

## **Implementing an efficient data envelopment analysis method for assessing suppliers of complex product systems**

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### **Abstract**

Reduction of complex product systems (CoPS) manufacturing costs are the main factors of sustainability and survival of the manufacturers. Choosing proper CoPS suppliers can dramatically reduce these costs and increases competitive capability for manufacturers. This is due to the fact that in the complex industries, the costs of raw materials for the production processes or the purchase of components includes a substantial part of the product costs. In this regard, in this paper, a tailored data envelopment analysis (DEA) model is deployed to assess and select the supplier of CoPS, helping to deduct these costs as well as eventuate in productivity of the products. In the proposed model, various suppliers of CoPS are evaluated based on a set of economic, technical, and geographic criteria. The suppliers are ranked in accordance with the obtained scores and then the best ones are chosen. Eventually, to examine the applicability and usefulness of the proposed method, a case study is conducted via which important managerial outcomes are extracted.

**Keywords:** Data Envelopment Analysis, complex product systems, supplier selection, efficient frontier, anti-efficient frontier.

### **1- Introduction**

As the selection of the suitable suppliers has a great deal of influence on the strategic and operational efficiency of the organization, it is taken into account as a vital factor. Meanwhile, it shortens the product development cycle, enhances the products quality, alleviates inventory levels, reduces production costs, ameliorates flexibility and satisfies customers' expectations (Çebi and Otay, 2016). In view of the fact that the problem of supplier selection, which is the most basic process for finding the best supplier to buy the items required for the final product, it is incumbent upon to be investigated comprehensively (Ayhan and Kilic, 2015). Along the same lines, CoPS, goods, systems, networks, infrastructures, engineering structures, and services are at the expense of many software sectors that are critical to economic growth and modern economics (Davies and Hobday, 2005). Broadly speaking, these products can be defined as costly, having high-volume engineering and IT, including a large number of subsystems and components that are custom-made (Hansen and Rush, 1998). CoPS is one of the areas that has the most added value for the economies of the countries and increase competitive capability for manufacturers. In this manner, most countries endeavor to have a good presence in this field. Table (1) summarizes the studies done in different fields of CoPS.

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**Table 1.** Examples of studies on different fields of CoPS

Section/industry	Example
Aerial	Airplanes (Acha et al., 2004; Davies and Brady, 1998; Hansen and Rush, 1998), airplane engine (Acha et al., 2004; Davies and Hobday, 2005; Hobday, 2000) and flight simulation (Acha et al., 2004; Davies and Brady, 1998; Davies and Hobday, 2005; Hansen and Rush, 1998; Hobday, 2000).
Transportation	Rail transport system (Acha et al., 2004; Davies and Brady, 1998; Özdemir et al., 2011) and road traffic management systems (Davies and Hobday, 2005; Dehghani et al., 2018d; Diabat et al., 2017; Sadjadi et al., 2016).
Military uses	Military Services (Davies and Brady, 1998; Davies and Hobday, 2005; Hansen and Rush, 1998), Battleship and Ground-to-air missile control units (Davies and Hobday, 2005).
Energy	Nuclear power plant (Davies and Brady, 1998; Davies and Hobday, 2005) Electric power control systems (Davies and Hobday, 2005; Dehghani et al., 2018a) and the power distribution network (Hobday, 2000).
Electronic	Semiconductor material manufacturing plant and E-commerce systems (Davies and Brady, 1998; Davies and Hobday, 2005; Hobday, 2000) and Supercomputers (Davies and Hobday, 2005).
Other	Sea drilling rigs (Davies and Hobday, 2005; Hansen and Rush, 1998; Hobday, 2000), chemical material plant, communication networks (Acha et al., 2004; Davies, 1996; Hobday, 2000), Racing cars (Davies and Hobday, 2005; Dehghani et al., 2016) and intelligent structure (Acha et al., 2004; Davies and Hobday, 2005; Hobday, 2000).

As it can be seen, survival of any country in terms of infrastructure and technological advances in the world is depended on important and strategic products in this area. Remaining in the market for competition and their future advancement are highly interlocked to successfully present in this field. Likewise, one of the main requirements for entering is the choice of the appropriate supplier of these products, which in addition to reducing costs, elevates the competition and the speed of progress as well (Cook and Johnston, 1992; Dedehayir et al., 2014; Dehghani et al., 2018b; Hobday, 2007; Safdari Ranjbar et al., 2018). It is noteworthy that there are some economic, technical and geographical criteria that should be considered when CoPS' supplier is chosen.

In accordance with the above-mentioned discussion, a new model of DEA is presented in this paper to select the appropriate supplier. In the proposed method, based on the aforementioned criteria, suppliers of various CoPS are evaluated. The main advantage of the implemented method is that it can increase the distinction between different options by means of efficient and anti-efficient frontier information. Lastly, in a bid to assess the applicability and usefulness of the proposed method, a case study is carried out through which useful managerial outcomes are obtained.

This article is organized as follows. In the next section, the relevant literature is reviewed. In section 3, the necessity and importance of the concerned area are elaborated. Section 4, offers the used DEA model. In section 5, a case study is carried out and finally, the conclusions and avenues for the future researches are presented in section 6.

## 2- Literature review

In recent years, many attempts have been published to develop and optimize supplier selection models. These studies encompass the wide scope of models ranged from simple linear single product for deterministic problems. DEA, as a powerful optimization tool, is a mathematical model in order to assess the performance of homogeneous decision-making units (DMUs) according to the available data. This method is known as a non-parametric approach and it has been broadly exploited for the goal of selecting the supplier in the supply chain of CoPS. Banaeian et al. (2018) helped this area by comparing the criteria for using the methods of selecting multiple faulty sources in a fuzzy environment. Connecting the theory of fuzzy sets to TOPSIS, VIKOR, and GRA methods has been fully discussed in their article and then used to complete a green supply assessment and selection for a real food-processing industry's company. Cheng et al. (2017) proposed a hybrid model made and DEA. The stated model is divided into two sections of DEA and the learner. The DEA is a fuzzy multifunction for building expert databases, which includes appropriate and inappropriate suppliers. In this model, the learner is trained by AdaBoost with a specialized database. Therefore, DEA and derived learner are mixed as a combination model to reduce time consumption and computational complexity of choosing suppliers.

Amorim et al. (2016) proposed a bi-level complex numerical planning model for selecting suppliers in the food industry, which helps maximize profits and minimizes customer service risk. Among the parameters included in this model are the degradation of raw materials and final products, uncertainty in downstream and upstream parameters, and period dependent demand. They developed a solution based on multiple Benders decomposition and public distribution planning. Hosseininasab and Ahmadi (2015) presented a new two-phase selection method. The proposed method is based on the long-term trend of value, stability and potential supplier relationships. In the first stage, suppliers are evaluated and determine values will be compared to a set of criteria. In the second step, the multi-objective model is optimized. A supplier employer maximizing expected value and developing suppliers and minimizing related risks will be set through this model. Galankashi et al. (2015) used the nominal group technique (NGT) to extract the most important performance measures. They considered ten performance indicators as alternatives to select green suppliers. Then, a Fuzzy Analytical Network Process (FANP) was used to measure the extracted metrics and circumscribe their significance. Du et al. (2015) introduced a type of supply provider choice problem called the Supplier selection life-cycle in CoPS' system (CoPS & SSL). There are three types of choices for a manufacturer to complete CoPS: self-made, material purchase and outsourcing. A two-dimensional LSS and CoPS model, according to the CoPS operational phase is proposed to balance buy costs and operating costs. In addition, a combination of Pareto Genetic Algorithm (PGA) algorithm proposed with Multiple Crossover and Simulation (MSC) strategies to solve the two-objective problem. A dual chromosome is also used to represent variable length chromosomes. Finally, the ideal supplier was chosen to offer ideal equipment for a cement company by means of this approach. Huang and Goetschalckx (2014) and Setak et al. (2017) describes the design of the strategic supply chain as a set of Pareto optimal configurations, taking into account simultaneously the productivity and risk, where the risk with the standard deviation of the productivity of the size. The proposed model shares the costs of supplier development in accordance with an optimal ratio, the level of optimal effort and the optimal revenue of the main producer. In order to effectively identify all Pareto optimal configurations, a branch and bound algorithm was expanded using optimal cut and high frontiers to eliminate parts of the inaccessible area and Pareto's non-optimal area investigated the optimal cost-sharing model of the Nash equilibrium and the stackelberg equilibrium to analyze the status of cooperation between the main manufacturer and the suppliers.

Fallah-Tafti et al. (2014) initially developed a closed-loop supply chain network design, which made network design decisions in forwarding and inverted chain networks in a seamlessly integrated structure and also combines tactical decisions with strategic cases (including location and supplier selection) in each period. Then, a new interactive approach based on the known method of STEP was suggested for a multidimensional solution of a mixed integer linear programming model. To validate the proposed model and the solution method, a numerical test is performed using the probable STEM algorithm. The computational results indicate the suitability of the proposed model and the solution method. Chai and

Ngai (2015) examined the problem of selecting strategic suppliers in inappropriate decision-making environments. A soft decision-making model was proposed involving multiple stakeholders and multiple perspectives. Lee et al. (2015) considered the supplier assessment and selection as a multi-criteria decision making (MCDM) with the subjective and fuzzy set of decision makers about the evaluation criteria. They provided decision makers with a supportive system, which brings together Pareto Fronts, a set of top-notch high-end providers and business-level executives. The proposed system uses a fuzzy analytical hierarchy process (Fuzzy AHP) and a fuzzy technique to prioritize a similarity to the ideal solution (Fuzzy TOPSIS) in order to successfully determine the weight of the priorities of multiple criteria and select the most appropriate suppliers. Kar (2014) proposed a method for group decision-making support for supplier selection using the integrity of the fuzzy analytical hierarchy process (AHP) in group decision making and fuzzy logic programming for a distinct analysis. Bandyopadhyay and Bhattacharya (2013) developed a new multi-objective formulation for minimizing the total cost and minimizing the bullwhip effect of a two-echelon serial supply chain. They also proposed a new crossover algorithm for a fuzzy variable and a new mutation algorithm whilst applying Non-dominated Sorting Genetic Algorithm-II (NSGA-II) to the proposed problem. The formulated problem has been simulated by Matlab software and the results of the modified NSGA-II have been compared with those of original NSGAI. It is found from the results that the modified NSGA-II algorithm performs better than the original NSGA-II algorithm since the minimum values for both total cost and the bullwhip effect are obtained in the case of the modified NSGA-II. Wu et al. (2013) developed a stochastic fuzzy multi-objective programming model for supply chain outsourcing risk management in the presence of both random uncertainty and fuzzy uncertainty. Utility theory is proposed to treat stochastic data and fuzzy set theory is used to handle fuzzy data by them. They also designed an algorithm to solve the integrated model. The new model in their research is solved using the proposed algorithm for a three-stage supply chain example. Moncayo-Martínez and Recio (2014) proposed an ant colony-based algorithm to generate a set of SC configurations using the concept of Pareto optimality. Abdollahi et al. (2015) presented a framework for supplier selection based on product-related and organization-related characteristics of the suppliers. Due to the interaction between the criteria, analytical network process (ANP) is applied for determining the weight of each criterion for each alternative (supplier), and then DEA is used to rank them. The reason that DEA is used in this study is that when the number of suppliers increases, ANP approach tends to work inefficiently. Moreover, for determining the accurate interdependencies between the proposed criteria, fuzzy decision-making trial and evaluation laboratory (DEMATEL) is applied. The framework is applied to a real case to demonstrate its applicability and feasibility. Liu and Hipel (2012) proposed a hierarchical decision model to select the optimal quality control strategies among various alternatives to pursue the most satisfying quality improvement for the supply chain in producing a CoPS, such as an aircraft, warship, or satellite. More specifically, based on the relationships of the suppliers in the supply chain, an HSCQ network can be constructed and an associated multilevel multi-objective program can be established as the hierarchical decision model, which assists the enterprises in different tiers to choose the optimal quality control strategies for managing the quality of their outsourcing products. The result can significantly improve the overall quality performance of the supply chain. A case study on an aircraft production system is conducted to demonstrate the feasibility and effectiveness of the new model. Mahapatra et al. (2012) studied the two major collaborative supplier management strategies (direct investments in supplier development and close relationship building) for developing and accessing superior supplier capability across the growth and maturity stages of the product life cycle (PLC). Specifically, the study analyzes the influence of competitive intensity as an antecedent to supplier development and relational initiatives, and the role of the product lifecycle. Based on initial data and discussions with managers, the individual and integrative effectiveness of supplier development investments (SDI) and relationship orientation (RO) can be different due to the intensity of competition and the PLC stage. Zeydan et al. (2011) proposed a new method in order to increase the quality of selection and evaluation of manufacturer and in the first stage, qualitative performance evaluation is performed by using fuzzy AHP (Analytical Hierarchical Process) in finding criteria weights and then fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is utilized in finding the

ranking of suppliers. So, qualitative variables are transformed into a quantitative variable for using in DEA methodology as an output called quality management system audit. In the second stage, DEA is performed with one dummy input and four output variables, namely, quality management system audit, warranty cost ratio, defect ratio, quality management. Shankar et al. (2013) considered simultaneous optimization of strategic design and distribution decisions for three-echelon supply chain architecture consisting of following three players; suppliers, production plants, and distribution centers (DCs). The key design decisions considered are the number and location of plants in the system, the flow of raw materials from suppliers to plants, the number of products to be shipped from plants to distribution centers. To achieve this, the three-echelon network model is mathematically represented and solved using swarm intelligence based multi-objective Hybrid Particle Swarm Optimization algorithm (MOHPSO). Visani et al. (2016) considered a supplier total cost of ownership (TCO), which acted as a proxy for TCO and approximated the results of TCO with less effort. A new integrated DEA model for finding most efficient supplier with imprecise data was proposed by Toloo and Nalchigar (2011), which was capable of identifying most efficient supplier in presence of both ordinal and cardinal data. A systematic DEA approach was implemented by Shi et al. (2015) to scientifically determine and assess suppliers under the sustainable supply chain environment. Using a DEA-type supplier selection, Dobos and Vörösmarty (2018) proposed a methodology to handle managerial and green criteria. In addition to managerial and green criteria, the proposed methodology examined the impact of inventory-related costs on the selected supplier. Mahdiloo et al. (2015) devised a new multiple objective linear programming DEA model, for which they proposed a real world business case of the Hyundai Steel Company and its suppliers. For comprehensive reviews in the supplier selection with DEA, the interested readers can refer to Soheilrad et al. (2017). Regarding the literature review, innovations that distinguish this research from other above-mentioned studies are summarized as follows:

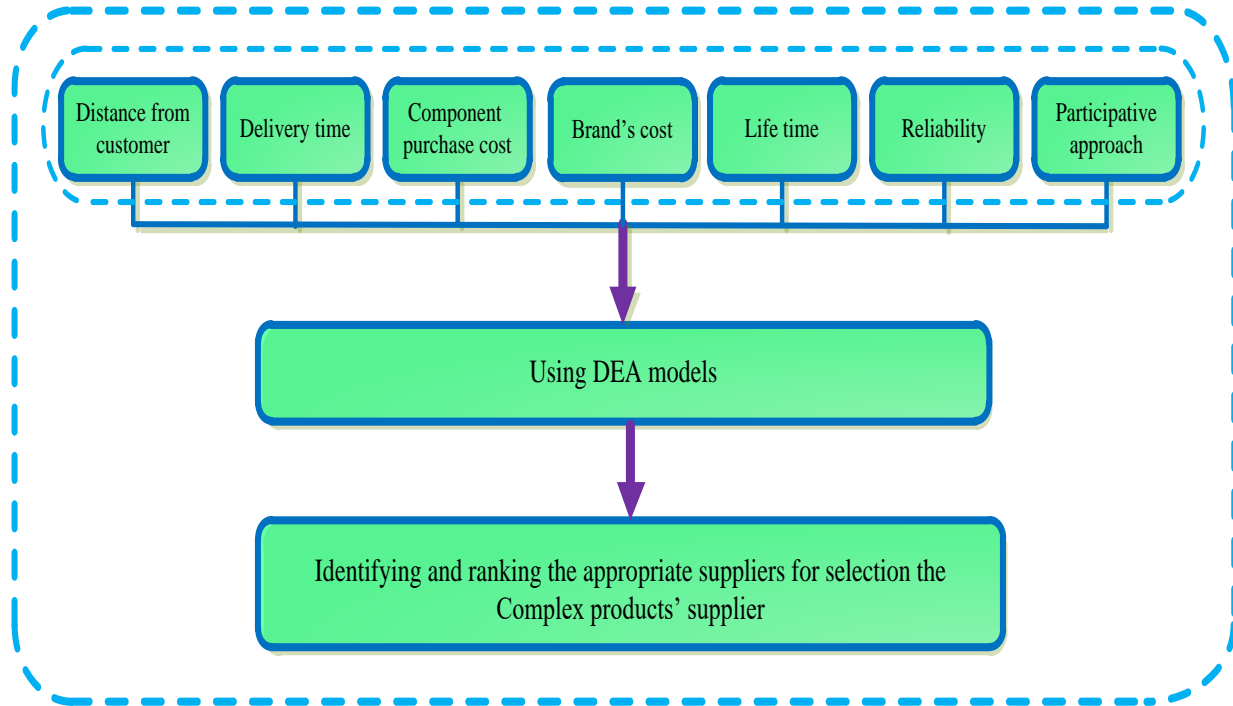
- Unlike most DEA methods used in the literature review, the method presented in this paper can increase the differentiation between options through using information about efficient and anti-efficient frontier.
- According to the literature review, this study is one of the first researches to select suppliers in CoPS.
- Considering the criteria, such as the percentage of suppliers and brand costs to strengthen the supplier's brand, such as advertising, is another feature of the research that distinguishes it.
- Finally, in order to assess the impact and usefulness of the proposed method, a real case study was carried out and useful managerial outcomes are extracted.

### **3- The necessity to enter this area**

CoPS form an increasingly important role in the economic activities of firms, industries, and nations. Due to changing markets and technologies, over the past several years there has been a shift towards CoPS, particularly in advanced industrial nations (Hansen and Rush, 1998). Currently, CoPS form a significant part of the value added of industrialized countries; the share that has been growing over the past decade and is considered as a major source of competitive advantage for these countries. Although most CoPS are produced for domestic consumption, over the past 30 years (and more), about 15% of global trade has been related to CoPS (Hobday, 2007). Therefore, most countries are trying to be successful in this extent. One of the main requirements for entering this domain is the supplier of these products. This is because the appropriate supplier, in addition to costs' abatement, will increase competition and speed of progress in this area. Given the importance of choosing a supplier in these products, we will propose a method to evaluate the suppliers of these products by using the DEA model below.

#### 4- Proposed method

The following figure shows the process of selecting the supplier of CoPS. As it is clear from this figure, the most appropriate suppliers are identified and evaluated based on a set of technical, economic, and geographical criteria using the DEA model.



**Fig 1.** The used approach in the article's process structure

#### 4-1- DEA model

In this model, using a DEA model, various suppliers are evaluated for selection based on a set of technical, economic, and geographic criteria. The proposed envelopment analysis model is able to increase the differentiation between options by employing efficient and anti-efficient frontier information. The DEA is a non-parametric method for evaluating decision-making units based on observation. This technique manages sophisticated relationships between inputs and outputs and does not require predefined weights. In addition, this method does not require the normalization of the input and output and the decision-making units. In our case, a specific supplier is considered as a decision maker. Meanwhile, this technique has been widely used to identify suppliers. Two basic research in the field of DEA are (Charnes et al., 1979; Farrell, 1957) studies. The offered envelopment analysis by Charnes et al. (1979) considers the constant return to scale. This model is known as the CCR model in literature. Later, the Banker (1984) considered a model involving the variable return to the scale, which in the literature is known as the BCC model. The main concept of the classical DEA is the identification of the production frontier, where decision-making units are efficient. Then, the score of the units that are not on the frontier is obtained through comparison with the efficient decision-making units. Note that units located on the frontier have the same rating and also the highest score. As previously mentioned, one of the important features of DEA is that there is no need to determine predetermined weights. In fact, weights are considered as decision variables, and their value is specified in a way which yields the highest returns. However, due to a large number of decision-making units located often on the frontier, this full flexibility may reduce discrimination and the ability to make a difference in DEA and compromise the performance of the DEA

rating. Therefore, many authors have tried to provide various methods aimed at improving the power of differentiation in DEA.

Takamura and Tone (2003) considered an inverted envelopment analysis model for site selection for the transmission of several government agencies abroad. Paradi et al. (2004) Also used an inverted model. Johnson and McGinnis (2008) employed both the efficient and anti-efficient frontiers to identify outliers and thus improve the accuracy of estimators in the second stage regression analysis. Entani et al. (2002) employed both inverted envelopment analysis models to obtain the upper and lower limits of effective options.

There are also studies which simultaneously compare good and bad decision makers through DEA models for example (Dehghani et al., 2018c; Shen et al., 2016; Sueyoshi and Goto, 2014).

In this study, we used Shen et al. (2016) to evaluate suppliers of CoPS. Unlike other groups, these methods have the advantage that they are not limited to a specific group and can be applied to different issues. In fact, Shen et al. (2016) in order to increase the DEA power of discrimination, use an indicator that simultaneously takes the distance from the efficient and anti-efficient frontier. In the proposed process, standard envelopment and inverted envelopment analysis are used simultaneously to provide more information about the frontiers. This will increase the DEA discrimination underlying power and provide a better rating. In the following, the approach used will be explained.

Suppose that there are  $n$  decision units so that their index is displayed with  $v(v=1, \dots, n)$ . Also, the inputs and outputs of the DEA model for the decision-making units are  $x_{kv} (k=1, \dots, g)$  and  $z_{rv} (r=1, \dots, q)$  respectively. The model below shows the standard cover analysis:

$$\text{Min } h_{bl}^* = \delta_l \quad (1)$$

$$\sum_{v=1}^n x_{kv} \eta_v \leq \delta_l x_{kl}, \quad v=1, \dots, g \quad (2)$$

$$\sum_{v=1}^n z_{rv} \eta_v \geq z_{rl}, \quad r=1, \dots, q \quad (3)$$

$$\eta_v \geq 0, \quad v=1, \dots, n \quad (4)$$

$$\delta_l \text{ unconstrained.}$$

Also, the inverted envelopment analysis model is as follows:

$$\text{Max } h_{wt}^* = \delta_l \quad (5)$$

$$\sum_{v=1}^n x_{kv} \eta_v \geq \delta_l x_{kl}, \quad k=1, \dots, g \quad (6)$$

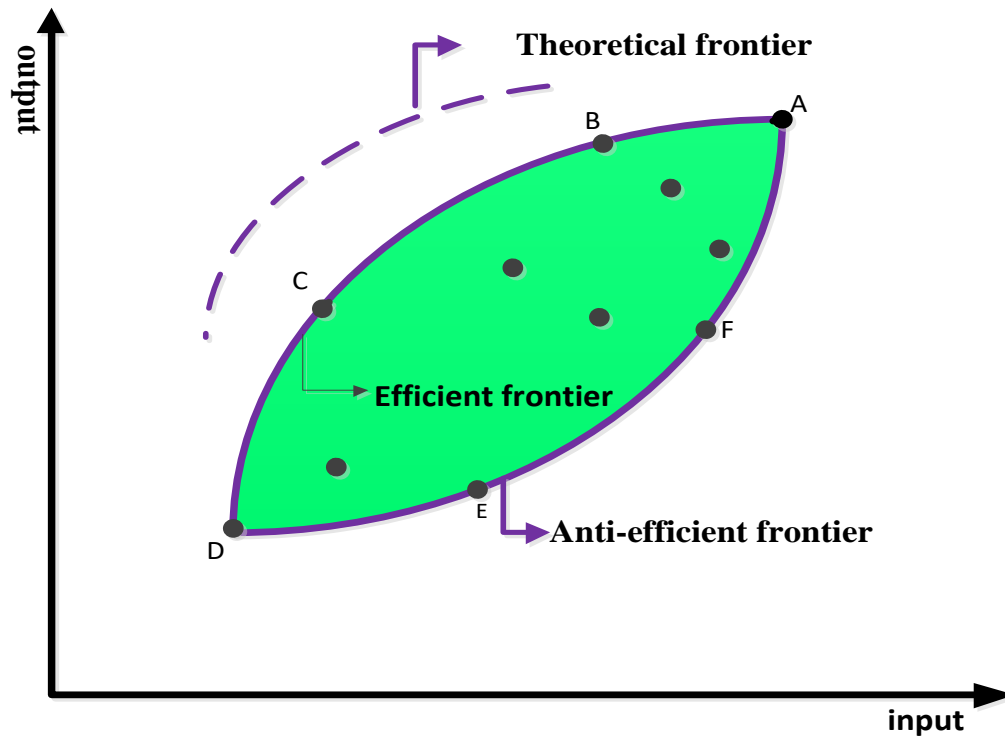
$$\sum_{v=1}^n z_{rv} \eta_v \leq z_{rl}, \quad r=1, \dots, q \quad (7)$$

$$\eta_v \geq 0, \quad v=1, \dots, n \quad (8)$$

$$\delta_l \text{ unconstrained.}$$

So that  $\delta_l$  is the decision-making unit's return is "1",  $x_{kl}$  and  $z_{rl}$  are respectively the inputs and outputs of the decision-making unit under consideration (the decision-making unit "l") and  $\eta_v$  is the dual weight associated with the total inputs and outputs of the decision-making unit "v".

Both of these models are solved for the "l" decision maker to achieve performance scores of  $h_{wl}^*$  and  $h_{bl}^*$ . Speaking intuitively, these two models are solved n times to determine the frontiers. Specifically, standard and inverted envelopment analysis models generate efficient and anti-efficient frontiers, respectively. The following figure shows the geometric meaning of efficient and anti-efficient frontiers:



**Fig 2.** Graphical illustrations of the efficient and anti-efficient frontiers

As it can be seen, the standard model of DEA has used the best decision-making unit A, B, C and D to create an efficient frontier, and the inverted model of DEA used the worst of them to form an anti-efficient frontier. For the use of both efficient and anti-efficient frontiers data and aggregation of efficiency scores for efficient and anti-efficient envelopment models, the following index for each decision unit is calculated as follows.



$$hi_i^* = \frac{\left[ h_{bl}^* + \left(1 - \frac{1}{h_{wl}^*}\right) \right]}{2} \quad (9)$$

Note that if the decision-making unit "I" is located on the anti-efficient frontier (for example, the decision-making unit F and E), then we'll have  $h_{wl}^* = 1$  and  $hi_i^* = \frac{h_{bl}^*}{2} \leq \frac{1}{2}$ , and if it is on both frontiers (for example, the decision-making unit A and D), that is  $h_{wl}^* = 1$ , and  $h_{bl}^* = 1$ , Then, if the decision-making unit is placed on the efficient frontier (that is, the decision-making unit B and C), then  $hi_i^*$  will be more than 0.5, which will make this decision unit more efficient than other units located on both frontiers.

## 5- Case study

According to the literature, there are important and strategic products in the field of CoPS that are necessary for the survival of each country in terms of infrastructure and technological advances in the world. Remaining in the market for competition and future developments has made Countries to present in this field. Therefore, selecting the right supplier for these products is one of the essential requirements participate successfully in it. In this regard, a case study has been carried out on the supply of products. There are three types of choices for purchasing suppliers for CoPS: 1. Purchasing ready-made components. 2. Purchasing materials that must be given to the manufacturing plants to process the materials to prepare the final product. 3. Outsourcing. To do this, 20 suppliers for component selection, 20 suppliers for material selection, as well as 20 suppliers for material processes are selected and evaluated for DEA.

### 5-1- Criteria selection method

**Table 2.** The criteria used in the proposed model

Criteria	Criteria extraction method
Purchase cost	(Du et al., 2015; Safdari Ranjbar et al., 2018)
Quality cost	(Dedehayir et al., 2014; Safdari Ranjbar et al., 2018)
Reliability	(Du et al., 2015)
Joint venture approach distance	Field experts (Du et al., 2015)
Timely delivery	Field experts
COPS lifespan	Field experts
Infrastructure and testing	Field experts
Experience	Field experts
Current ability	Field experts
Learning	Field experts
National interest rate	Field experts
network development ability	Field experts
Financial ability	(Du et al., 2015)

As can be seen in the table above, interviews with experts, institutions, organs (e.g., Cook and Johnston (1992), Dedehayir et al. (2014), Safdari Ranjbar et al. (2018), Du and Guo (2016), Hobday (2007), Du et al. (2015) ) and university professors, active in the field of the gas turbine, satellite, and automotive industry are done. Also, academic rank order of professors in interviewees is respectively two professors and two assistant professors. Therefore, given the above, a number of technical, economic, and geographic criteria that are important for choosing the CoPS supplier are considered. To this end, seven criteria (four criteria as input and three as output) for the DEA model and some other in the mathematical model were considered according to the experts' opinion.

## **5-2- Criteria used in DEA**

We define a set of economic, technical, and geographic metrics to evaluate suppliers of CoPS. The criteria by which the increase and decrease are desirable is considered as an output or an input parameter, respectively. Suppliers, who receive required privileges in the manager's point of view, are being used as suppliers in the chain of CoPS the defined criteria are as follows:

- **Distance from customer**  
The distance between the seller and the customer affects the waste of money. This means that the waste will increase by the distance to the supplier. Therefore, this parameter has a decreasing value and is considered as an input parameter.
- **Delivery time**  
It is therefore important that if the pieces of material are not delivered to the buyer in a timely manner, the continuation of the chain is disrupted and the timely delivery of these products can lead to the successful production process and reduce other costs, so this parameter is decreasing and is considered as an Input parameter.
- **Component purchase costs**  
This parameter is considered as important in this regard that costs must be reduced and lower cost per component or material purchase, leads to decrease the costs of manufacturing the whole product and has a declining index, which means that its increasing trend can increase the costs, so this indicator is considered as an input indicator.
- **Quality costs (brand strengthen)**  
Costs must be reduced and lower cost per component or manufacturing process will lead to lower costs in the overall product, and on the other hand, higher quality will result in a better product, that's why this parameter is important. It has a decreasing index and its increase leads to higher costs, so this index is considered as an input indicator.
- **CoPS lifetime**  
The CoPS higher reliability guarantees a long lifetime to reduce the error rate and improve efficiency. Lifetime is directly related to costs, the more costs lead to higher reliability, more lifetime and lower breakdown. As a result, this parameter is considered as an output parameter.
- **Reliability**  
Higher reliability reduces the cost of maintenance of products throughout the lifecycle and increases the life of components, so this parameter is considered as an output parameter.
- **Participative approach percentage in construction**  
Participation in the production of these products reduces costs and makes the manufacturing process faster, and the increase in this indicator improves cooperation, and the occurrence of events such as sanctions does not disrupt this relationship, so this parameter is considered as an output parameter.

## **5-3- Results from solving the DEA model**

### **5-3-1- Collecting and estimating the data**

These data gathered from a research lab. Also, the proposed algorithm is coded by GAMS software for obtaining the corresponding score, i.e. the efficiency and anti-efficiency scores and the CPLEX solver is

used to solve the models. Meanwhile, all experimental tests are performed using an Intel GPU GMA 4500M, 1GHz, 2GB RAM specification laptop. To this end, the model was solved for components suppliers' selection, material suppliers' selection, and process suppliers' selection once for each, and the results are presented in table 3.

**Table 3.** The results of suppliers' ratings using the Standard and inverted DEA for component 'a'

DMU	Suppliers	$h_{bl}^*$	Rank	DMU	Suppliers	$h_{wl}^*$
DMU1	1	0.929	10	DMU1	1	1.000
DMU 2	2	1.000	1	DMU 2	2	1.304
DMU3	3	1,000	1	DMU3	3	1.176
DMU4	4	0.811	18	DMU4	4	1.015
DMU5	5	0.975	8	DMU5	5	1.145
DMU6	6	0.864	12	DMU6	6	1.111
DMU7	7	1.000	1	DMU7	7	1.185
DMU8	8	0.771	20	DMU8	8	1.000
DMU9	9	0.856	15	DMU9	9	1.089
DMU10	10	0.844	16	DMU10	10	1.005
DMU11	11	0.834	17	DMU11	11	1.000
DMU12	12	0.982	7	DMU12	12	1.165
DMU13	13	0.863	13	DMU13	13	1.000
DMU14	14	1.000	1	DMU14	14	1.076
DMU15	15	0.973	9	DMU15	15	1.000
DMU16	16	0.905	11	DMU16	16	1.000
DMU17	17	1.000	1	DMU17	17	1.284
DMU18	18	0.786	19	DMU18	18	1.000
DMU19	19	0.863	13	DMU19	19	1.000
DMU20	20	1.000	1	DMU20	20	1.222

**Table 4.** Results of suppliers' ratings using the Standard DEA for component 'a'

DMU	Suppliers	$hi_l^*$	Rank
DMU1	1	0.464	12
DMU 2	2	0.617	1
DMU3	3	0.575	5
DMU4	4	0.413	18
DMU5	5	0.551	7
DMU6	6	0.482	10
DMU7	7	0.578	4
DMU8	8	0.385	20
DMU9	9	0.469	11
DMU10	10	0.425	16
DMU11	11	0.417	17
DMU12	12	0.562	6
DMU13	13	0.431	14
DMU14	14	0.535	8
DMU15	15	0.486	9
DMU16	16	0.453	13
DMU17	17	0.611	2
DMU18	18	0.393	19
DMU19	19	0.430	15
DMU20	20	0.591	3

Tables 3 and 4 are the results of the ranking of options for choosing “a” component. Table 3 illustrates the results of suppliers' rankings based on standard and inverted envelopment analysis. We see that several options, for example (2, 3 and 7), have the same value of 1 for component selection. Table 4 is used for envelopment analysis. Candidates are ranked first, which it can be seen that with regard to the model, the distinction between options has increased compared to the standard envelopment model.

**Table 5.** Results of suppliers' ratings using the Standard DEA for material 'b'

DMU	Suppliers	$h_{bl}^*$	Rank	DMU	Suppliers	$h_{wl}^*$
DMU1	1	0.910	12	DMU1	1	1.000
DMU 2	2	1.000	1	DMU 2	2	2.165
DMU3	3	1.000	1	DMU3	3	2.067
DMU4	4	0.776	17	DMU4	4	1.171
DMU5	5	0.709	19	DMU5	5	1.147
DMU6	6	1.000	1	DMU6	6	1.559
DMU7	7	1.000	1	DMU7	7	2.818
DMU8	8	1.000	1	DMU8	8	1.895
DMU9	9	0.918	10	DMU9	9	1.360
DMU10	10	0.745	18	DMU10	10	1.075
DMU11	11	0.891	13	DMU11	11	1.000
DMU12	12	0.791	15	DMU12	12	1.000
DMU13	13	0.875	14	DMU13	13	1.129
DMU14	14	1.000	1	DMU14	14	1.092
DMU15	15	0.551	20	DMU15	15	1.000
DMU16	16	0.787	16	DMU16	16	1.000
DMU17	17	0.916	11	DMU17	17	1.000
DMU18	18	1.000	1	DMU18	18	2.032
DMU19	19	1.000	1	DMU19	19	1.557
DMU20	20	1.000	1	DMU20	20	2.145

**Table 6.** Supplier ranking using DEA for material ‘b’

DMU	Suppliers	$hi_l^*$	Rank
DMU1	1	0.455	14
DMU 2	2	0.769	2
DMU3	3	0.758	4
DMU4	4	0.461	12
DMU5	5	0.418	16
DMU6	6	0.679	8
DMU7	7	0.823	1
DMU8	8	0.736	6
DMU9	9	0.591	9
DMU10	10	0.407	17
DMU11	11	0.446	15
DMU12	12	0.395	18
DMU13	13	0.495	11
DMU14	14	0.542	10
DMU15	15	0.276	20
DMU16	16	0.394	19
DMU17	17	0.458	13
DMU18	18	0.754	5
DMU19	19	0.679	7
DMU20	20	0.767	3

Tables 5 and 6 are the results of the ranking of options for choosing material b. Table 5 is the results from suppliers ranking using standard and inverted envelopment analysis. We can see that several options get the same amount. Table 5 was used for the envelopment analysis, in which the differentiation between options was increased in this method rather than the standard envelopment analysis method.

**Table 7.** Ranking of suppliers using standard and inverted DEA method for 'k' process

DMU	Suppliers	$h_{bl}^*$	Rank	DMU	Suppliers	$h_{wl}^*$
DMU1	1	0.718	17	DMU1	1	1.000
DMU 2	2	1.000	1	DMU 2	2	2.494
DMU3	3	0.848	13	DMU3	3	2.451
DMU4	4	0.660	18	DMU4	4	1.195
DMU5	5	0.654	19	DMU5	5	1.000
DMU6	6	1.000	1	DMU6	6	1.659
DMU7	7	1.000	1	DMU7	7	3.418
DMU8	8	1.000	1	DMU8	8	2.081
DMU9	9	1.000	1	DMU9	9	1.548
DMU10	10	0.813	14	DMU10	10	1.096
DMU11	11	0.895	11	DMU11	11	1.124
DMU12	12	0.799	15	DMU12	12	1.178
DMU13	13	0.948	9	DMU13	13	1.000
DMU14	14	0.849	12	DMU14	14	1.000
DMU15	15	0.576	20	DMU15	15	1.000
DMU16	16	0.790	16	DMU16	16	1.000
DMU17	17	0.921	10	DMU17	17	1.000
DMU18	18	1.000	1	DMU18	18	1.306
DMU19	19	0.982	8	DMU19	19	2.198
DMU20	20	1.000	1	DMU20	20	2.424

**Table 8.** Ranking of suppliers using standard DEA method for ‘k’ process

DMU	Suppliers	$hi_i^*$	Rank
DMU1	1	0.359	18
DMU 2	2	0.800	2
DMU3	3	0.720	6
DMU4	4	0.413	16
DMU5	5	0.327	19
DMU6	6	0.699	7
DMU7	7	0.854	1
DMU8	8	0.760	5
DMU9	9	0.677	8
DMU10	10	0.450	14
DMU11	11	0.503	10
DMU12	12	0.475	11
DMU13	13	0.474	12
DMU14	14	0.425	15
DMU15	15	0.288	20
DMU16	16	0.395	17
DMU17	17	0.460	13
DMU18	18	0.617	9
DMU19	19	0.763	4
DMU20	20	0.794	3

Tables 7 and 8 are the results of the ranking of options for choosing the “k” process. Table 7 shows the result of suppliers’ ranking using standard and inverted envelopment analysis method. We see that several options have the same value. Table 8 is used for envelopment analysis. First, candidates are ranked. Then, we also saw that the differentiation between the options was high in this method, and the suitable supplier was selected as standard.

What is apparent from these tables are that further information on the frontiers increases the power of the division of the DEA evaluation. Based on the management perspective, the minimum satisfaction rating for the proposed index is considered. Speaking intuitively, those DMUs whose index values exceed the amount required are selected.

Based on the results obtained from the above tables, candidate suppliers are introduced to choose the supplier of CoPS. In fact, suppliers who get the required points from a managerial point of view are introduced as candidates for supplying a CoPS. The minimum score for the considered index ( $hi_i^*$ ) based on managerial results equals to 0.5. In other words, units with a value of more than 0.5 are considered as eligible suppliers. Accordingly, 12 suppliers of all 20 suppliers A, and 10 suppliers of all 20 suppliers B, and 10 suppliers of all 20 k suppliers, reach satisfaction ratings, which as unsuitable suppliers to select CoPS in this project.



Selecting appropriate suppliers for CoPS can increase the efficiency of these products. In addition, the reduction in the number of suppliers from 20 to 8 suppliers for candidate a, from 20 to 10 for supplier b and from 20 to 10 suppliers for "k", eliminates the need for a significant number of evaluations. We also saw by means of standard envelopment analysis method that several options had the same value. For example, for Table 2, the standard envelopment used to prepare component a for selecting suppliers (2 and 3), as well as for table 2 for the inverted model, the options (18 and 19) have the same value of (1), but the method used has increased the distinction between these options and eliminated some inappropriate suppliers from the model.

In order to confirm the ranking obtained by the DEA model, a nonparametric test called the Spearman rank correlation is used (Sheskin, 2003). This method evaluates the positive relationship between the rankings obtained by the standard envelopment analysis model and the model presented by the following criterion:

$$\rho = \frac{6 \sum id_i}{n(n^2-1)} \quad (10)$$

Note that  $d_i$  represents the difference between the rankings of the method proposed for the decision maker  $i$  or the two methods mentioned. In this sense, we assume the zero assumption  $H_0$  versus the alternative hypothesis  $H_1$ .

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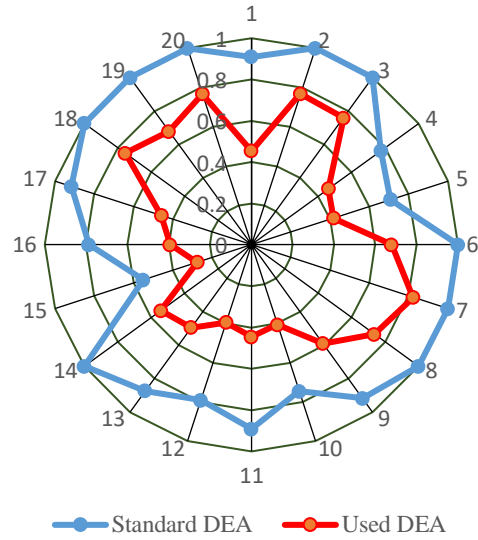
**$H_0$ :** There is no positive correlation between the ratings obtained from the envelopment analysis and the standard envelopment analysis.

**$H_1$ :** There is a positive correlation between the ratings obtained from the envelopment analysis and the standard envelopment analysis

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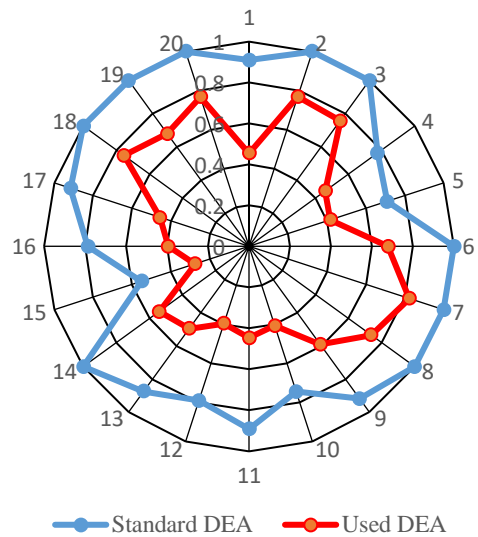
For this test, the confidence level (i.e.,  $1-\alpha$ ) is considered equal to 0.96. The test statistic and the value of the p-value were 0.938. Given the fact that the value of the p-value is less than  $\alpha$ , the assumption  $H_0$  is rejected and it can be claimed that there is an effective relationship between the standard envelopment analysis and envelopment analysis methods used. Therefore, the validity of the results is confirmed.

All in all, it can be concluded that the ranks reached by the proposed DEA model are compatible with the ones in the standard DEA model. That is, the obtained results from the proposed DEA model are verified. As such, Figure 4, Figure 5 and Figure 6 compare the scores acquired by the standard DEA model and the scores acquired by the proposed DEA model for suppliers of "a" component, "b" materials and "k" process. What is that the proposed DEA model increases the difference between DMUs and consequently rankings between the DMUs are easily carried out. More precisely, this highlights the validation of the results obtained by the proposed DEA model.



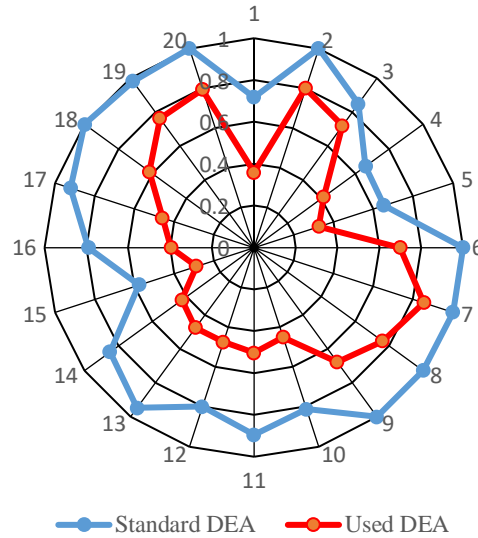
**Fig 3.** Comparison between suppliers' ratings using the standard DEA and the model used for component 'a'

As it can be seen, from the figure 3, options 2,3,7,14,17,20 got the same value of 1 in the standard envelopment analysis, but the distinction between options in the used method was increased.



**Fig 4.** Comparison between suppliers' ratings using the standard DEA and the model used for material 'b'

As it can be seen in figure 4, in the standard envelopment analysis method, a number of options have the same value, but in the used method, the distinction between options is increased.

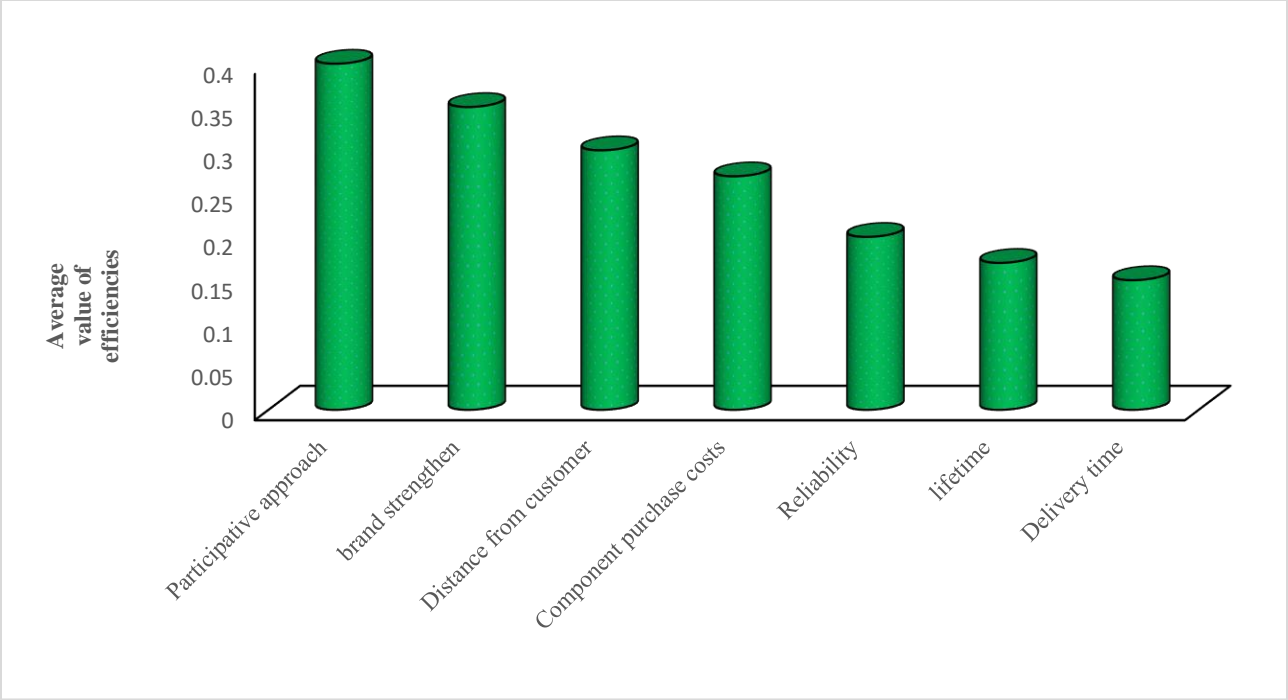


**Fig 5.** Comparison between suppliers ranking using the standard DEA and the model used for the ‘k’ process

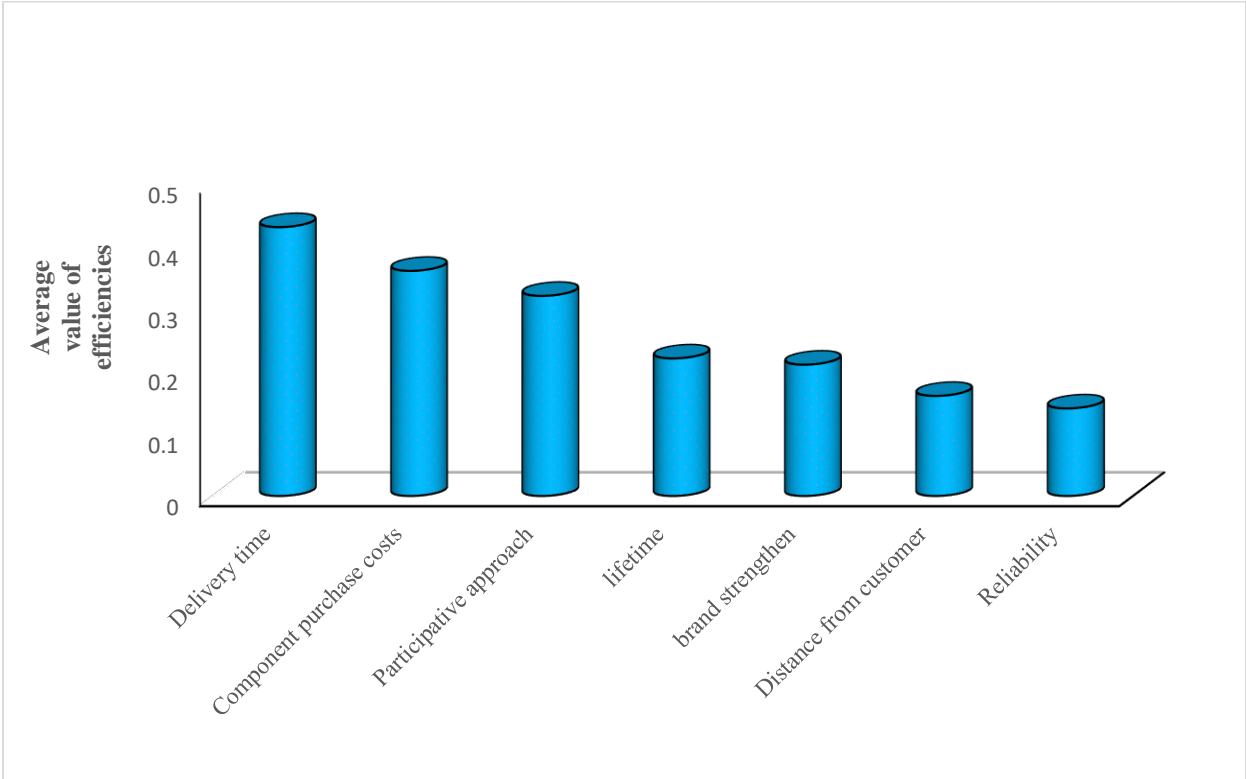
As it can be seen from figure 5, a number of options have obtained a certain amount in the Standard envelopment analysis method, which is more differentiated in the method used. Therefore, the obtained results are validated.

### 5-3-3- Sensitivity analysis

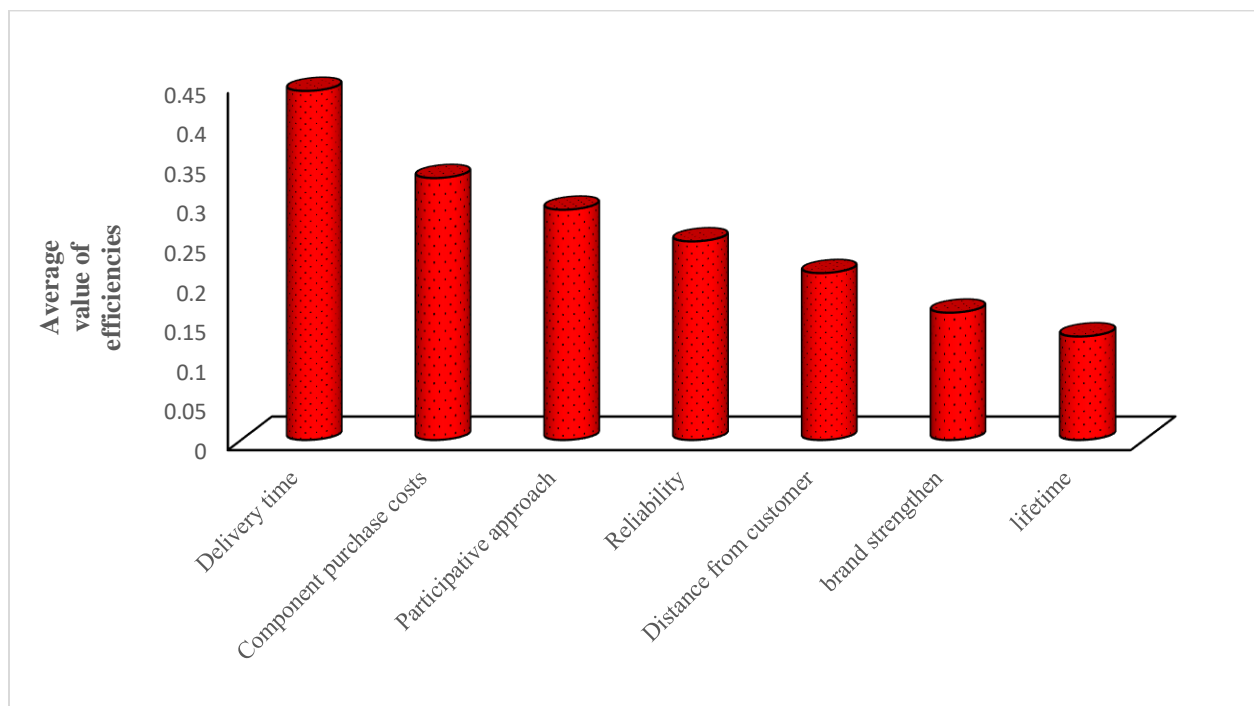
The aim of this section is to scrutiny the sensitivity of the criteria toward each other, and that how can the increase or decrease of each of these criteria affect the decision-making process. This analysis will help decision makers in this circuit to focus on which criteria. To this end, the model ran several times to identify the influence of each input and output criterion. In other words, each of them was separately changed and the model was executed and then we obtained the effect of it on the rest of the criteria. The results showed that the criterion of participatory approach percent for component suppliers is more important than other criteria and has the most influence on the CoPS suppliers’ selection. Also for material suppliers, the delivery time criterion has the highest coefficient, and eventually, the most important criterion to process suppliers is the delivery time criterion, which helps managers and manufacturers of CoPS to select the more efficient and appropriate suppliers for less. Figures 6, 7, 8 illustrate the ranking of criteria in terms of the importance of selecting a supplier of CoPS for the component, materials, and process respectively.



**Fig 6.** Ranking of criteria in terms of their significance and their changes relative to each other for component suppliers' selection



**Fig 7.** Ranking of criteria in terms of their significance and their changes relative to each other for material suppliers' selection



**Fig 8.** Ranking of criteria in terms of their significance and their changes relative to each other for process suppliers' selection

## 6-Conclusion

CoPS are one of the areas that bring the most value added to the countries' economies. This is due to the fact that there are important and strategic products in this field that will increase the competitiveness of it. Accordingly, most countries try to have a successful presence in this area. One of the main requirements to enter this area is the selection of the proper supplier of these products. The rationale behind this is that the proper supplier, in addition to reducing the costs, will increase competitive capability for manufacturers. In this regard, this paper presents a DEA model to evaluate and select the supplier in CoPS. In the proposed method, suppliers of various CoPS are evaluated based on a set of economic, technical and geographical criteria. More precisely, at this stage, inappropriate candidates are removed from the decision-making, and the candidates with the highest scores are chosen.

In order to evaluate the effectiveness and usefulness of the proposed method, a case study is conducted through which important managerial outcomes are extracted. For example, the results reveal that by using the DEA method, the difference and distinction between options are increased compared to when the standard envelopment analysis is deployed. In addition, in accordance with Spearman's nonparametric tests' results, it can be corroborated that there is an effective relationship between the used DEA model and standard DEA models.

This study is one of the first works done in the area of optimizing CoPS. Thus, it can be expanded to various promising aspects to enrich its literature. For example, using an appropriate mathematical model for selecting CoPS' suppliers is an appealing future research field with significant practical relevance. As such, implementing decision techniques such as AHP and TOPSIS to select suppliers of CoPS is another future avenue for this study. Finally, given the uncertain nature of the real environment, future researches may aim at taking into account uncertainty in the concerned criteria.

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