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## Comments

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# Benchmarking Environmental Efficiency of Ports using Data Mining and RDEA: The case of a U.S. Container Ports

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**Abstract**

This study provides stepwise benchmarking practices of each port to enhance environmental performance using joint application of data mining technique referred as Kohonen's Self-Organizing Map (KSOM) and Recursive Data Envelopment Analysis (RDEA) to address the limitation of conventional DEA. A sample of 20 container ports in the U.S were selected, and data on input variables (number of quay crane, acres, berth and depth), output variables (number of calls, throughput and deadweight tonnage, and $CO_2$ emissions) are used for data analysis. Among the selected samples, eight container ports are found to be environmentally inefficient. However, there appears to be a high potential to become environmentally efficient port. In conclusion, it can be inferred that, stepwise benchmarking process using two combined methodologies substantiates that, more applicable benchmarking target set of Decision Making Units (DMUs) is be projected that consider similarity of physical and operational characteristics of homogenous ports for improving environmental efficiency.

Keyword: Port Performance, Port Benchmarking, Environmental Efficiency, KSOM-RDEA, Data Mining

## 1. Introduction

Sustainability in every sector is crucial in order to maintain productivity for a prolonged period for current and future generations. Therefore, contemporary environmental impact has been of a prime concern in our society, hence, mitigating environmental impact of container port has become one of the lingering issues in management of sustainable port development. In this regard, the maritime sector plays an important role in growing the economic sector of a country and keeps moving industries around the world. Developing sustainability has become one of the most significant strategic goals in maritime operation because container ports play a critical role as international trade gates for every country (Song and Lee, 2012). Intermodalism is more effective and efficient by reducing the time of transferring goods from ship to shore and on-dock transportation. Ports have positive effect on national as well as regional economies (Deng et al., 2013), however, the environmental aspects of container ports are crucial in order to maintain sustainable, green logistics at ports since maritime activities have been recognized to be prime pollutant emitters in the U.S. generating environmental pollution, including but not limited to $CO_2$, $SO_2$, $NO_x$, and $SO_x$. Previous studies have highlighted that U.S Transport sector accounts for about 27% of overall energy consumption. Although the shipping sector uses only 2.5% of the global transport energy demand, but it only transports 90% of internationally traded goods. The container ships are considered to be as the backbone of the global economy, hence research and development regarding the economic and environmental aspect of port is significant (REN21, 2017). The common port activities include delay in port, loading and unloading processes using cranes, and transporting containers from ships to inland depots by truck and rail. Managing port operations is cumbersome because it deals with a variety of cargoes with different types of vessels from different countries. Poor operations management will cause port congestion and delay which will affect the whole operation of a port. Therefore, it is vital to measure the performance of a port in order to clearly identify the area to improve in the entire operation process. Performance measurement is common in industries where it identifies key elements to make sure daily operations are in good condition and running smoothly (Bergantino et al. 2013). Monitoring port performance is crucial for improving effectiveness and efficiency. Port operations are influenced by many

random factors, so the available resources such as the quay crane and berths should be utilized in efficient ways in order to reduce handling time, port congestion and any disruption during operations (Bichou, 2013).

Efficiency of port activities or operations is a critical aspect in order to achieve sustainability. International trade increases each year, leading to an increase in sea transport demand since it is a derived demand. Identifying facilities and services among ports in the U.S would be useful to government or port authorities to improve their port efficiency. As a key element of international trade, container ports in the U.S. should maintain their efficient performance in terms of container handling in loading and unloading processes while considering environmental aspects. Analyzing port efficiency by including $CO_2$ emissions is an effective way to measure the performance and develop policies to reduce the carbon footprint from port activities.

## 2. Literature Review

Port efficiency is one of the most important criteria in evaluating the port's daily operations performance. Improving the quality of port operations activities such as container handling will reduce the percentage of time delay in container movements. Efficient utilization of available equipment in container handling is a crucial part when dealing with high numbers of containers that creates complexity in the movements of containers from vessel to stacking area. Measuring the efficiency of these operations can lead to better insight for tackling specific problems that should be improved. Many studies on port operations were conducted by various researchers with different ideas and approaches to improve port efficiency.

One of the solution to improve the port effectiveness is outsourcing. Outsourcing is one of the elements in logistics that can reduce the dependency on other operational activities while focusing on the core business. This means the port management can focus on the overall control of the port by allowing other third-party companies to operate the cargo handling operations. Research by Talley et al. (2014) concluded that port services would be more effective by outsourcing their port's operations activities to a third-party

service provider. The service provider would utilize all resources available at the port in order to handle cargoes in an optimal time and cost.

Sakar and Cetin (2012) proposed a concept of sustainable port by taking into account the stakeholders' involvements in the planning of port activities. Stakeholder's involvements are important in the planning process due to its capability in strengthening and sustaining good businesses. Collaboration and integration between port authorities and the stakeholders can also lead to a more sustainable port along the supply chain (Denktas, 2012). Linking all stakeholders together in every aspect of port activities can improve the information flow while increasing the accuracy rate of information given. Moreover, Puig et al (2014) studied the operational performance of sustainable ports by identifying and selecting the Environmental Performance Indicators (EPIs), concluding that all entities in the port activities share common ideas of satisfying economic demands together with sustainable development.

Mora et al. (2005) carried out a study on an environmental analysis of port activities and found 21 potential environmental impacts in different port activities and improvements that should have been applied in the management of those activities. Mora et al. (2005) determined port authorities should take into account the environmental aspects in port operations in order to gain sustainability. Moreover, Gibbs et al. (2014) found that emissions from vessel at berth contribute emissions ten times greater than those from the other port handling operations.

In this regard, DEA is a nonparametric method which measure the efficiency of a decision-making unit (DMU) by considering multiple input and output (Cooper et al., 2007). Charnes et al. (1978) proposed the constant returns to scale data envelopment analysis (CCR-DEA). Banker et al. (1984) extended CCR-DEA to variable returns to scale DEA (BCC-DEA). Since then, DEA has been a widely used approach to identify the best management and benchmark practice within a set of DMUs and to measure efficiency in frontier analysis. The DEA model has been used to measure the efficiency and productivity as a benchmarking practice to many areas such as banks, transportation, and logistics (Schaffnit et al., 1997; Ross and Droge, 2002). With regard to the port industry, many studies have been conducted on efficiency and productivity using the DEA model, including a study about 16 ports in Australia and Europe (Tongzon,

2001), a comparison study between DEA and stochastic frontier analysis (SFA) (Cullinane et al., 2005; Cullinane and Wang, 2006), benchmarking port efficiency (Sarriera et al., 2013; Sharma and Yu, 2009; Munisamy and Singh, 2011), and coastal container terminal in China (Dan, 2013). Interestingly, Sharma and Yu (2009) developed a model that overcomes the traditional DEA bechmarking method by using stratification method called recursive data envelopment analysis (RDEA) to propose stepwise benchmarking process. In addition, Mithuan and Son (2009) proposed a new method of stepwise benchmarking target selection by combining self organizing map (SOM) with RDEA that is proven to be more realistic and effective method by which inefficient decision making units (DMUs) can select benchmarks in a same group. However, there is a certain limitation in that it is difficult to benchmark the most efficient DMU if there are few DMUs in the same group and it limits the benchmarking range to the same group. In contrast, this study applies stepwise benchmark target selection method based on similarity developed by Park et al. (2012) that considers a minimization-improving performance measure for improving port environmental efficiency.

Conventional practices of port operation only look at the port efficiency in a single aspect of minimizing cost and maximizing profit. Today, sustainability is concerned in every area of logistics activities at ports and the whole supply chain in general. Therefore, studies regarding environmental efficiency of port that take into account environmental impact are topics of interest for industry and academic researchers (Chang, 2013; Haralambides and Gujar, 2012). DEA model has been applied to many studies and the efficiency evaluations are significantly altered once the environmental aspects are factored into the model. With regard to measuring environmental efficiency, DEA model has been widely applied, such as 30 Organization for Economic Co-operation and Development (OECD) countries (Zhou et al., 2006), 26 OECD countries (Zhou et al., 2007), airport (Lozano and Gutiérrez, 2011) and transportation sector in the U.S. (Park et al., 2016). Zhou et al. (2006), Zhou et al. (2007), Lozano and Gutiérrez (2011) and Park et al. (2016) used SBM-DEA model by taking into account air pollutants as undesirable output in the model.

As far as managing environmental system of ports is concerned, there has been an increasing application of environmental management system (EMS), as a systematic method to prevent port from pollution (Florida and Davison, 2001). As Lam and Notteboom (2014) contends that constant monitoring is the one of the critical features of EMS. Peris-Mora et al. (2005) proposed a set of main environmental indicators for sustainable management of port for port authority that has been used in the port of Valencia. Environmental survey is used for 27 EU inland ports to quantify environmental performance and environmental index and has been computed using various features such as; waste, energy consumption, air quality, and carbon footprint (Seguí et al., 2016). Puig et al., (2017) analyzed the 2016 environmental benchmark performance of the EcoPorts members in European country using Self-Diagnosis Method (SDM), that provide key environmental priority for benchmarking and managing environmental performance of air quality, energy consumption, and noise. The above mentioned studies have addressed ecological issues in ports and port management policy with respect to green port development. It appears that research on green ports from environmental efficiency policy and management perspective is scarce. However, few studies exist on environmental performance related to port that provide comparison of environmental efficiency of local and global perspective utilizing standard DEA benchmarking model.

The main sources of environmental externalities in port operation are known to be atmospheric and water pollution. Chin and Low (2010) incorporated external environmental factor as an undesirable output in measuring environmental efficiency using DEA by comparing the 13 largest worlds' ports. Haralambides and Gujar (2012) discussed that combined undesirable factors into consideration in eco-DEA for measuring efficiency provides better efficiency score achieving balance between production and environmental externalities. More recently, Chang (2013) attempted to measure environmental efficiency of 23 Korean ports using slack based DEA by treating CO2 emissions as undesirable, and Liu and Lim (2015) measured environmental efficiency of U.S ports by incorporating toxic air pollution. Not only is there a need to assess environmental efficiency performance of port, there is a gap in the existing body of literature when it comes to environmental efficiency benchmarking study. As far as the author's understanding is concerned, there are no empirical comparative studies devoted to benchmarking study

for environmental efficiency of the U.S ports. Therefore, the purpose of this paper is to perform benchmarking analysis of environmental efficiency of U.S. container ports. Previous studies did not conduct benchmarking studies to provide environmental performance of the ports. Limited studies can be found related to benchmarking port efficiency (Hun et al., 2010; Sharma and Yu, 2009; Park and Sung 2016). In line with such motivation, this study will benchmark the environmental efficiency of container ports against best-practices in the U.S ports.

This study leverages two hierarchical methodological approaches to enhance the ability of DEA by applying Recursive Data Envelopment Analysis (RDEA) to provide a reference target to inefficient units based on their maximum capacity to improve environmental efficiency to its optimal level. Despite the fact that benchmarking in standard DEA that allows for the identification of targets for improvements, it still has certain limitations. One of the drawbacks in standard DEA benchmarking is that inefficient DMUs project only the efficient frontier, which ignores the differences in the efficiency score. Another drawback of the standard DEA model is that inefficient DMUs and its benchmarking target may not be similar to the operating practices (Doyle and Green, 1994). The cluster analysis is carried out using the unsupervised clustering tool Kohonen's self-organizing map (KSOM) to cluster DMUs in accordance with input similarity to be able to obtain appropriate benchmarking of environmental efficiency levels gained by RDEA analysis. Finally, a benchmarking projection diagram is constructed to provide the stepwise benchmarking process for benchmarking environmentally efficient ports. The rest of the paper is organized as follows: In section 3, methodology is explained in detail. In section 4, the results and discussion are presented. Finally, in section 5, conclusion and direction of future research are provided.

## 3. Methodology

### *3.1 Data*

This study attempts to measure environmental efficiency of US ports and provide stepwise benchmarking using RDEA and KSOM. For this purpose, the most recent available data is 2013 data on the top twenty US ports in terms of relevant input and output variables used for the model. The DMU was the individual container ports. Input variables for the model were the number of quay crane, area of terminal ($m^2$), length

of berth (meter), and depth (ft) in each port. Based on the literature the input variables used is gathered from various sources (Kwak et al.., 2015; Won et al., 2007; Cullinane and Song, 2006). Labor input is expunged as it is normally regarded as a fairly stable and as it has very close relationship between the number of cranes and the number of port workers at a container terminal (Notteboom et al, 2000). Input data are collected from Navigation data center in US Army Corps of Engineers which include the complete dock list and port facility attributes that include cargo-handling equipment, water depth alongside the facility, berthing space, and deck height. The proposed solution fulfils the data requirement for input, physical quantification of annual container throughput in TEU, number of calls which serves as an intermediate stop for a ship at container terminal for unloading and loading of cargo. Finally, deadweight tonnage (DWT) which is a measure of how much weight a ship at container terminal is carrying, was adopted as a basis for measuring the output of container terminal as the desirable outputs (Tongzon, 2001; ITOH, 2002). 2013 vessel calls in US ports and terminal data are downloaded from United States Maritime Administration (USMA) and output variables for containers are collected for each port. This study also incorporates $CO_2$ emission as the undesirable output. Since the data on $CO_2$ were not available, $CO_2$ emission for each port was estimated using the guideline proposed by Geerlings and van Duin (2011). The total $CO_2$ emissions of each container port were calculated as the sum of power consumption from the quay crane equipment per total throughput. The fixed energy consumption per container throughput is 6.0 kwh and its emission factor of 0.52 in kilograms of $CO_2$ emission is multiplied by the total number of quay cranes (Geerlings and van Duin, 2011), and finally unit of emissions are converted to US tons (1 kilogram =0.00110231 US tons). Table 2 shows the descriptive statistics of the input and output variables. The average quay crane usage was 19.7 ranging between 1 and 79. The average value of acres, berth, and depth were 580.26 $m^2$, 4463.75 m, and 145.24 ft, respectively. The average amount of $CO_2$ emission was 368,103.4 tons with a maximum of 2,030,098 tons and a minimum of 118.5 tons. As for the desirable output, the US port had 671.8 calls, 2,772,538 throughputs, and 35,765,109 DWT, on average.

**Table 2. Inputs and outputs data for 20 ports of US**

| CATEGORY | VARIABLE | MEAN | STD.DEV | MIN | MAX | SUM |
|---|---|---|---|---|---|---|
| **INPUT** | **Quay Crane** | 19.7 | 22.76678 | 1 | 79 | 394 |
| | **Acres** | 580.26 | 564.8509 | 11 | 1803 | 11605.2 |
| | **Berth** | 4463.754 | 7660.834 | 198 | 35545 | 89275.08 |
| | **Depth** | 145.25 | 120.5098 | 35 | 446 | 2905 |
| **UNDESIRABLE OUTPUT** | **$CO_2$** | 368103.4 | 622698 | 118.4876 | 2030098 | 7362068 |
| **DESIRABLE OUTPUT** | **Calls** | 671.8 | 643.5098 | 18 | 2156 | 13436 |
| | **Throughput** | 2772538 | 2978170 | 17226 | 9313313 | 55450751 |
| | **Dwt** | 35765109 | 38398751 | 209763 | 1.22E+08 | 7.15E+08 |

### *3.2 Recursive Data Envelopment Analysis and KSOM*

The conventional application of DEA to a multi-factor productivity measurement problem with multiple input(s) and/or output(s), which provides a single efficiency frontier (layer) where the efficient DMUs are spread. One of the typical concern with this method is that the benchmark outcomes are biased and lacks explicit improvement guidance for inefficient DMUs (Sharma and Yu, 2009). On the other hand, it is worthy to note that multi-layer efficiency frontiers can provide accurate and realistic improvement guidance when a recursive DEA approach is utilized (Sharma and Yu, 2009). Additionally, cluster analysis' results are incorporated with the multi-tier efficiency groups, inefficient DMUs can provide with stepwise self-improvement paths toward efficient frontier. Therefore, this has motivated us to develop a dual methodology to increase discriminatory power of DEA efficiency score and the sample heterogeneity. The research framework of combination of RDEA and KSOM analysis are shown in Figure 1.

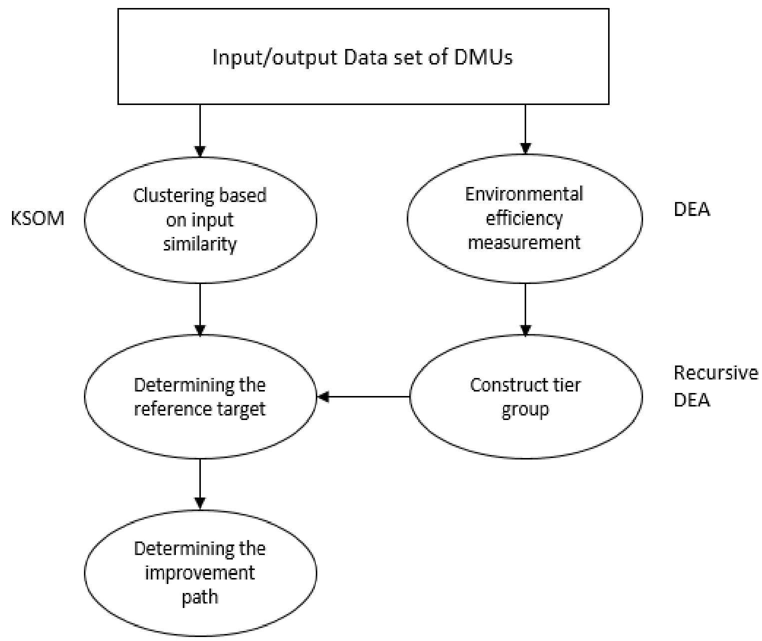


**Figure 1. Research framework**

The RDEA model was employed (Zhu, 2001) and each container ports were stratified into different deficiency levels. A DEA Frontier Excel Add-In, developed by Zhu (2001), was used to run the linear programming model of RDEA. The algorithm is as follow.

<u>Objective function</u>

$$\theta^*(l,k) = min\,\theta(l,k) \qquad (1)$$

<u>Subject to:</u>

$$\sum_{j \in F(J^l)}^{n} \lambda_j x_{ij} \le \theta(l,k) x_{ik} \qquad (2)$$

$$\sum_{j \in F(J^l)}^{n} \lambda_j y_{ri} \ge y_{rk} \qquad (3)$$

$$\lambda_j \ge 0 \qquad (4)$$

$$j \in F\ (J^l) \qquad (5)$$

λs are the dual variables, $x_{ij}$ is the amount of input i consumed by $DMU_j$ , $y_{ri}$ is the amount of output r yielded by $DMU_i$, $\theta$ is the efficiency score, and $x_{ik}$ and $y_{rk}$ are *i* th input variables and *r* th output variables of $DMU_k$. $J^l$ = { $DMU_j$, $j$ =1,…$n$ } define the set of n DMUs and iteratively define $J^{l+1} = J^l$-

$E^l$ where $E^l$= {DMU$_k$ ∈ $J^l$ | Θ* ($l$,$k$) =1}, and Θ*($l, k$) and Θ*($l, k$) represents the optimal objective value of the RDEA linear programming model that DMU$_k$ is under evaluation. $j \in F\ (J^l)$ represents DMU$_j$ ∈ $J^l$, which is to say, $F$ (·) indicates the corresponding subscript index set and $E^l$encompasses of all the efficient DMUs on the $l$th level (Zhu, 2001; Hun et al., 2010).

The steps of the RDEA algorithm for identifying the stratified efficient frontier are as follows (Park and Sung, 2016):

**Step 1**: set $l$ = 1. Use DEA analysis for the entire set of DMUs, $J^1$, to obtain first efficient tier group, $E^l$.

**Step 2**: eliminate the frontier DMUs for the next DEA run and set $J^{l+1} = J^l - E^l$.

**Step 3**: if $J^{l+1} = \phi$, then stop, otherwise keep the current run DEA for the remaining subset of DMUs for the next tier group $E^{l+1}$.

**Step 4**: then, let $l$ = $l$ + 1. Follow step 2 until the model find entire tier groups.

Analyzing RDEA, Kohonen's self-organizing map (KSOM) is applied for clustering units based on similar characteristics of input variables. Self-organizing maps (SOM) is a form of artificial neural network which uses unsupervised learning scheme to train, that was developed by Kohonen (1982). SOM is popularly known as Kohonen's self-organizing maps or simply Kohonen's network. SOM is mainly used for cluster analysis, feature extraction and data visualization. It mimics the way the mammalian brain physically maps sensory inputs. The structure of a SOM comprises of an input layer and an output layer. The output layer consists of neurons arranged in a two-dimensional grid pattern and connected laterally. The output layer is connected to the input layer. Figure 2 portrays the structure of a SOM (Burn and Home 2008). The neurons on the output layer "similar" to the input vector are clustered together.

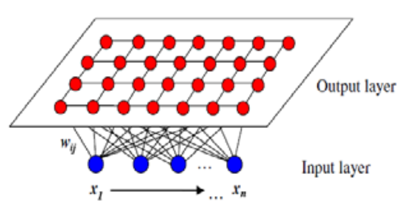


Figure 2. Structure of a SOM adapted from Burn and Home (2008)

SOM algorithm is summarized as follows (Cooper and Burns, 2007):

1. Initialize weight of input vector.
2. Calculate the Euclidean distance of each neuron on the grid from the input vector.
3. The output neuron with the shortest Euclidean distance becomes the winning neuron.
4. The weight of the winning neuron is then updated to be more like the input vector.
5. The weight vectors of neurons within the neighborhood of the winning neuron are also updated to be more like the input vector.
6. Repeat steps 2 to 6 until the required number of clusters are formed.

As it can be seen, the SOM performs clustering while preserving topology, however, for large output dimensions, the number of neurons in the adaptive grid increases exponentially with the number of function parameters. The pre-specified standard grid topology may not be able to match the structure of the distribution, leading to poor topological mappings (Du 2009). For KSOM analysis, NNclust software is used to cluster DMUs into several groups. The input variable used for the KSOM analysis consists of number of quay cranes, acres, berth, depth, desirable output and undesirable output. The learning parameter is chosen as 0.9 for a starting point, the training cycle is 100, and the ending learning parameter is 0.1 (Park et al., 2012; Egilmez et al., 2015). From the above addressed issue, we run a few different times to form an optimal clustering groups which have less testing error.

*3.3 Benchmarking Method based on the Input-Similarity*

Traditional benchmarking method without considering similar input characteristic does not provide stepwise benchmarking target and it is difficult if multiple benchmarking targets exist in reference target. In addition, it has to be understood that, low efficient DMU cannot directly improve to 100% efficiency, it reasonably need equivalent characteristics trades for benchmarking and improvement (Sharma and Yu, 2009). Appropriate benchmarking method is demonstrated for the selection of stepwise benchmark target considering input similarity (Hun et al., 2010; Park et al., 2012). Figure 3 illustrates the flow chart of finding an improvement path for each inefficient DMUs using RDEA and KSOM. First, inefficient DMUs

from the lowest tier group (n) from DEA analysis are selected, then determine the benchmarking DMUs from reference sets. DMUs were analyzed using SOM to categorize into same group. If same cluster group exist among DMUs, DMUs can benchmark DMUs in the same group at upper tier. Otherwise, input similarity function must be computed to find the benchmarking path as in equation 6 (Hun et al., 2010). Using equation 6, input similarity was computed.

$$\mathrm{CE}(DMU_i^*, DMU_i) = \frac{1}{d(gr(DMU_i^*), gr(DMU_i))} + w * \left(lr(DMU_i^*) - lr(DMU_i)\right) + \lambda_i \qquad (6)$$

Where, $DMU_i^*$ is a benchmark unit, $DMU_i$ is a benchmark target, CE($DMU_i^*, DMU_i$) is input similarity function of $DMU_i^*$ and $DMU_i$, $d(gr(DMU_i^*), gr(DMU_i))$ distance between group which is calculated by Euclidean distance (distance of same cluster group is 0.5), $lr(DMU_i^*) - lr(DMU_i)$ shows the difference between tier group distance, $\lambda_i$ is a weight when $DMU_i^*$ has set of reference target of $DMU_i$. $w$(0.01) was multiplied to $lr(DMU_i^*) - lr(DMU_i)$ to give higher weight for distance between clustered group and relatively lower weight for difference between two tier groups. Following the computation of CE, inefficient $DMU_i^*$ must benchmark the efficient $DMU_i$ among the identified target from the upper tier that has maximum value of input similarity function. This procedure can be repeated until rest of DMUs find the benchmarking target from the next higher tier.

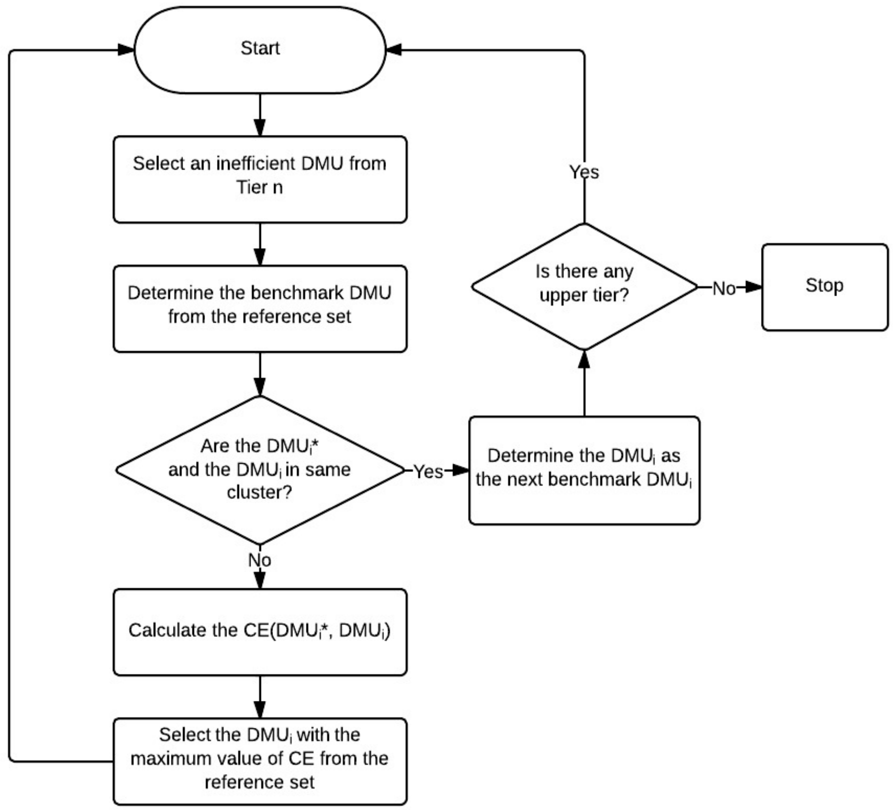


**Figure 3.** Flowchart of the benchmarking method based on the input similarity

## 4. Results

*4.1 Environmental efficiency performance*

The correlation was estimated between input and output variables in order to check whether there were significant relationships between them before analysis of DEA. As presented in Table 3, there were very high correlations between input and output variables, mostly over 0.8 between quay cranes and acres, acres and depth, depth and $CO_2$, throughput and $CO_2$, and throughput and Dwt. There were moderate correlations between berth and calls, berth and throughput, and berth and Dwt.

**Table 3. Correlation matrix for inputs and outputs**

| | Quay crane | Acres | Berth | Depth | $CO_2$ | Calls | Throughput | Dwt |
|---|---|---|---|---|---|---|---|---|
| **Quay crane** | 1 | | | | | | | |
| **Acres** | 0.839 | 1 | | | | | | |
| **Berth** | 0.782 | 0.676 | 1 | | | | | |
| **Depth** | 0.926 | 0.820 | 0.748 | 1 | | | | |
| **$CO_2$** | 0.947 | 0.806 | 0.779 | 0.858 | 1 | | | |
| **Calls** | 0.715 | 0.759 | 0.419 | 0.638 | 0.783 | 1 | | |
| **Throughput** | 0.813 | 0.820 | 0.526 | 0.738 | 0.865 | 0.967 | 1 | |
| **Dwt** | 0.803 | 0.814 | 0.514 | 0.727 | 0.860 | 0.970 | 0.999 | 1 |

Environmental efficiency (EE) scores for each port were calculated as it is portrayed in Figure 4. Out of 20 ports in the US, twelve ports are found to be environmentally efficient when considering the inputs, desirable output, and undesirable outputs. The environmentally efficient ports include Tampa, Savannah, San Diego, Port Everglades, New Orleans, Miami, Gulfport, Fernandina, Everett, Charleston, Boston and Anchorage. The average EE score of a port is 0.77. The inefficient ports are found to be New York/New Jersey, Baltimore, Seattle, Philadelphia/Delaware River Ports, Tacoma, Long Beach, Los Angeles, and Jacksonville, with EE scores ranging between 0.29 and 0.55. Therefore, there is great potential to improve the EE score in each port.

On average, a US port could accomplish about 23% improvement in EE. From the slack analysis of input and output variables in Table 4, it can be seen that only five ports indicate excess $CO_2$ emissions that include ports of Long Beach, Los Angeles, New York/New Jersey, Seattle, and Tacoma. However, among the five ports, New York/New Jersey port appears to indicate the greatest potential reduction in $CO_2$ emissions by accounting 1,454,687.3 tons followed by Los Angeles with 1,160,341.4 tons and Long Beach with 753,417.7 tons. There is no potential $CO_2$ reduction in the other fifteen ports. Interestingly, it was found that low-ranking EE tend to have high slack value in $CO_2$ emissions. When we further look into other input and output variables, the port of Long Beach shows high slack in quay cranes with 19, followed by New York/New Jersey with 8.5, and Seattle with 4.4. Most environmentally inefficient ports also show high shortage of output such as calls, throughput, and DWT. For example, the port of Jacksonville which

has the lowest EE score shows the greatest amount of shortage in calls with 1,030, throughput with 2,079,976.7, and DWT with 28,261,161.3.

Observing the environmentally inefficient ports, they seem to project to highly efficient ports with EE score of 1 for improvement. For instance, the port with a lower EE score (Jacksonville and Tacoma) benchmarks to port Everglades, and the other ports such as Long Beach and Los Angeles benchmarks to the port Savannah. However, in reality, ports have different functionalities such as operations, sizes and technologies. Therefore, it is very important to consider a stepwise benchmarking process that projects the inefficient ports to such a level that they can improve their environmental performance according to their maximum capacity (Sharma and Yu, 2009). Applying KSOM, we can solve the heterogeneity issues by clustering the DMUs into several homogenous groups based on their input similarity, therefore the more effective benchmarking processes can be performed by providing a set of benchmarking targets based on similar characteristics. The next section presents the application of the RDEA and KSOM analysis for benchmarking process of environmentally inefficient DMUs by accounting for their homogeneity.

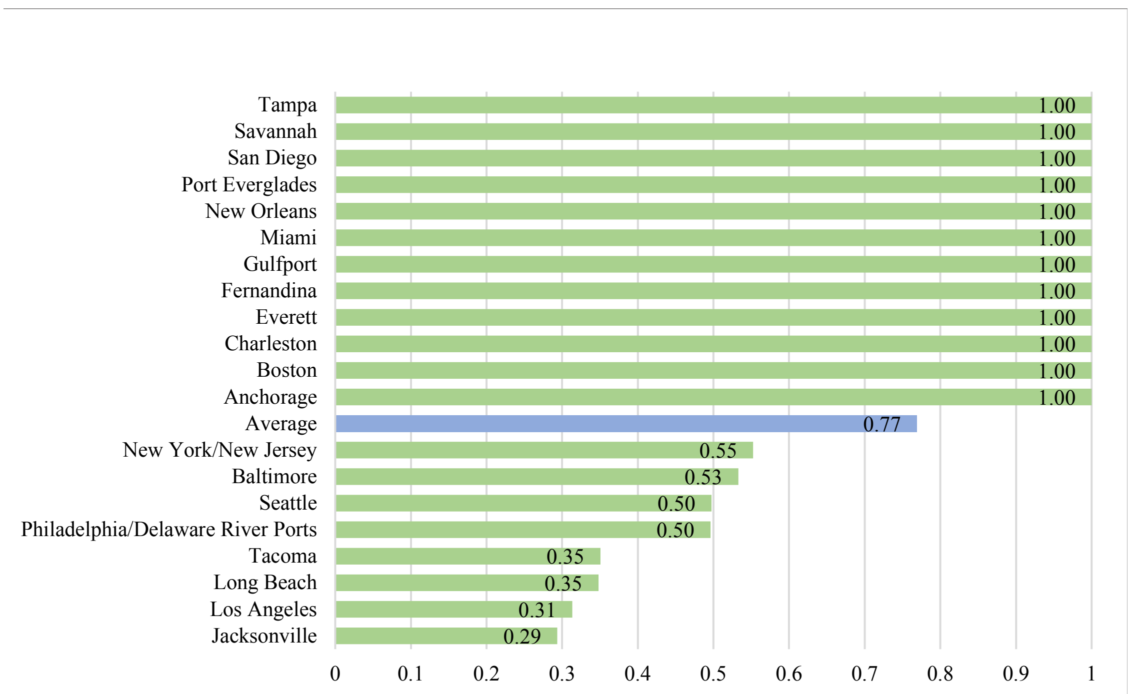


**Figure 4. Environmental efficiency score of each port**

**Table 4. Results of slack analysis**

| No. | DMUs | Input excess | | | | | Output shortfall | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Quay Crane | ACRES | BERTH | DEPTH | CO2 | CALLS | THROUGHPUT | DWT | Benchmarking Unit |
| **1** | Anchorage | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1 |
| **2** | Baltimore | 0.0 | 9.1 | 558.8 | 1.3 | 0.0 | 724.8 | 381575.8 | 5088329.3 | 15 |
| **3** | Boston | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 3 |
| **4** | Charleston | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 4 |
| **5** | Everett | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 5 |
| **6** | Fernandina | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 6 |
| **7** | Gulfport | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 7 |
| **8** | Jacksonville | 0.0 | 918.2 | 3430.4 | 0.0 | 0.0 | 1030.0 | 2079976.7 | 28261161.3 | 15 |
| **9** | Long Beach | 19.0 | 0.0 | 0.0 | 0.0 | 753417.7 | 3321.2 | 5661199.1 | 76309471.6 | 17 |
| **10** | Los Angeles | 0.0 | 0.0 | 16793.3 | 173.1 | 1160341.4 | 4416.8 | 9513665.9 | 125578323.1 | 17 |
| **11** | Miami | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 11 |
| **12** | New Orleans | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 12 |
| **13** | New York/New Jersey | 8.5 | 0.0 | 0.0 | 0.0 | 1454687.3 | 2398.7 | 2186093.0 | 28647367.9 | 15,17 |
| **14** | Philadelphia/Delaware River Ports | 2.4 | 20.2 | 1661.0 | 0.0 | 0.0 | 215.6 | 455330.0 | 5991022.3 | 15 |
| **15** | Port Everglades | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 15 |
| **16** | San Diego | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 16 |
| **17** | Savannah | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 17 |
| **18** | Seattle | 4.4 | 0.0 | 0.0 | 0.0 | 166282.9 | 963.2 | 1021138.3 | 15705871.2 | 15 |
| **19** | Tacoma | 2.8 | 0.0 | 0.0 | 0.0 | 44786.2 | 1376.8 | 2566216.7 | 36059360.9 | 15 |
| **20** | Tampa | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 20 |

### *4.2 Classification of DMUs based on RDEA and KSOM analysis*

In first step of measuring EE score was analyzing DEA for entire set of DMUs. The results presented in Fig 5 show the most efficient groups of DMUs with a score of 1 (marked as Tier 1). Tier 1 groups were Anchorage, Boston, Everett, Fernandina, San Diego, Tempa, Gulport, Miami, New Orleans, Port Everglades, Charleston, and Savannah. These groups were eliminated from the second DEA analysis in order to generate Tier 2 and Tier 3. Again, the efficient DMUs with a score of 1 are labeled as Tier 2. Tier 2 ports were New York/New Jersey, Philadelphia/Delaware River Ports, Baltimore, and Seattle. Then, these DMUs were excluded for further analysis to generate Tier 3. Tier 3 ports were Jacksonville, Long Beach, Los Angeles, and Tacoma. The DMUs in Tier 1 are superior in environmental efficiency to those in Tier 2 and Tier 3. DMUs in Tier 1 and Tier 2 are used as a reference set to find the benchmarking target after KSOM clustering of the ports based on their input similarity.

DEA provides a set of benchmarking targets for every inefficient DMU. Usually the benchmarking target can be determined by a pro-rated increase in the output of the inefficient DMUs. These can be

regarded as a composite unit which consists of a weighted average of peer units and the benchmarking target for inefficient units then set by the composite unit (Sharma and Yu, 2009). However, this method is not always desirable because of different characteristics between inefficient DMUs and benchmarking targets. Therefore, KSOM is used for the analysis, including all input and output variables to cluster DMUs into several groups based on similar properties. The result of KSOM is depicted in graphical format (see Fig 5), where the four different types of clusters are displayed.

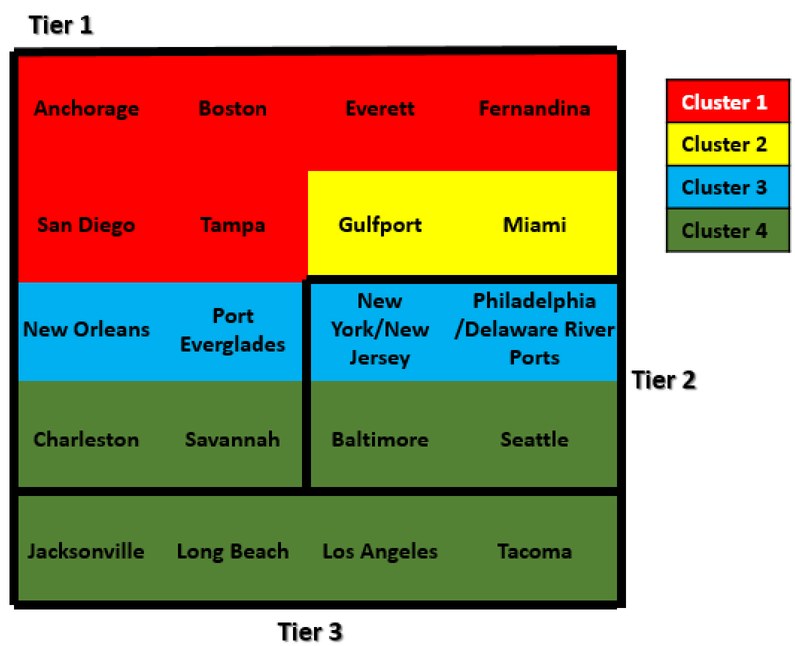


**Figure 5. Port classification based on RDEA and KSOM**

*4. 3 Benchmarking projection*

The RDEA analysis segments the ports based on their environmental efficiency score and KSOM analysis clusters them based on their similar input and output characteristics. In Figure 6, the benchmarking projections from the lowest EE ports to the most EE ports are illustrated. The application of RDEA and KSOM provides some interesting insight about benchmarking environmental performance improvement of each port. The benchmarking candidate sets are determined to be Baltimore or Seattle for DMUs in Tier 3, which are classified as same cluster of 4. For Baltimore, its benchmarking candidates are

determined to be Charleston or Savannah in Tier 1. When we consider the port New York/New Jersey in Tier 2 and cluster 3, its benchmarking targets include the port of New Orleans and Port Everglades. The same procedure can be applied to other ports for improvement projections.

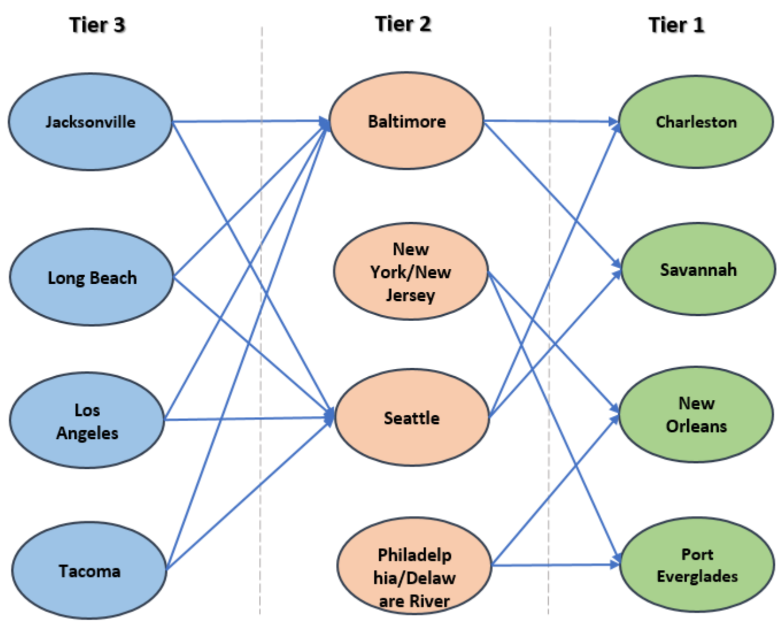


**Figure 6. Result of stepwise benchmarking process**

*4.4 Discussion*

We are witnessing that U.S ports have been attempting to increase their competitiveness by increasing economic prosperity as well as improving environmental performance. Their strenuous effort helps existing ports to operate their ports in an environmentally friendly manner due to the increasing awareness and concerns of their stakeholders and public health emanating from global warming. Therefore, more ports must evaluate their environmental facilities to be agile to meet the needs of existing concerns of their stakeholders, mainly nearby communities that maybe impacted (Chang et al., 2013). This study provides implications in the practice of sustainable port operations and management. Management of port

sustainability requires a holistic and integrated approach (Le et al., 2014; Yap and Lam, 2013), and the requisite to mitigate the impact of port emission and port authority best practices for environmental performance are seem as s critical research topic in the body of literature review. To that effect, this study contributes to setting the foundation for this research agenda by developing environmental efficiency benchmark of port in US. The use of the KSOM and RDEA model to examine the environmental performance of US ports and to provide stepwise benchmarking for best practice was first attempt. The theoretical and practical idea behind of this research can lead to further application in the area of management of sustainability of port even for other discipline. Some of the many managerial implications of this research are the followings. First the results confirm that most environmentally efficient ports are those with ports which implement proactive and early measures to tackle the effects of carbon emissions in ports. Port of San Diego has developed a green port program for managing natural resource, waste reduction that support regional economy and environment. Other environmentally efficient groups have followed best practices of oil spill prevention programs, water conservation strategy and sustainable port facility management. By implementing of better practices of cargo handling devise such as using less water and being more energy efficient in its own operations compared with the inefficient ports. After assessing the stepwise benchmarking target, Jacksonville could then establish an environmental efficiency improvement strategy for the effective benchmarking. Length of berth, acres, and $CO_2$ were concerned uncontrollable resources which had the strongest influence on environmental efficiency for Jacksonville to achieve each stepwise benchmarking target. Intensifying the existing number of cranes can also increase the environmental efficiency more than other resources, which has a strongest influence in benchmarking operation. Implementing the proposed method to the real case study, we can learn that the suggested method could provide more practical environmental benchmarking information than a general DEA due to following advantages; first, the proposed method can choose more rational benchmarking targets by considering the minimization of resource improvement and maximization of desirable output; second, the proposed method can provide an effective environmental efficiency improvement method by prioritizing and clustering ports that are inherently similar with respect to their inputs. Thus, inefficient ports can

strategically improve environmental efficiency performance by benchmarking the port with the highest score in a same cluster. The proposed method can be utilized by upper level managers and policy makers for improving environmental efficiency of container terminals through benchmarking.

## 5. Conclusion

This study measures the environmental efficiency and provides benchmarking target for environmentally inefficient ports to improve environmental performance of ports in the US. Conventional application of DEA may provide biased results in benchmarking, due to the fact that, it does not take into consideration of both physical and operational traits of homogenous ports. Therefore, this study use joint application of data mining technique referred as Kohonen's Self-Organizing Map (KSOM) and Recursive Data Envelopment Analysis (RDEA) to address the limitation of conventional DEA. This stepwise benchmarking method is more applicable since inefficient DMUs are projected to the efficient frontier line which does not ignore the difference in the efficiency score. Such integrated benchmarking tool would achieve a synergy effect in individual applications of each model that would not have been possible. The obtained results were found to be environmental efficiency scores of US ports ranged from 0.29 to 1 and 12 container ports were found to be environmentally efficient. The average EE score of US ports was found to be 0.77. Eight container ports were found to be environmentally inefficient that there appears to be a high potential to become environmentally efficient port. Out of the eight inefficient ports had to refer only to the twelve limited ports for improvement and environmentally inefficient DMUs are projected to the efficient frontier disregarding the differences in the environmental efficiency score. Finally, benchmarking projection diagram was developed to shed light to some of the inefficient ports (Jacksonville, Long Beach, Los Angeles, and Tacoma). The benchmarking projection portrayed that inefficient DMUs can benchmark more effectively and efficiently in appropriating benchmarking target selection. For example, Jacksonville with EE of 0.29 could make stepwise improvement projection to the port with EE score of 1 by targeting the port with similar characteristics. Also, slack analysis provided that high excess of input resource such as crane equipment utilization, unnecessary use of facility area of terminal and berth,

and $CO_2$ emissions are the key inputs that could improve the environmental efficiency of ports. Therefore, considering resource improvement strategies and adopting the best practices by selecting appropriate benchmarking targets will assist practitioners to formulate sustainable port development.

Irrespective of the advantages of the method, the following limitations of method are; if there appears to be many DMUs and many intermediate ports between each group, the applied method can create some cumbersome where too many benchmark steps may cause significant hurdles in benchmarking practices (Park and Sung 2016). Future research should address this problem to minimize the benchmarking target pathway. Another limitation of this study is that only 1-year cross-sectional data were used rather than panel data. In the foreseeable future, panel data should be collected to analyze dynamic change of environmental efficiency and benchmarking over time of the US port industry and to identify possible environmentally inefficiency perturbing factors, such as competition level, congestion rate as well as the impact of relevant port sustainability regulations and policies. (Liu and Lim, 2015). In addition, it will be interesting to see how port environmental efficiency can be attributed to stevedoring employment data once complete data is accessible. Several studies made by Chang et al. (2013) and Liu and Lim (2015) which measured port environmental efficiency in Asia and US, and port efficiency in European Union (Cullinane and Song, 2006; Cullinane and Wang, 2012) can be further supplemented using KSOM and RDEA model to consider their environmental efficiency benchmarking.

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