liberalization of business have a direct impact on the number of goods transported through port container terminals. In this regard, the intention to manage performance has increased in recent years. Many researchers proposed performance measurement systems but the majority of those systems focus on the financial performance [6] and neglect the industrial and logistical performance which represents one of the primary goals of the seaport in the supply chain management. However, the unfulfilled gap here is the absence of a method able to evaluate and measure the global performance system. Regarding this, we used the proposed key performance indicators developed by Fri et al. [7](see table1).

| Key driver [7]                  |          |
|---------------------------------|----------|
| Administrative Management (AM)  | Safety and Security (SS) |
| Management of Ship Services (MSS)| Port Sizes (PS) |
| Management of Quay Operations (MQO)| Port Equipment (PE) |
| Yard Operations (YO)            | Exploitation of Technology (ET) |
| Employee Performance (EP)       | Services and Organizations (SO) |
| Financial Health (FH)           | Competitive Position (CP) |
| Competitive Position (CP)       | Safety and Security (SS) |

3. Hybrid Framework

The proposed hybrid framework is based on three steps illustrate in figure 1. In the first step, we identify the performance measures objectives and the indicators, the sub-indicators affecting our system. In the second step, we compute the efficiency scores by the CCR model (oriented inputs) [8]. In the last step, the improved grey wolf algorithm employed as a new method for training ANN to determine the efficiency scores. In our case the learning will be enhanced by improving the grey wolf algorithm.

![Figure 1. The proposed hybrid framework.](image_url)
3.1. Improved Grey Wolf Algorithm

Grey wolf optimizer (GWO) algorithm is one of the latest bio-inspired optimization techniques, which mimicking the social leadership and hunting technique of grey wolves in nature. This algorithm was proposed by [9]. Grey wolves live in group, they have very strict rules in the dominant social hierarchy. This hierarchy is simulated by categorizing the population of search agents in four types of individuals [9], i.e., alpha, beta, omega and delta.

1. The alpha wolf is the leader of the group; he is the maker of all decisions. The alpha’s decisions are ordered to the group.
2. The beta wolf is the subordinate of alpha. Beta wolf help alpha wolf in making decisions and the other activities. The beta is most qualified to be the alpha in the future.
3. The omega wolf is the scapegoat. He is all time obliged to submit to the dominant wolves and he is the last one allowed to eat.
4. The delta wolf must obey alpha and beta, but he dominates the omega. This category includes the Scouts, the sentinels, the elderly, the hunters, and the caretakers. The scouts are responsible for observing the frontiers of the territory and alerting the group if there is any danger. The sentinels safeguard and protect the group. The elders have extensive experience who has been in the level of alpha or beta. The hunters support the alpha and beta in hunting and providing food for the other members of the group. Finally, the caretakers are responsible for watching over the sick wolves, the weak and the wounded wolves in the group.

Grey Wolf Optimizer Algorithm

1: Initialization. Population of grey wolf, NP, the maximum of iterations $T_{\text{max}}$, A, C, a;
2: Initialize the grey wolf $(X_i = 1, 2, \ldots, N)$;
3: For each wolf, calculate the fitness value;
4: Rank the wolf pack as alpha $(X_\alpha)$, beta $(X_\beta)$, delta $(X_\delta)$;
5: for $i = 1$ to $\frac{NP}{5}$ do
6: $X_i^{t+1} = X_i^{t}_{\text{worst}} + \alpha \oplus \text{Levy}(\lambda)$
7: if $(F(X_i^{t+1}) < F(X_i^{t}_{\text{worst}}))$ then
8: $X_i^{t+1}_{\text{worst}} = X_i^{t+1}$
9: $F(X_i^{t+1}_{\text{worst}}) = F(X_i^{t+1})$
10: end if
11: end
12: while (stop criterion) do
13: for $i = 1$ to NP do
14: Update the position by equations (5)-(8);
15: end for
16: Obtain the updated wolf pack;
17: Update A, C and a;
18: Recalculate the fitness values of the wolves;
19: Rank the updated wolf pack as alpha $(X_\alpha)$, beta $(X_\beta)$, delta $(X_\delta)$;
20: end while
21: Return the position of alpha $(X_\alpha)$ as the final solution.

In conventional Grey Wolf Algorithm, it may converge prematurely without enough exploration of search space. In order to increase the diversity of the population against premature convergence and accelerate the convergence speed, this paper proposes an improved grey wolf optimizer based on Levy flights. Levy flights, represents a kind of non-Gaussian stochastic process whose step sizes are
distributed based on a Levy stable distribution to generate new solutions. When a new solution is produced, the following Levy flight is applied:

\[ X_{i}^{t+1} = X_{i}^{t} + \alpha \odot \text{Levy}(\lambda) \] (1)

Here, \( \alpha \) is the step size that is relevant to the scales of the problem. The product \( \odot \) means entry-wise multiplications. Levy flights essentially provide a random walk while their random steps are drawn from a Levy distribution for large steps:

\[ \text{Levy}(\lambda) = u = t^{-\lambda}; \ 1 \leq \lambda \leq 3 \] (2)

In this paper, we will use the algorithm proposed by [9], which is one of the most efficient algorithms used to implement Levy flights.

4. Numerical Results

In this section, we conduct investigations in the efficiency of the proposed hybrid framework for evaluating the global performance of port container terminal. The dataset is partitioned based on DEA into 66% for training data and 34% for testing data. The results of port datasets are presented in Table 02 based on the average (AVE) and standard deviation (STD). The main scope to employ these two measures is to indicate the ability of algorithms to avoid local minima. By analyzing the Table 2, the first thing that can be observed in the results of the highest performance obtained by the proposed method, this behavior is a result of the great ability to avoid the local optima, significantly better than other algorithms. In addition, a convergence comparative experiment was carried out to confirm that Improved Grey Wolf Algorithm has better convergence performance than Algorithm Genetic and Particle Swarm Optimization. Figure 3 – (a) shows the convergence of Improved Grey Wolf Algorithm, Biogeography-Based Optimization, Particle Swarm Optimization and Algorithm Genetic. To validate our model, we conducted a case study based on two ports container terminals namely: Tangier Med and Casablanca port. Table 03 shows the obtained results. Additionally, the show the efficacy of the proposed method, we are benchmarked it on four selected standard classification data sets from the University of California at Irvine (UCI) Machine Learning Repository: XOR, balloon, Iris, breast cancer. Table 4 – 8. The results of Improved Grey Wolf Algorithm-ANN follow by those of Biogeography-Based Optimization-ANN, Algorithm Genetic-ANN and Particle Swarm Optimization-ANN for all datasets. Since the difficulty of this dataset and MLP structure is high for this dataset, these results are strong evidence for the efficiency of Improved Grey Wolf Algorithm in training MLPs. The results testify that this algorithm has superior local optima avoidance and accuracy simultaneously. In addition, a convergence comparative experiment was carried out to confirm that Improved Grey Wolf Algorithm has better convergence performance than the benchmark for data classification and approximation function datasets. Figure 3 (b-e) shows the convergence of Improved Grey Wolf Algorithm for XOR, Baloon, Iris and Cancer data sets respectively.
**Figure 3.** Overall Convergence Curves.

### Table 2. Experimental results for Ports datasets.

| Algorithm                               | AVG ± STD       | Performance – Error |
|-----------------------------------------|-----------------|---------------------|
| Improved Grey Wolf Algorithm            | 3.3002 ± 1.549e-07 | 0.5725             |
| Biogeography-based optimization [10]    | 3.1126 ± 0.04898 | 1.2210              |
| Particle Swarm Optimization [10]        | 2.0106 ± 0.23041 | 2.8324              |
| Algorithm Genetic [10]                  | 2.0096 ± 0.18295 | 3.8081              |

### Table 3. Moroccan Case Study

| Ports           | Target | Obtained-Performance | Rank |
|-----------------|--------|----------------------|------|
| Tangier Med     | 200%   | 157% 108% 120% 164.22% | 1    |
| Casablanca Port | 200%   | 122% 92.7% 95% 127.35% | 2    |

### Table 4. Classification datasets

| Classification datasets | Number of attributes | Number of training samples | Number of tests | Number of classes |
|-------------------------|----------------------|----------------------------|-----------------|------------------|
| 3-bits XOR              | 3                    | 8                          | 8               | 2                |
| Balloon                 | 4                    | 16                         | 16              | 2                |
| Iris                    | 4                    | 150                        | 150             | 3                |
| Breast Cancer           | 9                    | 599                        | 100             | 2                |
| Heart                   | 12                   | 80                         | 187             | 2                |

### Table 5. Experimental results for XOR datasets.

| Algorithm                               | AVG ± STD       | Classification rate(%) |
|-----------------------------------------|-----------------|------------------------|
| Improved Grey Wolf Algorithm            | 3.31E – 09 ± 0.000000 | 100                   |
| Biogeography-based optimization [10]    | 3.65E – 07 ± 0.000000 | 100                   |
| Particle Swarm Optimization [10]        | 0.084050 ± 0.035945 | 35                    |
| Algorithm Genetic [10]                  | 0.000181 ± 0.000413 | 100                   |

### Table 6. Experimental results for balloon datasets.

| Algorithm                               | AVG ± STD       | Classification rate(%) |
|-----------------------------------------|-----------------|------------------------|
| Improved Grey Wolf Algorithm            | 9.1952E – 31 ± 4.8474E – 33 | 100                   |
| Biogeography-based optimization [10]    | 8.09E – 27 ± 1.51E – 42 | 100                   |
| Particle Swarm Optimization [10]        | 0.000585 ± 0.000749 | 100                   |
| Algorithm Genetic [10]                  | 5.08E – 24 ± 1.06E – 23 | 100                   |

### Table 7. Experimental results for Iris datasets.

| Algorithm | AVG ± STD       | Classification rate(%) |
|-----------|-----------------|------------------------|
| IGWO      | 0.015766 ± 0.0004059 | 92                    |
| BBO [10]  | 0.019150 ± 3.66E – 18 | 90                    |
| Particle Swarm Optimization [10] | 0.228680 ± 0.057235 | 37.33                |
| Algorithm Genetic [10] | 0.089912 ± 0.123638 | 89.33                |
Table 8. Experimental results for Cancer datasets.

| Algorithm                                  | AVG ± STD            | Classification rate (%) |
|--------------------------------------------|----------------------|-------------------------|
| Improved Grey Wolf Algorithm               | 0.001388 ± 3.1451e-05 | 98                      |
| Biogeography-based optimization [10]       | 0.002807 ± 0.000000   | 95                      |
| Particle Swarm Optimization [10]           | 0.034881 ± 0.002472   | 11                      |
| Algorithm Genetic [10]                     | 0.003026 ± 0.001500   | 98                      |

5. Conclusion
This paper uses the methods ANN and DEA to cover the drawbacks of DEA especially in statistical noise. For that we started by identifying the objectives and the indicators affecting our system. Then, we applied the CCR model (oriented inputs) to evaluate the scores. As a result, we employed an improved grey wolf algorithm as new trainer for ANN to enhance the performance of the system. In addition, the algorithm was compared with the renowned benchmarks. Finally, the reported results prove that the improved grey wolf is able to outperform the Biogeography-based optimization, algorithm genetic and Particle Swarm Optimization on the collected port datasets and on almost of classification and approximation datasets.

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