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MEASURING EFFICIENCY CHANGE IN TIME APPLYING MALMQUIST PRODUCTIVITY INDEX: A CASE OF DISTRIBUTION CENTRES IN SERBIA

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Abstract. *In the last decade, more and more attention has been paid to the efficiency of logistics systems not only in the literature but also in practice. The reason is the huge savings that can be achieved. In a very dynamic market with environmental changes distribution centers have to realize their activities and processes in an efficient way. Distribution centers connect producers with other participants in the supply chain, including end-users. The main objective of this paper is to develop a DEA model for measuring distribution centers' efficiency change in time. The paper investigates the impact of input and output variables selection on the resulting efficiency in the context of measuring the change in efficiency over time. The selection of variables on the one hand is a basic step in applying the DEA method. On the other hand, the number of basic and derived indicators that are monitored in real systems is increasing, while the percentage of those used in the decision-making process is decreasing (less than 20%). The developed model was tested on the example of a retail chain operating in Serbia. The main factors changing the efficiency have been identified, as well as the corresponding corrective actions. For measuring efficiency change in time Malmquist productivity index is used. The developed approach could help managers in the decision-making process and also represents a good basis for further research.*

Key words: *Distribution Center, Efficiency, Logistics performance, Data Envelopment Analysis, Malmquist productivity index*

1. INTRODUCTION

Survival in the logistics market has become increasingly challenging in recent years. Competition is becoming fiercer, service users are becoming more demanding, social responsibility is increasing. In such circumstances, more and more companies recognize the efficiency of operations as a key factor of success and a prerequisite for business

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improvement. Distribution centers (DCs) of trading companies and DCs, in general, represent complex logistics systems with a very important place and role in the supply chains [1-3]. They connect producers with other participants in the chain including end-users. In that manner logistics performances are very important [4-6]. Due to a complex structure, estimating their efficiency is a very complicated process. „Single ratio" indicators have been used for a long time to estimate the efficiency of DCs. Recently, an increasing number of authors have been advocating the use of approaches such as the Data Envelopment Analysis (DEA) method [7, 8]. The DEA method is used for estimating the efficiency of homogeneous Decision-Making Units (DMUs). Starting with the initial papers [9, 10] and making the foundations of the DEA method, as well as the introduction of the DMU concept, an expansion of papers in this field, can be observed. The universality of applicability and quality of obtained results have influenced the usage of this method in various profit and non-profit organizations [11, 12].

The DEA method is widely used in logistics. For estimation of Third-Party Logistics providers' (3PL) efficiency both from the provider's perspective [7] and from a user's perspective [13]. Zhou et al. [14] used the DEA method to define benchmark values of performances for 3PL providers in China. They also discuss the change of efficiency in time as well as the mutual influence of certain factors on performances. DEA method is applied for estimating the efficiency of 3PL providers with an emphasis on warehouse operations [15]. They compare the results of two DEA models with and without weight restrictions. Certain papers analyze the efficiency of reverse logistics channels including solid waste [16] and also container terminals [17]. DEA is used for estimating container port efficiency [18], as well as DCs efficiency, as a part of complex supply chains [19]. They also analyze efficiency change in time. De Koster and Balk [20] used the DEA method for benchmarking and monitoring international warehouse operator's performances. A model with multiple inputs and outputs to evaluate the efficiency of warehouse systems is proposed by Hackman et al. [21]. They also confirm conclusions concerning the relation between warehouse size, level of technology and efficiency. Cook et al. [22] applied the DEA method for estimating efficiency in supply chains. The DEA method is often combined with other methods. Combining DEA and Analytic Hierarchy Process (AHP) method it is possible to evaluate the warehouse provider from the aspect of qualitative and quantitative criteria [23]. Park and Lee [24] used the DEA method to assess the efficiency of large logistics providers in Korea. A combination of DEA and AHP can be used for different problems in logistics [25, 26]. The stochastic frontier analysis (SFA) is also combined with the DEA method [27]. PCA-DEA model is used for estimating DC efficiency [8, 28]. Momeni et al. [29] used a fuzzy network slacks-based DEA model for evaluating the performance of supply chains with reverse logistics. Mihajlović et al. [30] used AHP and a Weighted Aggregated Sum-Product Assessment (WASPAS) for the logistics distribution fruit center location selection in the Southern and Eastern Serbia region. Pamučar and Božanić [31] used the neutrosophic MABAC model to locate multimodal terminals.

Malmquist productivity index is used for technical efficiency analysis of container terminals in India [32]. Lei et al. [33] investigated the impact of logistics technology progress on employment structure based on the DEA-Malmquist method. Mavi and Mavi [34] applied the Malmquist method for the analysis of the energy and environmental efficiency. Shahverdi and Ebrahimnejad [35] used DEA and Malmquist productivity indices in order to measure group performance in two periods.

Based on the previously described and extensive review of the literature, it can be concluded that most papers focus on specific examples of efficiency measurements, but not examining the impact of variable selection on the resulting efficiencies as well as their change over time. To the best of our knowledge, there is a lack of papers in the literature concerning the field of logistics which analyze the impact of input and output variables selection on the resulting efficiency. In this paper, the impact of input and output variables selection on the applicability of the model and efficiency change in time is analyzed.

The main objective of this paper is to develop a model which would provide the efficiency change evaluation of DCs that represent the distribution network of one trading company in Serbia. The paper describes the impact of input/output variables selection on the resulting efficiency as one of the most important steps in the process of applying the DEA method. This paper also analysis efficiency changes in time as a result of a dynamic environment. Developed models are tested on real data and the model which successfully describes the DC's operations is selected. The main contribution and novelty of the developed approach are reflected in the identification of main (elimination of insufficiently authoritative) indicators, development of a model for measuring changes in efficiency over time, identification of factors influencing changes in efficiency, and defining corrective actions from the manager's perspective. Based on the literature research, there are no papers that integrate all the mentioned aspects into a unique methodological procedure applicable in real logistics systems. The model's concept could provide easier decision-making of the company management on corrective actions that would improve DC's operations.

The paper consists of seven sections. After the introduction, the second section describes the DEA method. The third section describes the distribution center's efficiency as well as the developed methodology. Developed models for estimating DCs efficiency are described in the fourth section. After that, the orientation of the model is analyzed. Corrective actions of developed models are described in the sixth section. Malmquist productivity index was used for analyzing efficiency and productivity change of distribution centers. At the end of the paper, the concluding remarks and directions of future research are described.

2. DEA METHOD

DEA is a non-parametric linear programming technique that enables the comparison of efficiencies of different DMUs, based on multiple inputs and outputs. The efficiency is relative and relates to the set of units within the analysis. Charnes et al. [10] proposed a non-parametric approach for efficiency estimation, where they reduce multiple inputs to a single virtual input and multiple outputs reduced to a single virtual output using weighting coefficients. In the set of homogeneous units, the DEA finds the most efficient DMUs and according to them, it defines the efficiency of other units. This method is also used for obtaining information about corrective actions of inefficient DMUs. Obtained efficiencies are relative since they relate only to a set of observed DMUs and they cannot be considered as absolute.

The DEA method was chosen primarily because of the large number of advantages, as well as the specificity of the problem that was solved in this paper. This non-parametric approach provides, among other things, the possibility of an objective assessment of efficiency over time. The approach completely excludes the subjectivity of experts. Also, the DEA approach allows quick and easy integration of multiple outputs and inputs into a single measure of efficiency. An additional advantage of this approach is reflected in the relatively simple application that would allow wider application in practice and help improve logistics systems.

The basic CCR [10] model presents the basis of all present models. In the original form, this model presents the problem of fractional programming. According to the appropriate transformations, the model is reduced to the linear programming problem. In order to estimate DMU efficiency, it is necessary to have data of consumed input and realized output variables. In the process of DEA method application, the CCR model is preferable as the initial model. As in linear programming problems, the CCR model also has two formulations: primal and dual. A dual formulation of the CCR model was used in this paper [10]. The mentioned formulation is well known, and it is not necessary to describe it in more detail.

3. Methodology for Measuring DC Efficiency

There are numerous problems with measuring the efficiency of DC and logistics systems in general. One of the basic ones is their complexity. For successful evaluation of DC efficiency, it is first of all necessary to define activities that are realized within it, and then to quantify them [36]. According to the process approach, proper definition of all activities and processes in the logistics system enables managers to create a clear image of the system operating and to identify any possible failures and defects. According to Aminoff et al. [37] the main activities in DC, among others, are: receiving, shipping, control, packing, storage, order picking, order processing, etc. To assess the efficiency of each of them, it is necessary to define certain inputs/outputs that best characterize them. As mentioned earlier according to the process approach DC efficiency depends on the subsystems, process and activity efficiencies, and therefore, it is even more difficult to assess the overall efficiency. DC is characterized by a number of different input/output variables. In this paper, the efficiency of a DC of a trading company is observed, with a special emphasis on the warehouse subsystem. In observed DCs, as well as in most real systems, performances are evaluated by „single ratio“ indicators such as: turnover per employee, turnover per pallet place, warehouse utilization, etc. Mentioned variables are not good indicators of DC efficiency since they do not provide enough information about their operating style. DEA method provides the possibility of integrating a large number of different indicators into a unified measure of efficiency [12].

The development of appropriate models for estimating DC efficiency is an iterative process. Defining an acceptable model requires fewer or more iterations. For each iteration, it is necessary to analyze the obtained results. The methodology of model development and its application for measuring DC efficiency change in time is given below:

- Step 1 – defining potential input and output variables;
- Step 2 – a selection of input and output variables and model defining: Model 1, Model 2 and Model 3;
- Step 3 – model testing;
- Step 4 – model selection;
- Step 5 – testing model orientation.

The process of model testing and result analysis was made on the example of one trading company with DCs located in different parts of Serbia. There are some recommendations in the literature for DMU selection and the relation of the number of DMU and the number of input and output variables. Some authors recommend that the minimum number of DMUs is at least twice the total number of inputs and outputs in the proposed DEA model [12, 14, 38]. For these reasons, in this paper, smaller models are developed. For estimating the efficiency of seven DMUs (in this case DCs) models with two input variables and one output variable ("2+1"), and models with one input and two output variables ("1+2") were developed. Observed DCs are in larger cities where there are competitive companies and customers with different demands and characteristics.

4. Selection of Input and Output Variables and Model Development

For the successful application of the DEA method, one of the key steps is the selection of input and output indicators. The choice of indicators itself greatly affects the resulting efficiencies and discriminatory power of the model. The results of the model are efficiency scores of observed DCs. According to these values, it is possible to define corrective actions for input and output variables in order to improve the efficiency of every DC. On one hand, it is necessary to determine a set of values that in the best way describe the system operating and provide obtaining real operating indicators of DCs efficiency. On the other hand, the objective is to select variables that are appropriate for applying corrective actions and which can be changed in real conditions [8].

In this paper, the initial list of input and output variables was reduced after consultations with managers in DCs, quantitative analyses and preliminary results obtained by applying potential models. During the preliminary analysis, all those variables that did not provide new information and represented duplication of indicators were eliminated. In this way, the well-known problem of excessive indicators that are monitored in DC, but are not used in the decision-making process, has been overcome. Based on the research conducted in this paper, it was found that over 80% of the indicators monitored are not used in the decision-making process. Also, preliminary tests have shown that one part of the indicators has no effect on the discriminatory power of the model. These indicators were also excluded from further consideration. The selected input and output variables are shown in Table 1. These variables are used as the basis for creating different DEA models for estimating DC efficiency. Three models were tested in this paper: Model 1, Model 2 and Model 3. Three suggested models have the same mathematical formulations but they represent different combinations of input and output variables. All models are input-oriented. Model 1 is based on indicators that are most commonly used in the literature. Input variables in the model are warehouse floor space and number of employees, and the output variable is the warehouse utilization. Models similar to this one in literature are applied to estimate the efficiency of banks, libraries, etc. [39]. A similar model is used for estimating the efficiency of 3PL providers [15]. In Model 1, warehouse floor space is taken for the first input variable. A number of employees represent the total number of employees in DC where the largest number of employees is engaged in the warehouse and on receiving, shipping, order picking procedures, etc. The output variable is the warehouse utilization which is obtained as the ratio of the number of the occupied pallet places and a total number of pallet places. This variable is expressed in percentage (%).

Table 1 Summary of input and output variables

DMU	Warehouse floor space (m2)	Employees (No.)	Utilization (%)	Forklifts (No.)	Turnover (10^6 mon. unit)	Pallet places (No.)	Retail stores (No.)	Realized deliveries (No.)
DMU 1	14856	107	81.33	24	483.13	6775	1285	11232
DMU 2	750	14	100.00	2	52.42	548	386	4458
DMU 3	8147	114	98.24	24	522.90	4486	934	11834
DMU 4	10609	82	100.00	28	333.72	6286	876	9491
DMU 5	4272	64	100.00	13	146.11	3234	688	6198
DMU 6	6993	68	91.68	15	216.61	5241	733	4982
DMU 7	5708	32	78.92	9	89.70	4824	551	5705

The increasingly intensive application of financial indicators led to Model 2 [23, 40]. The input variables are warehouse floor space and the number of forklifts, and the output variable is the turnover of DC. The number of forklifts represents one of the equipment indicators that are used for the realization of basic logistics activities. It is possible to take other equipment indicators instead of this variable: energy consumed, number of working hours, etc. The output variable is the turnover. Turnover is the most frequently used variable not only in logistics but in all other areas. This variable is expressed in the monetary units (m.u).

The idea of developing Model 3 is to define a model that best describes all aspects of DC functioning. The main idea was to select variables that describe the operation of DCs of trading companies in a good way from a large number of variables. Three typical variables are: a number of pallet places, the number of retail stores that DC supplies, as well as the number of successfully realized deliveries. Unlike the variables in previous models (warehouse floor space, number of employees, number of forklifts, turnover) that are strategic, in Model 3 the operational variables are included. Such variables are more appropriate for measuring the efficiency and implementation of appropriate corrective actions in DC. A number of retail stores represent some kind of gravity area. This variable is determined by the way DC operates, by the position and competitors in the region. All retail stores are similar in size. The number of realized deliveries is the total number of successfully realized customer's demands. The number of pallet places provides more information on the facility capacity than warehouse floor space since the height of the facility is taken into account. In literature, some authors put an emphasis on the lack of warehouse floor space as a space indicator [15]. Testing and selection of models for further analysis of changes in efficiency over time are described in detail in Chapter 5.

5. Model Selection and Orientation Testing

All previously described models were tested on a real example. A detailed analysis of the results was done in accordance with the real situation in the company. The results of all three models are shown in Table 2. Those DMUs that have a value of 1 in Table 2 can be considered completely efficient.

Table 2 DCs efficiencies according to different models

DMU	Model 1	Model 2	Model 3	Model 4
DMU 1	0.1064	0.7680	0.6899	0.6899
DMU 2	1.0000	1.0000	1.0000	0.9115
DMU 3	0.1206	0.9183	1.0000	1.0000
DMU 4	0.1707	0.4547	0.8551	0.8551
DMU 5	0.2188	0.4893	0.7129	0.7110
DMU 6	0.1888	0.5509	0.5364	0.5364
DMU 7	0.3453	0.3802	0.8172	0.8172

The universality of Model 1 is reflected in the fact that it uses the variables that are most common in the literature. However, the results of this model do not correspond to the real state of observed DCs. For example, DC with the most modern equipment – DMU 3 according to this model, has an efficiency of only 12%. The first reason is the larger number of employees in this than in other DCs. The other reason is the large throughput which this DC realizes. Throughput is an important element of efficiency that is not taken into consideration by this model. The main disadvantage of applying this model in practice is the implementation of corrective actions. The change of surface and number of employees are more strategic than operational decisions that are difficult to implement in the case of complex logistics systems such as DC.

In order to overcome the problem, Model 2 gives greater focus to financial indicators. The results of this model are more appropriate for the real state of observed DCs. There are different opinions in the literature on the application of financial indicators. There are authors who advocate the use of these variables as the key elements of efficiency. The use of financial indicators is often overemphasized in logistics systems, especially in those companies whose main activity is not the provision of logistics services (as is the case in the considered trading company). On the other side, there are authors who propose the use of non-financial indicators that better describe the state of the system. Due to the company's core activity (trade company), financial variables can present suitable input and output variables in the developed models.

In order to include more authoritative indicators that better describe the functioning of logistics systems, Model 3 was developed. This model estimates the efficiency according to variables that describe DC operating in a good way (the number of pallet places, number of retail stores and number of realized deliveries). Comparing to the first two models, the efficiencies scores of Model 3 are the most appropriate for the real state of DC. DMU 3 and DMU 2 are the most efficient and the least efficient is DMU 6.

Model orientation is a very important step in the efficiency measurement process. In DEA terminology, there are input and output-oriented models. Input orientation involves minimizing input variables with the same or greater outputs, and output orientation maximizing output with the same or fewer inputs. Model orientation does not change efficiency value but only the way of achieving those values. The application of input and output models depends on the type of system, specific conditions and management decisions about the variables that are appropriate for corrective actions. Based on the resulting efficiencies it is possible to define appropriate corrective actions that reduce input values and increase output values.

Output-oriented Model 4 was developed on the basis of the input-oriented Model 3. This model features one input and two output variables. The input variable is the number of retail stores that DC supplies and the output variable is the number of realized deliveries and turnover. Model 4 results, regardless of the change of orientation and number of input and output variables, correspond to Model 3 results and the real state of DC (Table 2). Tables 3 and 4 show values of virtual inputs and outputs for Model 3 and Model 4 i.e., target values of input and output variables that enhance the efficiency of observed DCs. In the DEA approach, the target values for each observed variable represent the values that the observed DMU must achieve in order to improve its efficiency. They are the result of the model and show the extent to which a particular DMU must implement corrective actions. In that sense, these values show to what extent it is necessary to reduce the input variables, i.e., to what extent it is necessary to increase the output variables.

Table 3 Target values – Model 3

DMU	Pallet places		Retail stores		Realized deliveries	
	Target value	%	Target value	%	Target value	%
DMU 1	4257.80	37.15	886.49	31.01	11232	0
DMU 2	548.00	0.00	386.00	0.00	4458	0
DMU 3	4486.00	0.00	934.00	0.00	11834	0
DMU 4	3597.82	42.76	749.08	14.49	9491	0
DMU 5	2305.60	28.71	490.49	28.71	6198	0
DMU 6	1888.56	63.97	393.21	46.36	4982	0
DMU 7	2162.64	55.17	450.27	18.28	5705	0

Table 4 Target values – Model 4

DMU	Pallet places		Realized deliveries		Turnover	
	Target value	%	Target value	%	Target value	%
DMU 1	1285	0	16281.25	44.95	719.40	48.91
DMU 2	386	0	4890.71	9.71	216.10	312.24
DMU 3	934	0	11834.00	0.00	522.90	0.00
DMU 4	876	0	11099.13	16.94	490.42	46.96
DMU 5	688	0	8717.12	40.64	385.17	163.63
DMU 6	733	0	9287.28	86.42	410.37	89.45
DMU 7	551	0	6981.30	22.37	308.47	243.91

By applying Model 3 and Model 4 slack values of input and output variables are obtained and they show the possibility of their change with the aim of improving DC efficiency (Table 5). Table 6 shows reference sets of inefficient DMUs in both models. By analyzing the results, it is possible to define appropriate corrective actions for every DC which will improve their efficiency.

Table 5 Slack values

DMU	DMU 1	DMU 2	DMU 3	DMU 4	DMU 5	DMU 6	DMU 7
Model 3	416.10	0.00	0.00	1777.41	0.00	922.88	1779.46
Model 4	19.09	158.59	0.00	100.16	179.68	6.58	198.71

Table 6 Reference sets

		DMU 1	DMU 2	DMU 3	DMU 4	DMU 5	DMU 6	DMU 7
Model 3	DMU 2	/	1.0000	/	/	0.0385	/	/
	DMU 3	0.9491	/	1.0000	0.8020	0.5093	0.4210	0.4821
Model 4	DMU 3	1.3758	0.4133	1.0000	0.9379	0.7366	0.7848	0.5899

6. Corrective Actions and Managerial Implications

One of the main advantages of applying the DEA method is information on the necessary corrective actions of inefficient units. As mentioned in previous chapters, this is one of the reasons for choosing this method. Model 3, as input-oriented, strives to minimize the number of pallet places and the number of retail stores that DC supplies with the same or more successfully realized deliveries. In general, DCs can perform some of three corrective actions: reducing the number of pallet places, reducing the number of retail stores that DC supplies, or increasing the number of realized deliveries.

Based on the results of Model 3, inefficient DMUs in order to improve their business must implement corrective actions such as reducing the number of pallet places and the number of retail stores. According to this model, increasing the number of realized deliveries does not present the necessary corrective action for achieving efficiency. The number of pallet places presents a type of resource that DC uses in order to realize the delivery. Common to all inefficient DMUs is the fact that they can realize the same number of deliveries with a smaller number of pallet places. According to the discussion with managers of observed DCs, it was concluded that the implementation of these corrective actions was justified.

From a mathematical perspective (Table 3), it can be concluded that inefficient DMUs can increase their efficiency by reducing the number of retail stores. This means that there are efficient DCs that realize a larger number of deliveries while supplying a small number of retail stores. This information may be useful to managers of inefficient DCs. However, the implementation of these corrective actions, in this case, is not justified. Regardless of the fact that this corrective action will not be performed, managers of inefficient DCs know very well that their customers have a relatively small number of delivery requests. It is necessary that the management of the company analyzes in detail the reasons for such a situation. Some of the potential reasons may be the structure of customers, the existence and functioning of competition, etc.

The results in Table 3 unequivocally show that only 2 DCs have an efficiency value of 1 (DMU 2 and DMU 3). This further means that they form an envelope. DMU 2 and DMU 3 present DCs with the best combination of input and output values. Common to all inefficient DCs is the need for reducing the number of pallet places with the aim of improving efficiency. The results analysis indicates that DMU 3 is an example of good practice for all inefficient DMUs. This result can be fully explained by the real situation in this system. DMU 3 is a modern distribution center that was planned for this purpose, unlike DMU 1, which was converted from a production plant to a warehouse facility. It is equipped with modern technology that enables a better flow of information and goods.

Model 4, as an output-oriented model, strives to reach the maximum number of realized deliveries and turnover with the same or smaller number of retail stores. In general, one can expect the following corrective actions: reducing the number of retail stores that DC supplies, increasing the number of realized deliveries, or increasing the turnover.

By applying Model 4, and according to target values (Table 4), it can be concluded that inefficient DCs can become efficient by increasing the number of realized deliveries and turnover which was confirmed by DC's managers. According to this model, it is not necessary to perform corrective actions which relate to reducing the number of retail stores which is consistent with the result analysis of Model 3.

The results of measuring efficiency using Model 4 indicate that only one unit of DMU 1 is effective. The efficiency scores of other DMUs are relatively similar to the scores from Model 3, except that the efficiency of DMU 2 is smaller and it is 91.15% (Table 2). The fact is that the reference set is made only of DMU 3 and that all other DMUs have deficits in realized turnover (Table 5).

In this paper, it was found that the results of Model 3 and Model 4 are fundamentally different in the way corrective actions are taken to improve efficiency. Namely, DMU 4 can improve operating in two ways. In the first case, DMU 4 can improve operating by reducing the number of pallet places, without changing the number of realized deliveries, while in the second case DMU 4 can improve operating by increasing the number of realized deliveries and turnover, without reducing the number of retail stores. It is possible to define the efficiency of other inefficient DCs in the same way.

Orientation in these models has not influenced the DC efficiency, but it greatly defines the corrective actions. In the case of output-orientated models, better results are obtained by including two outputs and one input, while for input-oriented models it is better to use two inputs and one output. In this sense, Model 3 is developed for input-oriented models while Model 4 is developed for output-oriented models.

7. Efficiency Analysis over Time

A very important aspect is the analysis of the change in efficiency over time under the influence of various internal and external factors. An extremely dynamic environment affects changes in DC efficiency. This paper analyzes the changing efficiency trend over time as well as changes in multifactor productivity with the aim of determining the factors that influence the change of DC efficiency. Analyses were done for the period of 12 months of the observed year, applying the Malmquist index (*MI*).

7.1. Trend analysis

Previously obtained model testing results were performed in the relevant month, December. In the long run, measuring efficiency is a much more complex problem. The change of efficiency of seven DCs in the observed year according to Model 3 is shown in Table 7.

According to Table 7 there are three groups of DCs. The first group consists of efficient DCs with stable performances – DMU 2 and DMU 3, which were efficient in the observed period. It should be mentioned that DMU 3 had certain decreases in efficiency, but these decreases were not below 95%, and they were the consequence of certain technological and organizational changes as well as of redistribution of tasks between DMU 1 and DMU 3. The second group consists of DCs whose efficiency varies significantly in time – DMU 6 and DMU 1. Large efficiency increases of DMU 6 are achieved in July, summertime when the turnover of most DCs increases. During the holiday season, increased sales are recorded and that period, together with the period of New Years' holidays (December) presents a „peak“ in the trade. The efficiency of DMU 1 in the first half of the year increases while in the second half it decreases. This phenomenon has a real explanation since in the second half of the year part of the tasks is taken by DMU 3, and the efficiency of DMU 1 decreases. At the very end is the third group consisting of inefficient DCs with relatively stable performances: DMU 4, DMU 5, DMU 7. These DCs can to some extent provide useful information on stability and resistance to various factors that affect their functioning.

Table 7 Trends of DC efficiency change

	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
DMU 1	0.28	0.76	0.8	0.78	0.8	0.8	0.76	0.73	0.78	0.71	0.63	0.69
DMU 2	1	1	1	1	1	1	1	1	1	1	1	1
DMU 3	0.43	1	1	1	1	1	1	0.98	0.97	1	1	1
DMU 4	0.27	0.67	0.6	0.62	0.68	0.75	0.8	0.84	0.75	0.69	0.7	0.86
DMU 5	0.39	0.72	0.68	0.68	0.62	0.65	0.66	0.68	0.62	0.57	0.61	0.71
DMU 6	0.24	0.46	0.46	0.47	0.49	0.56	0.78	0.74	0.57	0.54	0.49	0.54
DMU 7	0.17	0.67	0.69	0.73	0.72	0.78	0.83	0.8	0.81	0.76	0.71	0.82

7.2. Analysis by Malmquist productivity index

In order to obtain a complete and true picture of the change in efficiency in the observed time period, the *MI* index was applied. *MI* index was presented by the authors [41, 42]. Later *MI* has been used frequently [35, 43, 44]. Productivity can be presented as the ratio between input and output, while the change of productivity presents the change of that ratio in time. Over time, system productivity may change due to a frontier shift which appears as the consequence either of technological progress which has happened or due to the change of relative efficiency of DC.

A detailed procedure for calculating the main components is shown below. To calculate *MI,* it is necessary to determine four indexes of relative distance, i.e., to solve four linear programming problems. *MI* of the company's productivity change is calculated as:

$$MI = \sqrt{\frac{D_0^t(B_{t+1})}{D_0^t(B_t)} \frac{D_0^{t+1}(B_{t+1})}{D_0^{t+1}(B_t)}} \tag{1}$$

where $D_0^t(B_t)$ is the efficiency of point B_t in the moment t, D_0^{t+1} is the efficiency of point B_t in the moment $t+1$, $D_0^t(B_{t+1})$ is the efficiency of point B_{t+1} in the moment t, and $D_0^{t+1}(B_{t+1})$ marks the efficiency of point B_{t+1} in the moment $t+1$. The previous formulation can be decomposed into an index of relative technical efficiency change (*TEC*) and index of frontier shift (*FS*) in the following way:

$$MI = TEC * FS = \frac{D_0^{t+1}(B_{t+1})}{D_0^t(B_t)} \sqrt{\frac{D_0^t(B_{t+1}) D_0^t(B_t)}{D_0^{t+1}(B_{t+1}) D_0^{t+1}(B_t)}} \tag{2}$$

The efficiency of seven DCs is estimated in this paper over the period of 12 months. For every period three values were calculated: *MI*, *TEC* and *FS*. Obtained results are shown in Table 8. The values were calculated based on the Eqs. (1) and (2). The period of change ($t; t+1$) is one month as indicated in the second column of Table 8.

Table 8 Indicators of efficiency change in time

	Period	DC						
		DMU 1	DMU 2	DMU 3	DMU 4	DMU 5	DMU 6	DMU 7
Malmquist Index (MI)	Jan/Feb	0.955	0.872	0.984	0.969	0.909	1.057	1.018
	Feb/Mar	1.180	1.083	1.060	1.008	1.055	1.126	1.154
	Mar/Apr	0.947	1.000	0.982	0.997	0.967	0.990	1.026
	Apr/May	1.023	0.979	0.999	1.094	0.920	1.051	0.978
	May/Jun	0.946	0.985	0.975	1.039	0.981	1.075	1.025
	Jun/Jul	0.902	0.936	0.977	1.015	0.975	1.330	1.016
	Jul/Avg	0.928	1.066	0.956	1.017	0.984	0.902	0.930
	Aug/Sep	1.112	1.020	1.027	0.925	0.945	0.799	1.049
	Sep/Oct	0.948	1.000	1.016	0.958	0.957	0.974	0.969
	Oct/Nov	0.949	1.000	1.000	1.010	1.040	0.955	0.967
	Nov/Dec	1.057	1.041	0.992	1.183	1.148	1.062	1.115
Techical efficiency change (TEC)	Jan/Feb	2.757	1.000	2.312	2.483	1.854	1.905	3.855
	Feb/Mar	1.050	1.000	1.000	0.897	0.937	1.001	1.027
	Mar/Apr	0.979	1.000	0.998	1.030	0.999	1.023	1.060
	Apr/May	1.026	1.000	1.002	1.097	0.923	1.054	0.981
	May/Jun	1.001	1.000	1.000	1.100	1.038	1.138	1.085
	Jun/Jul	0.945	1.000	1.000	1.064	1.022	1.395	1.065
	Jul/Aug	0.968	1.000	0.977	1.060	1.026	0.941	0.970
	Aug/Sep	1.069	1.000	0.992	0.889	0.909	0.769	1.009
	Sep/Oct	0.899	1.000	1.033	0.918	0.916	0.949	0.939
	Oct/Nov	0.900	1.000	1.000	1.020	1.082	0.912	0.934
	Nov/Dec	1.087	1.000	1.000	1.217	1.166	1.093	1.147
Frontier shift (FS)	Jan/Feb	0.346	0.872	0.426	0.390	0.490	0.555	0.264
	Feb/Mar	1.124	1.083	1.060	1.124	1.126	1.124	1.124
	Mar/Apr	0.968	1.000	0.984	0.968	0.968	0.968	0.968
	Apr/May	0.997	0.979	0.998	0.997	0.997	0.997	0.997
	May/Jun	0.945	0.985	0.975	0.945	0.945	0.945	0.945
	Jun/Jul	0.945	0.936	0.977	0.945	0.945	0.945	0.945
	Jul/Aug	0.959	1.066	0.979	0.959	0.959	0.959	0.959
	Aug/Sep	1.040	1.020	1.036	1.040	1.040	1.040	1.040
	Sep/Oct	1.055	1.000	0.984	1.044	1.045	1.027	1.032
	Oct/Nov	1.054	1.000	1.000	0.990	0.961	1.047	1.035
	Nov/Dec	0.972	1.041	0.992	0.972	0.985	0.972	0.972

Values of the frontier shift are relatively stable and up to July they have a value less than 1, and after that period values become higher than 1 which presents technological progress. The technological progress of the observed sample is necessary according to market conditions. It is likely that this trend will continue in the future. Variations in these values are directly caused by competition and lower prices of services and products, and thus lower profitability. The established technological progress corresponds to the results obtained in research on examples of other industries such as [45, 46]. DMU 2 and DMU 3 do not change significantly since the ratio of efficiency in certain time intervals is 1. The efficiency of other DCs changes over time to some extent.

The multifactor productivity index is shown in the first part of Table 8. *MI* values higher than 1 indicate a positive change and values lower than 1 indicate a negative change of multifactor productivity. DMU 3 records a positive change of multifactor productivity which largely corresponds to the real situation. *MI* values for DMU 1 vary significantly which corresponds to the real situation. This phenomenon is a direct consequence of operation changes. DMU 3 takes over a large number of retail stores of DMU 1. DMU 1 has specialized for specific groups of retail stores and products. Common for most of the DCs is the positive change of *MI* in a period of „peak“: November-December.

One of the shortcomings of this analysis is a relatively short period of observation. Despite the large number of time sections (in this case 12 months), the total period of observation is only one year. During this period some significant and radical technological developments cannot be expected. However, some changes in the way of operating of some DCs quickly reflect on the positive change of *MI*. For example, DMU 3 records positive changes of *MI* in the long period of six months, as a direct result of the introduction of better and more convenient Warehouse Management System (WMS). These and similar changes are prerequisite for successful operation of DC. The limitation of this research is reflected in the relatively small number of DCs considered. More authoritative conclusions could be obtained if the developed model were applied to other companies and in other market conditions (other countries). This could fully explain the impact of markets, environments and organizational changes on the efficiency of logistics systems. A special aspect of future research is sustainability efficiency [47].

7. Conclusion

One of the most important factors for market survival is measuring, monitoring and improving efficiency change in time. The main objective of this paper is the development of a model which measures DC efficiency in an appropriate way and defines appropriate corrective actions that can be applied in real logistics systems. Models are tested on real data of one company in Serbia. By analysing the results, the models which did not adequately describe the operation of DCs were rejected. After testing, Model 3 was further analysed and varied with the aim of improvement. Model orientation was studied and in the case of output orientation. A more detailed analysis of input and output variables shows that variables which are mostly used in DEA method application are not suitable for analysing DC efficiency. The first problem that has been successfully solved in this paper relates to the choice of variables to be used in the model. The problem of a large number of indicators in logistics systems that are monitored but not used in the distribution process has been successfully overcome. It was found that less than 20% of the indicators monitored are used in the further decision-making process. Preliminary testing also eliminated those variables that do not affect the discriminatory power of the model. In this paper, among the great number of potential input and output variables which in the best way describe DC operation, the following were chosen: number of pallet places, number of retail stores and number of realized deliveries. The selection of input and output variables greatly affects efficiency scores and corrective actions.

Malmquist productivity index was used for measuring efficiency change over time. The results show efficiency changes in a relatively short period (12 months). In the process of model development, the assumption from the literature was confirmed. Smaller DCs are more efficient than larger DCs [21]. In almost all models presented in the paper, the smallest DC in the sample, DMU 2, had an efficiency of over 90%, which confirms the assumption. The frontier shift was found to be stable until July when values greater than 1 were observed and technological progress was recorded. *MI* values show that some decision units have positive and some negative changes in multifactor productivity. A positive change in the efficiency of DMU 3, which fully corresponds to the technological changes (introduction of more advanced WMS) and redistribution of activities with other DCs. A positive change in *MI* during the peak period (November-December) was found. This is a direct consequence of better resource utilization and higher turnover.

In literature, there is a lack of case studies, i.e., model testing in the concrete DC examples. This fact indicates the insufficient amount of researches in this area. This paper shows how a theoretical model can be applied in practice. The developed methodology represents support in the decision-making process.

Models presented in this paper, with minor adjustments, can be used for measuring and improving the efficiency of providers, warehouses, suppliers, etc. Presented models are a good basis for the development of future models with a larger number of input and output variables. In future research, models should include qualitative indicators as input or output variables. It is also important to use hybrid models that combine different approaches and methods. An additional direction of future research is the measurement of potential savings that can be achieved by applying the proposed approach. On the one hand, it is necessary to examine the savings that are achieved by eliminating the monitoring of indicators that are not used (savings in time, savings in the workforce that is currently doing it, savings in equipment, etc.). On the other hand, it is necessary to examine the savings that would be achieved by improving the efficiency of inefficient distribution centres.

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