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Evaluating Team Efficiency in Manufacturing Industry Using Data Envelopment Analysis

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Abstract

The increasing global demand for sophisticated designs and specifications has forced manufacturing industries to depend on the efficiency and delivery performance of their employees who work in factories. Analyzing the efficiency of factory teams is essential to enable continuous improvement efforts and necessary interventions. This research employs Data Envelopment Analysis (DEA) to analyze team efficiency of manufacturing workers. The research utilizes a case study from the garments industry where various teams were evaluated based on input factors such as target productivity, standard minutes value, incentive, number of workers in the team, and overtime and output factors such as production rate and work in process. Both constant return to scale (CRS) and variable returns to scale (VRS) DEA models were utilized. Overall efficiency, technical efficiency, and scale efficiency were determined, and the results indicated that there is a discrepancy between overall efficiency and technical efficiency that indicates the teams are not working in an optimal scale working environment. This study provides valuable insights into team efficiency assessment and the impact of various variables on team performance not only in manufacturing industries but also in other areas including healthcare, education, and service industries. Therefore, necessary interventions can be taken to facilitate improvements and achieve better efficiency.

Keywords
Team efficiency, data envelopment analysis (DEA), sensitivity analysis, garments industry, work measurement.

1. Introduction

The garment industry plays a vital role in the industrialization of developing countries like Bangladesh, India, and Vietnam, driven by cheap labor and abundant natural resources. As a labor-intensive sector, workers manually handle tasks, including machine operation and garment processing. To meet rising global demand, efficiency, and delivery performance are crucial, making it essential to assess team productivity in factories and identify efficient and less efficient teams for continuous improvement. However, inefficiency occurs in two ways: using excessive inputs for a given output and employing a suboptimal input mix relative to cost and productivity [1]. An efficient Decision-Making Unit (DMU) operates at its highest productivity level while maintaining an optimal input-output balance [2, 3].

Data Envelopment Analysis (DEA) is a non-parametric linear programming method used to measure the relative efficiency of DMUs based on multiple inputs and outputs [4]. DEA models include Constant Returns to Scale (CRS), where efficiency remains independent of production scale, and Variable Returns to Scale (VRS), which accounts for efficiency variations due to scale changes [5]. DMUs with an efficiency score of 1 form the efficiency frontier, serving as benchmarks for evaluating less efficient units.

2. Problem Description

The efficiency of homogeneous DMUs, such as organizational units (e.g., garment manufacturing, healthcare microsystems) or teams within an organization, can be calculated by dividing output by input. However, in real-world scenarios, where DMUs have multiple inputs and outputs, efficiency is determined by the weighted sum of outputs divided by the weighted sum of inputs. Since applying a consistent set of weights across all DMUs is crucial, defining appropriate weights is essential. This study utilizes DEA to (1) evaluate team efficiency in teams performing manufacturing tasks, (2) identify the most efficient teams, and (3) assess the sensitivity of efficiency to the variations in the input variables.

3. Related Research

Researchers have extensively used DEA across industries, including financial institutions and manufacturing, to compare efficiency across units and teams. A method was developed to optimize variable selection for DEA, successfully applying it in the computer industry [6]. Efficiency dynamics were analyzed in a manufacturing firm, and no changes were found despite variable modifications [7]. CRS and VRS DEA models were used to assess the efficiency of Pakistan's top 14 manufacturing companies, using two input and two output variables [8].

In garment manufacturing, DEA is widely applied for performance assessment. DEA and Malmquist Productivity Index (MPI) were combined to evaluate 10 Vietnamese textile enterprises, using total assets, cost of goods sold, and liabilities as inputs, and total revenue and gross profit as outputs [9]. Efficiency in Indian ready-made garment firms was analyzed by decomposing into pure and scale efficiency, identifying plant size impact [10]. DEA was used to measure export efficiency in Turkish textile firms, considering workers and production quantities as inputs and export values in dollars as output [11]. Input-oriented VRS DEA was applied to Turkish textile industries [12]. Five Bangladeshi garment factories were assessed, identifying material and labor costs as key efficiency drivers using CRS input-oriented DEA and Pearson correlation analysis [13]. However, the studies focused on team efficiency in garment factories are limited. This study aims to investigate team efficiency in a garment factory's sewing department.

4. Methodology

This study applied DEA to assess the efficiency of 12 teams in a garment manufacturing sewing floor. A crucial step in DEA is selecting appropriate input and output variables. Initially, 15 variables were considered, but four were excluded as they served as team identifiers—including work date, day of the week, month quarter, and department. The team number was retained as it represented the 12 DMUs. The remaining 10 variables were categorized into 8 inputs and 2 outputs. However, three input variables—idle time, number of idle men, and number of style changes—contained predominantly zero values, which is unsuitable for DEA. As a result, these columns were removed from the dataset before analysis. The proposed research methodology is shown in Figure 1. Table 1 describes the input variables and output variables considered in this study.

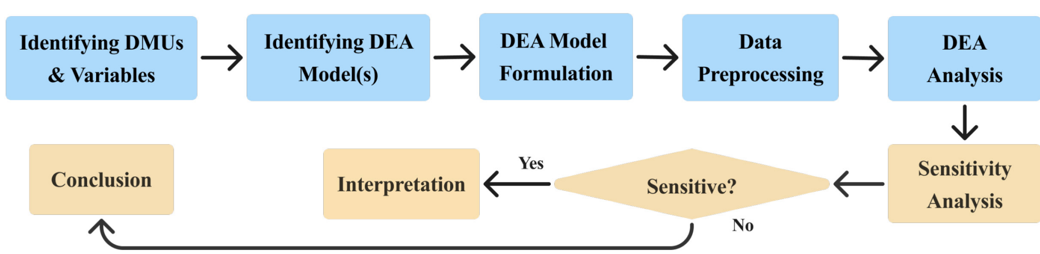

Figure 1: Proposed research methodology.

Table 1: Description of the input and output variables.

Variable Type	Variable	Description
Input variables	TP	Targeted Productivity in percentage set for each team for each day
	SMV	Standard Minute Value, it is the allocated time for a task.
	OT	Represents the amount of Overtime by each team in minutes.
	NW	Number of Workers in each team.
	IN	Amount of financial incentive.
Output variables	WIP	Work in progress i.e., the number of unfinished items for products.
	AP	Actual Productivity in percentage delivered by the workers.

4.1 DEA Model Formulation

The dynamic nature of production floors, like garment manufacturing sewing floors, often prevents teams from operating at an optimal scale. To account for this, both CRS and VRS models were used in this study. The CRS model is suitable for evaluating efficiency assuming all DMUs operate at an optimal scale and the VRS model is useful when DMUs are operating at different scales. The VRS model, known for its flexibility in dynamic environments, measures technical efficiency [10], while the CRS model identifies overall efficiency. To analyze discrepancies between these efficiencies, scale efficiency was calculated by dividing overall efficiency by technical efficiency.

This study adopted input-oriented models which allow for sensitivity analysis to assess the impact of input changes on team efficiency. The DEA model, originally a fractional linear program, was transformed into a linear programming problem using the Charnes-Cooper transformation [14], which linearizes the objective function to maximize the relative magnitude of inputs. However, while the model provides weights for multiple inputs and outputs, it lacks a clear benchmark for the efficiency frontier. An equivalent dual formulation with intensity weights, developed using duality theory [4], was applied in this study to develop CRS and VRS input-oriented dual formulation models. The CRS input-oriented model assumes that any proportional reduction in inputs results in a proportional decrease in outputs. The objective here is to minimize the total inputs required to produce a given level of output while maintaining the same output level. The VRS input-oriented model allows for proportional reductions in inputs that do not necessarily lead to proportional reductions in outputs. The objective here is to minimize the inputs required to achieve the same level of output while accounting for variable returns to scale.

$K = 12\,; \qquad K = ['1','2','3', \ldots\ldots, '12']$
$i = 5\,; \qquad i = ['targeted\_productivity', \ 'smv', \ 'overtime', no\_g\_workers', 'incentive']$
$j = 2\,; \qquad j = ['wip', 'actual\_productivity']$

CRS input–oriented model:

$$Min\ E^{CRS} = \theta \qquad (1)$$

s. t.,

$$\sum_{k=1}^{12} \lambda_k X_{ki} \leq \theta X_i, \qquad \forall i = 1, 2, 3, 4, 5$$

$$\sum_{k=1}^{12} \lambda_k Y_{kj} \geq Y_j, \qquad \forall j = 2$$

$$\lambda_k \geq 0, \quad \forall k = 1, 2, 3, \ldots\ldots, 12$$

Where X_{ki} is the input vector for DMU k and input i, Y_{kj} is the output vector for DMU k and output j. λ_k is the weights used to form a convex combination of other DMUs. θ is the efficiency score for the evaluated DMU.

VRS input-oriented model:

$$Min\ E^{VRS} = \theta \qquad (2)$$

s. t.,

$$\sum_{k=1}^{12} \lambda_k X_{ki} \leq \theta X_i, \qquad \forall i = 1, 2, 3, 4, 5$$

$$\sum_{k=1}^{12} \lambda_k Y_{kj} \geq Y_j, \qquad \forall j = 2$$

$$\sum_{k=1}^{12} \lambda_k = 1$$

$$\lambda_k \geq 0, \qquad \forall k = 1, 2, 3, \ldots\ldots, 12$$

The notations for the VRS model are similar to those used in the CRS model. The constraint $\sum_{k=1}^{12} \lambda_k = 1$ ensures that the DMUs are evaluated under variable returns to scale, which allows for flexibility in scaling the inputs.

4.2 Data Collection and Preprocessing

The dataset for this study was obtained from the UC Irvine Machine Learning Repository [15]. Columns with predominantly zero or null values were removed, and rows with occasional zero values were dropped. Outliers were detected using the Interquartile Range (IQR) method, with 51 outliers for targeted productivity, 15 for SMV, 22 for WIP, 34 for overtime, 124 for number of workers, and 58 for actual productivity (Figure 2). Instead of removing outliers, the capping method was applied to retain values within the interquartile range. The refined dataset was then normalized using the max-min method, scaling all variables between 0 and 1 for consistency. Python programming was used for data preprocessing, and Table 2 presents the minimum, maximum, and mean values of the variables.

Table 2: Descriptive statistics of the variables.

	TP	SMV	SIP	OT	IN	NW	AP
Min value	0.07	10.05	7.00	0.00	0.00	26.00	0.23
Max value	0.80	54.56	23122.00	25920.00	138.00	89.00	1.10
Mean	0.72	23.25	1190.47	6508.21	44.48	52.45	0.72

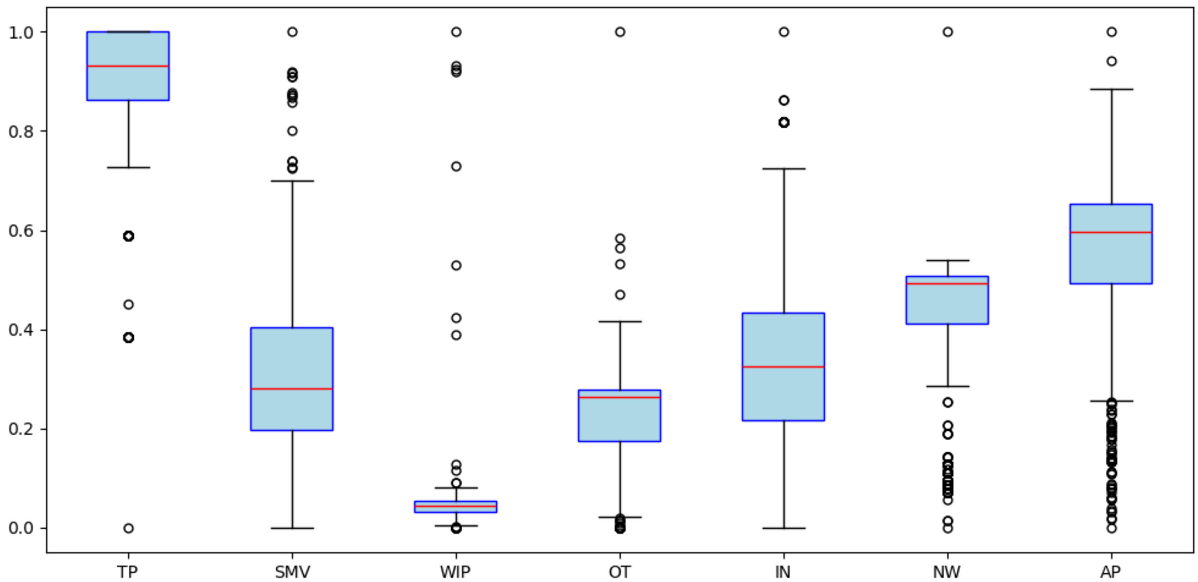

Figure 2: Boxplots of the variables showing outliers.

4.3 Data Analysis

Correlation analysis was performed using between variables to assess interdependency. DEA was conducted using CRS and VRS models to calculate three types of efficiencies. Set and parameter building were performed before running the models, and visualizations were generated to depict the results. A sensitivity analysis was conducted to evaluate the impact of input changes on teams' technical efficiency, as it measures how effectively inputs were utilized, making it key for input-sensitivity assessment. The necessary reduction in input variables for maximizing efficiency was determined. All analyses were performed using the Python programming language.

5. Results

5.1 Correlation Between Variables

The correlation analysis provides valuable insights into how variables influence each other, as presented in Table 3. The results indicate that actual productivity has a strong positive correlation with targeted productivity (0.698) and incentive (0.804), suggesting that increases in these inputs significantly impact productivity. In contrast, another output variable, WIP, does not exhibit any significant correlation with other variables. A moderate correlation (0.578) was observed between SMV and the number of workers, implying a potential relationship between operational time and workforce size. Additionally, targeted productivity and incentives showed a slight correlation (0.486).

Table 3: Correlation analysis between variables.

Variable	TP	SMV	WIP	OT	IN	NW	AP
TP	1.00						
SMV	-0.03	1.000					
WIP	0.062	-0.04	1.00				
OT	-0.08*	0.26**	0.02	1.00			
IN	0.49**	-0.09*	0.17**	0.11**	1.00		
NW	-0.08*	0.58**	0.03	0.35**	0.08*	1.00	
AP	0.70*	-0.16*	0.13**	-0.02	0.80**	0.00	1.00

* Significant at $p < 0.05$, ** Significant at $p < 0.01$

5.2 Team Efficiency

Table 4 presents the overall and technical efficiency scores for each team. Figure 3 shows that teams 1, 10, and 12 are the most efficient, achieving an overall efficiency of 1.0. While the remaining teams demonstrate good relative efficiency, they do not match the performance of these top teams. Additionally, teams 5, 6, and 11 are among the most efficient in technical efficiency, though their overall efficiency is affected by scale inefficiencies. This indicates that the teams are operating in a non-optimal scale environment.

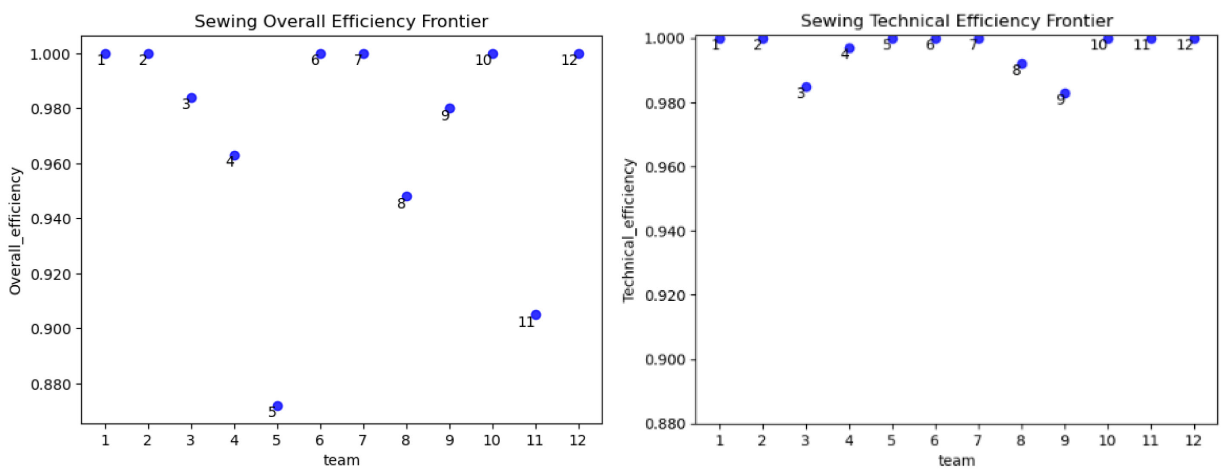

Figure 3: Overall efficiency (left) and technical efficiency (right) of the teams.

5.3 Sensitivity Analysis

The sensitivity analysis results, summarized in Table 4, indicate that partially efficient teams can achieve full efficiency by reducing specific input parameters. For example, team 3 would reach full efficiency if targeted productivity decreased by 1.38%, SMV by 0.005 minutes, overtime by 0.004 minutes, incentives by 0.006 BDT, and the workforce was reduced by 0.007 workers. Similarly, teams 2, 7, and 10 can achieve full efficiency by adjusting their respective input values. However, the team efficiency was significantly sensitive only to targeted productivity and it was for team 3.

Table 4: Technical efficiency sensitivity to input variables.

Team	TP	SMV	OT	IN	NW
3	0.0138	0.0052	0.0041	0.0061	0.0074
4	0.0027	0.0011	0.0009	0.0010	0.0015
8	0.0069	0.0030	0.0021	0.0018	0.0039
9	0.0157	0.0157	0.0047	0.0058	0.0081

6. Conclusions

In manufacturing industries, teams work in a complex environment with many variables and circumstances. Therefore, team efficiency is impacted both technically and by the scale of the working environment. This study evaluates team efficiency using a GitHub repository dataset on garment manufacturing and applies Data Envelopment Analysis (DEA) with five input and two output variables. The dataset includes productivity, work in process (WIP), overtime, standard minutes value (SMV), incentives, workforce size, and idle time. After data preprocessing, DEA was performed using Constant Returns-to-Scale (CRS) and Variable Returns-to-Scale (VRS) models to assess the impact of scale on efficiency. Results show some teams achieved full efficiency, while few of them demonstrated high technical efficiency but were affected by scale inefficiencies. Sensitivity analysis revealed that only targeted productivity significantly influenced team efficiency. The study highlights the role of the work environment in overall efficiency and offers insights into how input adjustments can improve performance. However, limitations include missing data. The deletion of columns with a high percentage of missing values may have impacted the evaluation. Future research should focus on comprehensive data collection for a greater number of teams with minimal missing values to enhance accuracy and incorporate all relevant efficiency factors.

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