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DEVELOPMENT OF NETWORK-RANKING MODEL TO CREATE THE BEST PRODUCTION LINE VALUE CHAIN: A CASE STUDY IN TEXTILE INDUSTRY

Abstract. *The main reason for creating value chain is fulfilling needs and organizational resources with the least cost and highest quality. Application of most of the current techniques has merely intended to choose the best scenario. But industrial units need to build an ideal scenario as a value chain which focuses on intangible interstitial and hidden factors: good (good nature), bad (bad nature), fixed (obligatory nature) and free (not identifying their nature) and creates value. Therefore, the model presented in this article answers this issue. First of all we present a model based on the network approach of data envelopment analysis, then we assess and rank the stages based on the scenarios for the stages forming the value chain and finally, the ideal decision unit is presented. For this reason, the general efficiency is designed with two natures; 1.input-centered (concentration on the costs) and 2.output-centered (concentration on the incomes).*

Key words: *Best Value Chain; Data Envelopment Analysis (DEA), Network-Ranking Models, Ideal Decision Making Unit.*

JEL Classification: C02, C44, C61, C81, D85, L14, L67

1. Introduction

Value chain refers to network including different units which are connected to each other in different ways. To supply needs and organizational recourses optimally; is the main reason for forming value chain in which the manager is able to guarantee the survival of the organization, to obtain profit and to improve it gradually. In organizations, one of the most important issues of decision makers is to select the best value chain. Even organizations which are separated legally; are considered connected from viewpoint of material, information and financial flow and they form the value chain. But flexible supplier-manufacturer relationship is the key enabler in the supply chain management, without the flexibility at the vendor side the supply chain can't respond fast. Therefore, the relationship with the supplier should be flexible enough to meets the changing market needs (Arvind Jayant et al. 2012). In many techniques used for evaluating the value chain, organizations are evaluated separately. Then, based on this approach, the value chain is ranked. There are different techniques available, to identify and to select the best unit and value chain. In this concern, different articles explain the suitable techniques. ANP fuzzy technique can be named out of these techniques which select the best value chain trough pair comparison. Also, by means of ANP we may evaluate the decision making concerning selection of best value from different aspects. TOPSIS (Technique of Packaging Selection in multi-criterion decision making Issues) is one of the supper efficient evaluation techniques for electing the best supplier (the best value chain) (Chamodrakas & Martakos, 2011). Data envelopment analysis is one of the techniques which is used for selecting the best value chain. This technique is used to compare the units in order to compute their proportional efficiency. In comparison to other techniques, DEA has different advantages. One of them is the ability to compare the input weights and outputs in the pair comparison processes and based on their importance for each decision unit (Charnes et al., 1978). Nevertheless there are different criticisms about DEA Classic models. Generally, in DEA Classic models the units are considered as Black Boxes and the internal processes of units are not considered in computing their proportional efficiency. To compensate this weak point, different approaches are suggested which were able to cover weak points of classic model and to develop them. Liang (2005), in their thesis, have presented a two-stage level via a non-linear method based on the exploratory search to compute the efficiency of unit networks. In the present article, by means of network approach, the goal programming- data envelopment analysis model is improved and developed. Any value chain includes separated units forming a chain. In network approach, each of units is considered as one stage. Therefore in the efficiency approach, any value chain will form total efficiency of the forming units of the chain. This network and careful viewpoint will give the ability to compute the efficiency of value chain efficiency to decision makers in the best way. So, decision makers are able to compare different value chains and select the best value chain. The presented techniques in this article have a special notion among different stages. It should be mentioned that, the final decision maker will be able to make more decisions with broader view and more information by means of this technique. Since, while he is making decision concerning the factors, is evaluating the efficiency of value chain totally and based on the effects of each stage on each other. Therefore, in the presented model in this article, all important and efficient dimensions in the decision making stages are noticed. The changes in the global economic scenario have posed considerable threats to many companies, especially SMEs as they strive to stay competitive in world markets. This change in paradigms demands more flexibility in product designs. These challenges combined with increased variety and very short lead times has a great impact on the business of small to medium companies in securing a significant proportion of markets in which they operate (Ayyaz Ahmad et al. 2012).

In the present article, firstly the data envelopment analysis is described. The highest notification is paid to the communication between stages. In the case study part, the efficiency of different scenarios is computed. Then, based on the output of the presented models, a new ranking is proposed for chain values. Finally, based on the evaluation of value chain, the best value chain (best scenario) is analyzed. This value chain is formed by combination of different value chains.

2. Literature Review

The first model of DEA was proposed by Charnes et al., (CCR) (1978) which works under constant returns to scale (CRS). Then, the CCR model was adjusted by Banker et al. (BCC) (1984) by adding convexity constraint to calculate variable returns to scale (VRS). The DEA has been applied in many different settings such as agricultural economics) André et al., 2010, supply chain management (Farzipoor Saen, 2010), sports (Ramón et al., 2012), universities (Abramo et al., 2011), banking (Schaefer et al., 2012) etc.

2.1. Network data envelopment approach

Network DEA (NDEA) was developed to fill the void of Total Data Envelopment Analysis (TDEA) models to consider internal structure of DMUs. In other words, the TDEA models consider the whole production process as a black box. The TDEA takes into account only initial inputs and final outputs. The NDEA has been employed in many settings such as banking (Akther et al., 2013), sport (Lewis et al., 2009), transportation (Zhu, 2011), etc. Yu and Lin (2008) employed NDEA to measure passenger and freight technical efficiency, service effectiveness, and technical effectiveness of 20 railways. Lewis et al. (2009) used the NDEA approach to measure efficiency scores of baseball teams. Kao and Hwang (2010) provided a NDEA model in which it distributes the system inefficiency into its components. Cook et al. (2010) studied the open multistage process to estimate the overall performance of the network. In the future a novel NDEA model can be developed in the presence of flexible factors, bad outputs, and fuzzy data. Razavi et al. (2013) presented a fuzzy data envelopment analysis approach based on parametric programming.

2.2. The ideal DMU Concept

Wang et al. (2008) created an interval DEA model in which efficiency was calculated within the range of an interval. The upper bound of the interval was set to one and the lower bound was established by introducing a virtual ideal DMU, whose performance was superior to any DMU. Jahanshahloo et al. (2010) developed two ranking methods using positive ideal DMU. They ranked 20 Iranian bank branches by two ranking methods. Hatami-Marbini et al. (2010) provided a four-phase fuzzy DEA framework based upon the theory of displaced ideal. They made two hypothetical DMUs namely the ideal and nadir DMUs as reference points to rank the DMUs. Jahanshahloo et al. (2011) proposed an interval DEA model to attain an efficiency interval including evaluations from both the optimistic and the pessimistic perspectives. In their method, the lower bounds of the DMUs are increased to obtain the maximum value one. The derived points from this method were called ideal points. Then, the ideal points are employed to rank DMUs. Wang et al. (2011) developed new DEA models for cross-efficiency evaluation by introducing a virtual ideal DMU (IDMU) and a virtual anti-ideal DMU (ADMU). The purpose of their study was to measure the cross-efficiencies in a neutral and more logical way.

3. Proposed Methodology

To evaluate scenarios based on the communication between stages. In this part, firstly, a model based on data envelopment analysis approach network is analyzed, and then the ideal decision unit is presented. The model is described via the following diagram:

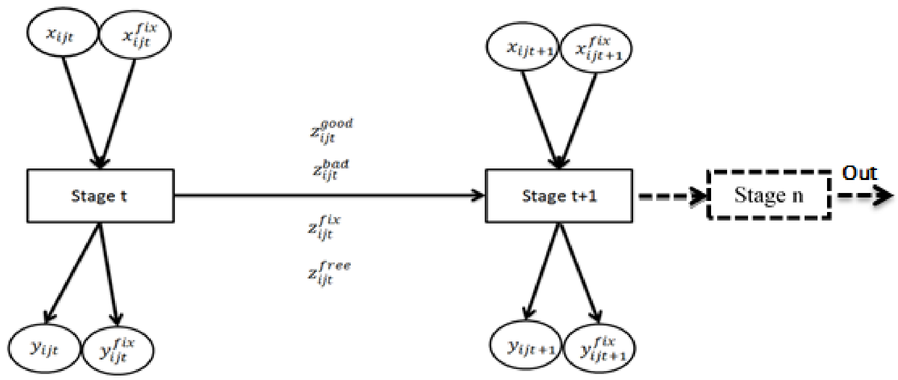

Figure (1): Network Model

- ✓ x_{ijt} = controllable input (i= 1 , 2 , 3 , ……. , m)
- ✓ x_{ijt}^{fix} = un-controllable fixed input and (i= 1 , 2 , 3 , ….. , p)
- ✓ y_{ijt} = Controllable output (i= 1 , 2 , 3 , …… , s)
- ✓ y_{ijt}^{fix} = un-controllable output (i= 1 , 2 , 3 , ….. , r)
- ✓ j= 1 , 2 , 3 , ….. , n = (or the ability to produce scenario)
- ✓ n = number of scenarios
- ✓ t= production stage and (t= 1 , 2 , ……. , T)
- ✓ i= number of input or output (i^{th} input and or i^{th} output)

Referring to the image (i), we are describing n production ability collection as n decision unit (or n scenarios) in which (n=1,…, N) and we are going to evaluate them in t stages (t=1,…,T). in each stage, (scenario) decision units, hold m controllable input (i=1,2,…,m) and p uncontrollable fixed input (i=1,…,p) and also s controllable output (i=1,…,s) and r uncontrollable fixed output (i=1,…,r). Also we describe four types of communications with Zgood, Zfix,Zfree, Zbad. In this basis, for example, signs such as (t=1,…,T), (j=1,…,n) (i=1,…,ngood) z good ijt are used to show good communications. In other words, based on the communication of intermediate factors of good, bad, free and fixed which are described as follows, the model is evaluating n stages value chain.

z_{ijt}^{good} = Are the intermediate factors with good nature, trying to maximize the factors such as the high-quality thread which is produced in t stage and is entered the weaving stage (t+1 stage) which is a good and valuable factor

z_{ijt}^{bad} = The intermediate factors with bad nature which are going to minimize them such as low-quality thread in the above sample

z_{ijt}^{fix} = Intermediate factors with fixed nature and the fixed input and outputs which are necessary for different stages. For example, this is necessary to send 1000 kg of threads as output of the weaving unit to weaving stage.

z_{ijt}^{free} = Intermediate factors with no nature which are not recognizable. Such as types of abrasions which are made on fabric and weaving stage and shall be studied whether or not the investment on them is suitable for improving them at the completion and dying stages and or they shall be sold with lower prices in the market as the grade 2 materials.

Therefore, production ability collection is described as following and a complete model including the sub-collections are registered and repeated to the number of the scenarios we have had:

$$x_{it} \geq \sum_{j=1}^{n} x_{ijt}\lambda_j^t \qquad (i = 1, \ldots, m\ ; t = 1, \ldots, T) \qquad (1)$$

λ_j^t = *Benchmark of j^{th} scenario in t^{th} stage*

$$x_{it}^{fix} = \sum_{j=1}^{n} x_{ijt}^{fix} \lambda_j^t \qquad (i = 1, \dots, p\,; t = 1, \dots, T) \qquad (2)$$

$$y_{it} \le \sum_{j=1}^{n} y_{ijt} \lambda_j^t \qquad (i = 1, \dots, s\,; t = 1, \dots, T) \qquad (3)$$

$$y_{it}^{fix} = \sum_{j=1}^{n} y_{ijt}^{fix} \lambda_j^t \qquad (i = 1, \dots, r\,; t = 1, \dots, T) \qquad (4)$$

$$z_{it}^{good} \le \sum_{j=1}^{n} z_{ijt}^{good} \lambda_j^t \qquad (i = 1, \dots, n\ good\,; t = 1, \dots, T) \qquad (5)$$

$$z_{it}^{bad} \ge \sum_{j=1}^{n} z_{ijt}^{bad} \lambda_j^t \qquad (i = 1, \dots, n\ bad\,; t = 1, \dots, T) \qquad (6)$$

$$z_{it}^{free} : free\ (i = 1, \dots, n\ free : t = 1, \dots, T) \qquad (7)$$

$$z_{it}^{fix} = \sum_{j=1}^{n} z_{ijt}^{fix} \lambda_j^t \qquad (i = 1, \dots, n\ fix\,; t = 1, \dots, T) \qquad (8)$$

$$\lambda_j^t \ge 0\ (j = 1, \dots, n : t = 1, \dots, T) \qquad (9)$$

Relation 9: Benchmark of j^{th} scenario related to $t^{\,th}$ stage

$$\sum_{j=1}^{n} \lambda_j^t = 1 \quad (t = 1, \dots, T) \qquad (10)$$

The final equation is the weighted average which is equal 1. This limitation shows the output which is changeable based on the scale. If the limitation is omitted, a model with an outcome in proportion to the fixed scale is obtained.

λ = shows inefficient unit benchmarks; benchmarks (scenarios) are repeated in line with the number of stages in which $\lambda^t \in (t = 1, \dots, T)$

R^n = intensity vector in the t^{th} stage

R^n = weight vector in the t^{th} stage (intensity vector in the t^{th} stage)

n fix = number of fixed connections

n bad = number of bad connections

n free = number of free connections

If the limitation is omitted, a model with fixed scale proportion is obtained. Note that the right sides of formulas listed above (x_{ijt}, x_{ijt}^{fix}, y_{ijt} y_{ijt}^{fix}, z_{ijt}^{good} z_{ijt}^{bad}, z_{ijt}^{fix}) are positive. The left sides of the formula (x_{it}, x_{it}^{fix}, y_{it},, y_{it}^{fix} , z_{it}^{good} , z_{it}^{bad} , z_{it}^{fix}, z_{it}^{free}*)* are connected to each other by λ_{jt}. The continuity of connection flow between the t^{th} and *t*+1 stages is guaranteed under the following conditions:

$$\sum_{j=1}^{n} x_{ijt}^{\alpha} \lambda_j^t = \sum_{j=1}^{n} z_{ijt}^{\alpha} \lambda_j^{t+1} \qquad (\forall i; t = 1, \dots, T-1) \qquad (11)$$

This formula uses good, free, bad, fix instead of α and repeats them in each time stage. The presence of these limitations is important to the network model, since they relate the t^{th} stage to the t+1 stage and there is no guarantee of creation of a national network. Considering these variants, the decision unit (scenario) is described as follows:

$$x_{iot} = \sum_{j=1}^{n} x_{ijt}\lambda_j^t + s_{it}^- \qquad (i = 1, \dots, m; t = 1, \dots, T) \qquad (12)$$

Relation 3 is as the same as relation (1) to which a slack has been added for standardization. The left side of the relation shows the number of controllable inputs for the scenarios under study in the t^{th} stage.
0 = scenarios under study

$$x_{iot}^{fix} = \sum_{j=1}^{n} x_{ijt}^{fix}\lambda_j^t \qquad (i = 1, \dots, p; t = 1, \dots, T) \qquad (13)$$

$$y_{iot} = \sum_{j=1}^{n} y_{ijt}\lambda_j^t - s_{it}^+ \qquad (i = 1, \dots, s; t = 1, \dots, T) \qquad (14)$$

$$y_{iot}^{fix} = \sum_{j=1}^{n} y_{ijt}^{fix}\lambda_j^t \qquad (i = 1, \dots, r; t = 1, \dots, T) \qquad (15)$$

$$z_{iot}^{good} = \sum_{j=1}^{n} z_{ijt}^{good}\lambda_j^t - s_{it}^{good} \qquad (i = 1, \dots, n\ good; t = 1, \dots, T) \quad (16)$$

$$z_{iot}^{bad} = \sum_{j=1}^{n} z_{ijt}^{bad}\lambda_j^t + s_{it}^{bad} \qquad (i = 1, \dots, n\ bad; t = 1, \dots, T) \qquad (17)$$

$$z_{iot}^{free} = \sum_{j=1}^{n} z_{ijt}^{free}\lambda_j^t + s_{it}^{free} \qquad (i = 1, \dots, n\ free; t = 1, \dots, T) \quad (18)$$

$$z_{it}^{fix} = \sum_{j=1}^{n} z_{ijt}^{fix}\lambda_j^t \qquad (i = 1, \dots, n\ fix; t = 1, \dots, T) \qquad (19)$$

$$\sum_{j=1}^{n} \lambda_j^t = 1 \qquad (t = 1, \dots, T) \qquad (20)$$

Relation (20) is the limitation (10) which is repeated.

$$s_{it}^{free}: free\ (\forall i, t)\ و\ s_{it}^{bad} \geq 0, s_{it}^{good} \geq 0, s_{it}^{+} \geq 0, s_{it}^{-} \geq 0, \lambda_j^t \geq 0 \quad (21)$$

Here, *s* is the variant that results in standardization of the limitations. In addition, s_{it}^{-} , s_{it}^{+} , s_{it}^{good} , s_{it}^{bad} *and* s_{it}^{free} are the side variants that show extra input, output shortage, ideal connection shortage, undesirable extra connections and connection deviation. More concisely, s_{it}^{free}: free $(\forall i, t)$ is related to relation (18), which describes the variant. If relation (16) is negative, the factor was changed to good. If positive, extra factor $= s_{it}^{bad}$ is the bad factor of relation (17); if it is (0), it is the fixed factor located in relation (19) (It is the undesirable connection in relation (17) and its selection as a negative larger or equal item that will neutralize the (+) sign.)

s_{it}^{good} = desirable connection shortage

s_{it}^{+} = output shortage (income shortage)

s_{it}^{-} = output extra (cost excessiveness)

s_{it}^{free} = connection deviation

All five items mentioned above are undesirable and should be minimized in global function:

λ_j^t = repetition of relation (9)

3.1. Goal and efficiency function

Total efficiency has two forms: efficiency with an input-based nature (stresses cost); efficiency with an output-based nature (stresses income). Models with input-based natures maintain the current output while decreasing inputs. Dynamic SBM (DSBM) is the side variant for the inputs; side variants for the bad connections are maximized. Models with output-based natures maintain the current input while maximizing outputs. In the DSBM model, the variants for output increase simultaneously. The difference in the two models is their effective on goal function.

3.2. Model with input-based nature

Total efficiency in a model with an input-based nature of θ_0^* is represented by relation (22):

$$\theta_0^* = \min \sum_{t=1}^{T} w^t \left[1 - \frac{1}{m + n\,\text{bad}} \left(\sum_{i=1}^{m} \frac{w_i^- s_{it}^-}{x_{iot}} + \sum_{i=1}^{n\,\text{bad}} \frac{s_{it}^{bad}}{z_{iot}^{bad}}\right)\right] \tag{22}$$

in which:

θ_0^*= determines efficiency of the j^{th} scenario (scenario under study)

m = number of inputs in the scenario under study

n bad = number of bad connections of stage under study

w_i^- = weight of i^{th} input

w^t = weight of t^{th} stage

$\left(\sum_{i=1}^{m}\frac{w_i^- s_{it}^-}{x_{iot}}+\sum_{i=1}^{n\ bad}\frac{s_{it}^{bad}}{z_{iot}^{bad}}\right)$ = bad cost-making factor

The goal function is based on a non-radius model with an input-based nature that contains undesirable connections in addition to extra inputs. The limitations of (1-10) and (12-21) in this goal function are w_i^- and w^t, variants that indicate the i^{th} input weight and t^{th} stage. If all weights are equal, w_i^- and w^t can be considered equal to 1. In model 22, the amount of efficiency is 0 to 1 ($0 \le \theta^* \le 1$). For example, if the efficiency of the production stages of four textile industries equal 0.5, 0.4, 0.9 and 1, the total efficiency of the network will be the sum of the weights by the efficiency of each stage:

Total network efficiency = W∗ 0.5+w∗0.4+w∗0.9+w∗1

It is clear that the only scenario that can obtain the total network efficiency of 1 is one that has an efficiency of 1 at all forming stages. The result of *n* bad in the denominator of relation (22) is that the model will possess an input-based nature. The goal is for the inside to present items inclined toward zero (s_{it}^- and s_{it}^{bad} incline to 0). Here, the efficiency of the stage will incline toward 1 and the same goal will be obtained. The only scenario to obtain an efficiency of 1 for the total network is that which obtains an efficiency of 1 in all forming stages.

Note that the simultaneous presence of s_{it}^- and s_{it}^{bad} variants in the goal function results from the common specifics of these two items, i.e., the lower the value of these two variants, the better. Undesirable connections are mediators between courses and are not inputs. Each course inside the bracket of model 22 indicates the efficiency of the t^{th} stage; if all side variants incline toward 0, the inside bracket will equal 1. Therefore, model 22 is the average symmetric efficiency of the time period for all courses and varies from 0 to 1 ($0 \le \theta^* \le 1$). The optimum amount (*) is the efficiency of the t^{th} stage with an output-based nature as follows:

$$\theta_{ot}^* = 1 - \frac{1}{m+n\ bad}\left(\sum_{i=1}^{m}\frac{w_i^- s_{it}^-}{x_{iot}}+\sum_{i=1}^{n\ bad}\frac{s_{it}^{bad}}{z_{iot}^{bad}}\right) \quad , \quad (t = 1, \ldots, T) \qquad (23)$$

Relation (23) is the amount of the inside bracket of relation (22) and identifies the efficiency of the t^{th} stage of the j^{th} scenario.

A model is presented based on the importance of each scenario to achieve a suitable weight based on its importance. The weights are selected for the managers, but to eliminate the effect of the human factor of the results, model (24) uses the input-based approach to select weights. Note that the W_p weights show the proportional importance of each stage in comparison to all stages. The method of determining W_p is to calculate the total mass of the resources allocated to the p^{th}

stage of all stages. This shows the proportional importance of that stage, i.e., the t^{th} stage input/total inputs that enter the stages of the scenario.

In other stages, different connections are available beside inputs for each stage; this means that the inputs of the stage may include bad, fixed or free connections. Relation (24) is used to compute the weights for each stage of the W_p model. If formula $\sum_{j=1}^{n} x_{ioo}^{\alpha} \lambda_j^t + \sum_{j=1}^{n} z_{ioo}^{\alpha} \lambda_j^{t+1}$ is a fraction, it will represent the symmetric total unit inputs (scenarios) in the stage under study. The weights of other stages for each decision unit (scenario) are denoted as W_p in the input-based approach:

$$W_p = \frac{\sum_{j=1}^{n} x_{ioo}^{\alpha} \lambda_j^t + \sum_{j=1}^{n} z_{ioo}^{\alpha} \lambda_j^{t+1}}{\sum_{j=1}^{n} x_{ijt}^{\alpha} \lambda_j^t + \sum_{j=1}^{n} z_{ijt}^{\alpha} \lambda_j^{t+1}} \tag{24}$$

The first stage of the W_1 formula for computing the weights in special cases is:

$$W1 = \frac{\sum_{j=1}^{n} x_{ioo}^{\alpha} \lambda_j^t}{\sum_{j=1}^{n} x_{ijt}^{\alpha} \lambda_j^t + \sum_{j=1}^{n} z_{ijt}^{\alpha} \lambda_j^{t+1}} \tag{25}$$

Note that the difference between stage (1) and the other stages is that no intermediate factor enters the first stage. In other stages, at least one of the following factors is available:

$$\sum_{j=1}^{n} x_{ijt}^{\alpha} \lambda_j^t + \sum_{j=1}^{n} z_{ijt}^{\alpha} \lambda_j^{t+1} \qquad (\forall i; t = 1, \dots, T-1) \tag{26}$$

Formula (26) is the denominator of fraction (25), which includes all inputs studied in the different scenarios. But the numerator of fraction (25) will include only the inputs of stage 1 which are in proportion. In this case, α denotes the bad, fixed or free relations. Based on the nature of connection of inputs, α may denote controllable and uncontrollable inputs. If the expression $\sum_{j=1}^{n} x_{ioo}^{\alpha} \lambda_j^t$ is a fraction, it will show the total input weights used for the decision unit (scenario) in the related stage. Note that no connection will enter the model in the first course and the model will only have controllable and uncontrollable inputs. In the first course, α denotes the total symmetric input for the uncontrollable and controllable inputs.

The total efficiency of each scenario is computed based on total symmetric efficiency in different stages using the exploited weights. In this sample, total efficiency denotes the efficiency for the input-based nature in the t^{th} stage. Total efficiency θ_0^* denotes the total symmetric efficiency of θ_{ot}^* courses as mentioned in formula (27):

$$\theta_0^* = \sum_{t=1}^{T} W_p \theta_{ot}^* \tag{27}$$

in which:

$\theta_0^* =$ total efficiency

W_p = weight at the p^{th} stage

θ_{ot}^* =efficiency of the t^{th} stage of the **j**th scenario

Right side of relation (27) = relation (24) × relation (23)

If the optimal answers for model 22 are applied as $\theta_{ot}^* = 1$, the related (decision unit) scenario for the input-based nature in the t^{th} stage is an efficient scenario. It means that side variants of s_{it}^- and s_{it}^{bad} in the t^{th} stage in model 23 all equal zero, i.e., their undesirable connections equal zero. If $\theta_0^* = 1$, the input-base (decision unit) scenario is efficient and s_{iot}^{*-} and s_{iot}^{*bad} variants in all stages equal zero.

3.3. Model with output-based nature

Total efficiency for the output-based nature is as follows:

$$\frac{1}{\tau_0^*} = \max \sum_{t=1}^{T} w^t \left[1 - \frac{1}{s+n\ good}\left(\sum_{i=1}^{m} \frac{w_i^+ s_{it}^+}{y_{iot}} + \sum_{i=1}^{n\ good} \frac{s_{it}^{good}}{z_{iot}^{good}}\right)\right] \qquad (28)$$

The portion inside the bracket shows the income shortage (bad). Based on the limitations of relations (1-10) and (12-21), w_i^+ is the i^{th} output, as in condition (29):

$$\sum_{i=1}^{s} w_i^+ = s \qquad (29)$$

In the fraction denominator, the goal function of (28) is to deal with output shortage and desirable connections as the variants. Please note that, in this goal function, there is a variant for shortage of good connections and one for shortage of output. Since these are naturally similar to output and have common specifics; as they increase, they become ideal. This is shown in relation (5):

$$z_{it}^{good} \leq \sum_{j=1}^{n} z_{ijt}^{good} \lambda_j^t \qquad (i = 1, \dots, n\ good\ ; t = 1, \dots, T) \qquad (5)$$

The good connections are not output, but they play the role of connectors of two stages. Any expression inside the *brackets* corresponds to the goal function of (28) with the efficiency of the t^{th} stage. If the side variants inside the expression equal zero, the amount inside the bracket will equal 1. The goal function is steady in relation to the measuring unit and is ≥ 1. Therefore, the average symmetry efficiency of the t^{th} stage with an output-based nature for τ_{ot}^* are shown as (30):

$$\tau_{ot}^* = \frac{1}{1 - \frac{1}{s+n\ good}\left(\sum_{i=1}^{m} \frac{w_i^+ s_{it}^{+*}}{y_{iot}} + \sum_{i=1}^{n\ good} \frac{s_{it}^{good*}}{z_{iot}^{good}}\right)} \quad , (t = 1, \dots, T) \qquad (30)$$

A model is next presented based on the importance of each stage to obtain the suitable weights for each stage:

$$W_p = \frac{\sum_{j=1}^{n} y_{ioo}^{\alpha}\lambda_j^t + \sum_{j=1}^{n} z_{ioo}^{\alpha}\lambda_j^{t+1}}{\sum_{j=1}^{n} y_{ijt}^{\alpha}\lambda_j^t + \sum_{j=1}^{n} z_{ijt}^{\alpha}\lambda_j^{t+1}} \tag{31}$$

in which:

Nominator: output of related t^{th} stage of related scenario

Denominator: All outputs which are quitting all related scenario stages The W_p weights denote the proportional importance of each stage in comparison with all stages. Based on the output-centered model, the proportional criteria of the stage is to select the W_p amount of decision units (scenario) in the output of each stage to total outputs in the studied levels. In the W_p model, the nominator of (31) of $\sum_{j=1}^{n} y_{iot}^{\alpha}\lambda_j^t + \sum_{j=1}^{n} z_{iot}^{\alpha}\lambda_j^{t+1}$ denotes the total output weight of each stage and includes outputs, good connections, free and fixed connections. The denominator of the fraction of $\sum_{j=1}^{n} y_{ijt}^{\alpha}\lambda_j^t + \sum_{j=1}^{n} z_{ijt}^{\alpha}\lambda_j^{t+1}$ shows total output weight output and includes the total output and the good, fixed and free connections that exit the stages. The amount of controllable and non-controllable output used instead of α is based on the nature of the connection. The total efficiency of each scenario (decision unit) is based on the symmetric average efficiency at different stages from the weights. To compute τ_{ot}^* in formula (30), it is repeated *T* times. The total efficiency for the output-based nature for the τ_{ot}^* stage is the symmetric total efficiency defined as:

$$\tau_o^* = \sum_{t=1}^{T} W_p\, \tau_{ot}^* \tag{32}$$

Relation (32) = relation (31) × relation (30)

Since there is no intermediate factor sent for the next stage, to compute the weight of the final stage weight (*T* stage), the only outputs used are those that can quit the scenario, i.e., formula $\sum_{j=1}^{n} z_{ioo}^{\alpha}\lambda_j^{t+1}$ is omitted from the nominator of formula (31).

4. Case Study

In this part, textile industry value chain is evaluated. This value chain is formed of 4 stages which are located at direction of each other. The forming stages are shown in the diagram (2) and also 10 scenarios (decision unit) which are offered by Scientific-experimental experts are evaluated. pth stage connections are entered the p+1 stage as the input. Also, in the input stage there are (intermediate factors) which are entered the connection separately and are described as inputs. Now, in table 1, the amount of each factor for 10 scenarios is observed in value chain.

Table 1. Number of connections, inputs and outputs for 4 stages of value chain

Scenarios			A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}
Spinning	Inputs	w/p percent	45/55	45/55	45/55	45/55	45/55	20/80	20/80	20/80	20/80	20/80
		Worker's cost	1.6	1.6	1.8	2	2	0.7	0.7	0.9	1.1	1.1
		Energy cost	0.9	0.9	1.1	1.2	1.2	0.4	0.4	0.5	0.6	0.6
		Maintenance cost	0.5	0.5	0.6	0.6	0.6	0.2	0.2	0.3	0.3	0.3
	Good Connection	Thread quality	14	16	18	20	20	10	12	14	16	18
		Quality	35	35	40	55	64	30	30	35	50	54
	Bad Connection	Thread swing	11.3	11.3	12.6	14.1	14.1	4.5	4.5	6	7.4	7.4
	Fixed connection	Point	40	40	48	60	60	40	40	48	60	60
	Free Connection	Price	16.2	16.2	18	20.2	20.2	6.4	6.4	8.6	10.6	10.6
Weaving	Inputs	Worker's Cost	1.1	0.9	1.1	1.2	1.1	0.4	0.3	0.4	0.5	0.4
		Energy Cost	0.8	0.5	0.7	0.8	0.6	0.2	0.2	0.2	0.3	0.2
		Maintenance Cost	0.3	0.2	0.3	0.4	0.3	0.1	0.1	0.1	0.2	0.1
	Good Connection	One meter weight	400	330	330	330	280	400	330	330	330	280
		Quality	60	65	70	75	80	50	55	60	65	70
	Free Connection	One meter price	10.5	8.6	11.2	12.2	10.5	3.8	3.1	4	4.4	3.8
Completion and Dying	Inputs	Worker's Cost	0.7	0.6	0.8	0.8	0.7	0.2	0.2	0.3	0.3	0.2
		Raw material cost	1.5	1.2	1.6	1.7	1.5	0.5	0.4	0.6	0.6	0.5
		Energy cost	1	0.9	1.1	1.2	1	0.4	0.3	0.4	0.4	0.4

		Color and side material Cost	0.4	0.3	0.5	0.5	0.4	0.2	0.1	0.2	0.2	0.2
	Good Connection	Quality	60	65	70	75	80	50	55	60	65	70
	Free Connection	Price of each meter	15	12.3	16	17.4	14.9	5.4	4.4	5.6	6.2	5.4
Garment	Inputs	tweedy fabric cost	45	36.9	48	52.2	44.7	16.2	13.2	16.8	18.6	16.2
		Worker's Cost	63	51.6	67.2	72.9	62.6	22.7	18.4	23.5	26	22.7
		Control Cost	9	7.4	9.6	10.4	8.9	3.2	2.6	3.4	3.7	3.2
		Energy Cost	4.2	3.4	4.5	4.8	4.2	1.5	1.2	1.5	1.7	1.5
	Outputs	Quality	60	65	70	75	80	50	55	60	65	70
		Suit price	210	172.2	224	243	208.6	75.6	61.5	78.3	86.7	75.6

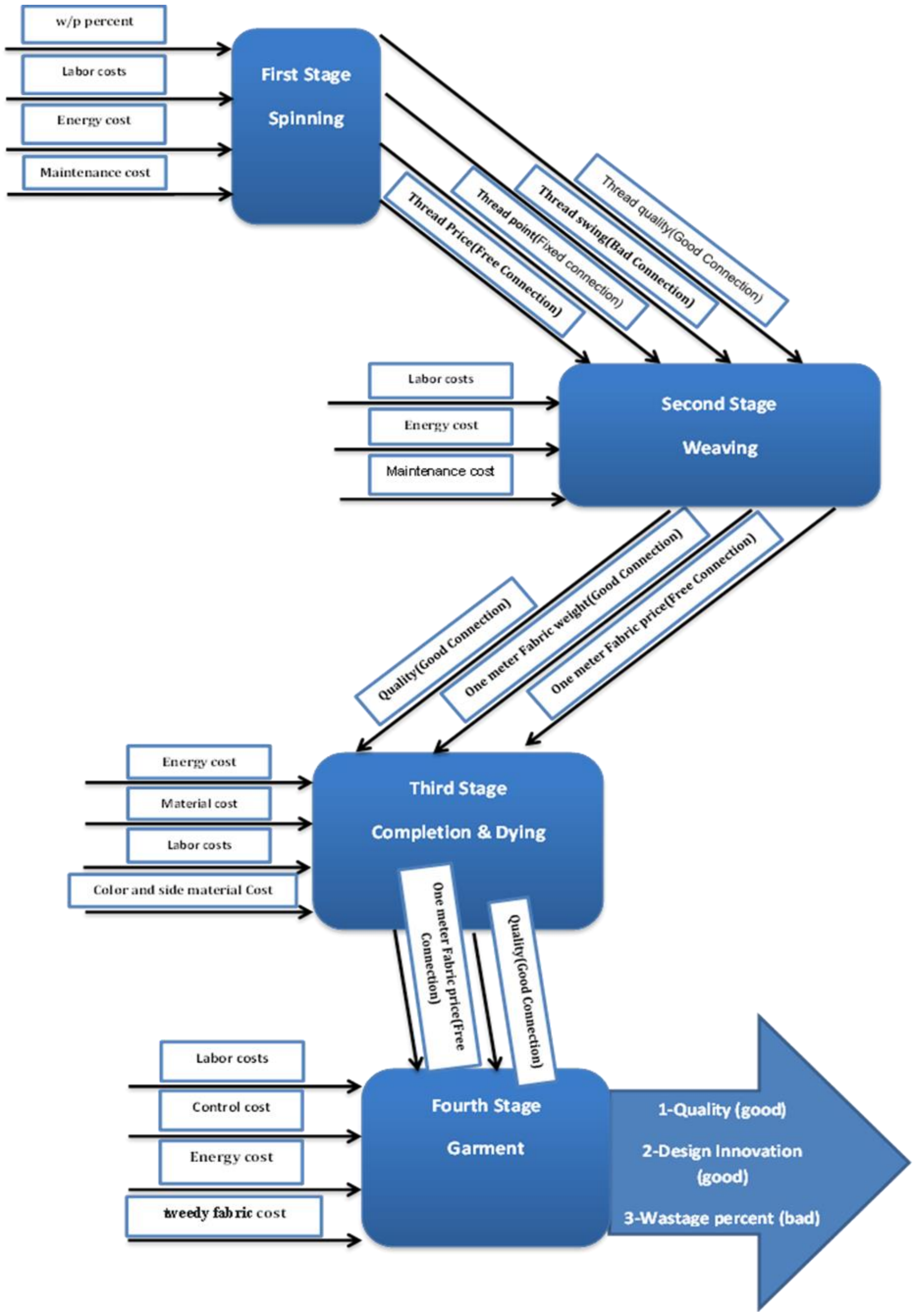

Figure 2: The connection between different production stages

Table 2: Results of solving 10-stage scenario of four-stage garment production stages based on model

DMU	θ_1	θ_2	θ_3	θ_4	W_1	W_2	W_3	W_4	Overall score
DMU_1	0.928	0.91	0.856	0.854	0.268	0.238	0.246	0.248	0.8876
DMU_2	0.943	0.925	0.878	0.866	0.234	0.217	0.307	0.242	0.9005
DMU_3	0.937	0.923	0.836	0.875	0.285	0.315	0.153	0.247	0.9018
DMU_4	0.963	0.89	0.812	0.871	0.245	0.354	0.273	0.128	0.8841
DMU_5	1	0.821	0.897	0.882	0.224	0.239	0.266	0.271	0.8978
DMU_6	0.897	1	0.941	0.899	0.242	0.347	0.201	0.21	0.942
DMU_7	0.923	0.991	1	0.992	0.227	0.229	0.313	0.231	0.9786
DMU_8	0.921	0.983	0.961	0.957	0.21	0.193	0.321	0.276	0.9557
DMU_9	0.963	0.977	0.972	0.918	0.317	0.22	0.263	0.2	0.9554
DMU_{10}	0.975	0.796	1	1	0.264	0.339	0.208	0.189	0.9242

5. Finding (Ideal Decision Making Unit)

The tenth scenario is introduced as an optimal scenario in the stages of completion and dying (third stage) and garment (forth stage); nevertheless, in the symmetric average, the proportional efficiency rank slower than for the 7th scenario. In this ranking, scenario (7) obtains the rank of the best scenario followed by scenarios (8), (9) and (6). The evaluation is presented in Table 2 and indicates that the ideal scenario for the value chain is based on a combination of the 10 scenarios that it is shown in the table (3).If the two ideal chain value scenarios are solved with the previous10 scenarios using model by Lingo software, they will prove to be strictly efficient.

Table 3-Results of ideal scenarios for 4 stages of value change in textile industries

Stages	First stage	Second stage	Third stage	Forth stage
Ideal scenario of value chain (1)	Scenario 5	Scenario 6	Scenario 7	Scenario 10
Ideal scenario of value chain (2)	Scenario 5	Scenario 6	Scenario 10	Scenario 10

If these two ideal chain value scenarios are solved with 10 previous scenarios by means of model (1); these two ideal scenarios are highly efficient. In the present article, in addition to ranking of the available scenarios and since no scenario was able to be introduced as efficient value chain; based on establishment of an ideal decision making unit with network approach, the ideal scenario is established. The established scenario that is not available between scenarios is introduced as an artificial scenario; but, from the other side, this scenario is formed of different stages which are among the main scenario and therefore it is real.

4. Conclusions

This model is formulated as network-ranking through linear programming in way that net profit management strategy is assessed and evaluated through efficiency according to the connections between the stages and interstitial factors.

In designing this model, n factory types (in the case study: 4 types; spinning, weaving, finishing & dyeing and clothing) that usually operate separately, are considered both in discrete and combination and integrated.

This model has focused most of its attention on the connections between the stages constituting the intended value chain. In this mode 4 connection types (good, bad, fixed and free) are introduced for the stages of value chain and the presented scenarios are assess and ranked based on this. At the end of this part an ideal scenario is introduced for the value chain that is created with a general lookout and attention to the constituting stages and connections between stages. In fact the model evaluates different scenarios based on the process-oriented management according to the connection between different stages of production (4stages in textile industries)

In n-stage production industries, formulation of competitive strategies are getting more critical for survival, profit and growth in profits and major decision-makers and planners in production units have required these industries for rational management of costs and incomes and interstitial factors and finally effective efficiency , that this model is a tool for reaching this goal.

DEA was used to determine the relative efficiency of the DMUs. One applications of a DEA is to set benchmarks for inefficient DMUs. These benchmarks help inefficient DMUs find improvement strategies. This paper introduces a new approach for ranking efficient DMUs using a network structure. The constructed ideal DMU offers real and practical solutions for improvement in efficiency.

With respect to the results of this paper following research topics are proposed for future:

Using goal programming, the goals of managers and experts can be incorporated into the constructed ideal DMU.

The same approach can be repeated to determine ideal networks in sustainable supply chain management.

REFERENCES

[1] **Abramo, G., Cicero, T., & Andrea D'Angelo, C. (2011),** ***A Field-Standardized Application of DEA to National-Scale Research Assessment of Universities***. *Journal of Informatics* 5(4), 618–628;

[2] **Akther, S., Fukuyama, H., & Weber, W. L. (2013),** ***Estimating Two-Stage Network Slacks-Based Inefficiency: An Application to Bangladesh Banking.*** *Omega*, 41(1), 88–96;

[3] **André, F. J., Herrero, I., & Riesgo, L. (2010),** ***A Modified DEA Model to Estimate the Importance of Objectives with an Application to Agricultural Economics.*** *Omega*, 38(5): 371–382;

[4] **Arvind Jayant , S . Wadhwa , P . Gupta , S. & Garg, K. (2012),** ***Simulation Modeling of Outbound Logistics of Supply Chain***. *International Journal of Industrial Engineering*, 19(2), 90–100;

[5] **Ayyaz Ahmad, A., Mazha, M. I. & Howard, I. (2012),** ***A Framework for the Adoption of Rapid Prototyping for Smes: From Strategic to Operational***. *International Journal of Industrial Engineering*, 19(3), 161–170;

[6] **Banker, R., Charnes, A. & Cooper, W.W.** (**1984),** ***Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis.*** *Management Science*, 30(9), 1078–1092;

[7] **Barth, W. & Staat, M. (2008),** ***Restructuring the Branch Network of a Bank: The Dynamic Perspective***. *International Journal of Business and Systems Research*, 2(3), 272–284;

[9] **Chamodrakas, I. & Martakos, D. (2011),** ***A Utility-Based Fuzzy TOPSIS Method for Energy Efficient Network Selection in Heterogeneous Wireless Networks.*** *Applied Soft Computing*, 11(4), 3734–3743;

[10] **Charnes, A., Cooper, W.W. & Rhodes, E. (1978),** ***Measuring the Efficiency of Decision Making Units.*** *European Journal of Operational Research*, 23(1), 429–444;

[11] **Cook, D., Zhu, J., Bi, G. & Yang, F. (2010),** ***Network DEA: Additive Efficiency Decomposition.*** *European Journal of Operational Research*, 207(2), 1122–1129;

[12] **Farzipoor Saen, R. (2010),** ***Restricting Weights in Supplier Selection Decisions in the Presence of Dual-Role Factors.*** *Applied Mathematical Modelling*, 34(10), 2820–2830;

[13] **Hatami-Marbini, A., Saati, S. & Tavana, M (2010),** ***An Ideal-Seeking Fuzzy Data Envelopment Analysis Framework.*** *Applied Soft Computing*, 10(4), 1062–1070;

[14] **Jahanshahloo, G. R., Hosseinzadeh Lotfi, F., Khanmohammadi, M., Kazemimanesh, M. & Rezaie, V. (2010),** ***Ranking of Units by Positive Ideal DMU with Common Weights.*** *Expert Systems with Applications*, 37(12), 7483–7488;

[15] **Jahanshahloo, G. R., Hosseinzadeh Lotfi, F., Rezaie, V. & Khanmohammadi, M. (2011),** ***Ranking Dmus by Ideal Points with Interval Data in DEA.*** *Applied Mathematical Modelling*, 35(1), 218–229;
[16] **Kao, C. & Hwang, S.N. (2010),** ***Efficiency Measurement for Network Systems: IT Impact on Firm Performance.*** *Decision Support Systems*, 48(1), 437–446;
[17] **Liang, F. (2005),** ***Bayesian Neural Networks for Nonlinear Time Series Forecasting.*** *Statistics and Computing*, 15(1), 13–29;
[18] **Lewis, H. F., Lock, K. A. & Sexton, T. R. (2009),** ***Organizational Capability, Efficiency and Effectiveness in Major League Baseball: 1901–2002.*** *European Journal of Operational Research*, 197(2), 731–740;
[19] **Ramón, N., Ruiz, J. L. & Sirvent, L. (2012),** ***Common Sets of Weights as Summaries of DEA Profiles of Weights: With an Application to the Ranking of Professional Tennis Players.*** *Expert Systems with Applications*, 39(5), 4882–4889;
[20] **Schaefer, A., Burger, A. & Moormann, J. (2012),** ***Sophisticating Business Performance Management for Banks: Using Data Envelopment Analysis on Business Process Level.*** *International Journal of Business Performance Management*, 13(3/4), 227–243;
[21] **Wang, Y-M, Chin, K-S, & Luo, Y. (2011),** ***Cross-Efficiency Evaluation Based on Ideal and Anti-Ideal Decision Making Units.*** *Expert Systems with Applications*, 38(8), 10312–10319;
[22] **Wang, N-S, Yi, R-H. & Wang, W. (2008),** ***Evaluating the Performances of Decision-Making Units Based on Interval Efficiencies.*** *Journal of Computational and Applied Mathematics*, 216(2), 328–343;
[23] **Yu, M. M. (2010),** ***Assessment of Airport Performance Using the SBM–NDEA Model.*** *Omega*, 38(6), 440–452;
[24] **Zhu, J. (2011),** ***Airlines Performance Via Two-Stage Network DEA Approach.*** *Journal of CENTRUM Cathedra: The Business and Economics Research Journal*, 4(2), 260–269;
[25] **Razavi, S. H.; Amoozad, H.; Zavadskas, E. K.; Hashemi, S. S. (2013),** ***A Fuzzy Data Envelopment Analysis Approach Based on Parametric Programming.*** *International Journal of Computers Communications & Control*, 8(4), 594–607.