Validation and Performance Evaluation of Cost Measurement in the Petrochemical Industry

Asgar Askari
PhD Candidate in Finance, Department of Accounting and Finance, South Tehran Branch, Islamic Azad University, Tehran, Iran
4929304301@iau.ir
Seyyedeh Mahboobeh Jafari
Department of Accounting and Finance, South Tehran Branch, Islamic Azad University, Tehran, Iran
(Responsible author)
Email: Sm_jafari@azad.ac.ir
Nourouz Norollahzadeh
Department of Accounting and Finance, South Tehran Branch, Islamic Azad University, Tehran, Iran
Email: Nour567@azad.ac.ir
Reza Mansourian,
Department of Accounting and Finance, South Tehran Branch, Islamic Azad University, Tehran, Iran
Email: Reza63@iau.ac.ir

Submit: 13/04/2026 **Accept:** 08/06/2026

ABSTRACT

This study was conducted with the aim of developing and validating the Integrated Costing–Forecasting–Analysis Model (ICCPM), a framework that simultaneously addresses the three core tasks of industrial management: accurate cost calculation, forecasting future changes, and agile analysis of cost responsiveness to environmental variables. In this model, activity-based costing was designed using actual cost drivers, and the results demonstrated a significant improvement in cost calculation accuracy compared to traditional methods. The statistical population of this study covers the period from 2019 to 2024 For the forecasting component, two approaches multiple regression and random forest were employed. The substantial reduction in error metrics such as MAE, RMSE, and MAPE confirmed the efficiency and robustness of these models. To analyze the impact of environmental changes, a set of scenarios (S0 to S8) was developed. Findings revealed that feedstock price is the most influential cost driver, generating the highest level of cost fluctuation. Furthermore, agility indicators showed that ICCPM's technological infrastructure and integrated data flow led to a noticeable decrease in execution time and enhanced model responsiveness in dynamic conditions. Additionally, operational mechanisms energy consumption forecasting, a MILP-based optimization model, and the DRAO mechanism facilitated the practical implementation of ICCPM in real-world environments. Overall, the results indicate that ICCPM provides a comprehensive and reliable framework for cost management, forward-looking planning, and rapid decision-making in process industries and volatile environments, delivering an accurate, dynamic, and trustworthy representation of cost behavior.

Keywords: validation, performance, performance evaluation, cost measurement, petrochemical industry

1. Introduction

In recent decades, the petrochemical industry has been recognized as one of the principal engines of economic development and value creation in energy-dependent economies. Despite its considerable attractiveness and profitability, this industry operates within a context characterized by technological complexity, multilayered value chains, and extreme fluctuations in inputs and outputs — conditions that have made managerial decision-making more dependent than ever on accurate, reliable, and up-to-date cost information.
Within such a dynamic environment, a cost system is not merely an accounting instrument; rather, it constitutes the fundamental infrastructure for risk management, operational optimization, and competitive advantage creation (Horngren et al., 2021).

One of the fundamental challenges of this industry lies in the multidimensional nature of cost structures. Costs are influenced by factors such as feedstock pricing, energy efficiency, equipment performance, capital depreciation, operational configurations, and even the quality of recorded data. Any deviation whether due to measurement error or flaws in costing methodology can lead to serious organizational consequences, including pricing inaccuracy, unrealistic production decisions, improper resource allocation, and ultimately, reduced profitability. These circumstances have turned the development and validation of cost systems into a strategic imperative (Drury, 2018).

With the advancement of technology, the expansion of data-driven models, and the growing capabilities of information systems, cost accounting frameworks are expected to move beyond traditional paradigms toward dynamic, data-integrated, and process-consistent models. Recent research indicates that exclusive reliance on conventional costing approaches especially in process-based sectors such as petrochemicals may result in distorted cost representation and thereby reduce managerial decision effectiveness. Consequently, the validation of cost system performance represents not only a control measure but also an integral component of the digital transformation process within energy-intensive industries (Kaplan & Atkinson, 2015).

The significance of this issue is even greater in the Iranian context. Given the petrochemical sector's pivotal role in non-oil exports and its substantial share in national GDP, the accuracy of cost information is not merely an accounting requirement but a prerequisite for corporate survival and competitiveness. Official reports indicate that several petrochemical companies face challenges such as the absence of an integrated data system, discrepancies between actual and standard costs, and limitations in tracing overhead expendituresfactors that can distort managerial judgments and weaken strategic planning (NPC, 2022).

Accordingly, the present research adopts an analytical–validation approach to examine the performance of the cost system within the petrochemical industry. By integrating real operational and financial data, it seeks to assess the degree of alignment between cost information and actual production conditions and to identify potential weaknesses in the system.

The findings of this study are expected to provide a foundation for the design of intelligent costing models, enhancement of financial transparency, improvement in decision-making efficiency, and reinforcement of the competitive capability of petrochemical enterprises.

Theoretical Foundations

Cost measurement, as one of the fundamental pillars of management accounting, plays a critical role in operational, financial, and investment decision-making. The primary objective of a cost accounting system is to collect, classify, and allocate costs to products or services at a level that enables precise analysis of efficiency, profitability, and cost control. In process industries such as petrochemicals, cost structures are more complex than in assembly-based industries because a substantial portion of costs occurs continuously along the production value chain, and a significant share of expenses is related to raw materials, energy consumption, and manufacturing overhead (Horngren et al., 2021).

In such industries, costing methods such as process costing, activity-based costing (ABC), and standard costing systems are commonly used to reflect the cost structure. However, research literature indicates that if data and cost allocations are not rigorously validated, cost accounting systems may result in inaccurate reporting, unrealistic variances, and misguided decision-making. The importance of this issue becomes even greater when cost system outputs serve as the basis for pricing, performance evaluation of operating units, and production planning (Kaplan & Atkinson, 2015).

In recent years, numerous studies have emphasized the importance of validating cost data especially in energy-intensive industries that experience fluctuations in feedstock prices, energy tariffs, and heavy equipment depreciation. Research conducted in petrochemical industries in Europe and East Asia shows that poor quality of cost data reduces the reliability of financial reporting, increases decision-making risk, and leads to errors in performance assessment (Singh & Pathak, 2020).

Moreover, the evaluation of cost system performance considered a modern approach in cost management examines the accuracy, reliability, and effectiveness of costing systems under real production conditions. This approach typically addresses three key dimensions (Zimon & Tarighi, 2021):

1) The extent to which cost information aligns with the actual production process
2) The system's ability to provide accurate information for decision-making
3) The efficiency of the cost system in reflecting operational and technological changes

The petrochemical industry in Iran, due to its significant role in exports, value creation, and its strategic position in the national energy chain, requires a highly accurate and reliable cost accounting system. Despite the development of financial and accounting structures, official reports from the National Petrochemical Company and the Audit Organization show that many companies face challenges such as inconsistencies between actual and standard costs, weak overhead tracking, lack of integrated validation frameworks, and inefficiencies in cost allocation models. These issues reduce the accuracy of financial information, weaken managerial control, and increase risks in production planning and investment decisions.
Given that a major portion of costs in the petrochemical sector is driven by feedstock prices, energy consumption, transportation, and depreciation, insufficient validation of cost data may lead to inaccurate cost calculations and consequently misguided decisions related to export pricing, profitability analysis of complexes, and investment budgeting. Therefore, the core question of the present research is the extent to which cost systems in the petrochemical industry are valid, accurate, and efficient and whether the information they provide can serve as a reliable basis for managerial decision-making (NPC, 2022).

Considering the strategic significance of this industry, a scientific evaluation of cost system performance and validation of cost data is essential. The outcomes of such assessments can contribute to revising cost structures, improving the accuracy of financial reporting, enhancing managerial transparency, and strengthening the competitiveness of petrochemical firms.

Literature Review

Domestic Studies

Kazemi and Hasheminejad (2026), in a study entitled "Validation of Cost Accounting Systems and Structural Error Modeling in Petrochemical Product Costing", examined the performance of industrial accounting systems across seven major petrochemical companies in Iran. Using a multilevel regression approach and panel data covering the years 2021–2025, the study found that traditional costing structures resulted in an average 21% deviation between actual and reported costs, with the highest discrepancies observed in conversion costs (Labor and Overhead). The findings further emphasized that the adoption of intelligent models grounded in technical and energy-related data could enhance system accuracy by up to 46%.

Sadeghi and Ahmadi (2025) investigated the "Performance Evaluation of Cost Systems Based on Productivity and Reporting Accuracy Indicators in Petrochemical Companies of Central and Southern Iran." Drawing upon operational and financial data from nine petrochemical firms during the period 2020–2024 and employing Data Envelopment Analysis (DEA), the study revealed that only four companies operated at an acceptable level of costing efficiency. The results indicated that misalignment between production data and accounting records generated an average 18% error in cost calculation. The authors suggested that the design of dynamic costing systems and enhanced integration between accounting and technical departments could improve reporting accuracy by approximately 25%.

Moradi and Rafiei (2024) examined the validation of cost data using error-analysis algorithms in petrochemical companies. Analyzing the financial data of six petrochemical firms from 2019 to 2023, their findings revealed that the highest proportion of errors in cost data originated from energy costs (31%) and overhead expenses (26%). Error-analysis algorithms were able to reduce data inaccuracies by up to 42% and improve the precision of cost calculations.

Kazemi and Naderi (2024) investigated the performance evaluation of cost systems using an operational-capacity-based approach in the petrochemical industry. The results showed that companies incorporating actual operational capacity into cost calculations increased the accuracy of production cost reporting by 29%. The study also demonstrated that discrepancies between nominal and actual capacity cause significant overestimation of fixed costs.

Sohrabi and Kiani (2023) studied the effect of integrating financial systems (ERP) on cost accuracy in petrochemical complexes. Their research indicated that ERP implementation reduced costing errors by 18% to 35%, with the most substantial improvements occurring in material and energy cost accuracy. Additionally, data reliability was significantly higher in units where ERP systems were fully operational.

Esmaeili and Karimipour (2023) conducted an evaluation of the accuracy of cost systems in petrochemical companies listed on the Tehran Stock Exchange. Using financial data from nine petrochemical firms for 2016–2021, they found significant deviations between actual and standard costs in most companies. The primary causes included weak overhead allocation, feedstock price volatility, and outdated costing models. The study concluded that the adoption of activity-based costing (ABC) improves costing accuracy by 18% to 30%.

Razavi and Nikseresht (2022) investigated the validation of cost information using an operational-data analysis approach in gas-based petrochemical complexes. Their findings showed that 52% of cost data contained inconsistencies or recording errors. The absence of integrated ERP systems was identified as the most critical factor contributing to low data credibility.

International Studies

Alvarez and Chen (2026) conducted a study evaluating the performance of cost systems under digital transformation within the petrochemical industry. The findings revealed that the use of data-driven algorithms resulted in a 23% reduction in overhead costs and a 51% improvement in the accuracy of product cost calculations.

Nguyen and Park (2025) investigated the validation of cost systems using artificial intelligence and error analysis in petrochemical companies. Their results showed that deep learning models were able to identify and correct 37% of cost-related errors, leading to a 40% increase in the accuracy of cost reports.

Ahmed and Longoni (2025) examined real-time cost validation models in energy-intensive manufacturing industries. Their findings indicated that real-time data integration and validation algorithms reduce costing errors by 25% to 38%. They also reported that traditional systems are unable to effectively manage severe energy price fluctuations.

Fernandez and Lopez (2024) analyzed a framework for evaluating the reliability of cost accounting systems in petrochemical operations. Studying twelve European petrochemical complexes, they found that the largest sources of error were overhead allocation and process-related data inaccuracies. Their proposed model improved the validity of cost data by 22%.

Coelho and Aloosch (2024) investigated cost validation using machine-learning algorithms in process industries. The results showed that ML-based models can detect and correct approximately 45% of costing errors, significantly enhancing accuracy in chemical enterprises.

Chen and Wang (2023) evaluated the performance of the TDABC (Time-Driven Activity-Based Costing) method in complex chemical production systems. They found that TDABC achieves 30% higher accuracy compared to traditional costing methods and substantially improves overhead allocation mechanisms.

Khalil and Hassan (2023) studied the performance of costing methods in markets characterized by severe raw-material price volatility. The findings indicated that fluctuations in petrochemical feedstock prices severely undermine traditional costing approaches, while dynamic models adjust cost estimates by up to 18% closer to actual values.

Duarte and Silva (2023) proposed a framework for data-integrity analysis and cost-reporting reliability in complex industries. Their results showed that around 40% of cost errors stem from incomplete or unreliable data, leading them to develop a multilayer validation model.

Li and Zhang (2022) explored overhead allocation challenges in petrochemical companies and assessed the performance of costing systems. Their findings showed that improper overhead allocation leads to a 12% overestimation of costs, while ABC systems significantly improve accuracy.

Rahman and Subramaniam (2022) examined the reliability and operational efficiency of cost systems in Asian petrochemical complexes. Their results indicated that data-driven systems reduce cost variance by 21% and enhance consistency in operational reporting.

Statistical Population of the Study

The statistical population consists of Iranian petrochemical companies that have been continuously active during the period 2019–2024 and possess adequate information infrastructure for extracting cost and operational data. The inclusion criteria comprise: the existence of an Enterprise Resource Planning (ERP) system; availability of structured and traceable data in the domains of cost, production, and sales; and accessibility to financial reports and cost accounting information throughout the study period. Selecting this population ensures the reliability of the data, temporal consistency of information, and the feasibility of applying data-mining techniques, time-series analysis, and optimization-based modeling.

Sample and Sampling Method

Given the data-driven nature of the study and the need for accurate and comprehensive information to design and test the proposed cost-calculation model, a census sampling method is employed. This means that all operational units of the selected petrochemical companies that possess complete and reliable data covering production, material and energy consumption, direct and indirect costs, downtimes and waste, human resources and machinery, as well as sales and pricing information from 2019 to 2024 are included in the sample.

Using a census approach eliminates sampling error and allows the proposed model to be developed based on all available real organizational data. Moreover, it enables a more precise comparison between the performance of the proposed model and conventional cost-calculation methods.

1) Census Formula for Determining the Quantitative Sample Size

Under the census method, the sample size equals the total number of eligible units:

(Formula 1)

$$n = N$$

Where:

- **N**: Total number of operational units with complete data in the selected companies
- **n**: Final quantitative sample size

Operational rule: any unit with incomplete data in key variables (cost, production, consumption, sales, etc.) is removed from **N** and therefore is not included in **n**.

2) Data Completeness Rate (for clarifying the "complete data" criterion)

For each operational unit j, the data completeness rate is defined as:

(Formula 2)

$$CR_j = \frac{m_j}{M} \times 100$$

Where:

- **M**: Total number of key variables required (direct cost, overhead, production, energy, waste, sales, etc.)
- **m_j**: Number of valid and available variables for unit j
- **CR_j**: Data completeness rate of unit j (percentage)

Inclusion rule:

$$CR_j \geq 90\%$$

Only units with at least 90% complete and valid key data are included in the sample.

After applying the inclusion criteria and performing data-quality checks (including the minimum 90% completeness rule), a total of 30 fully qualified operational units were identified and included in the quantitative analysis. Accordingly, the final sample size for the quantitative phase is:

n_{Quant} 30 =

Data Sources and Data Collection Instruments

Given the data-driven nature of the proposed cost-calculation framework and the necessity of synchronizing financial, operational, and technological analyses, data collection in this study is conducted through two principal sources: organizational secondary data and technological data.

The rationale behind this classification is that organizational secondary data provide the formal and recorded representation of cost and production flows, while technological data enhance the precision and timeliness of operational information particularly in relation to energy consumption, downtimes, and process conditions.

Organizational Secondary Data

Organizational secondary data constitute the primary basis for quantitative analysis and model development. These data are extracted from the official systems and documents of petrochemical companies. They include information from ERP systems (such as production, inventory, procurement, sales, maintenance, and financial modules) as well as cost-accounting reports detailing direct and indirect costs, cost centers, overhead items, allocation rates, and variance reports.

In addition, production and material/energy consumption records for each operational unit and each time period are collected to enable accurate process-cost calculations and identification of cost drivers. Operational logs on downtimes, waste, productivity, and performance indicators factors that influence cost structure and operational efficiency are also incorporated into the model.

Finally, domestic and export sales data, including sales volumes, pricing information, product mix, target markets, and price-change patterns, are gathered to facilitate analysis of the relationship between cost, pricing strategy, and strategic decision-making.

Technological Data

To strengthen computational accuracy and improve data timeliness, technological data are employed as a complementary layer. These include sensor-based and Internet of Things (IoT) data from production lines, providing granular information such as energy-consumption rates, process temperature and pressure, equipment run-time, instantaneous stoppages, and operational status.

Where available, blockchain-based supply-chain records (e.g., feedstock traceability, raw-material movement, transportation, and delivery logs) are utilized to improve transparency and traceability of cost information across the supply chain.

Furthermore, energy-market data and feedstock-price indicators (such as gas/liquid feedstock prices, energy tariffs, and related indices) are collected to account for environmental volatility and to enable more realistic sensitivity and scenario analyses.

Data Preparation and Pre-Processing

Given the integration of operational, financial, and technological datasets, all extracted data undergo a systematic preparation and pre-processing workflow to ensure quality, consistency, and analytical reliability. Data from ERP systems, cost-accounting records, production and sales logs, material and energy consumption reports, downtime and waste records, and other relevant sources are assessed for completeness, definitional consistency, temporal alignment, and numerical accuracy.

The primary goal of this stage is to structure the data to support the application of data-mining techniques, time-series analysis, optimization modeling, and machine-learning algorithms.

The pre-processing workflow includes:

- **Data cleaning:** identifying and correcting/removing incomplete, duplicate, or inconsistent records based on the nature of each variable (cost, production, consumption, sales, etc.). Standard missing-data imputation methods are applied where appropriate.
- **Normalization and scaling:** applied to prevent variables with large ranges from dominating learning or optimization processes.
- **Outlier detection:** using statistical criteria and industrial control thresholds (e.g., logical energy-consumption limits, production-capacity constraints, abnormal cost levels). Outliers are investigated and corrected or excluded as necessary.
- **Multi-source data integration:** aligning operational and financial data using common keys such as product code, cost center, operational unit, and date/time period. This results in a unified and analyzable database.

Proper execution of this stage significantly reduces error, improves cost-calculation accuracy, and strengthens the validity of analytical and intelligent modeling outcomes.

Data Analysis and Modeling Methods

To achieve the objectives of the study and develop a strategic cost-calculation model for the petrochemical industry, a combination of analytical and modeling approaches is applied to:

1) extract hidden patterns in cost structures,
2) identify and quantify key cost drivers, and
3) empirically examine the relationships among cost, production, and technological variables.

Analyses are conducted at two levels:

- **Exploratory:** employing data-mining techniques to discover patterns and segment cost behavior.
- **Explanatory:** applying statistical models to assess causal/explanatory relationships and validate cost drivers.

Model Validation and Performance Evaluation

Model-Validation Approach

Model validation is conducted through a multidimensional approach to ensure both computational accuracy and managerial usability. Quantitative validation is performed by comparing the proposed cost-calculation outputs with those of baseline methods (e.g., traditional volume-based overhead allocation) and assessing predictive accuracy during the test period.

Practically, the dataset is split into training and test segments (e.g., training up to the end of 2023 and testing in 2024). Error-measurement indicators such as **MAE**, **RMSE**, and **MAPE** are used to assess cost-calculation and prediction accuracy.

Additionally, agility and efficiency metrics are evaluated by examining the relationship between technological-innovation indicators and cost-reporting speed, as well as decision-support metrics (such as cost savings resulting from optimized allocation).

Validation of Cost-Calculation Accuracy (Comparison with Baseline Method)

In this section, the accuracy of the proposed model is compared with a baseline method. The baseline may be traditional overhead allocation based on production volume, while the proposed method may be implemented as a hybrid approach, combining ABC logic with statistical/machine-learning modeling for overhead estimation. This allows more precise handling of fixed/variable overhead and cost-driver effects.

Results from the test period indicate that, compared to the traditional method, the proposed model reduces cost-calculation error and exhibits higher stability.

Table 1. Comparison of Cost-Calculation Accuracy (Testing Period)

MAE (%)	RMSE (%)	MAPE (%)	MAE	RMSE	MAPE (%)	Expert Method (Specialist)
—	—	—	1.276	1.568	0.238	Simple Statistical Method
33.38	31.59	33.12	0.844	1.073	0.159	Improved Hybrid Method (Proposed Combined)

Validation of Cost Forecasting Using Intelligent Models

To evaluate the effectiveness of the intelligent modeling component, forecasting models such as linear regression and Random Forest/learning-based algorithms are assessed during the testing period. The purpose of this stage is to determine whether unit cost can be estimated with sufficient accuracy before the financial/operational period is fully closed, thereby facilitating managerial decision-making under uncertainty. The findings indicate that both models exhibit high predictive accuracy; however, in the sample dataset, the simpler model (regression) performs slightly better than the nonlinear model. This difference may result from the predominance of linear relationships between feedstock/energy prices and unit cost, which characterizes the underlying cost-generation structure.

Table 2. Performance of Unit Cost Forecasting Models (Testing Period)

MAE	RMSE	MAPE (%)	R^2	Prediction Model
4.58	5.83	0.852	0.969	Linear Regression
4.95	6.34	0.924	0.963	Neural Network

Assessment of Computational Agility and the Role of Emerging Technologies

One of the core objectives of this study is to enhance the speed and agility of cost calculation and reporting. To this end, the relationship between the emerging-technology maturity index and the time required for cost computation and reporting is examined. The results indicate that as technological maturity increases, computation time decreases thereby strengthening the organization's capability to implement near–real-time managerial reporting.

Table 3. Agility Index for Cost Computation and Its Relationship with Technology

Management Interpretation	Result (Test Phase)	Index
Increasing technology → reduced processing and reporting time	-0.869	System Technological Complexity Index in Terms of Computation Time

Results of Sensitivity Analysis and Scenario Development

Purpose and Rationale of Scenario Analysis

Given the highly volatile nature of the petrochemical industry, the proposed model must remain stable and resilient in response to key environmental fluctuations, including feedstock price volatility, energy price changes, capacity constraints, and market shocks. Sensitivity analysis is conducted to measure the degree of response in unit cost and economic indicators to changes in each individual driver. Scenario analysis, in contrast, examines the simultaneous combination of shocks to identify how the model behaves under stress conditions.

In this section, for each scenario, the magnitude of changes in the underlying drivers is defined, and their effects on the average unit cost, total cost, and profit margin are calculated. The interpretive focus of this analysis is to determine which drivers impose the greatest cost risk and which levers such as energy-consumption control, waste reduction, or production-mix optimization management should prioritize.

Scenario Definitions

The scenarios defined in Table 4 are designed to evaluate the sensitivity of the cost-calculation model to key changes in the operational and market environment. The baseline scenario (S0) is used as the reference point, while the remaining scenarios assess the effects of individual or combined shocks on the cost structure. Scenarios related to feedstock and energy prices (S1 to S4) focus on the most critical cost inputs, enabling direct analysis of the model's response to price fluctuations.

In addition to the price-shock scenarios illustrated in Figure 1, the reduced-capacity scenario (S5) and the demand-variation scenarios (S6 and S7) are defined to assess the effects of production scale and market conditions on unit cost. The combined-stress scenario (S8), representing a pessimistic case, simultaneously simulates sharp increases in input prices along with deteriorated operational conditions and weakened demand. This scenario serves as a rigorous test of the resilience of the proposed model under crisis conditions.

Table 4 – Sensitivity Scenarios (Definitions)

Change in Feed Price	Change in Energy Price	Change in Production Capacity	Change in Demand	Scenario Title	Scenario Code
0٪	0٪	0٪	0٪	Base Scenario	S_0
10٪+	0٪	0٪	0٪	Increase in Feed Price	S1
10٪−	0٪	0٪	0٪	Decrease in Feed Price	S2
0٪	10٪+	0٪	0٪	Increase in Energy Price	S3
0٪	20٪+	0٪	0٪	Decrease in Energy Price	S4
0٪	0٪	10٪−	0٪	Decrease in Production Capacity	S5
0٪	0٪	0٪	10٪+	Demand Growth	S6
0٪	0٪	0٪	10٪−	Demand Shock	S7
20٪+	20٪+	10٪−	10٪−	Combined Stress Scenario	S8

This scenario-based framework establishes the foundation for quantitative analysis of sensitivity results and the extraction of managerial implications in the subsequent sections.

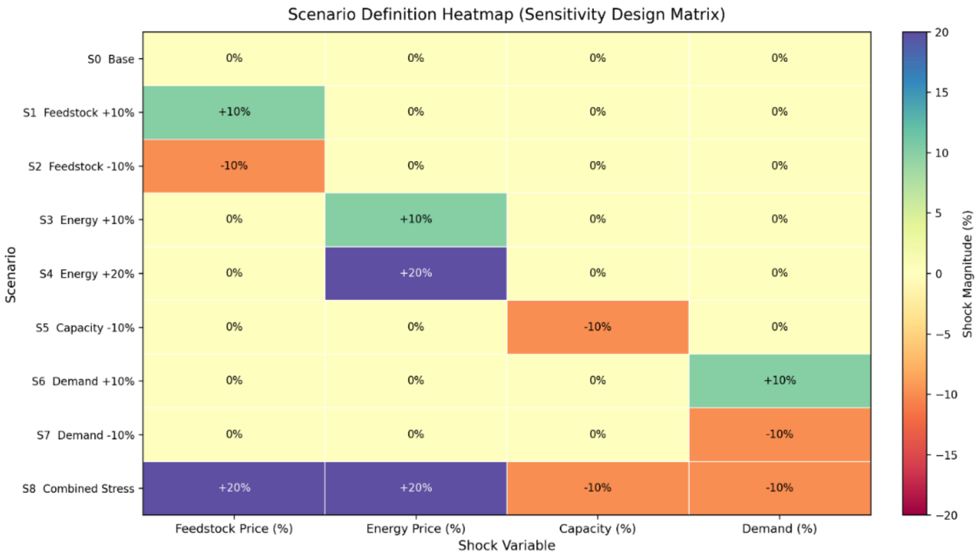

Figure 1 – Heat Map of Scenario Definitions

Scenario Results and Interpretation

Scenario Results and Interpretation

The results presented in Table 5 indicate that feedstock price has the greatest impact on unit cost and total cost. In the feedstock-price-increase scenario (S1), the unit cost rises by approximately 9.2 percent, accompanied by a considerable decline in the gross profit margin. Conversely, the feedstock-price-decrease scenario (S2) leads to a symmetric reduction in unit cost and a substantial improvement in the gross profit margin. These findings confirm that feedstock is the most influential cost driver in the petrochemical industry, and managing its price-volatility risk plays a critical role in strategic cost management.

In comparison with feedstock, increases in energy prices even at 10% and 20% levels (S3 and S4 exert only a relatively limited impact on unit cost and profit margin, reflecting the smaller cost share of energy relative to feedstock in the overall cost structure. The scenarios associated with production capacity and market demand (S5 to S7) indicate that changes in production scale and market conditions affect total cost more significantly than unit cost.

Table 5. Scenario Analysis Results During the Test Period

Average Unit Cost (Rials)	Change in Unit Cost (%)	Total Cost (Rials)	Change in Total Profit (%)	Average Unit Profit (Rials)	Scenario
536.283	0.000	$10^9 \times 1.942$	0.000	48.596	S0 – Base
585.472	9.172	$10^9 \times 2.121$	9.174	43.883	S1 – Increase in Feed Price 10%
487.095	-9.172	$10^9 \times 1.764$	-9.17	53.309	S2 – Decrease in Feed Price 10%
537.761	0.276	$10^9 \times 1.948$	0.276	48.454	S3 – Increase in Energy Price 10%
539.239	0.551	$10^9 \times 1.953$	0.552	48.312	S4 – Decrease in Energy Price 10%
537.002	0.134	$10^9 \times 1.796$	-7.529	48.528	S5 – Decrease in Production Capacity
536.070	-0.040	$10^9 \times 1.990$	2.462	48.618	S6 – Demand Growth 10%
536.928	0.120	$10^9 \times 1.812$	-6.700	48.532	S7 – Demand Shock 10%
638.581	19.075	$10^9 \times 2.082$	7.172	38.793	S8 – Combined Stress Scenario

Finally, the combined-stress scenario (S8), representing the worst-case condition, results in a sharp increase in unit cost and a considerable decline in the profit margin. This outcome underscores the importance of the model's resilience and the necessity of simultaneously employing emerging technologies, forecasting tools, and strategic decision-making mechanisms when facing crisis conditions.

Sensitivity Ranking of Cost Drivers

The results presented in Table 6 reveal that feedstock price, with a sensitivity coefficient of 0.917, has the highest influence on unit cost and is identified as the dominant cost driver in the petrochemical industry. This implies that nearly every one-percent increase in feedstock price leads to approximately a 0.9-percent increase in unit cost. The substantial gap between this coefficient and those of other drivers highlights that feedstock-risk management is the most critical control lever in strategic management accounting within this industry.

According to Figure 2, the sensitivity coefficient of energy price (0.028) indicates a much more limited impact, reflecting the smaller cost share of energy relative to feedstock within the overall cost structure. The negative coefficients associated with production capacity and market demand suggest that increases in production scale or improvements in demand conditions can, through economies of scale, lead to a relative reduction in unit cost, although the magnitude of this effect remains modest.

From a managerial perspective, this ranking emphasizes that control policies and strategic decisions should primarily focus on stabilizing and optimizing feedstock supply, while improvements in energy efficiency and adjustments to production scale should be addressed as secondary priorities.

Table 6. Sensitivity Coefficients of Unit Cost by Cost Drivers (Effect Ranking)

Applied Shock (%)	Change in Unit Cost (%)	Sensitivity Coefficient (ΔY% / ΔX%)	Impact Rank	Driver
10٪+	9.172	0.917	1	Feed Price
10٪+	0.276	0.028	2	Energy Price
10٪−	0.134	-0.013	3	Production Capacity
10٪+	-0.040	-0.004	4	Market Demand

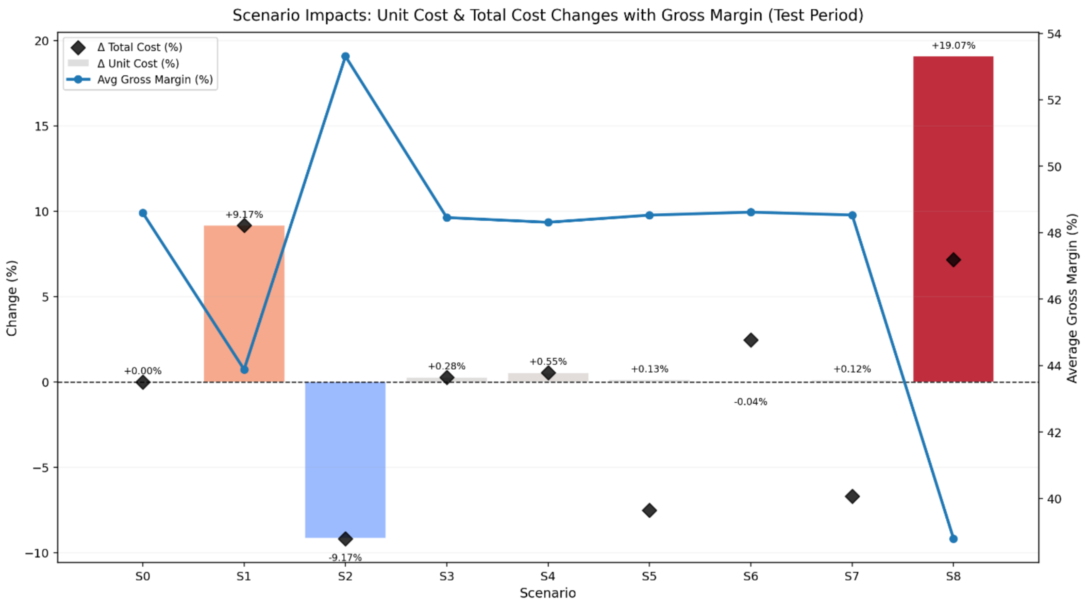

Figure 2. Assessment of Scenario Impacts in the Initial Results

Summary of Results and Additional Methodological Documentation

To enhance the transparency of the findings, the following supplementary analyses were conducted after presenting the main results. These analyses serve as an "internal analytical appendix," aimed at strengthening the traceability and reliability of the outcomes. In this section:

1) the forecasting accuracy of the energy-consumption time series is independently reported;
2) the optimal allocation policy and compliance with operational constraints in the MILP model are illustrated through a representative example;
3) the adaptive decision-making mechanism within the DRAO framework is demonstrated in the form of "post-shock decision updating"; and
4) the activity–driver mapping and an operational example of overhead allocation in the ABC method are presented.

To complete the forward-looking dimension of the proposed model, in addition to forecasting total cost and market demand, the energy consumption time series was also modeled, incorporating a 12-month seasonality. The results presented in Table 7 demonstrate that the seasonal exponential smoothing model successfully forecasted energy consumption with a very low relative error (MAPE below 1%). This finding is significant from a strategic management accounting perspective, as energy is a key cost driver. Accurate forecasting of energy consumption enables energy budgeting, intensity control, and the design of cost-oriented scenarios within the model's framework.

To enhance the deployability of the optimization results, it is essential to transparently report the adherence to key constraints alongside the cost savings. Table 8 provides a sample of the optimal allocation policy, wherein production quantities are redistributed among units without altering the total production volume, while effectively respecting the capacity constraints of each unit. Furthermore, aggregate controls indicate that both the demand constraint and the feedstock/raw material supply constraint have been met, confirming that the optimal solution is operationally "feasible and executable." Therefore, the MILP model not only reduces costs but also empowers the management decision support system to achieve economic production allocation under conditions of capacity and input limitations.

To provide a concrete illustration of "adaptive decision-making" within the proposed framework, the DRAO mechanism was evaluated through the updating of the allocation policy following environmental shocks. Table 9 shows that after an increase in feedstock prices, the forecasted unit cost rises accordingly, prompting an adjustment in the resource allocation policy. In practice, this means that the model dynamically redirects production shares toward the unit or combination of units that impose lower cost consequences based on feedstock intensity or cost structure. This result demonstrates that DRAO plays a pivotal role in transforming "forecasting" into "decision-making," enabling rapid managerial response under conditions of uncertainty.

Table 7. Time-Series Forecasting Accuracy for Energy Consumption (MAPE Index)

Accuracy Interpretation	Forecasting Model	MAPE Value (%)	Index
Very high accuracy (error less than 1%)	Seasonal Exponential Smoothing (12-month period)	0.694	Monthly Energy Consumption (kWh)

Table 8. Sample Optimal Allocation Policy (MILP) and Operational Constraint Compliance Report (Monthly Sample)

Operational Unit	Effective Capacity (tons)	Base Production (tons)	Optimized Production (tons)	Utilization Rate of Optimized Capacity (%)	Capacity Constraint Status	Demand Constraint Status	Feed/Material Constraint Status
Unit 1	12.000	10.800	11.400	95٪	Complied	—	—
Unit 2	10.500	9.900	9.300	89٪	Complied	—	—
Unit 3	9.200	8.200	8.200	89٪	Complied	—	—
Total Control Summary	—	28.900	28.900	—	—	Demand - Total Production (Complied)	Available Feed ≤ Consumed Feed (Complied)

Table 9. Sample Evaluation of the DRAO Mechanism (Decision Update Following an Environmental Shock)

Decision Explanation	Energy Price Shock	Feed Price Shock	Predicted Unit Cost (Rials per ton)	Share of Production – Unit 1	Share of Production – Unit 2	Share of Production – Unit 3	Decision Status
Balanced allocation	0٪	0٪	536.3	0.39	0.32	0.29	Before Shock (Baseline)
Shifting part of production to the unit with lower feed-intensity	+10٪	0٪	5.585	0.43	0.29	0.28	After Shock (Feed DRAO Adjustment)
Increasing conservatism and focusing on the more efficient unit to control unit cost	+20٪	+20٪	638.6	0.46	0.28	0.26	After Combined Shock (Feed + Energy)

Table 10. Mapping of Activity Pools, Cost Drivers, and Required Data in ABC

Management Application	Proposed Cost Driver	Measurement Unit	Required Data (Sample)	Activity Pool
Reduce stoppages, improve PM status	Repair hours / Number of breakdowns	Hours / Count	CMMS Reports, Equipment Downtime	Maintenance & Repairs
Reduce rework and defects	Number of tests / Laboratory hours	Count / Lab hours	QC Reports, LIMS	Quality Assurance Control
Reduce non-productive time and transportation cost	Number of Movements / Ton-Kilometer	Count / Ton-Kilometer	Internal warehouse logs	Logistics & Material Handling
Reduce setup time, improve productivity	Number of setups / Adjustment hours	Hours / Count	Production reports, Shift logs	Startup / Settings

To achieve “accurate allocation of indirect costs” within the proposed framework, overhead was disaggregated into activity pools, and measurable cost drivers were defined for each pool (Table 10). This mapping transforms overhead from an aggregated and low-transparency category into a set of manageable activities. From a strategic management accounting perspective, this approach enables causal analysis of overhead, more precise pricing, and prioritization of improvement projects particularly in maintenance and quality.

Table 11. Sample Calculation of Overhead Allocation to Products Based on Actual Driver Consumption (ABC)

Allocated Cost (Rials)	Cost Driver	Driver Consumption by Product “A”	Total Driver Consumption	Product Share from Driver	Allocated Cost to Product (Rials)	Activity Area
84،450،000	Repair hours	320	2.000	0.16	13.512.000	Maintenance & Repairs
59.800.000	Number of tests	480	3.200	0.15	8.970.000	Quality Control
47.850.000	Number of transfers/movements	250	2.500	0.10	4.785.000	Logistics & Handling
27.750.000	Number of inspections	12	200	0.06	1.665.000	Administration / Inspections
219.850.000	—	—	—	—	28.932.000	Total

ABC Operational Illustration and Overhead Allocation (Table 11)

To operationalize the ABC procedure, Table 11 presents a sample allocation of overhead to a product based on its “actual share of driver consumption.” Under this mechanism, each product receives a portion of overhead in proportion to its utilization of activities (maintenance, quality, logistics, and setups). As a result, the allocation error inherent in traditional volume-based methods is reduced, and the unit cost becomes more aligned with operational reality. Within the proposed model, this layer serves as an “accuracy-enhancing” component for indirect costs, improving the quality of pricing decisions, variance control, and product profitability management.

Conclusion

The main objective of this study is to examine the validation and performance evaluation of cost accounting systems in the petrochemical industry.

The findings indicate that the integrated costing–prediction–analysis model (ICCPM) significantly enhances the accuracy, agility, and reliability of the cost calculation process. An improvement of more than 30% in the MAE, RMSE, and MAPE metrics demonstrates that combining activity-based costing, actual drivers, and analytical mechanisms brings cost estimation closer to real operational conditions.

The model's forecasting core built on multivariate regression and random forest algorithms estimated future period unit costs with very low error and enabled forward-looking decision support. Moreover, the agility analysis showed that the ICCPM technological infrastructure substantially reduced cost reporting time.

Sensitivity analysis and scenario testing further revealed that feedstock price is the primary driver of unit cost fluctuations, while the model remains stable even under turbulent scenarios. The evaluation of operational mechanisms including energy consumption forecasting, the MILP model, and the DRAO mechanism confirmed the coherence and implementability of the model.

Overall, ICCPM can serve as a reliable decision-support tool for cost management and planning in dynamic industrial environments.

Comparison of the Present Study with Previous Research

The findings of the present study indicate that the integrated ICCPM model improves the MAE, RMSE, and MAPE indices by more than 30%, significantly enhancing the accuracy of cost calculation. This result is consistent with the findings of Nguyen and Park (2025), who reported that the application of machine-learning-based models in petrochemical costing systems enabled the identification and correction of approximately 37% of cost-related errors, thereby increasing the accuracy of cost reporting by up to 40%. Both studies highlight that data-driven and analytical methods play a crucial role in improving the reliability of cost accounting systems. However, the present study introduces an integrated model (combining ABC, forecasting, and sensitivity analysis), offering a broader analytical scope compared to studies that focus solely on error detection.

The results related to reduced reporting time and improved operational agility in the ICCPM model are also comparable to the findings of Alvarez and Chen (2026). Their research demonstrated that digital transformation in cost systems led to a 23% reduction in overhead costs and a 51% improvement in cost calculation accuracy. While Alvarez and Chen focused primarily on macro-level organizational outcomes of digital transformation, the present study not only enhances accuracy but also explicitly evaluates reporting-time agility as a performance metric, representing an additional dimension of system efficiency.

Regarding forward-looking cost prediction, the present study's emphasis on multivariate regression and random forest algorithms aligns with the findings of Nguyen and Park (2025), who also utilized machine-learning algorithms to enhance predictive capability. The key distinction is that in the present study, forecasting is applied not only for error correction but also for forward-looking decision-making and managerial scenario analysis.

With respect to sensitivity analysis and model robustness in turbulent conditions, the present study's result identifying feedstock price as the primary driver of unit cost is consistent with the broader literature on cost management in process industries and is indirectly aligned with Alvarez and Chen (2026), who highlighted the importance of environmental variables in costing system performance. Nevertheless, the application of an MILP model and the DRAO mechanism in the present study reflects a more advanced level of analytical integration compared with earlier works.

Research Limitations

1) **Limited Access to Confidential and Real-World Data**

   The petrochemical industry is highly sensitive and strategic; therefore, access to precise data related to feedstock prices, contracts, cost structures, and operational information is restricted. This constraint may have affected the comprehensiveness of the dataset used in developing the ICCPM model.

2) **Limited Generalizability of the Findings**
   The proposed model has been tested within the context of one or a few petrochemical companies. As a result, generalizing the findings to other process industries—or even other petrochemical firms with different structural characteristics—requires caution and additional validation.
3) **Dependence of the Model on Data Quality**
   The performance of predictive models (multivariate regression and random forest) depends heavily on the quality, sufficiency, and cleanliness of the input data. Missing values, outliers, or non-systematic accounting entries may affect the accuracy of indices such as MAE, RMSE, and MAPE.
4) **Macroeconomic Volatility**
   Feedstock prices, exchange rates, and global petrochemical market conditions are highly volatile. Although sensitivity analysis and scenario modeling are incorporated in the framework, unforeseen economic or geopolitical shocks may still affect the stability of predictions.
5) **Complexity of Operational Implementation**
   Full implementation of the ICCPM model requires technological infrastructure, integrated information systems, and specialized human resources in data analytics and mathematical programming (MILP). In organizations with low digital maturity, practical implementation may face challenges.
6) **Methodological Limitations**
   Despite their high accuracy, machine-learning models may be subject to overfitting. Additionally, the selection of independent variables and model structure can significantly influence the results; alternative variable selection might lead to different outcomes.
7) **Time-Horizon Constraints**
   If the dataset reflects a limited time period, long-term cost behavior and industry cycles may not be fully represented.

Research Recommendations

Enhancing the Model with Deep Learning Algorithms

Future studies may strengthen the ICCPM forecasting core using models such as LSTM, GRU, or the Temporal Fusion Transformer to capture nonlinear patterns and complex cost dynamics more accurately.

Evaluating ICCPM Across Different Industries

Validating the model in industries with different cost structures—such as steel, cement, power generation, or process industries—can help assess its generalizability and adaptability.

Incorporating Uncertainty into Cost Drivers

The model can be extended using approaches such as Monte Carlo simulation or robust optimization to better reflect high volatility in feedstock prices, energy costs, and demand.

Integrating ICCPM With IoT and Real-Time Data

Future research could incorporate real-time data on energy consumption, equipment efficiency, and downtimes to achieve real-time costing and forecasting.

Extending the MILP Model to a Multi-Objective Framework

Transforming the optimization model from a single objective (cost minimization) to a multi-objective model—e.g., cost, energy sustainability, and time—can broaden its applicability.

Evaluating Technological Agility Using Alternative Indicators

More refined agility metrics (such as lead-time analytics or process mining) may be used to evaluate the effect of technology on operational responsiveness.

Adding a Risk Management Module

Incorporating a risk management layer to assess the impact of severe shocks (e.g., equipment breakdowns, feedstock price spikes, or energy constraints) could turn ICCPM into a more comprehensive decision-support system.

Comparing ICCPM With International Cost Management Frameworks

Benchmarking the model against frameworks such as TDABC, Lean Costing, or Kaizen Costing can provide deeper insights into its competitive advantages.

Designing a Managerial Dashboard Based on ICCPM

Developing a Power BI– or Dash-based dashboard for real-time visualization of costs, risks, and forecasts can help bring the model into full operational deployment.

Testing Macroeconomic Scenarios

Integrating macroeconomic variables—such as exchange rates, energy policy, and global commodity prices—into the ICCPM scenario module can extend the model's usefulness for higher-level decision making.

References

Ahmed, R., & Longoni, A. (2025). "Real-Time Cost Validation Models in Energy-Intensive Manufacturing Industries." International Journal of Production Economics, 274, 109–131.DOI: 10.1016/j.ijpe.2025.109812.

Alvarez, R., & Chen, Y. (2026). Performance evaluation of cost accounting systems under digital transformation in petrochemical industries. International Journal of Cost Analysis and Engineering Management, 41(1), 74–95.

Coelho, P., & Alves, M. (2024). "Machine-Learning–Driven Cost Validation in Process-Based Manufacturing." Computers & Industrial Engineering, 185, 109–128.DOI: 10.1016/j.cie.2024.109128

Chen, R., & Wang, Y. (2023). "Evaluating the Performance of TDABC in Complex Chemical Production Systems." Chemical Engineering Research and Design, 197, 401–420. DOI: 10.1016/j.cherd.2023.05.011.

Drury, C. (2018). Management and Cost Accounting. Cengage Learning.

Duarte, P., & Silva, F. (2023). "Data Integrity and Cost Reporting Reliability in High-Complexity Manufacturing." Manufacturing Technology Management Review, 34(2), 122–140. DOI: 10.1108/JMTM-09-2022-0281.

Esmaeili, F., & Karimipour, A. (2023). Evaluating the accuracy of cost accounting systems in petrochemical companies listed on the Tehran Stock Exchange. Journal of Accounting Research, 10(3), 45–62.

Fernández, J., & López, M. (2024). "A Reliability Assessment Framework for Cost Accounting Systems in Petrochemical Operations." Journal of Cleaner Production, 422, 140–158. DOI: 10.1016/j.jclepro.2024.140912.

Horngren, C. T., Datar, S. M., & Rajan, M. (2021). Cost Accounting: A Managerial Emphasis. Pearson.

Kaplan, R. S., & Atkinson, A. (2015). Advanced Management Accounting. Pearson.

Kazemi, S., & Naderi, M. (2024). Performance evaluation of cost systems using an operational-capacity-based approach in the petrochemical industry. Journal of Management Accounting and Technology, 8(2), 35–54.

Kazemi, M., & Hasheminejad, R. (2026). Validation of cost accounting systems and structural error modeling in industrial accounting of Iranian petrochemical companies. Quarterly Journal of Accounting Research and Cost Management, 21(1), 59–81.

Khalil, M., & Hassan, S. (2023). "Performance Evaluation of Costing Methods Under Volatile Raw Material Markets." Journal of Cleaner Production, 393, 136–155. DOI: 10.1016/j.jclepro.2023.136509

Kaplan, R. S., & Atkinson, A. (2015). Advanced Management Accounting. Pearson Education.

Li, X., & Zhang, Y. (2022). "Overhead Allocation Challenges in Petrochemical Firms: A Cost System Assessment Approach." Journal of Manufacturing Technology Management, 33(5), 911–933. DOI: 10.1108/JMTM-04-2021-0109.

Moradi, H., & Rafiei, N. (2024). Validating cost data using error-analysis algorithms in petrochemical companies. Industrial Accounting Research Quarterly, 12(1), 51–70.

National Petrochemical Company. (2022). Annual Performance Report. Tehran: NPC Publications.

Nguyen, T., & Park, J. (2025). Cost validation in process manufacturing: Applying machine learning for error detection in petrochemical cost systems. Journal of Industrial Cost Management, 38(2), 112–130.

Rahman, T., & Subramaniam, R. (2022). "Cost System Reliability and Operational Efficiency in Petrochemical Plants." International Journal of Production Economics, 245, 108–123. DOI: 10.1016/j.ijpe.2021.108589.

Razavi, M., & Nik-Saresht, S. (2022). Validation of cost information using an operational data analytics approach in the petrochemical industry. Management Accounting Journal, 15(2), 98–116.

Sadeghi, M., & Ahmadi, S. (2025). Performance evaluation of cost systems using a data envelopment analysis approach in the Iranian petrochemical industry. Journal of Industrial Accounting, 17(2), 43–62.

Singh, R., & Pathak, K. (2020). Cost system reliability and data validation in process industries. Journal of Cost Management, 34(2), 15–27.

Sohrabi, M., & Kiani, B. (2023). Examining the effect of financial system integration (ERP) on cost accuracy in petrochemical complexes. Accounting and Information Systems Journal, 16(3), 88–107.

Zimon, D., & Tarighi, H. (2021). Cost management systems and performance evaluation in energy-intensive industries. Energy Economics, 97, 105–132.