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Development of Multi-Stage Supplier Performance Evaluation using DEA and Econometrics

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Abstract

Many supply chain research schools believe "competition is no longer between companies; it is between supply chains". In order to create agile supply chains, dynamic (time-dependent) performance evaluation system for assessing trading partners has become necessary. This has led to multi-stage development of mathematical models using inter-disciplinary approaches. In this study, Gear suppliers of a tiller and tractor manufacturing company have been considered. The proposed performance evaluation framework has been synthesized under five stages of model development using data envelopment analysis (DEA) and econometrics. Further, the multi-stage evaluation incorporates non-controllable and categorical formulation, which makes the model realistic from buyers' perspective. Nonetheless, in the last stage of model development, an attempt to convert static to dynamic DEA model has been made considering inter-temporal effects between input-outputs. This effect has been captured as the lagged effect using Vector Auto Regression (VAR) model. Lastly, the proposed framework has been validated using system efficiency DEA model and Wilcoxon-Mann-Whitney rank sum test. Results have revealed that static evaluation overestimates dynamic evaluation by 4 to 5%. In addition, proposed dynamic evaluation system yielded better DEA results in terms of efficient Decision Making Units (DMUs) in numbers, average efficiency (~23%) and standard deviation (~38%). Therefore, multi-stage supplier performance evaluation methodology considering lagged effect has been considered as the original contribution in this study. In summary, combining DEA and econometric models, offer wide scope for the buyer to carry out performance evaluation under Multi Criteria Decision Making (MCDM) environment.

Keywords: Vector auto regression, dynamic model, multi criteria decision making, impulse response.

Introduction

This study demonstrates multi-stage supplier performance evaluation using DEA and econometrics considering dynamic (time dependent) factors. Thus, the proposed methodology differs from Malmquist index or frontier shift concept which neglects lagged effect between two consecutive periods. The methodology has evolved over five stages of development with reference to basic DEA output oriented model. 20 Gear suppliers (Gi) of a leading tiller and tractor manufacturing company has been considered for pilot study where 'i' indicates the supplier code. Moreover, trading partners have been analyzed with respect to variable Returns to Scale (v-RTS) characterization which helps buyer for tactical (mid-term) planning. Further, RTS deals with proportional relationship with inputs and outputs considered for performance evaluation. In the proposed model development, evaluation of suppliers from stage 1 to 4 has been carried out under static (time independent) consideration and stage 5 deals with dynamic consideration. In addition, stage 4 and 5 systems (static and dynamic) have been compared using system efficiency model in DEA by projecting all DMUs to the efficient frontier. Further the model has been statistically validated using Wilcoxon-Mann -Whitney rank sum test. It has been observed that efficiency scores under static consideration overestimates dynamic consideration leading to bias in performance evaluation. In principle, synthesizing supplier performance evaluation model under multi-stages for buying organization considering lagged effect using inter-disciplinary approaches has been considered as the original contribution.

Related work: Review on Supply Chain Management (SCM) research highlights the shift in trend from exploratory research to mathematical modeling and testing[1] in addition to green SCM concept[2]. Further, development of inter-disciplinary models for performance evaluation has been warranted[1] along with data mining tools[3]. Moreover, the need for MCDM for evaluating supply chain members using DEA approach has been emphasized[4,5]. Nevertheless, DEA approach identifies most efficient trading partners along with the improvement directions for inefficient group. By emulating the referred efficient trading partner known as *'best peer'*, the inefficient trading partner can reach the frontier[6]. In addition, Seydel supported both simple multi-attribute and DEA technique provide similar results based on aggregation procedure[7]. However, lack of inter-disciplinary mathematical models for performance evaluation has been signified[5] with modifications to existing DEA model. For instance, Kumar and Narahari proposed a *'Make-Shift'* methodology by estimating net dependence risk from suppliers' perspective for further DEA evaluation[8]. Similarly, need for incorporating uncontrollable factors in supplier selection process has been highlighted[9]. In setting direction towards model building, Weber *et al.* combined multi-objective programming and DEA to optimize the number of suppliers for a buying situation[10]. More recently, integrated approach for supplier relationship management portraying domain-specific to holistic perspective of performance evaluation process has been advocated[11]. Contrarily, DEA approach based on Total Cost of Ownership (TCO) for supplier selection has been demonstrated[12]. But management accounting lacks engineering meaning and has to be complemented by combining with other approaches. Accordingly, interdisciplinary methodology by integrating TCO and Analytical Hierarchy Process using DEA for supplier selection has been portrayed[13]. Consequently, dynamic vendor evaluation model using trait based approach in 0 to 10 linear scale has been verified[14]. Nonetheless, this type of scaling technique has been considered subjective in nature. Therefore, supplier selection model under uncertainty from economic perspective has been signified[15,16]. Since supply chain operates in a dynamic (time dependent) environment, performance evaluation from operations perspective considering lagged effected using inter-disciplinary approaches has been considered rationale for this study.

Research Methodology

Initially, analysis of suppliers under static consideration has been carried out using DEA methodology by selecting appropriate inputs and outputs from buyer perspective. Basically, DEA envelopes the observation data to identify frontier and evaluates each DMU relative to the efficient frontier. In DEA, DMU under study has been represented as 'DMU_o'. In continuation, the selected outputs have been converted to dynamic outputs using econometric model known as VAR. Further, DEA methodology has been applied to the dynamic output, which includes lagged effect. The five stage supplier evaluation methodology has been portrayed.

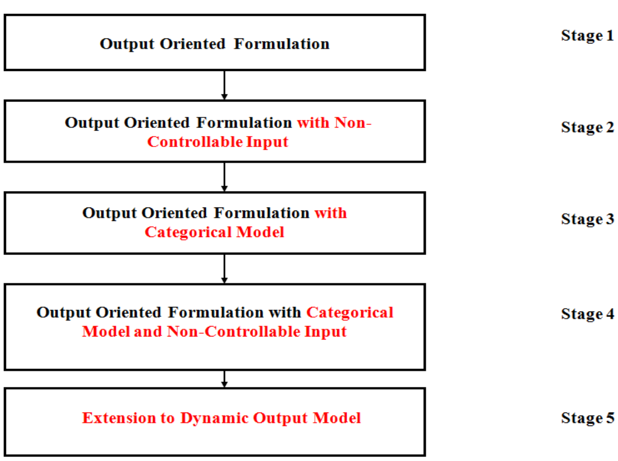

Figure-1
Stages of model development

In the study, appropriate inputs and outputs have been selected from buyer organisation perspective. The principle adapted for selecting input-output combination has been as follows: i. Lower the better for input value, ii. Higher the better for output value.

In order to overcome degrees of freedom issues in DEA, the following condition has been satisfied.
Number of DMUs 'n' $\geq$ max {(m*s), (3*(m+s))} (1)

Where 'm' refers to number of inputs and 's' refers to number of outputs. Input and output parameters considered have been shown below.

Table-1
Input and output parameters

Input Parameters	Output Parameters
1. Quantity Scheduled in Numbers	1. Quantity Accepted in Numbers
2. Main Customers to the Supplier in Numbers	2. Revenue Spend in USD
----	3. Number of Components Supplying

Stages of model development for supplier analysis: Stage 1: In the study, '**X**' and '**Y**' represent input and output vectors respectively considered calculating efficiency 'η'. The basic output oriented DEA model can be represented for a particular DMU_o as follows:

Max. η
Subject to constraints
$x_o - \mathbf{X}\mu \geq 0$
$\eta y_o - \mathbf{Y}\mu \leq 0$
$e\mu = 1$
$\mu \geq 0$ (2)

where 'e' has been considered as row vector with all elements unity and 'μ' represents column vector of inputs and outputs. Hence, for each DMU, the above Linear Programming Problem (LPP) has to be solved using simplex method to calculate 'η'. Moreover, LPP solutions and projections for all Gear supplier DMUs has been obtained using DEA-Solver (V3) package. These results rank the suppliers and guide inefficient suppliers to become efficient through projection details using frontier analysis.

Stage 2: From the basic model in stage 1, an attempt to improve the model through non-controllable input has been executed. In the mathematical formulation, superscript 'C' signifies controllable input or output and superscript 'N' represents non-controllable input or output. For instance, non-controllable input deals with the situation wherein input cannot be controlled by decision maker. The mathematical formulation for the proposed model with non controllable input '*main customers to the supplier*' has been reported as follows:

Max. η
Subject to constraints
$$x_o^C - X^C\mu \geq 0$$
$$\eta y_o^C - Y^C\mu \leq 0$$
$$x_o^N = X^N\mu \quad (3)$$
$$e\mu = 1$$
$$\mu \geq 0$$

Stage 3: In order to evaluate suppliers under MCDM environment, hierarchical category model has been proposed after categorizing the suppliers using *Kraljic's matrix*. Figure-2 shows the categorization of Gear suppliers obtained from '*Make-Shift*' methodology using supply chain analytics[8]. Parameters like scheduled, received and accepted quantity, quality and delivery performance, main customers, business spend has been considered for categorization along with criticality of sourcing for the study.

Gear supplier DMUs in category-1 faces severe competition compared to category-2, similarly category-2 faces significant competition compared to category-3. Lastly category-3 faces relatively higher competition compared to category-4 in a hierarchical manner. Therefore Gear supplier DMUs in category-1 has been evaluated within their group; suppliers in category-2 have been evaluated with reference to category-1 and category-2 and so forth for other categories. Even though categorical model looks similar to basic DEA model, LPP has been formulated by not considering upper category basic variables when evaluating lower category DMUs.

Stage 4: In this stage of model development, merger of non-controllable input and categorical model has been conducted to capture both effects simultaneously. Although the mathematical formulation looks similar to stage 2 LPP, upper category DMUs have not been considered as basic variables for lower category evaluation. Contrarily, the input parameter, '*main customers to the supplier*' has not been considered. As supply chain branches into different tiers, evaluating suppliers across these tiers through categorization makes this model necessary. Thus, decision maker can deal with both controllable and non-controllable input – output parameters. Hence this model appears to be realistic and practical.

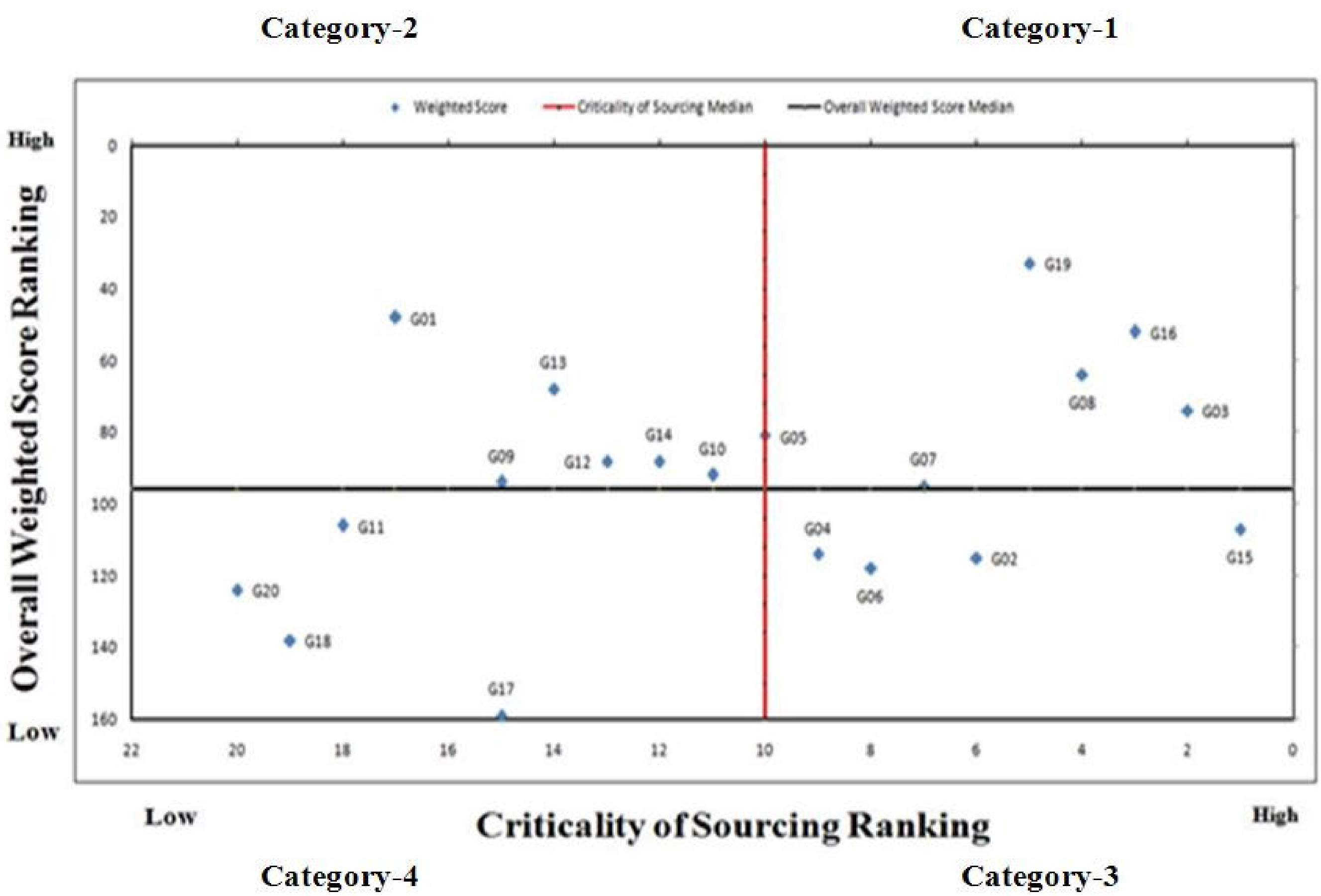

Figure-2
Categorization of gear suppliers'

Stage 5: Moving forward, analysis of suppliers under dynamic consideration has been carried out in this stage. Time dependency (dynamic) factors in evaluation of suppliers have been considered important. However, not much research has been reported in the literature for this aspect. In order to accurately measure the performance, dynamic inter-relationships have to be incorporated for efficiency measurement. Therefore, dynamic inter-relationship in DEA entails estimating inter-temporal (lag) effects between input and outputs. Contrarily, existing DEA models rely on static approach for performance evaluation. Thus, applying static DEA in dynamic supply chain environment leads to rank reversal problem and changes in efficiency score. In addition, input parameters contribute to current and future outputs. Figure-3 portrays *'k-period'* lag model for an arbitrary time period 'p_a'. Consequently, the solid lines infer concurrent effects and dotted line implies the lagged effect. In principle, this type of performance evaluation has been considered different from frontier shift methodology as put forward in Malmquist index. Additionally, Malmquist index neglects lagged effect between two consecutive periods and focuses on optimization at single period.

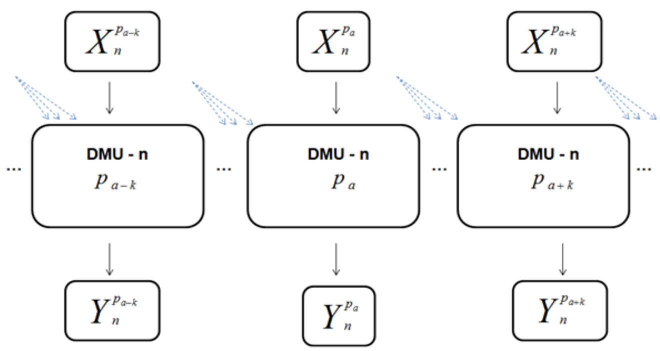

Figure-3
k-period lag productive effect model[16]

In order to incorporate dynamic effect, time series econometric model has been applied which captures the lagged effect between inputs and outputs. Therefore, time series data of possible input and outputs in supply chain environment have been considered for the study. On the other hand, stationary data have been retained without any change for DEA analysis.

Test for non-stationary dataset: Validation tests of the output time series datasets have been carried out to check for non-stationary condition using following econometric tests: i. Graphical analysis, ii. Unit root or Augmented Dickey-Fuller test

Following null (**H_o**) and alternative (**H_1**) hypotheses have been formulated to check for non-stationary condition:
H_o: Output variable has the unit root (non-stationary condition),
H_1: Output variable does not have unit root (stationary condition)

In summary '**H_o**' has been accepted under all conditions which portray non-stationarity of dataset. Hence, considering dynamic inter-relationships for performance evaluation adds value in arriving at efficiency scores. Therefore, estimating lagged effects between input and outputs using dynamic econometric models have been warranted.

Dynamic econometric model: VAR model has been considered to find the impact of dynamic effect from the given panel input and outputs. In VAR, all the variables have been considered as endogenous (dependent) variables in order to give equal weight for input and outputs. The term 'Auto Regression' signifies appearance of lagged values of the dependent variable as independent variable in the ordinary least square regression model. Similarly 'Vector' resembles dealing with two or more variables. Hence, VAR model has been considered in order to overcome the subjectivity in identifying endogenous and exogenous (independent) variables as criticized by Christopher Sims[17]. The VAR model for 'k' period lags with input '**X**' and output '**Y**' to yield dynamic output for time period '$\mathbf{\tilde{Y}_{ip}}$' has been shown below.

$$\tilde{Y}_{ip} = a_i + \sum_{j=1}^{k} b_j Y_{ip-j} + \sum_{j=1}^{k} \beta_j X_{ip-j} + u_{ip} \quad (4)$$

where,
i = corresponding input and output, a_i = intercept, b_j = output slope coefficients and β_j = input slope coefficients, k = lag length period, p = time period, u_{ip} = impulse responses

The VAR model has been represented as shown in figure-4. For the study, only outputs have been considered due to output oriented approach. In addition, two month lag period has been considered based on '*Schwarz*' criterion. Therefore, in order to obtain the dynamic output '$\tilde{Y}_{ip}$', the k-lag effect of input and outputs have been considered along with impulse responses 'u_{ip}'. Impulse response identifies the responsiveness of the dependent variable in VAR model when a shock has been added to the error term. This enables the behavior of VAR model whenever shock has been added. In order to calculate the impulse responses, *Cholesky adjusted model* has been used for ordering the variables in Eviews econometrics package.

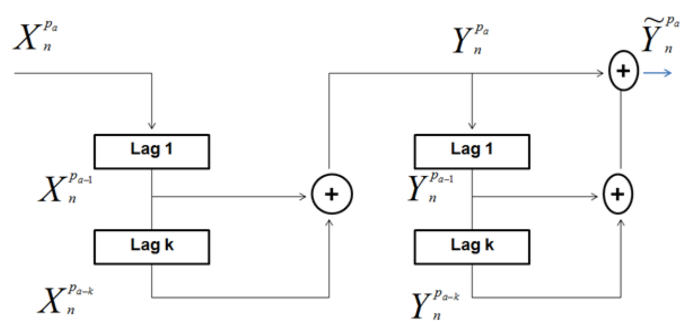

Figure-4
VAR model framework

For example, two dynamic outputs of VAR estimation model for 'G03' supplier with two lags and period five has been represented respectively. The following slope coefficients have been obtained:

(Output-1, $\tilde{Y}_1$) $\tilde{Y}_{15} = 13367.34 - 1.4031Y_{14} + 0.6843Y_{13} + 0.5494X_{14} - 0.6710X_{13} + u_{15}$ (4a)

(Output-2, $\tilde{Y}_2$) $\tilde{Y}_{25} = 111961.70 - 1.3Y_{14} + 0.6913Y_{13} + 4.0106X_{14} - 5.7773X_{13} + u_{25}$ (4b)

Similarly, nine month aggregate values of 'G03' supplier have been depicted as shown below.

Table-2
Static and dynamic output comparison

Sr. No.	Parameter	Static-Y_i	Dynamic-$\tilde{Y}_i$
1	**Output – 1** (Quantity Accepted in Numbers)	64,299	81,610
2	**Output – 2** (Revenue Spend in USD)	5,42,601	6,86,688

Results and Discussion

In summary, the contribution of static and dynamic output datasets for all the Gear suppliers have been reported. The above mentioned framework enumerates conversion of static to dynamic dataset by incorporating lagged effect between input and outputs. Using the dynamic output of stage 5 in DEA models, performance evaluation has been carried out.

Thus for all Gear supplier DMUs, the above mentioned mathematical formulation with respect to different stages has been carried out. In summary, stage-wise average efficiency scores have been shown in figure-6.

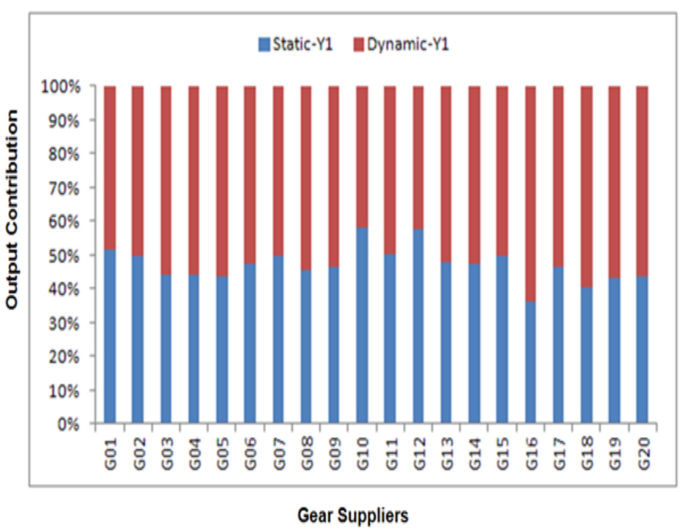

Figure-5a
Output-1 static and dynamic contribution

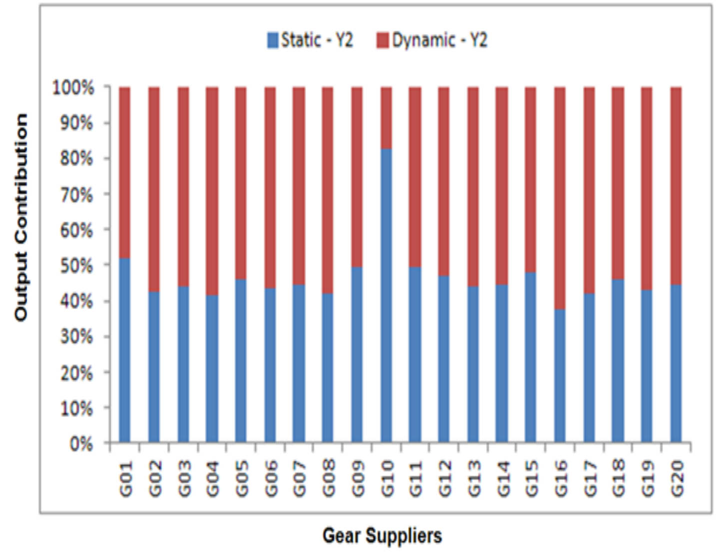

Figure-5b
Output-2 static and dynamic contribution

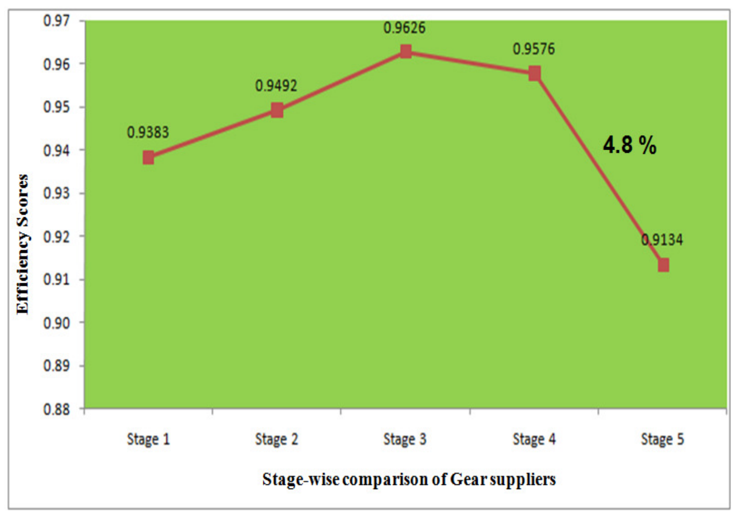

Figure-6
Stage-wise average efficiency scores

It has been observed that, the average efficiency improves along the model development till stage 4 and decreases drastically in stage 5. This phenomenon of occurrence reflects extension from static to dynamic model of performance evaluation. Hence, static models over-estimate the efficiency scores by neglecting the lagged effect leading to bias in evaluation technique. Therefore, dynamic model has been proposed to measure performance accurately considering lagged effects. In view of stage 5 results, the overall output projections in percentage have been shown. Nevertheless, projection details for individual DMU shows the possible target area with reference to different outputs (*best peer*) to reach the efficient frontier.

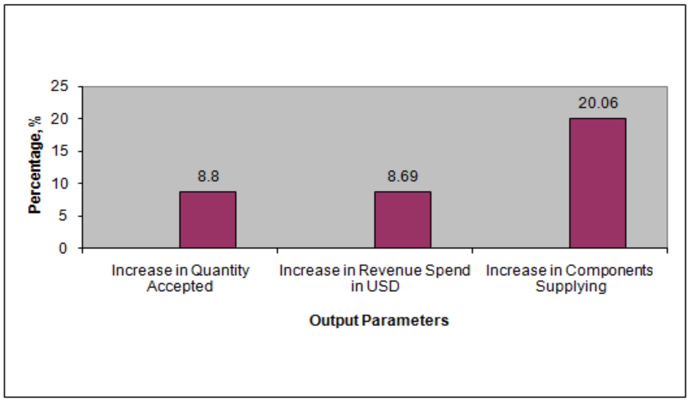

Figure-7
Output summary projections

Similarly, category wise average efficiency scores have been depicted to incorporate hierarchical consideration for DEA evaluation. It has been observed that, average efficiency score decreases with higher category Gear supplier.

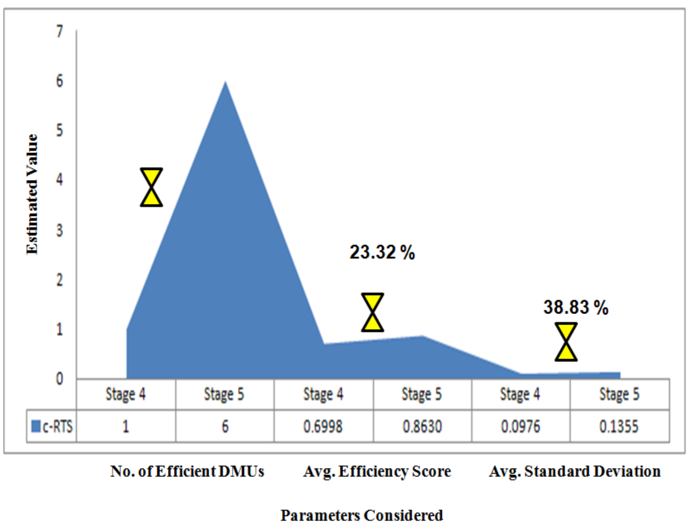

Figure-8
System efficiency comparison between stage 4 and 5

Validation studies: In order to validate extension from static to dynamic model as the better performance evaluation approach, system efficiency DEA model has been applied for stage 4 and 5 under constant RTS (c-RTS) to compare efficient frontiers. For this purpose, all the DMUs have been projected to the frontier and combined to formulate virtual dataset. After combining, system efficiency DEA model has been applied. Further comparison between stage 4 and 5 system has been reported. It has been observed that stage 5 system results have been better than stage 4 in terms of number of efficient DMUs (five times), average efficiency (~23 %) and standard deviation (~38 %). Therefore stage 5 has been considered as the final improvement over stage 4 of the proposed performance evaluation model. Since the distribution of DEA efficiency scores has been considered statistically independent, it becomes rationale to deal with non-parametric statistics. Hence, Wilcoxon-Mann-Whitney rank sum test has been implemented to find out significant frontier shift between stage 4 and 5 systems. However, '$\mathbf{H_o}$' has been accepted at the 5% significance level revealing that improvements in stage 5 follows the same distribution of stage 4 and hence statistically significant.

Conclusion

It has been observed that static evaluation overestimates dynamic evaluation by about 4 to 5%. This study highlights contemporary performance evaluation methods which ignores dynamic effect leading to bias in evaluation process and rank reversals.

Proposed dynamic evaluation system yields better DEA results compared to static system as follows: Five times increase in number of efficient DMUs, ~ 23% increase in average efficiency scores, ~ 38% increase in terms of standard deviation.

In the dynamic model, increase in standard deviation between DMUs infers that lagged effect plays an important role in performance evaluation. In addition, the proposed model demonstrates better way of discriminating among suppliers in the form of multi-stage evaluation.

Combining DEA-Econometric models offer wide scope for the buyer to carry out performance evaluation under MCDM environment.

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