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Manufacturing Process Performance Measurement Model using Categorical DEA Approach – a Case of Dry-Docking

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Abstract. This paper describes the improved performance measuring model for vessel dry-docking. Dry-docking represents the operation where the vessel is put out of the water to clean and coat the vessels, and equipment check. This model deals with data collected from thirty-four completed dry-dockings, all supported by the Data Envelopment Analysis (DEA) methodology. To solve the limits appearing from extreme values for some vessels, an extension in the form of the categorical model was introduced. By the categorical model implementation, a more precise efficiency measurement was enabled. The performance calculation results contain the efficiency scores for all vessels and target improvements for the inefficient vessels. Inefficiency sources were detected using the DEA methodology, and the proposed solutions are based on process knowledge and data set. This model also introduced and set the parameters for category division and revealed the benchmarks among the studied vessels. The model introduced can be used for efficiency measurement of similar vessels, or as a prediction-based model by introducing vessels with hypothetic data. This model could also be utilized for similar manufacturing processes which can be found in civil engineering, project manufacturing, or transportation. Further research could be conducted based on the slack-based-measure model, respecting the limitation of data homogeneity.

Keywords: Data envelopment analysis; Dry-docking; Manufacturing; Performance measurement; Shipbuilding

1. Introduction

1.1. Dry-docking process

This paper describes the dry-docking performance measurement model based on Data Envelopment Analysis (DEA) methodology. DEA is a linear-programming-based, non-parametric, multi-criteria decision-making method. This method is applied to a population of thirty-four vessels under the final stage of construction (also called newbuildings), which are transferred by their own propulsion to the repair shipyard where they are lifted up from the water. During the vessel's dry-docking, the underwater part is cleaned, checked, and recoated. Upon undocking, the vessel is ready for sea trials and a five-year service

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period until the subsequent dry-docking. The dry-docking project is a work-intensive, cost-sensitive process carried out in a remote place linked with logistic challenges. Therefore, the necessity for a performance measurement model creation has appeared. The management staff involved in the newbuilding dry-docking is faced with a huge amount of technical and business data. Consequently, the performance targets are needed for proper managerial decision-making.

The scope of the mainline of dry-docking activities is: i) vessel's outer shell underwater part cleaning from fouling and grease by means of high-pressure washing and solvents application, ii) steelwork such as launching the supporting structure removal, and shell plates welding/grinding, iii) spot grit blasting to remove damages, and coating system application, usually four touch-ups and one full coat, iv) check-ups of the main propulsion, steering, sea chests, side thrusters and underwater sensors.

The dry-docking period is also used to carry out the vessel's systems check before the upcoming sea trials. This time frame could be used to complete works that were delayed in the previous time while the vessel remained berthed in the shipyard. The place of vessel dry-docking depends on the following factors: i) dry-docking place suitability based on vessel weight and overall dimensions, ii) dedicated dry-dock facility availability in a scheduled time window, iii) forecasted weather conditions.

The DEA methodology allows the dry-docking to be described as a process determined by its inputs and outputs for performance measurement purposes. The categorical DEA model is going to be used in order to refine the process research and efficiency measurement.

The performance measurement model is to be improved compared to the basic one formulated in the paper prepared by (Rabar et al., 2021).

1.2. Literature review

The literature review shows a limited number of papers dealing with the dry-docking practice. The dry-docking practice has been comprehensively described in (House, 2015). Working activities usually carried out during the regular dry-dockings were described and categorized by (Butler, 2012). The dry-docking cost estimation model was developed by (Apostolidis et al., 2012). For the development of this model, data related to the vessels' age, size, and purpose were used by (Surjandari & Novita, 2013) and (Surjandari et al., 2015) using the Data Mining method and Numerical Ant-Colony Decision Tree algorithm, which considers the dry-docking time as shipyard productivity parameter as well as the vessel's service downtime impact related to dry-docking. The dry-docking data analysis model using linear regression for dry-docking duration, depending on the vessel's size and age, was made by (Dev & Saha, 2015). The improved multiple regression model dealing with the labor needed for dry-docking depending on the vessel size, deadweight, and age was introduced by (Dev & Saha, 2016). Further research improvement in the dry-docking process and labor was completed by (Dev & Saha, 2018). An analysis using the DEA studying twelve repair shipyards in China was published by (Yang & Wang, 2017). The Croatian shipbuilding industry analysis using DEA methodology, assessing the shipyard's performance over time, identifying sources of inefficiency as well as propositions for increasing performance and altering decisions, was proposed by (Rabar, 2015). The United States East Coast repair shipyards capability estimation using DEA was made by (Mayo et al., 2020) to find the optimal repair solution for the ferry vessel fleet.

The literature review revealed the useful samples of DEA methodology use, such as (Putri et al., 2016), where the comprehensive performance measurement on the industrial level was carried out. The DEA application in analysing two manufacturing processes was carried out by (Jain et al., 2011), allowing getting a deeper insight into manufacturing process efficiency measurement. A good opportunity for the use of DEA methodology in process optimization was noticed in (Gunawan et al., 2018) where the "ex post" principle in process analysis could be useful. As referred by (Jandhana et al., 2018), the production function used is a good impulse for performance measurement in project manufacturing processes such as shipbuilding, and consequently, the dry-docking in this particular case.

The literature review conclusion discloses a gap in research in relation to new building dry-docking performance measurement. The improvements of the existing papers could be achieved using the extended DEA models. This paper should at least partially fill the research gap by introducing the improved new building dry-docking efficiency measurement model using basic DEA model extensions. The DEA categorical model, which is not common in performance measurement research, has been used in this research in order to sort out the researched vessels by their technical characteristics, and it has resulted in the more precise efficiency measurement scores. The authors believe that the proposed methodology could be useful in various manufacturing performance measuring applications.

2. DEA Methodology

The Data Envelopment Analysis (DEA) as an efficiency measuring methodology was launched by (Charnes et al., 1978). This methodology will be adapted for the improved dry-docking performance measurement in this paper. DEA is based on linear programming; it is a non-parametric methodology used to evaluate the operating entities called Decision Making Units (DMU). For the purpose of this research, every single researched vessel represents a DMU. Each DMU has an empirical data homogenous set, divided into inputs and outputs. Following the DEA calculations, the DMU's efficiency score is calculated. The efficiency score values range from 0 to 1, where the higher efficiency score means that a DMU is more efficient. All efficient DMUs have an efficiency score equal to 1, and they create the efficient frontier, and these DMUs are considered best practice units. All DMUs with an efficiency score less than one is considered inefficient because they are placed outside of the efficient frontier. There are two basic DEA models considered in this paper. The first is the CCR model, which considers the constant returns to scale, and was named after Charnes, Cooper, and Rhodes (Charnes et al., 1978). The second is the BCC, variable returns to scale model, named after Banker, Charnes, and Cooper (Banker et al., 1984). Relative efficiency measurement and evaluation, benchmarking, and target setting, as well as the best practice identification, are the DEA's basic purposes. The main points of the DEA methodology value-added potential are expressed in the simplified display of the underperforming DMUs, the ability to point the peers and to calculate the projection of inefficient DMUs to the efficient frontier, as well as to quantify the improvements needed to reach the efficient frontier. According to (Cooper et al., 2007), if there are n DMUs $\left(DMU_j, j = 1, 2, \dots, n\right)$, every single DMU produces s outputs by means of m inputs. Let the $x_j = \left\{x_{ij},\ i = 1, 2, \dots, m\right\}$ be the input vector, and $y_j = \left\{y_{rj},\ r = 1, 2, \dots, s\right\}$ the output vector of $\mathrm{DMU_j}$. The data set is described by the input matrix $X = \left(x_{ij},\ i = 1, 2, \dots, m,\ j = 1, 2, \dots, n\right)$ and output matrix $Y = \left(y_{rj},\ r = 1, 2, \dots, s,\ j = 1, 2, \dots, n\right)$. The sought virtual DMU, with inputs and outputs determined as a linear combination of inputs and outputs belonging to the remaining DMUs from the studied DMU set, is the basic principle of the efficiency assessment of $DMU_o, o \in \{1,2, \dots, n\}$. The $X\mu$ and $Y\mu$ are the vectors where $\mu = (\mu_1, \mu_2, \dots, \mu_n)$, $\mu > 0$ fits proportionally to the contributions of efficient DMUs to the projections of DMU_o to the efficient frontier, while e is a row vector with all elements equal to 1. The virtual DMU needs not to be worse but preferably better than DO_o. Pursuing the virtual DMU could be solved by the linear programming methodology.

Output oriented model:

$$\max_{\eta,\mu} \eta \tag{1}$$

subject to:

$$X\mu \leq x_o \tag{2}$$

$$\eta y_o - Y\mu \leq 0 \tag{3}$$

$$\mu \geq 0 \tag{4}$$

$$e\mu = 1 \tag{5}$$

where η represents the reciprocal of the efficiency score in output-oriented model. The constraints determined by formulae from (1) to (4) create the CCR model, and the BCC model is determined by the constraints expressed in formulae from (1) to (5). The formula (6) describes the input excesses and the output shortfalls, i.e. "slack" vectors:

$$t^- = x_o - X\mu \quad \text{and} \quad t^+ = Y\mu - \eta y_o \tag{6}$$

where the efficiency score θ is described as:

$$\theta = \frac{1}{\eta} \tag{7}$$

$(\eta^*, \mu^*, t^{-*}, t^{+*})$, is the result of maximizing η and minimizing the sum of t^{-*} and t^{+*}. If a DMU_0 reaches $\theta^* = 1$, it is considered efficient, otherwise, it is not efficient.

During this research, it has been noted that some of the observed DMUs were in a more favourable position compared to the rest of the DMU set. Therefore, a kind of DMU categorization needs to be introduced in the form of the DEA categorical model extension introduced by (Banker & Morey 1986) in order to reduce discrimination among the DMUs due to some DMU's technical characteristics which are impossible to overcome. It is assumed, according to (Cooper et al., 2007), that each of n entities (i.e., DMUs) could be categorized into one of the K different categories, commencing from category 1, as the lowest one, up to category K, which is the highest one. In order to adjust the DEA model to the described categorization, the following new attributes are introduced: $G = \{1, 2, \dots, n\} = G_1 \cup G_2 \cup \dots \cup G_K$, where G is the index set of all DMUs, and G_l is index set of DMUs belonging to category l where $l = 1, 2, \dots, K$. It needs to be pointed out that each DMU belongs to only one category, i.e., the category set intersection is an empty set, meaning that $G_j \cap G_l = \emptyset$ for every $j \neq l$. To determine the efficiency of DMU_0 from category $L \in \{1, 2, \dots, K\}$, all the DMUs from this category and all the lower categories have to be considered, which implies that only the DMUs indexed in the set $\cup_{l=1}^{L} G_l$ will be considered.

The expressions from (8) to (11) and from (8) to (12) represent respectively the extended output-oriented CCR and BCC models previously shown by (1) to (4) and (1) to (5). The second step in efficiency calculation is now dealing with slacks expressed as input excesses (13) and output shortfalls (14):

Output oriented categorical model:

$$\max_{\eta,\mu} \eta \tag{8}$$

$$\textstyle\sum_{j \in \cup_{l=1}^{L} G_l} x_{ij}\mu_j \leq x_{io}, \; i = 1, \dots, m \tag{9}$$

$$\eta y_{ro} - \textstyle\sum_{j \in \cup_{l=1}^{L} G_l} y_{rj}\mu_j \leq 0, \; \mathrm{r} = 1, \dots, \mathrm{s} \tag{10}$$

$$\textstyle\sum_{j \in \cup_{l=1}^{L} G_l} \mu_j \geq 0 \tag{11}$$

$$\textstyle\sum_{j \in \cup_{l=1}^{L} G_l} e_j\mu_j = 1 \tag{12}$$

$$t^{-} = x_{io} - \Sigma_{j \in \cup_{l=1}^{L} G_l} x_{ij}\mu_j,\ i = 1, \dots, m \quad (13)$$

$$t^{+} = \Sigma_{j \in \cup_{l=1}^{L} G_l} y_{rj}\mu_j - \eta y_{ro}, r = 1, \dots, s \quad (14)$$

3. Results and Discussion

The dry-docking performance measurement research is carried out on a set of thirty-four dry-docked vessels. Dry-docking is adjusted to the DEA requirements and shown as a process with inputs and outputs. It has also been checked and confirmed that the data set for each studied vessel is homogenous. The data set has been used in a non-parametric form in order to avoid misuse. Uncontrollable variables such as gross tonnage and area are combined with the controllable variables in the data set to get the highest possible freedom for DEA model calculation. This is achieved by variables combination on the input process side such as i) length of launching supporting structure divided by the vessel's GT (STEEL GT, X1) – this ratio favourites steelwork activities reduction and a higher vessel's volume, ii) multiplication of the underwater area and the time period between launching and dry-docking (AREATIME, X2), in favour to the less area treated in dry-dock and less time period spent afloat, iii) ratio between embarked and optimum crew (CREW, X3), which favours less crew embarkment and considers less delayed works.

The data usage in the form of ratios was recommended by (Sarkis, 2000) and (Dyson et al., 2001). The model outputs consist of various cost categories followed by their symbols in brackets, such as i) dry-dock rent and preparation cost (DD COST,Y1), ii) dry-dock services cost (SERV COST, Y2), ii) steelwork and staging cost (STEEL COST, Y3), iii) coating process cost (COAT COST, Y4), iv) cost of vessel transfer from the shipyard to the dry-dock and back, including the cost of waiting time out of dock and delays cost (TRANSF DELAY, Y5), vi) crew cost (CREW COST, Y6). Dry-docking process modelling resulted in the improved model presented in Figure 1, which is intended for the measurement and assessment of the dry-docking efficiency that includes the decision member related to the categorical model.

According to the DEA methodology, the inputs tend to be decreased, and outputs tend to be increased. In this particular situation, it causes the outputs to become undesirable. The undesirable output issue is going to be solved by data scaling. The output data scaling is carried out by taking reciprocals as recommended by (Liu et al., 2010), and (Cook et al., 2014). The management objective determines the DEA model orientation. In this particular case, the objective is to reduce expenses. Therefore, for the purpose of this study, the output model is favourable. The model with constant returns to scale is designated as CCR-O, while the model with variable returns to scale is designated as BCC-O. Suffix "O" means that the models are output-oriented.

The CCR-O and BCC-O model's efficiency scores are shown in Figure 2. The dry-docked vessels are DMUs numbered from DMU01 to DMU34. It is noted that some DMUs have superior performance, which impacts all the DMU's performance results. These DMUs are DMU27 and DMU28 of the same vessel type, and DMU31, DMU32, DMU33, and DMU34 of another vessel type.

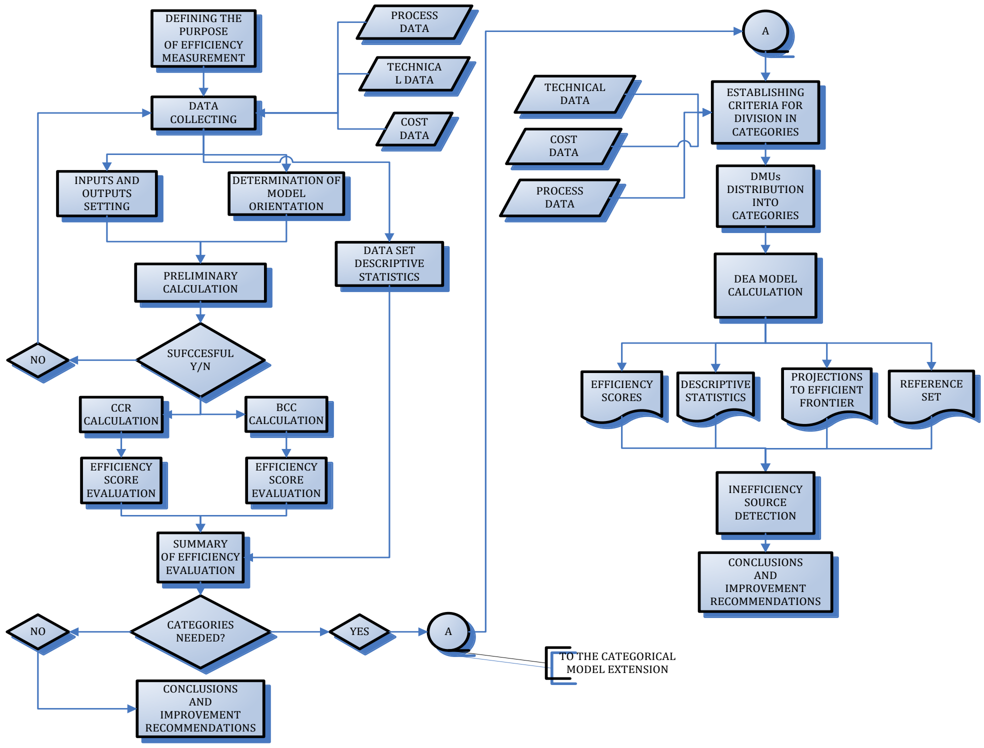

Figure 1 The dry-docking efficiency model

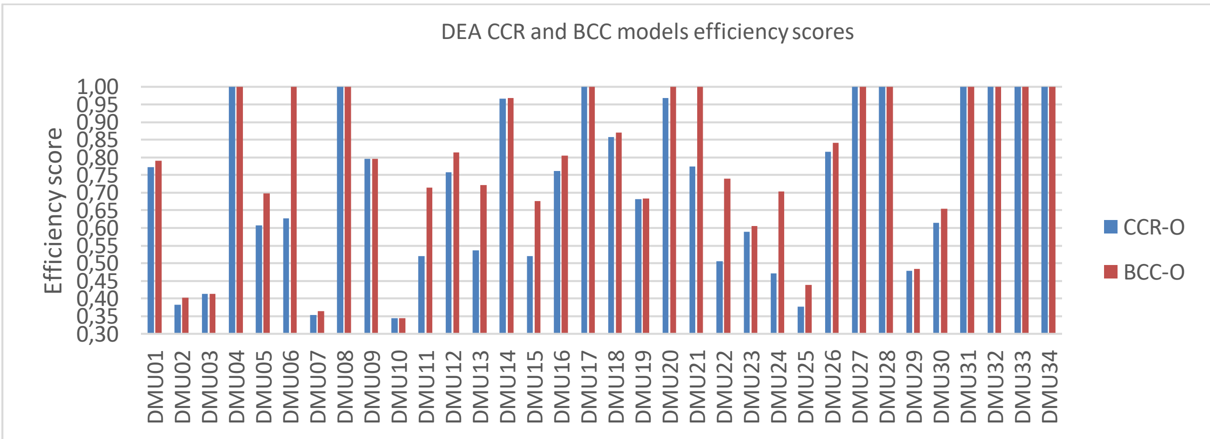

Figure 2 DEA CCR and BCC models efficiency scores

These six DMUs represent vessels with the lowest dimensions, which per contributes to greater efficiency, and therefore should be classified into a separate category. The criteria for DMUs division into categories are, therefore, gross tonnage and underwater part surface because those technical criteria clearly demonstrate the differences between the categories. The cut-off for the classification into the categories is determined as 20,000 for the gross tonnage and 5,500 sq. meters for the underwater part area. The first category, referred to as "category 1", includes 28 vessels. The second category, referred to as "category 2", consists of the six vessels with superior performance calculated by CCR-O and BCC-O models. The overall length and breadth, gross tonnage, underwater part surface and steelwork structure length of category 2 vessels show the lower absolute values compared to all the studied vessels. Due to these characteristics, the dry-docking process for the six vessels from category 2 requires a shorter period of time as well. These characteristics are definitely not attainable by the other studied vessels from category 1, which indicates the necessity of the vessels categorization in order to reduce discrimination among the vessels.

DMU04, DMU08, and DMU17 are efficient in both CCR-O and BCC-O categorical models, while DMU20 and DMU21 are efficient in the BCC-O model only. Table 1 contains input and output data used in performance measurement calculations. These data are sorted by the established vessels categorization. It should be noted that the dry-docking duration expressed in days is very important due to time-related increases in the costs which are related to the dry-docking process, such as dry-dock rent, dry-dock services, and crew cost and delays cost. A shorter dry-docking period has overall benefits for the ship construction process as well.

Table 2 shows the descriptive statistics in relation to the dry-docking duration and underwater part area differences between category 1 and category 2 vessels, as well as the dry-docking duration. The gross tonnage, underwater area, and dry-docking duration are not directly expressed in table 1, but it is needed to derive them from the original data for categorization purposes.

Table 1 Input and output data descriptive statistics

		CREW RATIO (X1)	STEEL GT (X2)	AREA TIME (X3)	DD COST (Y1)	SERV COST (Y2)	STEEL COST(Y3)	COAT COST(Y4)	TRANSF DELAY (Y5)	CREW COST (Y6)
Category 1	Maximum Value	2.17	6.55	31607	20.39	16.33	26.13	28.14	88.51	91.06
	Minimum Value	1.10	2.61	9778	10.56	4.83	5.35	9.87	4.52	32.24
	Medium Value	1.55	4.66	20015	14.77	8.45	14.37	17.78	21.48	60.75
	St. Deviation	0.29	1.51	5946	3.00	3.06	6.87	4.88	18.43	16.25
	Max./Min.Ratio	1.98	2.51	3.23	1.93	3.38	4.88	2.85	19.59	2.82
Category 2	Maximum Value	1.61	7.02	50553	8.66	3.50	7.30	10.87	9.38	30.86
	Minimum Value	1.14	1.17	10942	1.78	1.32	2.71	5.41	5.92	19.60
	Medium Value	1.36	5.07	23025	3.70	2.16	4.88	8.37	7.44	25.87
	St. Deviation	0.20	3.02	15096	2.92	0.95	1.74	1.80	1.59	4.70
	Max./Min.Ratio	1.42	6.01	4.62	4.86	2.66	2.70	2.01	1.59	1.57
Category 1 + 2	Maximum Value	2.17	7.02	50553	20.39	16.33	26.13	28.14	88.51	91.06
	Minimum Value	1.10	1.17	9778	1.78	1.32	2.71	5.41	4.52	19.60
	Medium Value	1.52	4.73	20546	12.82	7.34	12.70	16.12	19.00	54.59
	St. Deviation	0.28	1.81	8051	5.20	3.70	7.25	5.76	17.54	20.04
	Max./Min.Ratio	1.98	6.01	5.17	11.43	12.40	9.66	5.20	19.59	4.65

Table 2 Descriptive statistics by categories

		GROSS TONNAGE	UNDERWATER AREA	DRY-DOCK DAYS
Category 1	Maximum Value	47300	8825	14
	Minimum Value	27207	5641	8
	Medium Value	35152	7467	10.29
	St. Deviation	7677	1236	1.98
	Max./Min.Ratio	1.74	1.56	1.75
Category 2	Maximum Value	17130	5378	7
	Minimum Value	8547	3492	6
	Medium Value	11408	4121	6.50
	St. Deviation	4432	974	0.55
	Max./Min.Ratio	2.00	1.54	1.17
Category 1 + 2	Maximum Value	47300	8825	14
	Minimum Value	27207	3492	6
	Medium Value	37254	6888	9.62
	St. Deviation	14208	1830	2.32
	Max./Min.Ratio	1.74	2.53	2.33

Table 3 shows the efficiency scores results obtained by both categorical models used. It is also noted that both efficient frontiers (CCR and BCC) are created by the same DMUs with the exception of the DMU25. According to (Cooper et al., 2007), it is concluded that the data set generally shows a constant return to scale behaviour, which implies that further calculations will be performed by the CCR-O model only. It is also noticed that the use of the categorical model maintains category 1 efficiency scores on a higher level.

Table 3 Ranking and efficiency scores, categorical CCR-O and BCC-O models

DMU	Category	CAT CCR-O Score	CAT CCR-O Rank	CAT BCC-O Score	CAT BCC-O Rank	DMU	Category	CAT CCR-O Score	CAT CCR-O Rank	CAT BCC-O Score	CAT BCC-O Rank
DMU01	1	0.89867	23	0.95091	21	DMU18	1	1	1	1	1
DMU02	1	0.58613	32	0.70195	30	DMU19	1	0.93538	19	0.93563	22
DMU03	1	0.79023	28	0.80361	29	DMU20	1	1	1	1	1
DMU04	1	1	1	1	1	DMU21	1	1	1	1	1
DMU05	1	1	1	1	1	DMU22	1	0.9262	21	0.9263	23
DMU06	1	1	1	1	1	DMU23	1	0.66652	30	0.67345	31
DMU07	1	0.60067	31	0.63661	34	DMU24	1	0.88916	24	0.89782	26
DMU08	1	1	1	1	1	DMU25	1	0.93174	20	1	18
DMU09	1	0.95381	18	0.95994	20	DMU26	1	1	1	1	1
DMU10	1	0.56829	34	0.64096	33	DMU27	2	1	1	1	1
DMU11	1	0.9051	22	0.9051	25	DMU28	2	1	1	1	1
DMU12	1	0.88323	25	0.90801	24	DMU29	1	0.58045	33	0.65975	32
DMU13	1	0.80388	27	0.81763	27	DMU30	1	0.68303	29	0.80539	28
DMU14	1	1	1	1	1	DMU31	2	1	1	1	1
DMU15	1	0.8527	26	0.99998	19	DMU32	2	1	1	1	1
DMU16	1	1	1	1	1	DMU33	2	1	1	1	1
DMU17	1	1	1	1	1	DMU34	2	1	1	1	1

The categorical CCR-O results for category 1 show an average score of 0.8734, a minimum efficiency score of 0.5683, and nine DMUs show an efficiency score lower than the average one. The DEA categorical model calculation results in more accurate efficiency scores for DMUs belonging to category 1 because they are not evaluated with category 2 DMUs. It needs to be stressed that category 2 DMUs have got the underwater part area and gross tonnage values which are not reachable for category 1 DMUs.

Figure 3 shows the proposed input and output improvements for inefficient DMUs. By reaching the proposed improvements, the inefficient DMU becomes an efficient one. These improvements are a measure of input reduction and output augmentation, finally reaching the efficient frontier for each particular inefficient DMU. The improvement's direction and intensity are shown in figure 3, but the causes of inefficiency are placed in the dry-docking process. In figure 3, the efficient DMUs from category 1 and all the (efficient) DMUs from category 2 are omitted because those DMUs create the efficient frontier, and therefore, their projection values do not differ from their original values. It needs to be noted that inefficient DMUs' proposed input and output improvements are expressed in relative values in order to make differences more distinct. Figure 3 also contains CAT CCR-O efficiency score data in order to emphasize the relation between lower efficiency scores and higher demands for output values reduction (efficiency scores are also expressed in percentages). According to data retrieved from figure 3, it could be noticed that the greater improvement potential is contained in output TRANSF DELAY (Y5) with an average 46.68%, followed by the CREW COST (Y6) with an average 34.67% potential improvement. Both outputs have the delay-dependent improvements. TRANSF DELAY (Y5) is mainly dependent to the waiting time before dry-docking commencement and dry-docking delays due to weather conditions and dry-dock staff non-organization. CREW COST (Y6) output values are caused by engaging more crew in order to complete delayed works, which are supposed to be completed before dry-docking; when crew engagement is combined with time delay, there is even more room for improvements. At the completion of the modelled process, the following data become available i) efficiency scores and ranking of DMUs, ii) results' descriptive statistics, iii) inefficient DMUs projections to the efficient frontier. The obtained data, together with the process data and dry-docking process knowledge, lead to conclusions and improvement recommendations. According to its sources, inefficiency could here be divided into three main groups: i) inefficiency related to technical/technological issues, ii) inefficiency related to planning and organization, and iii) inefficiency due to unfavourable weather conditions.

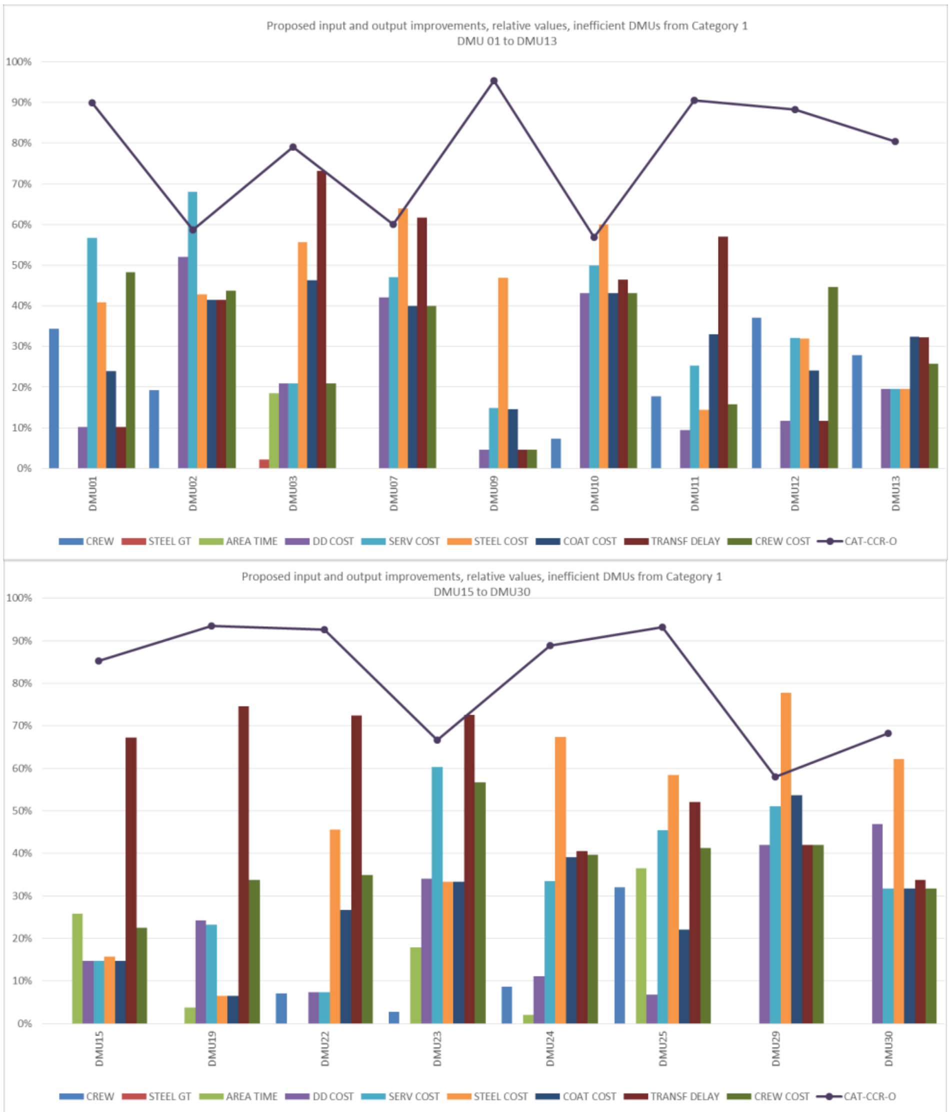

Figure 3 Proposed input and output improvements, inefficient DMUs from Category 1, relative values /Source: authors' calculation

Technically/technologically related inefficiency is determined within the process inputs. Namely, the quantity and fixing solutions of the launching supporting structure affect the steelwork cost. Improvements in the way of the launching supporting structure design could reduce the steelwork cost. There is a similar situation in the coating process.

Reducing the damages caused by the steelwork activities can reduce the coating process cost. Generally, reducing the number of spot damages on the underwater part can reduce the coating process cost. The choice of the coating system used for the vessel's underwater part treatment can be improved. The improvements could be achieved by reducing the number of coats, the over-coating intervals, and the undocking time after the last coat application, which all reduces the time spent in the dry-dock and, consequently the overall cost. The inefficiencies related to planning and organization could be represented by the increased number of the enlisted crew on board the vessel and delays occurred during the dry-docking. The crew ratio input shows the measure of the remaining works/delayed activities to be completed at the dry-docking commencement. By reducing the crew ratio, the optimal overall crew cost could be achieved. Besides the technical/technological sources of inefficiency, the planning and organization of the dry-docking project are recognized as inefficiency sources as well. Delays while the vessel is in the dry-dock could be caused by i) planning and organization failures, ii) dry-dock staff underperformance, iii) unexpected scope of work on the underwater part, and iv) adverse weather conditions.

It needs to be pointed out that input improvements are strongly linked to the outputs because of the generated expenses in outputs, which are in fact, expenses divided into categories. These categories were created in order to enable a simpler and more precise improvement analysis on the output side.

The applied categorical DEA model assessed and detected the inefficiencies that occurred during the dry-docking projects.

4. Conclusions

An improved dry-docking performance measurement model has been introduced in this paper. This model is based on DEA, and it could serve as a benchmarking tool for organization management. The studied dry-docking projects data were adjusted to DEA methodology by expressing the dry-docking process efficiency. The orientation was chosen according to the management strategy to reduce dry-docking overall costs. The dry-docking model uses the DEA advantage that no expert opinion is necessary for input and output weights determination, but the model relies on process knowledge while choosing inputs and outputs. During the research, several DEA model calculations have been carried out. The CCR and BCC models calculations and data set descriptive statistics have been completed, with the conclusion that a kind of distinction among the DMUs needs to be made because six DMUs have superior results due to their technical characteristics. This distinction has been carried out by the categorical DEA approach. During the research, the categorization criteria have been determined based on input and output data. The categories have been established for further calculations. The subsequent DEA calculations were performed with the categorical CCR model after concluding that the CCR model represents the data set in a proper way. The chosen new building dry-docking performance measurement model using the DEA methodology with extension to the categorical CCR model has resulted in the establishment of the efficient frontier that contains the efficient DMUs, giving the efficiency score to each particular DMU and detecting benchmarks determined by categories. The projections to the efficient frontier show the direction and intensity of required improvements of inputs and outputs representing each inefficient DMU. And finally, based on the used data, the inefficiency sources have been detected among the data used and sorted into three main groups: i) technical/technological issues, ii) planning and organization, iii) unfavourable weather conditions. The decision-making process follows the "ex-post" principle, making conclusions on already dry-docked vessels, and giving recommendations for future dry-docking projects. This vessel population could be augmented with the new dry-docked vessels and evaluated in repeated calculations using the same model. The introduced model could be used for performance measurement in other project manufacturing enterprises related to but not limited to shipbuilding, civil engineering, mining, project manufacturing, etc. Further research on this topic could lead to the usage of DEA slack-based-measure (SBM) models in combination with the categories in order to achieve higher rate of discrimination among the DMUs in the same category and probably a more sensitive detection of inefficiencies. The research path for ranking the efficient DMUs' purpose could lead toward super-efficiency DEA models.

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