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Sensitivity Analysis of Inefficient Decision-Making Units in Data Envelopment Analysis (DEA) with a Focus on Boilers: A Case Study

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Abstract

This paper focuses on the sensitivity analysis of inefficient Decision-Making Units (DMUs) in Data Envelopment Analysis (DEA), particularly on boilers. The main objective of this study is to identify and evaluate the efficiency of boilers across various industries and to propose a modified model for their sensitivity analysis. Boiler performance criteria are inputs and outputs, and a case study is presented within an industrial plant. The paper introduces an enhanced DEA-based model to assess the sensitivity of inefficient boilers. The proposed model determines the instability radius of boilers concerning changes in inputs and outputs. Employing managerial coefficients offers greater flexibility in adapting strategies. A case study is implemented in a power plant.

Keywords: Data envelopment analysis, Power plant boilers, Efficient and inefficient decision-making units, Counterparty credit risk, Bidirectional consistency constraint.

1 | Introduction

In the power generation industry, boilers are key components for energy production and thermal power supply. These systems utilize thermal energy to generate steam, which drives turbines and produces electricity. Given the growing importance of environmental and economic issues, improving boiler efficiency has become crucial in reducing operational costs and minimizing pollutant emissions. Therefore, accurate evaluation of these units'units' performance is essential [1]–[4].

In this context, Data Envelopment Analysis (DEA) is applied as a non-parametric method to assess the efficiency of Decision-Making Units (DMUs). DEA identifies efficient and inefficient units by analyzing input and output data to define efficiency frontiers. However, one major limitation of traditional DEA applications

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is the lack of adequate sensitivity analysis-meaning it does not sufficiently examine how changes in inputs and outputs may lead to improvements in the performance of inefficient units [5]–[7].

This paper aims to develop a modified model for analyzing inefficient boilers within the DEA framework. By introducing coefficients that allow greater flexibility in adjusting inputs and outputs, this model helps decision-makers design more targeted improvement strategies. The process involves identifying and analyzing boilers' instability radius, which can then be used to propose solutions that bring inefficient units closer to the efficiency frontier.

A case study is conducted in an industrial power plant, focusing on boilers that have been identified as inefficient due to performance fluctuations. The sensitivity analysis is based on practical variations in inputs, such as fuel and water consumption, and outputs, such as steam production and emission levels. The results of this study can serve as a guide for power plant management and other similar industries to enhance productivity and reduce environmental impacts.

Ultimately, this research emphasizes the importance of utilizing advanced techniques, such as modified DEA models, to achieve higher efficiency and optimize resource consumption in boilers and other industrial equipment. Industries will be better equipped to analyze performance data and make more effective strategic decisions with the proposed model.

2 | Theoretical Foundations

Efficiency analysis in organizations and the improvement of products and services have always been primary concerns for managers and researchers. In this regard, methods such as data mining and DEA have been introduced as effective tools for performance and efficiency evaluation. This section explores various approaches used in efficiency and sensitivity analysis within the DEA framework, especially concerning inefficient DMUs.

3 | Introduction to Data Envelopment Analysis

Charnes and colleagues [8] first introduced DEA in 1978 as a method for measuring task efficiency using linear programming. The initial DEA model enabled researchers to analyze the performance of DMUs by incorporating multiple inputs and outputs. This method compares similar units and establishes operational efficiency frontiers [8].

3.1 | Sensitivity Analysis in Data Envelopment Analysis

Sensitivity analysis within the DEA framework investigates the impact of input and output variable changes on the final efficiency assessment of DMUs. This approach was proposed by Charnes et al. [9] in 1985 and has since been developed further. Research such as Neralic [10] and studies by Zhu and Seiford [11] have deepened this area, making it possible to analyze both individual and group data variations.

3.2 | Sensitivity Analysis Models

Several models have been developed for sensitivity analysis in DEA. For instance, the model proposed by Cooper and colleagues in [12] focuses specifically on inefficient DMUs. This model recommends using managerial coefficients instead of traditional models to better design performance improvement strategies. Other models include synchronous and asynchronous change analyses in inputs and outputs, enabling managers to develop strategic plans for efficiency and service enhancement [13].

3.3 | Application of Data Envelopment Analysis in Industry

The current paper proposes a modified sensitivity analysis model for inefficient boilers based on DEA, which is investigated through a case study in the power industry. This study aims to optimize boiler performance by identifying gaps and analyzing expectations versus actual output data.

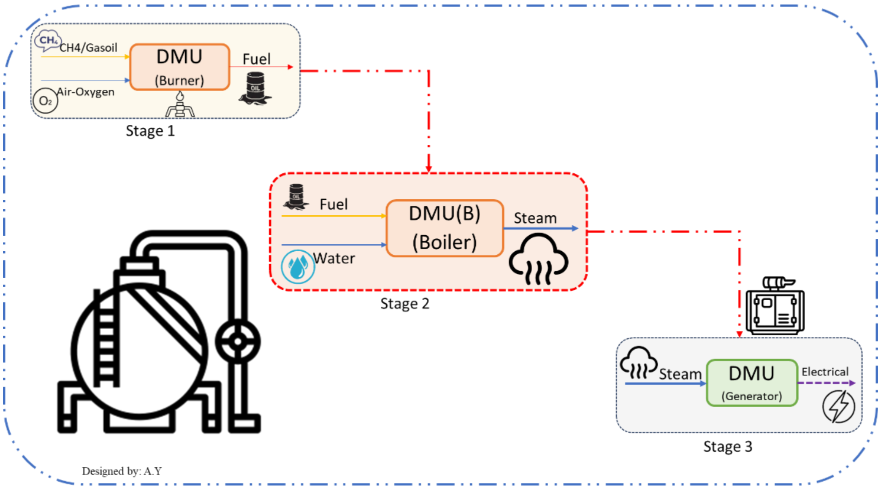

Fig. 1. General view for powerplant.

4 | Methodology and Findings

Logical input and output variables were first identified for 10 boilers to conduct the case study on boilers, representing their operational performance in a power plant. The aim was to evaluate their efficiency using the DEA model (*Table 1*).

Table 1 . Sample Inputs and Outputs in Boilers.

Inputs		Outputs	
Fuel consumption	(tons/day)	Steam output	(tons/day)
Water consumption	(m^3/day)	Power output	(MWh/day)
Operating costs	(USD/day)	Emission levels*	(Relative to allowed)
Maintenance time	(hrs/month)		

* Note: Emission levels are considered undesirable outputs, meaning their increase is unfavorable for the analysis.

Inputs:

I. Fuel consumption (tons/day): The fuel consumed by each boiler to generate energy.

II. Water consumption (m^3/day): The volume of water used for steam generation and cooling operations.

III. Operating costs (USD/day): Includes maintenance, labor, and energy expenses.

IV. Maintenance time (hrs/month): Time required to repair and replace key components.

Outputs:

I. Steam output (tons/day): The amount of steam generated contributes to electricity production and industrial processes.

II. Power output (MWh/day): The amount of electricity each boiler generates.

III. Emission levels (relative to standards): Emissions such as CO_2 and particulate matter, measured against permitted thresholds.

3.1 | Data Analysis

Using the data in *Table 1*, DEA can be applied to identify inefficient boilers and recommend efficiency improvements, which may include:

I. Optimization of fuel and water consumption based on the best-performing boilers.

II. Reduction in operational costs and maintenance time to enhance productivity.

III. Management and reduction of emissions to comply with environmental standards.

IV. These insights can support power plant managers in making optimal decisions to improve boiler efficiency and productivity.

3.2 | Sampling and Data Analysis

This section presents the case study on industrial boilers, focusing on relevant inputs and outputs to assess their efficiency and improve performance.

The case study focuses on industrial boilers within a power plant (*Table 2*). The main objective is to identify and analyze performance weaknesses using the modified DEA model and sensitivity analysis to propose improvement strategies.

Inputs:

I. Fuel consumption: Amount of fossil fuel or natural gas used, directly impacting operational costs and CO_2 emissions.

II. Water consumption: The volume of water needed for steam generation and temperature regulation affects the system's thermal efficiency.

Outputs:

I. Steam output (tons/hour): The volume of steam produced reflects the system's thermal performance.

3.3 | Data Analysis Process

The collected data were compiled via monitoring systems and processed using specialized optimization software.

Step 1. (Data collection and normalization) Input and output data were recorded over a specific period and normalized to ensure accurate comparisons between boilers.

Step 2. (Identifying performance gaps) Performance gaps were identified by analyzing the differences between the inputs consumed and the outputs produced by inefficient boilers.

Step 3. (Applying the DEA model) The DEA model was implemented with managerial coefficients to evaluate current boiler efficiency and identify inefficient units.

Table 2. Input and output data for the 10 Boilers.

Boiler	Inputs		Outputs
	Fuel (Ton/Day)	Water (M3/Day)	Steam (Ton/Day)
B1	200	400	150
B2	210	420	160
B3	190	380	140
B4	205	410	155
B5	215	430	162
B6	195	390	148
B7	220	440	165
B8	200	405	152
B9	205	415	160
B10	210	425	163

3.4 | Modeling

In this study, only two inputs (water and fuel) and one output (steam production) are considered to simplify calculations and data segmentation. As shown in *Fig. 1*, other criteria may be included in earlier or future stages or as part of a complementary project. The Counterparty Credit Risk (CCR) and Bidirectional Consistency Constraint (BCC) methods were applied, primarily emphasizing the BCC method.

CCR model

The CCR model is one of the earliest and simplest DEA models used to measure the relative efficiency of DMUs. It assumes Constant Returns to Scale (CRS). The CCR model aims to maximize the weighted ratio of outputs to inputs such that this ratio is ≤1 for all other units [14], [15].

Steps of sensitivity analysis using the CCR method

The initial linear programming model is based on *Formula (1)*, where x_{ik} and y_{rk} represent inputs and outputs for unit kkk, and uuu and vvv are the weights for outputs and inputs, respectively.

$$\max\theta = \frac{\sum_{r=1}^{s}\mu_r y_{rk}}{\sum_{r=1}^{s}\vartheta_i x_{ik}}. \quad (1)$$

Initial efficiency calculation

First, the relative efficiency of each boiler is calculated. These efficiency values help identify which boilers require improvement.

Performing sensitivity analysis

After identifying inefficient boilers, input and output values are altered to assess their impact on efficiency. In other words, we evaluate how reducing/increasing inputs like fuel or water or changing outputs like steam production influences overall efficiency. This aims to determine the stability radius (see *Table 3*).

Table 3. CCR model calculation results.

DMU'sDMU's	Input		Output	Productivity	Efficiency	Status
	Fuel (Ton/Day)	Water (M3/Day)	Steam (Ton/Day)			
B01	200	400	150	0.25000	0.96875	Inefficient
B02	210	420	160	0.25397	0.98413	Inefficient
B03	190	380	140	0.24561	0.95175	Inefficient
B04	205	410	155	0.25203	0.97663	Inefficient
B05	215	430	162	0.25116	0.97326	Inefficient
B06	195	390	148	0.25299	0.98034	Inefficient
B07	220	440	165	0.25000	0.96875	Inefficient
B08	200	405	152	0.25124	0.97355	Inefficient
B09	205	415	160	0.25806	1.00000	Efficient
B10	210	425	163	0.25669	0.99469	Inefficient

As shown in *Table 3*, only Boiler B09 is efficient. The Farrell efficiency diagram (*Fig. 2*) illustrates this.

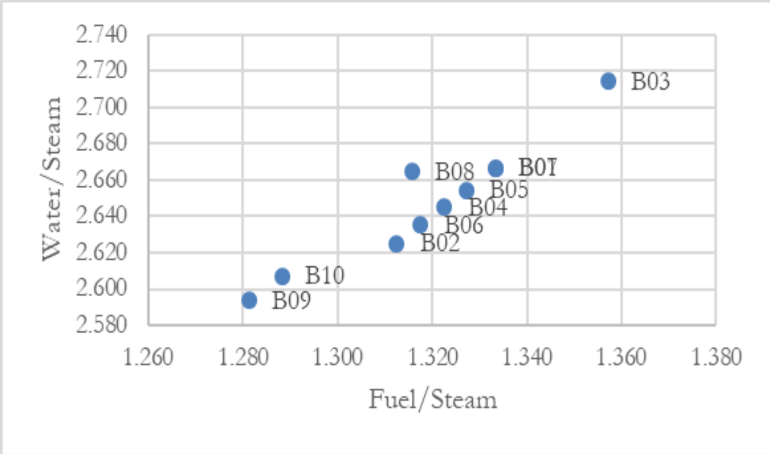

Fig. 2. Farel DEA model result.

BCC Model

The BCC model (*Formula 2*) is a modified version of CCR based on Variable Returns to Scale (VRS). In this study, the input-oriented BCC model aims to reduce inputs while maintaining maximum output.

$$\max\theta = \frac{\sum_{r=1}^{s}\mu_r y_{rk}}{\sum_{r=1}^{s}\vartheta_i x_{ik}}, \tag{2}$$

$$\min\sum_{i=1}^{m}\vartheta_i\, x_{ik} + w, \tag{3}$$

$$\sum_{r=1}^{s}\mu_r y_{rk} = 1, \tag{4}$$

$$\sum_{r=1}^{s}\mu_r y_{rk} - \sum_{i=1}^{m}\vartheta_i x_{ik} - w \leq 1, \tag{5}$$

$$\mu_r \,\&\, x_{ik} \geq 0, \quad j = 1\sim n, \quad W = \text{free}. \tag{6}$$

In this model, a free variable W is added to the CCR formula, and the equation is solved accordingly depending on whether an input-oriented or output-oriented perspective is used.

Table 4. BCC model results.

Boiler	Fuel	Water	Steam	Efficiency
B1	200	400	150	98.939%
B2	210	420	160	97.959%
B3	190	380	140	100%
B4	205	410	155	98.171%
B5	215	430	162	96.512%
B6	195	390	148	100%
B7	220	440	165	100%
B8	200	405	152	98.929%
B9	205	415	160	100%
B10	210	425	163	100%

As observed in *Table 4*, in addition to Boiler B9, Boilers B3, B6, B7, and B10 are also efficient under the BCC model. Boilers B1, B2, B4, B5, and B8 remain inefficient. Reference Boilers and Benchmarking (*Table 5*).

In the BCC model, inefficient boilers are compared to efficient ones to determine which units can serve as references. These reference units act as performance benchmarks for improvement.

Table 5. Reference Boilers for inefficient units.

Boiler	Reference Boiler	France	Efficiency
B1	B6-B9	0	Inefficient
B2	B6-B9	0	Inefficient
B3	B3	1	Efficiency
B4	B6-B9	0	Inefficient
B5	B9	0	Inefficient
B6	B6	5	Efficiency
B7	B7	2	Efficiency
B8	B6-B9	0	Inefficient
B9	B9	7	Efficiency
B10	B7-B9	0	Inefficient

4 | Key Findings

Table 6. Required adjustments for improving inefficient Boilers.

		Inputs (1)			Inputs (2)		
Boiler	Initial Fuel	Suggested Fuel	Fuel Reduction	Initial Water	Suggested Water	Water Reduction	Output (Steam)
B01	200	196.5	3.5	400	393.5	6.5	150
B02	210	203.5	6.5	420	411.4	8.6	160
B03	190	190	0	380	380	0	140
B04	205	200	5	410	402.5	7.5	155
B05	215	205	10	430	415	15	162
B06	195	195	0	390	390	0	148
B07	220	220	0	440	440	0	165
B08	200	197.8	2.2	405	397.1	7.9	152
B09	205	205	0	415	415	0	162
B10	210	210	0	425	423.3	1.7	163

I. Efficiency evaluation: Boiler B10 can become efficient with only a minor reduction in water usage (~1.7 m^3/day), showing that small operational adjustments can yield substantial improvements.

II. Least efficient Boiler: B5 is identified as the most inefficient, requiring the largest reductions in both water and fuel to reach the efficiency frontier.

III. Sensitivity insights: For example, reducing B1'sB1's fuel by 3.5 tons/day and water by 6.5 m^3/day significantly improves efficiency.

These targeted adjustments offer practical guidance for operators and maintenance teams to prioritize actions.

5 | Conclusion

The DEA method is a powerful tool for evaluating performance and identifying inefficiencies. It offers efficient insights without relying on rigid assumptions about the production function. Its flexibility in adjusting input and output weights allows managers to fine-tune operational plans and enhance overall system performance.

5.1 | Significance of Sensitivity Analysis

Sensitivity analysis is especially valuable for operational decision-making, as it reveals how small input/output changes can lead to significant performance improvements. This particularly applies to power generation and manufacturing industries, where operational costs are high, and optimization is critical.

By incorporating additional inputs and outputs into future models, a more comprehensive analysis of boiler performance can be achieved. Ongoing research is being conducted in this area to expand the model's model's capabilities.

6 | Applications

The results of this study can be used to develop optimization programs aimed at reducing costs and increasing efficiency. This approach contributes to environmentally conscious strategies by minimizing resource consumption and maximizing useful outputs.

Ultimately, integrating DEA and sensitivity analysis has proven to be a comprehensive strategy for enhancing boiler performance. Facilities can significantly improve efficiency and effectiveness by making intelligent adjustments to inputs and outputs. This not only reduces operational costs but also supports better resource management and lowers environmental impact.

7 | Recommendations

Based on the efficiency analysis of the boilers and the results obtained, the following recommendations are proposed to improve their performance:

I. Recommendations: Based on the efficiency analysis of the boilers and the results obtained, the following recommendations are proposed to improve their performance:

II. Scheduled maintenance planning: It is recommended that the maintenance schedule be carefully reviewed to ensure optimal system operation. Minimizing downtime and extending boiler lifespan can lead to overall efficiency gains.

III. Input and output engineering: Considering the role of inputs and outputs in DEA, efforts should focus on optimizing fuel and water usage. Enhancing steam and power output through energy efficiency techniques is also suggested.

IV. Enhanced staff training: Continuous training of personnel in optimal boiler operation and maintenance practices can significantly impact system performance. Boiler-specific training programs can address energy-saving and resource-management techniques.

V. Utilization of advanced technologies: Implementing modern control and monitoring technologies—such as automation and Internet of Things (IoT) systems-can help improve energy efficiency and reduce resource consumption.

VI. Decision-making based on sensitivity analysis: Managers should treat sensitivity analysis as a key decision-making tool. Operational priorities and action plans based on minor input/output adjustments can result in tangible improvements.

VII. Financial resource management: Reviewing operational expenses and identifying cost-cutting opportunities-without sacrificing service quality-can help boost boiler efficiency.

These recommendations can be incorporated into a comprehensive management strategy to improve boiler performance and resource efficiency. In addition to cost savings and stakeholder satisfaction, these actions can positively influence environmental sustainability and energy productivity.

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Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declares no conflict of interest.

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