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Enhancing the efficiency and sustainability of Tunisia's thermal power plants: A data envelopment analysis with policy insights

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ABSTRACT

Enhancing the efficiency of thermal power plants is crucial for achieving a more sustainable, cost-effective, and resilient energy system. This study presents a novel efficiency assessment of Tunisia's thermal power plants (TPPs) by integrating an advanced two-stage Data Envelopment Analysis (DEA) framework with the double bootstrap procedure of Simar and Wilson (2007). Unlike conventional DEA approaches, which often yield biased efficiency estimates, this methodology ensures greater statistical reliability and robustness. Using operational data from 18 TPPs between 2005 and 2013, the first stage estimates efficiency scores through the Banker-Charnes-Cooper (BCC) and Super Efficiency (SE) DEA models, while the second stage employs truncated bootstrap regression to identify key efficiency determinants. The results reveal substantial performance disparities among plants, with combined cycle units significantly outperforming gas turbine systems, particularly in peak-load operations. Regression analysis highlights plant age, capacity, and technology type as critical drivers of efficiency. By addressing existing methodological limitations in power plant efficiency analysis, this research contributes to the scientific community by offering a rigorous, bias-corrected evaluation framework applicable to other energy systems. Additionally, the study provides evidence-based policy recommendations, including targeted infrastructure investments, regulatory reforms, and incentive mechanisms to enhance efficiency and sustainability. These findings have significant implications for policymakers, energy planners, and industry stakeholders seeking to optimize resource allocation, reduce emissions, and accelerate the transition toward a more resilient electricity sector.

Nomenclature

BCC	Banker-Charnes-Cooper (DEA model with variable returns to scale)
CCR	Charnes-Cooper-Rhodes (DEA model with constant returns to scale)
DEA	Data Envelopment Analysis
DMU	Decision-Making Unit
DDF	Directional distance function
MW	Megawatt (unit of power)
MWH	Megawatt-hour (unit of energy)
OLS	Ordinary Least Squares
SE	Super Efficiency (DEA model extension)
SFA	Stochastic Frontier Analysis
STEG	Tunisian Electricity and Gas Company
TE	Technical Efficiency
TPP	Thermal Power plants
TEP	Ton of Oil Equivalent (unit of energy)
TND	Tunisian Dinar (currency unit)
TPP	Thermal Power Plant
VRS	Variable Returns to Scale

1. Introduction

Electricity generation is the backbone of economic development and energy security. As societies expand and industrialize, global energy demand continues to rise, placing increasing pressure on power systems to

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maintain a stable balance between supply and consumption. While the transition to renewable energy sources is accelerating, thermal power plants remain dominant, accounting for approximately 60 % of global electricity production (IEA, 2024). However, this continued reliance on thermal power generation presents significant challenges, including volatile fuel prices, rising operating costs, stricter environmental regulations, and the gradual depletion of fossil fuel reserves. In light of these complexities, improving the efficiency of thermal power plants is crucial. Enhanced efficiency not only reduces emissions and operational expenses but also strengthens grid stability and supports the transition toward a more sustainable energy future (e.g., Euchi and Kallel [21]; Mallek et al. [36]).

These challenges are particularly pronounced in Tunisia, where thermal power plants (TPPs) generate 97 % of the nation's electricity. This heavy reliance on TPPs, coupled with a 47 % dependence on imported energy, exacerbates operational inefficiencies, drives up production costs, and contributes to frequent grid disruptions—posing a serious threat to energy security and economic stability (ITA, 2023). Additionally, Tunisia's exposure to volatile global fuel prices and supply uncertainties further undermines its ability to meet growing energy demands. Although efforts to expand renewable energy are underway, progress has been slow due to financial constraints, limited technological adoption, and outdated regulatory frameworks (Mallek et al. [35,41,46]). Given these pressing challenges, a comprehensive assessment of Tunisia's TPP efficiency is essential. Identifying performance gaps and implementing targeted policies can enhance sustainability, reduce costs, and strengthen the resilience of the country's electricity sector.

Researchers have developed various methodologies, broadly classified into parametric and nonparametric approaches, to evaluate power plant efficiency. Parametric methods, such as Stochastic Frontier Analysis (SFA), estimate cost or production functions to measure efficiency [32,67]. In contrast, nonparametric methods, such as Data Envelopment Analysis (DEA), do not require predefined functional forms (Nakanishi et al., 2021; [45,69]). Unlike parametric approaches, DEA offers greater flexibility by avoiding the need for a predefined functional form, making it well-suited for modeling complex efficiency relationships. A key advantage of DEA is its ability to incorporate undesirable outputs, such as greenhouse gas emissions, enabling a more holistic assessment of operational and environmental performance, a critical consideration in the energy sector (e.g., Omri et al. (2019b); Euchi and Yassine [22]).

Despite the growing body of research on DEA-based efficiency analysis at the country level, there is a notable gap in studies explicitly addressing the performance of Tunisia's thermal power plants (TPPs). This gap highlights the need for more targeted evaluations, particularly given Tunisia's unique energy challenges. This study addresses this gap by conducting a comprehensive technical efficiency analysis of Tunisia's TPPs using the BCC-DEA model [4]. However, traditional DEA approaches have methodological limitations. One such limitation is their inability to differentiate among multiple fully efficient units, as all receive an efficiency score of one, making it challenging to rank decision-making units (DMUs). To overcome this limitation, the study employs the Super Efficiency (SE) model [3], a widely recognized approach used in numerous studies to evaluate power plant performance ([64]; Qu et al., 2024). By integrating the SE model, this study provides a more nuanced analysis, enabling the ranking of efficient DMUs and offering more profound insights into the performance of Tunisia's TPPs, thereby demonstrating the practical implications and applicability of the research.

While the Super Efficiency (SE) model enhances the ability to rank efficient units, conventional DEA approaches still face other methodological limitations that must be addressed. These limitations include sensitivity to outliers, an inability to account for statistical noise, and potential bias in efficiency scores, mainly when applied to small datasets. These challenges are further amplified in two-stage DEA methods, which often integrate Tobit regression to analyze external factors influencing efficiency. However, due to the bounded nature of efficiency scores and the correlation between explanatory variables and error terms, such methods frequently produce biased and inconsistent results [52].

Advanced methodologies have been developed to address these issues, such as the two-stage double bootstrap procedure [53]. These methods correct for bias, adjust for serial correlation and provide more reliable and robust efficiency estimates (Valiyattoor, V., & Bhandari, A. K., 2020).

This study conducts a comprehensive technical efficiency assessment of 18 thermal power plants (TPPs) in Tunisia using operational data from 2005 to 2013, addressing both operational and environmental challenges in the country's fossil fuel-dependent electricity sector. Despite the extensive application of Data Envelopment Analysis (DEA) in global power plant evaluations ([64]; Hafdhi and Euchi [26]; Qu et al., 2024), research examining Tunisia's TPPs remains limited, particularly with advanced frontier techniques. To bridge this gap, the study employs the two-stage double bootstrap DEA model [53], ensuring robust, bias-corrected efficiency estimates while overcoming methodological constraints inherent in traditional DEA approaches. Additionally, a truncated bootstrap regression is utilized to identify key performance determinants, such as plant age, size, and technology type, providing actionable insights for improving operational efficiency and guiding energy management strategies. By integrating these advanced methodologies, this research enhances the precision of efficiency assessments, contributes to evidence-based policy recommendations, and supports Tunisia's energy transition by optimizing resource allocation and strengthening the resilience of its electricity sector.

This study follows a structured approach to assessing the efficiency of Tunisia's thermal power plants. Section 2 provides a literature review, highlighting existing methodologies and identifying research gaps in power plant efficiency analysis. Section 3 outlines the research methodology, detailing the application of the two-stage DEA framework with the double bootstrap procedure for efficiency estimation and the truncated regression analysis to identify key performance determinants. Section 4 describes the dataset, including data sources, selection criteria, and key variables. Section 5 presents the empirical results, analyzing efficiency scores, performance disparities, and underlying factors influencing plant efficiency. Section 6 discusses the policy implications, offering recommendations for improving operational efficiency and supporting Tunisia's energy transition. Finally, Section 7 concludes the study by summarizing key findings and proposing future research directions.

2. Literature review

As global energy demand rises, optimizing resource allocation and enhancing power plant efficiency have become critical priorities, highlighting the need for robust performance evaluation tools. In this context, Data Envelopment Analysis (DEA) and its extensions have emerged as powerful quantitative methods for assessing efficiency across diverse energy systems. To illustrate these methodologies' evolution and growing application, Table 1 provides a comprehensive overview of selected studies, showcasing the progression and diversification of DEA approaches in evaluating power plant performance.

Numerous studies have employed traditional DEA models, such as the CCR and BCC models, to evaluate power plant efficiency. For instance, Sarica and Or (2007) assessed 65 thermal, hydro, and wind plants in Turkey, revealing that private and natural gas-fired plants outperformed public and coal-fired ones. Similarly, Shrivastava et al. [50] and Chandel et al. [10] analyzed coal-fired and state-owned thermal plants in India, identifying smaller plant sizes and excessive resource use (e.g., coal, fuel oil, and auxiliary power) as key drivers of ineffi-

Table 1
Selected research on efficiency analysis of power plants at country/ region level.

Article	Country	Power plants	Period	Methodology	
				Efficiency measurement	Second stage
Sarica and Or (2007)	Turkey	65 Thermal, Hydro, Wind	2007	CCR and BCC models	NO
Barros [5]	Portugal	25 hydroelectric	2001-2004	Malmquist DEA model and Bootstrap DEA	Tobit model
Barros & Peypoch [6]	Portugal	7 Thermoelectric	1996-2004	CCR and BCC models	Tobit model & Simar and Wilson model
Fleishman et al. [24]	USA	159 Caol and 171 Gas	1994–2004	BCC models	Tobit model
Sueyoshi et al. [56]	USA	136 coal-fired	1995–2007	CCR model and Range-Adjusted Measure model	NO
Shrivastava et al. [50]	India	60 coal-fired	2008	CCR and BCC models	NO
K. Singh & Bajpai (2013)	India	25 coal-fired	2009	CCR and BCC models	Tobit model & Simar and Wilson model
Zhao & Ma [70]	China	34 large fossil - fuel	1997-2010	CCR and BCC models and Bootstrap DEA	Simar and Wilson model
Zhang et al. [68]	China	252 fossil fuel	2010	Directional distance function model	Tobit model & Simar and Wilson model
Du and Mao [16]	China	518 coal-fired	2004-2008	Directional distance function model	Tobit model
Song et al. (2015)	China	34 coal-fired	2012	CCR and BCC models	Tobit model
Chandel et al. [10]	India	6 state-owned thermal	2009–2014	CCR and BCC models	NO
Sueyoshi et al. [57]	China	30 Fossil fuel	2005	Radial, non-radial and intermediate DEA	NO
Sahoo et al. [47]	India	69 coal fired	2009-2010	CCR and BCC models	Tobit model
Long et al. [33]	China	192 Thermal	2009–2011	Slack based Measure model	Simar and Wilson model
Wu et al. [64]	China	58 Coal fired	2015	BCC model and Super efficiency model	Tobit Model
Mahmoudi et al. [34]	Iran	24 Thermal	2019	Integrated DEA, multistage PCA, clustering and game theory	NO
Wu et al. [63]	China	528 Thermal	2009–2011	Epsilon-based measure model	Simar and Wilson model
Sueyoshi et al. [58]	China	14 Fossil fuel	2007 - 2017	Intermediate approaches, window index approach	NO
Jindal et al. (2020)	India	129 Coal-fired	2005–2014	CCR and BCC models Slacks-based measure	Simar and Wilson model
Du et al. (2021)	China	28 Fossil fuel	2005 - 2010	Direction distance model and restricted cost function	NO
Sojoodi et al. [55]	Iran	52 Thermal	2011 - 2019	Super efficiency model	NO
Nakaishi et al. (2021)	China	1270 coal-fired	2011	CCR and BCC models	Tobit regression
Zhang et al. [69]	China	91 Fossil fuel	2005 - 2015	Meta-frontier hybrid DEA model	NO
Xu et al. [65]	China	Thermal power	2014 –2019	Slacks-based measure DEA model	NO
Rahman et al. [45]	Malaysia	10 fossil fuel power plants	2015 –2017	Malmquist Total Factor Productivity	NO
Esfandiari and Saati [19]	Iran	14 Steam power plants	2015	Novel two-stage DEA models	NO
Ioannis Tsolas [61]	Greece	13 lignite-fired	2008	Super efficiency model and BCC model	Simar and Wilson model
Our study	Tunisia	18 Thermal	2005–2013	Super efficiency model and BCC model	Simar and Wilson model

ciency. However, advanced DEA models have increasingly addressed more complex analytical needs. Sueyoshi et al. [56] incorporated Range-Adjusted Measures (RAM) and intermediate approaches to study fossil fuel plants in the U.S. and China, demonstrating the positive impact of environmental regulations (e.g., the Clean Air Act) and highlighting regional disparities driven by technology and policy. Therefore, Zhang et al. [68], Du et al. (2021), and Xu et al. [65] utilized the Directional Distance Function (DDF) and Slacks-Based Measure (SBM) models to account for CO_2 emissions in China, uncovering a U-shaped regulatory effect and efficiency gains driven by innovation. Innovative approaches have further refined efficiency assessments. The Super Efficiency (SE) model ([55]; Ioannis [61]), Meta-Frontier Hybrid DEA [69], and a novel two-stage DEA with complex numbers [19] have integrated environmental, technological, and scale factors into their analyze.

A significant subset of studies utilizes second-stage regression analysis to identify the determinants of power plant efficiency following DEA. The Tobit model is commonly employed for its ability to handle censored efficiency scores. These studies highlight the primary factors driving efficiency, such as Barros [5], who attributed enhanced performance in Portuguese hydropower plants to technological innovations and optimal capacity utilization, while Fleishman et al. [24] and Du and Mao [16] focused on the importance of plant capacity, fuel quality, and CO_2 mitigation potential. However, due to the Tobit model's vulnerability to bias and serial correlation, researchers e.g., Zhao and Ma [70], Long et al. [33], and Jindal et al. (2020) have turned to the Simar and Wilson [53] double bootstrap method to improve robustness. This approach has been applied to assess factors like plant age, size, regulatory reforms, ownership, and coal quality in Chinese and Indian plants. Notable findings include the relatively small productivity gap between state-owned and independent producers [70], the adverse effects of coal consumption and regional technological disparities [33,63], and the superior performance of more extensive, privately owned plants (Jindal et al., 2020). These insights point to the critical need for technological upgrades and regional technology transfer to boost efficiency and enhance environmental performance, as further corroborated by Nakaishi et al. (2021), who identified a 19 % CO_2 reduction potential in China.

Despite extensive global applications of DEA in power plant efficiency analysis, critical limitations persist in tailoring these methodologies to Tunisia's thermal energy sector. First, while studies in countries like China, India, and the U.S. have leveraged advanced DEA frameworks (e.g., super-efficiency models, DDF, SBM) and robust second-stage regression techniques (e.g., Simar and Wilson's double bootstrap), there is a notable absence of region-specific analytical frameworks for Tunisia. Existing research fails to account for Tunisia's unique operational dynamics, such as its heavy reliance on natural gas imports, aging infrastructure, and evolving regulatory policies aimed at balancing energy security with decarbonization goals[37][40]. Second, methodological constraints in second-stage regression analyses remain underaddressed. Although the Simar and Wilson [53] bootstrap approach has been applied in other contexts to correct bias in efficiency determinants, its integration with a two-stage DEA framework—combining super-efficiency rankings for discriminating among efficient units and BCC models for variable returns to scale—has not been explored for thermal plants in developing economies, particularly those in North Africa. Third, prior studies often treat operational efficiency and environmental sustainability as isolated objectives, overlooking their synergistic optimization. For instance, while CO_2 emissions are frequently incorporated as undesirable outputs in DEA models, few analyses quantitatively link efficiency drivers (e.g., fuel quality, plant size) to emission-reduction potential in regions with limited carbon-pricing mechanisms, such as Tunisia.

These studies highlight the significance of advanced methodologies in delivering reliable insights for improving power plant efficiency and sustainability.

3. Methodology

This section outlines the methodological approach adopted in this study, which utilizes a two-stage double bootstrap Data Envelopment Analysis (DEA) to evaluate the efficiency of Tunisian thermal power plants (TPPs). Building on the framework developed by Simar and Wilson [52,53], the approach involves three key steps: first, DEA is applied to estimate technical efficiency; second, a smoothed bootstrap is used to correct for bias; and third, truncated regression is employed to analyze the impact of explanatory variables.

This method addresses several limitations of traditional DEA, such as bias arising from outliers and the censoring of efficiency scores (e.g., multiple decision-making units (DMUs) scoring 1), while mitigating serial correlation issues in standard inference methods. Unlike parametric alternatives like Stochastic Frontier Analysis (SFA), this approach does not require restrictive distributional assumptions, making it particularly well-suited for the heterogeneous operational contexts of TPPs. By providing bias-corrected efficiency estimates and precise confidence intervals, this robust non-parametric technique enhances the reliability and validity of the findings, offering a more accurate and comprehensive assessment of TPP performance in Tunisia.

3.1. Study framework

The two-stage double bootstrap DEA methodology was chosen for this study due to its ability to meet the dual objectives: (1) accurately assess the technical efficiency of Tunisia's thermal power plants (TPPs) and (2) identify key inefficiency drivers amid data constraints and operational variability. Here's why this approach is optimal:

- **Correcting Bias in Traditional DEA:** Traditional DEA methods can overestimate efficiency, especially with small sample sizes or outliers. The double bootstrap corrects this by resampling the data, providing more accurate efficiency scores and confidence intervals, which helps identify underperforming plants.
- **Improving Discrimination:** The Super-Efficiency (SE) model addresses DEA's limitation of not distinguishing among efficient units, enabling rankings above 1.0. This is crucial for identifying best practices, even among seemingly efficient plants.
- **Reliable Second-Stage Analysis:** The second stage uses truncated bootstrap regression to study inefficiency drivers, overcoming issues in traditional Tobit regression. It provides actionable insights, like the negative effect of plant age and the benefits of larger plant sizes, guiding policy recommendations.
- **Non-Parametric Flexibility:** Unlike parametric methods, DEA does not assume a specific production frontier, making it adaptable to the heterogeneous technologies and varying scales of TPPs in Tunisia.
- **Policy Alignment:** The methodology's robustness supports actionable results for policymakers, such as prioritizing modernization for inefficient plants and shifting toward baseload technologies, directly addressing the study's objectives.

This approach combines bias correction, enhanced discrimination, and robust regression, offering a comprehensive framework for improving Tunisia's energy sector and policy decisions.

Fig. 1 illustrates the study's framework, which follows a two-stage double bootstrap methodology. In the first step, decision-making units (DMUs), represented by thermal power plants, are identified, and relevant variables are selected. An isotonicity test ensures their validity by confirming monotonic relationships (e.g., positive correlations between inputs and outputs). Simultaneously, a sensitivity analysis evaluates the stability of efficiency scores under varying model assumptions (e.g., VRS vs. CRS) and variable specifications. The selected DEA model is then applied to measure efficiency. To correct for biases in these estimates, a data-generating process (DGP) based on Simar and Wilson [52] enables a smoothed bootstrap approach, approximating the asymptotic distribution of efficiency scores and enhancing accuracy.

In the second step, a truncated regression, based on Simar and Wilson [53], evaluates the influence of explanatory variables on the bias-corrected efficiency scores. This double bootstrap, two-stage approach effectively addresses challenges such as censored efficiency scores (e.g., multiple DMUs scoring 1) and serial correlation. The framework further strengthens its reliability by integrating sensitivity analysis and outlier robustness checks. Unlike standard inference methods, which are often inadequate, this enhanced double bootstrap technique delivers robust, accurate, and dependable results within the two-stage DEA framework.

The following sections provide a more detailed explanation of the modeling approach in the context of thermal power plants.

3.2. Software implementation

In this study, we utilize the FEAR 1.12 software package [53] within the R environment to conduct Data Envelopment Analysis (DEA) on 162 observations of Tunisian thermal power plants (TPPs), assessing their technical efficiency.

Following Algorithm #2 (Appendix A) of Simar and Wilson [53], we implement a double bootstrap procedure for robust estimation. In the first stage, the "dea" command in FEAR applies an input-oriented Variable Returns to Scale (VRS) DEA model to estimate TPP efficiency scores, validated through sensitivity analysis (e.g., VRS vs. CRS comparisons). To enhance accuracy, we generate 1000 bootstrap samples (up from 100) from a truncated normal distribution using the "rnorm.trunc" command, correcting biases in efficiency estimates via a smoothed bootstrap approach. In the second stage, the "trunc.reg" command performs truncated normal regression with maximum likelihood estimation (MLE), regressing bias-corrected efficiency scores on environmental variables (e.g., plant age, ownership).

A second bootstrap with 2000 replications strengthens parameter robustness, implemented with a fixed random seed (e.g., 1234) and Silverman bandwidth for reproducibility. Finally, bootstrap results construct 95 % confidence intervals, ensuring a precise and reliable evaluation of environmental impacts on TPP efficiency.

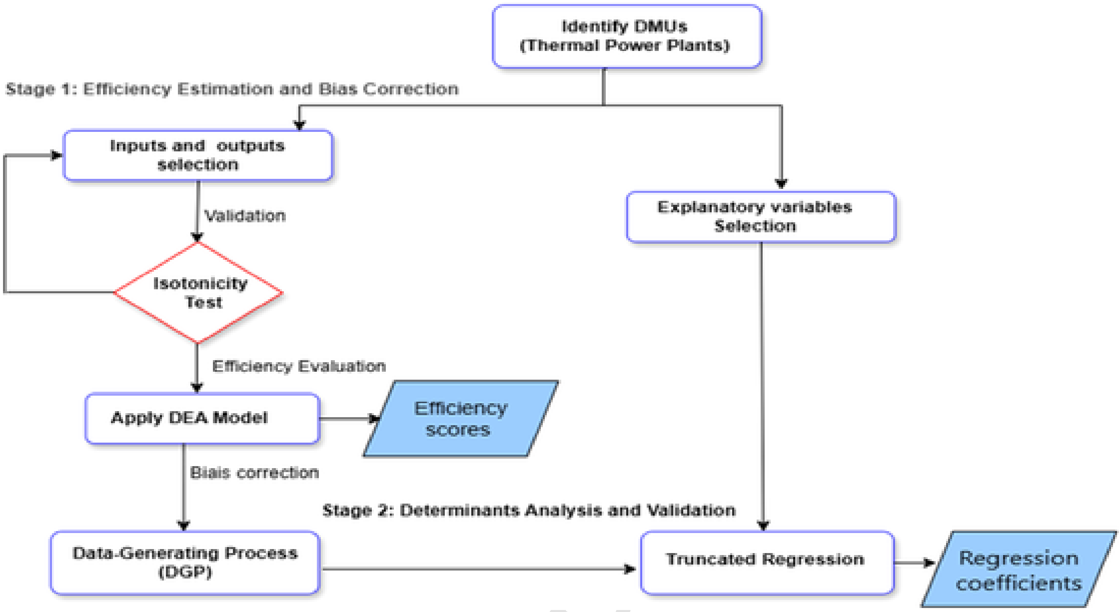

Fig. 1. Two-Stage Double Bootstrap Methodology for DEA Framework.

3.3. *DEA efficiency estimation*

This study begins by using Data Envelopment Analysis (DEA) to assess the technical efficiency of Tunisian thermal power plants (TPPs). DEA evaluates decision-making units (DMUs) by comparing them to an efficient frontier, assigning efficiency scores between 0 and 1, where a score of 1 signifies full efficiency. We adopt the BCC model [4], which incorporates variable returns to scale (VRS), making it well-suited for TPPs with diverse operational sizes. Our analysis employs an input-oriented approach, which focuses on reducing input usage while keeping output levels constant. This strategy aligns with Tunisia's goals of lowering costs and enhancing resource efficiency. The input-oriented BCC model calculates efficiency scores mathematically, identifying fully efficient TPPs with a score of 1, while scores below one highlight inefficiencies. The model is expressed as follows:

$$\begin{aligned}
&\mathrm{Min}\,\theta \\
&\text{s.t.} \\
&\sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{ij_0} \\
&\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{rj_0} \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \ge 0
\end{aligned} \tag{1}$$

Here θ represents the efficiency score, $\lambda_j$denotes the weights assigned to each DMU, $x_{ij0}$is the i^{th} input, and y_{rj0} is the r^{th} output for the DMU_{j0}under evaluation. The constraint $\sum_{j=1}^{n} \lambda_j = 1$ enforces the VRS condition, while $\lambda_j \ge 0$ ensures that all weights are non-negative. A TPPs achieves full efficiency if $\theta = 1$, values < 1 indicate inefficiency based on the input-output ratio.

To overcome the traditional DEA's limitation in distinguishing between fully efficient DMUs, we integrate the Super-Efficiency DEA (SE-DEA) model [3]. Unlike standard DEA, SE-DEA allows efficiency scores to exceed one by excluding the DMU being evaluated from its reference set. This adjustment provides a finer ranking of efficient TPPs, offering more profound insights into their relative performance. The input-oriented SE-DEA model is defined as:

$$\begin{aligned}
&\mathrm{Min}\,\theta \\
&\text{s.t.} \\
&\sum_{\substack{j=1 \\ j\neq j_0}}^{n} \lambda_j x_{ij} \le \theta x_{ij_0} \\
&\sum_{\substack{j=1 \\ j\neq j_0}}^{n} \lambda_j y_{rj} \ge y_{rj_0} \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \ge 0
\end{aligned} \tag{2}$$

In this model, the summation excludes the DMU under evaluation (denoted by $j \neq j_0$), preventing self-comparison and enabling scores above 1. By removing the evaluated DMU from its reference set, SE-DEA distinguishes between units scoring 1 in standard DEA, delivering a more precise efficiency ranking. Combining the BCC and SE-DEA models, this study provides a thorough and detailed evaluation of TPP efficiency, advancing Tunisia's energy sustainability objectives.

3.4. smoothed homogeneous bootstrapped DEA

A key drawback of traditional DEA is its vulnerability to outliers, which can skew efficiency estimates and produce unreliable results. Additionally, as a deterministic method, DEA does not account for statistical noise, potentially leading to biased outcomes [15]. To address these issues, we apply the smooth bootstrap method proposed by Simar and Wilson [51,52], which enhances the statistical reliability of DEA estimates. This technique resamples the data to mimic the data generation process (DGP), better reflecting real-world variability. By employing smooth bootstrapping, we can estimate the bias in DEA scores and construct confidence intervals, improving the robustness of our findings. Wider confidence intervals signal a higher risk of inaccurate efficiency estimates. In this study, we implement Simar and Wilson's [52] homogeneous bootstrap algorithm during the first stage to correct bias and strengthen the reliability of efficiency scores.

Echoing this, Essid et al. [20] note that while the DEA estimator is consistent, it remains prone to bias, which the bootstrap method can correct. The bias of the original estimate, $\theta$is calculated as:

$$\widehat{\text{Bias}}\left(\hat{\theta}\right) = \frac{1}{B}\sum_{b=1}^{B}\hat{\theta}^{*} - \hat{\theta} \tag{3}$$

Here$\hat{\theta}^{*}$ is the bootstrapped estimate, and $B$is the number of bootstrap iterations. While Efron and Tibshirani [18] suggest 1000 iterations for bias and standard deviation estimates, we use 2000 iterations to prioritize accurate confidence intervals. The bias-corrected efficiency score, $\tilde{\theta}$, is then computed as:

$$\tilde{\theta} = 2\hat{\theta} - \frac{1}{B}\sum_{b=1}^{B}\left(\hat{\theta}^{*}\right) \tag{4}$$

However, this correction can introduce additional noise [18], potentially increasing the standard error of $\tilde{\theta}$compared to $\hat{\theta}$Thus, we apply this adjustment only when needed. The confidence interval for the corrected estimator, at a confidence level of 1−α, is given by:

$$\left[\tilde{\theta} - z_{\alpha/2}\,.\,SE\left(\tilde{\theta}\right);\ \tilde{\theta} + z_{\alpha/2}\,.\,SE\left(\tilde{\theta}\right)\right] \tag{5}$$

In this expression, $\tilde{\theta}$is the corrected efficiency estimate, $z_{\alpha/2}$ is the critical value from the standard normal distribution for the chosen α, and $SE\left(\tilde{\theta}\right)$is the standard error of the corrected estimate. This interval indicates the likely range of the true efficiency score, accounting for bias correction and data uncertainty, with narrower intervals reflecting higher precision.

3.5. *Truncated bootstrapped regression*

In the second stage, we employ the truncated regression model of Simar and Wilson [53], specifically using Algorithm 2, to explore how explanatory variables affect efficiency levels. This analysis assumes that TPP efficiency is influenced by external environmental factors beyond their control. The regression model is formulated as:

$$\tilde{\theta}_i = \beta_0 + \beta_1 Z_i + \varepsilon_i \tag{6}$$

Here, $\tilde{\theta}_i$is the bootstrapped bias-corrected efficiency score for DMUi, Z_i is a vector of explanatory variables expected to drive efficiency variations, and βrepresents the parameters estimated to quantify these relationships. The error term $\varepsilon_i$follows a normal distribution with a mean of zero and a variance, truncated at the left tail.

We apply Algorithm 2 from Simar and Wilson [53], which uses a double bootstrap procedure to estimate the model. This method ensures bias correction and delivers more robust estimates of efficiency determinants. The detailed steps of the algorithm are outlined in Appendix A.

4. Data description

4.1. *Variables selection*

The efficiency of a power plant depends on two key variables: controllable and uncontrollable. Controllable variables, such as inputs and outputs directly managed by plant operators, are utilized in the first analysis stage to assess the technical efficiency of thermal power plants (TPPs). In contrast, uncontrollable variables, external factors beyond the operators' influence, are incorporated as explanatory variables in the second stage, offering more profound insights into drivers of inefficiency.

4.1.1. *Controllable variables*

Selecting appropriate input and output variables is essential for ensuring the robustness of a Data Envelopment Analysis (DEA). Although no universal criteria exist for variable selection, we adhere to three key principles to enhance the accuracy and relevance of our evaluation. First, we prioritize data availability to ensure reliability and consistency. Second, we consult industry experts to verify the practical relevance of the selected variables within the operational context of thermal power plants. Third, we conduct a comprehensive literature review to align our choices with established research frameworks and previous studies. The selected input and output variables are presented in Table 2, while Table 3 provides a statistical summary of the data collected from 2005 to 2013.

The significant variability in key variables, as demonstrated in Table 3, highlights the diverse operational scales, capacities, and resource utilization levels among Tunisia's thermal power plants (TPPs). This variability underscores substantial performance gaps, which are critical to understanding the efficiency landscape of the TPPs. However, for the Data Envelopment Analysis (DEA) model to accurately capture and analyze these differences, it must adhere to the fundamental assumption of isotonicity, as emphasized by Golany and Roll [25]. Isotonicity ensures that increasing inputs do not lead to decreasing outputs, which is essential for the robustness and reliability of DEA-based efficiency assessments.

The correlation matrix in Table 4 validates this assumption by revealing consistently positive and statistically significant relationships

Table 2
Inputs and outputs variable for model efficiency.

Variables	Name	Unit	Description
Output	Net Electricity generation	MWH	The total electricity generated by a power plant and delivered to the grid each year.
Labor Input	Wage	TND	The sum of all employee wages for each power plant, reflecting the human resources utilized in the production process.
Capital Input	Depreciation cost	TND	The decline in value of fixed assets due to usage in production over a given accounting period, capturing the wear and tear of equipment and infrastructure necessary for operation.
Energy Input	Fuel consumption	TEP	Fuel consumption in thermal power plants includes various fuel types, such as natural gas, gas oil (in m^3), and fuel oil (in tons), converted to ton of oil equivalent (TOP) units.

Table 3
Descriptive Statistics of inputs and outputs (18 TPPs from 2005 to 2013).

Variable	Electricity generated	Wage	Depreciation	Fuel Consumption
Mean	555,032,8	1040,059	2257,459	141,704,8
SD	807,426,3	1095,604	2694,087	192,079,1
Min	1	120,208	8832	1
Max	2 823 183	3999,670	9165,742	556,560

Table 4
Correlation Matrix of Inputs and Outputs.

	Electricity generated	Wage	Depreciation	Fuel Consumption
Electricity generated	1,0000			
Wage	0,8738**	1,0000		
Depreciation	0,8964**	0,6744**	1,0000	
Fuel Consumption	0,9970**	0,8740**	0,7851**	1,0000

Note: *$p<$,10, ** $p<$,05, All correlation coefficients are statistically significant.

between the selected inputs (e.g., fuel consumption, labor, and capital) and outputs (e.g., electricity generation). These correlations confirm that the variables are well-aligned for DEA modeling, even in the observed variability. This alignment is crucial because it ensures that the DEA model can accurately reflect the real-world dynamics of the TPPs despite their differences in scale and operational capacity.

4.1.2. Uncontrablle variables and expectations

Uncontrollable variables play a significant role in shaping DEA efficiency scores. Due to data constraints, this study examines four key uncontrollable factors: plant age, plant size, plant type, and heat rate. Below, we define these variables and discuss their expected impacts on efficiency, drawing on existing literature and theoretical insights.

a. Plant age

The age of a thermal power plant significantly impacts its operating efficiency. Newer plants generally benefit from state-of-the-art technology, improved energy efficiency, and modern maintenance strategies that enhance performance. On the other hand, older plants often face physical degradation and obsolete systems, reducing their efficiency over time. The research confirms the negative correlation between plant age and efficiency.

For instance, Sirasoontorn [54] found that older plants in Thailand's state-owned power sector exhibited significantly higher inefficiency. Similar findings were reported by Barros [5] in Portugal and, more recently, by Tsolas [61] in Greece, both highlighting inefficiencies in aging facilities. However, exceptions exist. Pollitt [43] observed that some older nuclear plants outperformed newer ones due to extensive optimization and accumulated operational experience. Jindal et al. (2020) further refined this perspective, proposing an inverted U-shaped relationship, where efficiency peaks around 22–23 years before declining sharply. Additionally, Yang and Pollitt [66] noted that new plants often undergo a "run-in" period characterized by outages and operational challenges, temporarily reducing efficiency in their early years.

b. Plant size

Plant size, typically measured by megawatts (MW) installed capacity, is crucial in determining power plant efficiency. Larger plants often benefit from economies of scale, enhancing operational efficiency through access to advanced infrastructure and superior managerial resources. Singh and Bajpai (2013) found that more extensive facilities outperform smaller ones, attributing this advantage to their excellent capabilities, while smaller plants often struggle with inconsistent management expertise. Similarly, Zhang et al. [68] identified a positive relationship between plant size and energy and carbon efficiency in Chinese fossil fuel power plants, reinforcing the benefits of scale.

However, the advantages of increased size are not without limitations. Sarica and Or (2007) noted that while economies of scale improve efficiency, they also introduce complexities in coordination, operations, and maintenance, potentially offsetting expected gains. Despite these challenges, Wu et al. [63] emphasized that larger plants contribute significant environmental benefits, particularly in reducing carbon emissions, underscoring their broader role in enhancing overall efficiency beyond purely operational metrics.

c. Plant type

Power plants are generally classified into two main types: baseload and peaking plants. Baseload plants are designed for continuous operation, providing a steady energy supply throughout the year and typically achieving higher efficiency. In contrast, peaking plants are smaller and operate intermittently, primarily during high demand or unexpected outages. Due to their irregular operation and lower utilization rates, peaking plants generally exhibit lower efficiency than baseload plants, which are optimized for sustained, long-term output.

Färe et al. [23] analyzed the technical efficiency of 100 U.S. steam plants and found that non-baseload plants (those with capacity factors below 60 %) and publicly owned plants significantly impacted overall efficiency. Their findings underscore the strong influence of plant type and operating mode on efficiency, with baseload plants consistently outperforming peaking plants due to their continuous, high-efficiency operation.

d. Heat rate

Heat rate measures the plant's efficiency in converting fuel into useful heat energy. It represents the ratio of useful heat energy output to the total energy input from the fuel. A higher heat rate indicates that the plant uses more fuel for productive heat, resulting in higher efficiency. Improving the heat rate is critical because it directly affects the plant's fuel consumption and environmental impact by reducing waste and emissions.

4.2. Data collection and sources

In Tunisia, comprehensive data on thermal power plants is limited, presenting a notable challenge for in-depth analysis. To overcome this limitation, we systematically gathered data from the Tunisian Electricity and Gas Company (STEG) annual reports and the Dispatching Office, ensuring a reliable and comprehensive dataset for this study. The final dataset encompasses 18 thermal power plants, classified into four categories: Combined Cycle, Steam Turbine, Gas Turbine TGE 9000, and Gas Turbine 20/30, as outlined in Table 5.

5. Results and discussion

This study evaluates the technical efficiency and explores the determinants of 18 Tunisian thermal power plants (TPPs) from 2005 to 2013 using the double two-stage bootstrapping methodology described in Section 3.

5.1. Technical efficiency scores

We evaluated the technical efficiency of each power plant using the BCC-DEA model, followed by the Super-Efficiency model, with results presented in Table 6. The analysis offers valuable insights into the efficiency levels of thermal power plants (TPPs). Across the sample period, the average technical efficiency score for all TPPs was 0.674, suggesting that plants could, on average, reduce input consumption by approximately 32.6 % without compromising electricity output. This result highlights substantial opportunities for efficiency improvements across the sector. A standard deviation of 0.227 further reveals significant variability in efficiency among plants, indicating that some outperform others markedly.

Table 6 also illustrates distinct efficiency differences across power generation technologies. Steam power plants demonstrated high efficiency, with an average score of 0.987. Notably, Sousse B and Rades A achieved perfect scores 1.000, reflecting optimal performance, while

Table 5
Classification of Thermal Power Plants in Tunisia by Technology.

Technologies	Thermal Power plants
Combined cycle	Rades A, Sousse B, Rades B,
Steam Turbine	Sousse C
Gas Turbine TGE 9000	Bir Mecherga, Bouchema3, Sfax Tyna, Feriana, Goulette
Gas Turbine 20/30	Ghannouch TG, Tunis Sud, Bouchema 2, Sfax Gremda, Menzel Bourg, Korba, Kasserine, Robena, Zarzis

Table 6
Original DEA efficiency scores, bias and bias-corrected efficiency scores.

TPPs/Technologies	BCC	SE	Bias Corrected	Bias	LB	UB	Ranking
RADES A	1000	1201	0804	0196	0655	0998	3
RADES B	0962	0967	0799	0163	0634	0943	4
SOUSSE B	1000	1268	0769	0231	0624	0998	1
Steam	0987	1145	0790	0197	0638	0980	
SOUSSE CC	1000	1596	0827	0173	0673	0998	2
Combined cycle	1000	1596	0827	0173	0673	0998	
BIR MCHERGA	0681	0684	0621	0061	0508	0681	7
BOUCHEMMA 3	0681	0681	0613	0068	0501	0680	8
SFAX TYNA	0881	1013	0766	0115	0619	0879	6
FERNANA	0891	1042	0769	0122	0624	0889	5
GOULETTE TG	0653	0652	0611	0042	0511	0653	9
Gas Turbine TGE9000	0757	0815	0676	0081	0553	0756	
GHANNOUCH	0531	0537	0486	0045	0398	0531	11
TUNIS SUD TG	0514	0509	0472	0042	0385	0513	12
BOUCHEMA 1/2	0485	0486	0448	0037	0373	0484	15
SFAX GREMDA	0494	0493	0474	0020	0406	0494	13
MANZEL BOUR	0461	0452	0450	0011	0395	0461	16
KORBA TG	0613	0598	0541	0072	0430	0612	10
KASSERINE	0488	0489	0466	0022	0401	0488	14
ROBENA	0435	0461	0427	0008	0383	0435	17
ZARZIS	0367	0382	0362	0005	0331	0367	18
Gas Turbine 20–30	0488	0490	0458	0029	0389	0487	
All TPPS Mean	0674	0751	0595	0080	0492	0672	
Min	0197	0276	0192	0004	0169	0197	
Max	1000	1842	0897	0280	0751	0999	
Max	0227	0357	0164	0072	0126	0225	

Rades B scored 0.962, indicating strong efficiency. Steam technology's consistently high-performance stems from its reliable, well-established design, which efficiently converts thermal energy into mechanical energy, making it ideal for stable baseload electricity production despite minor variations. Combined-cycle plants similarly excelled, with Sousse C achieving a perfect score of 1.000. This underscores the technology’s effectiveness in optimizing input utilization and maximizing output. Combined-cycle plants enhance fuel efficiency and minimize energy losses by recovering waste heat from gas turbines to drive a steam turbine, positioning them among the most efficient power generation methods.

In contrast, gas turbines exhibited lower efficiency levels. The TGE9000 gas turbine plants recorded efficiencies ranging from 0.653 to 0.891, with Sfax Tyna (0.881) and Fernana (0.891) showing moderate performance. Gas turbine plants in the 20–30 category, primarily deployed for peak demand with lower load factors, averaged an efficiency of 0.488, with Zarzis posting the lowest score of 0.367. These results emphasize the urgent need for technological upgrades. The reduced efficiency of gas turbines, even in baseload operation, stems from their inherently lower fuel efficiency, particularly in the 20–30 technology class. This inefficiency markedly impairs their overall performance, underscoring the necessity for advancements to enhance competitiveness and narrow the efficiency gap with steam and combined cycle technologies.

Fig. 2 depicts the distribution of bias-corrected efficiency scores for 162 Tunisian thermal power plants (TPPs), calculated in the first stage of the double bootstrap DEA methodology using FEAR 1.12 in R [52]. The histogram displays efficiency scores ranging from 0 to 1, with a smoothed bootstrap (1000 iterations) refining initial estimates from the input-oriented Variable Returns to Scale (VRS) DEA model. A notable cluster of TPPs achieves scores close to 1, indicating optimal resource utilization. In contrast, lower scores (e.g., <0.7) in older plants reflect physical degradation, such as material wear and increased fuel consumption due to diminished heat transfer efficiency. Robustness is confirmed through sensitivity analysis (VRS vs. CRS) and outlier removal (excluding decision-making units and DMUs, with input-output ratios exceeding two standard deviations), reinforcing the reliability of these findings for pinpointing underperforming plants.

Since numerous plants achieved a perfect efficiency score of 1.0 in the BCC-DEA model, distinguishing their relative performance became challenging. To overcome this limitation, we employed the Super-Efficiency (SE) model, which enables further differentiation and ranking of plants at the efficiency frontier. Table 6 highlights key differences between SE and BCC efficiency scores. The SE model yields a more favorable average score of 0.751, compared to 0.674 for the BCC model. Sousse B, the top performer, recorded an SE score of 1.596 substantially exceeding its BCC score of 1.000—securing its first-place ranking. In contrast, Zarzis, the least efficient plant, showed marginal improvement with an SE score of 0.382 versus 0.367 in the BCC model yet remained notably inefficient.

We conducted nonparametric tests to assess the consistency between the two DEA models: the Spearman correlation test (Table 7) and the Wilcoxon Signed-Rank Test (Table 8). Despite potential infeasibility issues in the SE model, it produced reliable results. The Spearman correlation coefficient of 0.988 (significant at the 0.01 level, $p = 0.000$) indicates strong agreement in rankings between the SE-DEA and BCC models. However, the Wilcoxon Signed-Rank Test ($Z = -5.635$, $p = 0.000$) reveals significant differences in the distribution of efficiency scores, suggesting that while rankings align closely, the SE model tends to generate higher scores. These findings confirm that both

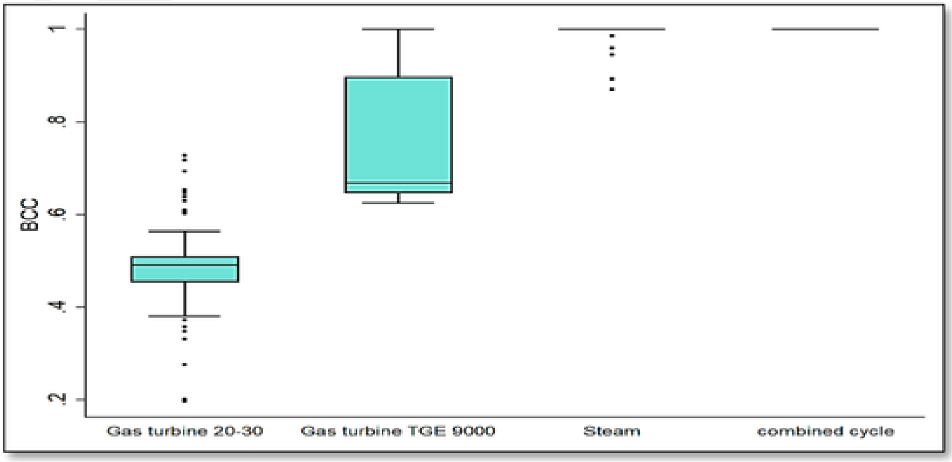

Fig. 2. Comparison of BCC Efficiency Scores Across Technologies.

Table 7
Spearman Correlation test results.

	DEA-BCC	SE-DEA
DEA-BCC		
Coefficient of Correlation	1.000	0.988**
Sig.	-	0.000
N	162	162
SE-DEA		
Coefficient of Correlation	0.988**	1.000
Sig. (2-tailed)	0.000	-
N	162	162

** The correlation is significant at the 0.01 level.

Table 8
Wilcoxon Signed-Rank Test.

Comparison	N	Mean Rank	Sum of Ranks
SE-BCC < BCC (Negative Ranks)	7	11.29	79.00
SE-BCC > BCC (Positive Ranks)	46	29.39	1352.00
SE- BCC= BCC (Ties)	109	-	
Total	162		
Z-Value			−5.635
Asymptotic Sig. (2-tailed)			0.000

models rank thermal power plants effectively, though the SE model provides a nuanced perspective by amplifying score disparities.

5.2. Smooth bootstrap results

As outlined in Section 3, bias-corrected energy efficiency scores and their 95 % bootstrap confidence intervals were computed using 2000 bootstrap samples to enhance the accuracy of efficiency estimates. Table 6 juxtaposes the original technical efficiency scores with their bias-corrected counterparts, presented in the fourth column. The average bias-corrected technical efficiency score was 0.595, implying that Tunisian thermal power plants (TPPs) could reduce input consumption by 40.5 % while sustaining current output levels operating at full efficiency. This discrepancy between bias-corrected and original scores underscores the limitations of the traditional DEA model, which overlooks data variability in efficiency estimates. Though the average difference appears modest, it significantly altered plant rankings. For instance, Sousse B and Sousse CC were initially assigned perfect BCC scores of 1.0, which declined to 0.769 and 0.827, respectively, after bias correction. Similarly, Rades A dropped from 1.0 to 0.804. No plant retained a perfect efficiency score post-correction, suggesting that the traditional DEA model may overestimate performance.

A nonparametric Kruskal-Wallis test was conducted to evaluate whether TPP rankings varied according to the DEA model. With a p-value < 0.01, the test confirmed a highly significant difference in rankings across models. This finding emphasizes the critical role of bias correction in delivering a more realistic assessment of TPP efficiency, highlighting that reliance on traditional DEA alone risks obscuring key performance disparities.

Fig. 3 compares Tunisian thermal power plants' average technical efficiency scores (TPPs) from 2005 to 2013, derived from the standard DEA model and bias-corrected estimates. The scores were nearly identical, but a divergence emerged in 2006, with the DEA model consistently overestimating efficiency relative to the bias-corrected scores. The DEA scores peaked at 0.702 in 2008, while the bias-corrected scores remained more conservative at 0.695. Post-2008, both models reflected a decline, with bias-corrected scores dropping to a low in 2011, likely influenced by the Tunisian revolution. By 2013, both exhibited recovery, though the gap persisted, underscoring the DEA model's tendency to inflate efficiency estimates.

Building on these findings, Table 9 reports bias-corrected efficiency scores across different TPP technologies. Combined cycle and steam technologies achieved the highest average scores of 0.827 and 0.790, respectively, with 17.3 % and 21 % improvement potentials. In contrast, gas turbine technologies exhibited markedly lower performance. The TGE9000 gas turbine group averaged 0.676, requiring a 32.4 % enhancement, while the Gas Turbine 20–30 group recorded the lowest score of 0.458, indicating a substantial 54.2 % improvement needed to attain full efficiency.

To further illustrate the variability in efficiency scores, Fig. 4 illustrates the lower and upper bounds of technical efficiency for each Tunisian thermal power plant (TPP) derived from 2000 bootstrap samples. TPPs with lower efficiency scores exhibited narrower gaps between bounds (minimum gap: 0.005), reflecting limited performance variability. In contrast, highly efficient TPPs showed wider gaps (maximum gap: 0.333), indicating more significant variability. This range highlights the necessity of accounting for variability in DEA assessments to yield more robust and reliable efficiency estimates, ensuring rankings reflect actual performance while addressing uncertainty.

5.3. Determinants of inefficiency

We investigate the factors influencing technical inefficiency in Tunisian thermal power plants using the bootstrapped truncated regres-

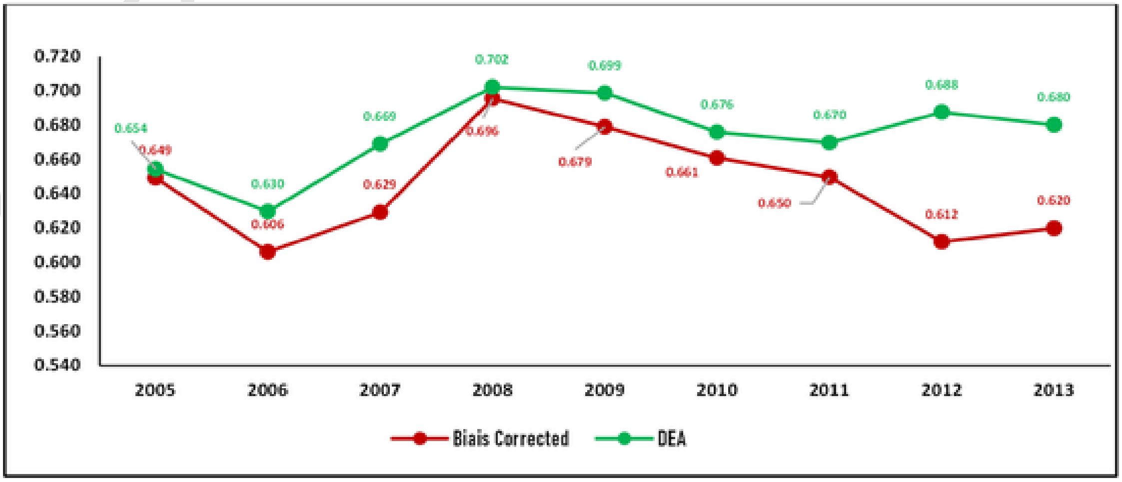

Fig. 3. Comparison of Average DEA and Bias-Corrected Efficiency Scores.

Table 9
Average Bias-Corrected Efficiency Scores Based on Technologies of TPPs.

Technologies groups	Mean	[95 % Conf, Interval]		Improvement
Combined cycle	0.827	0673	0998	17.3 %
Steam	0.790	0638	0980	21 %
Gas Turbine TGE9000	0.676	0553	0756	32.4 %
Gas Turbine 20–30	0.458	0389	0487	54.2 %

sion approach developed by Simar and Wilson [53]. The selection of determinants is guided by the existing literature and centers on the plants' technical characteristics, including age, size, operational type (baseload or peaking), and heat rate. Table 10 provides definitions of these variables and their expected directional impacts. The regression results are reported in Table 11, with the econometric model specified in Eq. (7).

$$\widehat{\widehat{\theta}} = \alpha_0 + \alpha_1 PlantAge_i + \alpha_2 Plant\text{Type}_i + \alpha_3 PlantSize_i + \alpha_4 Heatrate_i + \varepsilon_i; \quad (7)$$
$$powerplanti\ :\ 1\ldots18$$

The results in Table 11 present the determinants of technical efficiency in Tunisian thermal power plants using the Tobit model and Simar and Wilson algorithms (1 and 2). The coefficient for Plant Age is positive in both the Tobit model (0.0019) and Simar and Wilson Algorithm 1 (0.0020), suggesting that their efficiency slightly improves as plants age. However, in Simar and Wilson Algorithm 2, the coefficient is negative (−0.0026), indicating a slight decrease in efficiency as plants age. The effects are minor in all models, with no indication of statistical significance due to the lack of significance markers. For Plant Size, the Tobit model (0.2441) and Algorithm 1 (0.2529) show a positive and relatively strong effect on technical efficiency, implying that larger plants tend to be more efficient. In Algorithm 2, however, the coefficient is much smaller (0.0013), indicating a negligible positive effect that is likely not significant.

The impact of Plant Type (baseload or peaking) varies across the models. The coefficients in the Tobit model (−0.0010) and Algorithm 1 (−0.0011) are negative, suggesting that peaking plants may have slightly lower efficiency than baseload plants. In contrast, Algorithm 2 shows a significant adverse effect (−0.2994), suggesting that peaking plants are associated with much lower efficiency in this model. For Rendement (heat rate), all three models consistently show a negative relationship with efficiency, with coefficients around −0.0078 to −0.0080. This result indicates that plants with higher heat rates (meaning less fuel efficiency) tend to have lower overall technical efficiency. Given the consistency across the models, the results appear statistically significant. Finally, the constant term is positive and significant in all models, representing the baseline level of technical efficiency for the plants in the study.

6. Policy implication

This study provides key insights into enhancing the efficiency of Tunisian thermal power plants through a comparative analysis of technological performance, offering several policy recommendations for the national energy sector.

First, the findings highlight the superior efficiency of combined cycle plants and steam turbines compared to older gas turbine technologies. Combined cycle plants, which integrate gas and steam turbines to recover waste heat, optimize fuel utilization and reduce greenhouse gas emissions. In contrast, older gas turbines operate on a single-cycle process without heat recovery, leading to lower thermal efficiency and higher operational costs. This technological disparity underscores the need for a gradual phase-out of outdated power generation methods in Tunisia’s energy mix.

Second, the analysis demonstrates that plant age and size significantly impact efficiency. Larger and newer facilities, such as SOUSSE B and RADES A, benefit from modern engineering advancements and economies of scale, allowing for optimized fuel use and improved thermal performance. Conversely, smaller and older plants, such as ZARZIS, ROBBANA, and GOULETTE TG, face operational inefficiencies due to aging infrastructure and technological limitations. To address these disparities, targeted interventions are required, including government-supported modernization initiatives and technical assistance programs. Retrofitting inefficient plants with combined cycle or steam turbine technologies can enhance performance, while comprehensive training programs for operators can facilitate the adoption of advanced energy systems.

A deeper analysis of the observed efficiency trends suggests that the physical reasoning behind these variations lies in thermodynamic principles governing power plant operations. Combined cycle plants achieve higher efficiency through the Brayton-Rankine cycle integration, where waste heat from the gas turbine is repurposed to drive a steam turbine, maximizing energy extraction. Older gas turbines, operating solely on the Brayton cycle, suffer from significant heat losses and suboptimal fuel combustion, leading to reduced energy conversion efficiency. Additionally, plant aging leads to mechanical wear, reduced combustion precision, and higher maintenance requirements, all of which contribute to declining operational efficiency. These physical factors explain the performance gaps observed in the efficiency graphs, providing a foundation for policy-driven technical improvements.

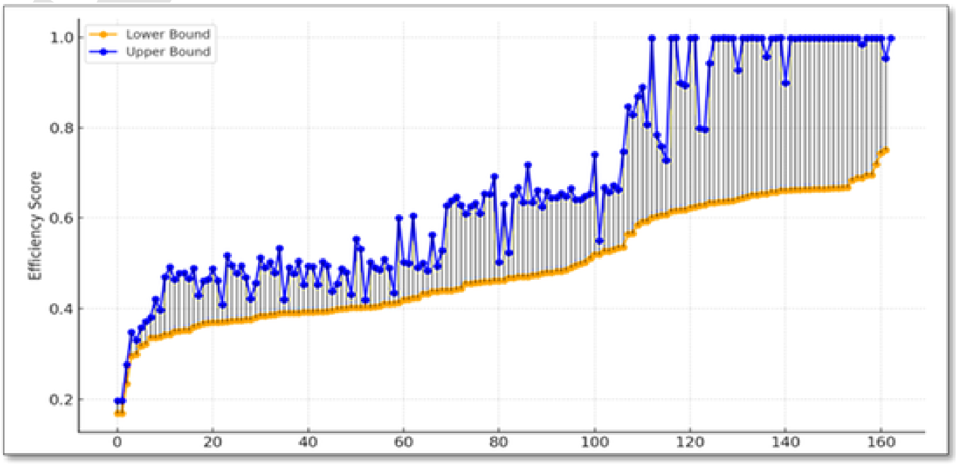

Fig. 4. Lower and upper bounds of technical efficiency for each TPPs.

Table 10
Descriptive of determinants variables.

Efficiency determinants	Variable type	measurement	Expected sign
Plant age	Value	Weighted average plant age	Positive/negative
Plant type	Dummy	1 = base-load plants 0 = peaking plants	Negative
Plant Size	Value	Installed capacity (MW)	Negative
State energy subsidy	Value	Amount of state subsidy (in currency)	Negative
Heating Performance	Value	Efficiency ratio (useful heat/total energy input %)	Positive

Table 11
Combined Results: Tobit, Simar & Wilson Algorithms (1&2).

	Tobit model		Simar and Wilson algorithm 1		Simar and Wilson algorithm 2	
Variables	*Observed Coef.*	*Std. Err*	*Observed Coef.*	*Std. Err*	*Observed Coef.*	*Std. Err*
Plant Age	0.0019	0.0016	0.0020	0.0016	−0.0026	0.0017
Plant size	0.2441	0.1000	0.2529	0.1032	0.0013	0.0009
Plant Type	−0.0010	0.0007	−0.0011	0.0008	−0.2994	0.1220
Rendement	−0.0078	0.0035	−0.0079	0.0035	−0.0080	0.0050
Consant	0.7354	0.0845	0.7395	0.0886	0.7976	0.1247

Notes: Significant at: ***, **, and * denote 1 %, 5 %, and 10 %, respectively. Total number of iterations = 2.000.

Finally, long-term improvements in Tunisia's thermal power sector require a comprehensive strategy. Policymakers should prioritize plant modernization through financial incentives, such as tax breaks, subsidies, or low-interest loans, to facilitate investment in energy-efficient technologies. Establishing mandatory efficiency benchmarks tailored to different plant types (e.g., combined cycle, steam, and gas turbines) can promote industry-wide improvements. Enforcing compliance through regulatory mechanisms, including penalties for underperforming plants, would ensure alignment with Tunisia's energy and environmental goals. By integrating these policy measures with broader sustainability objectives—such as reducing carbon emissions and enhancing energy security—Tunisia can achieve a more resilient and efficient electricity sector.

7. Conclusion

This research examined the operational efficiency of 18 thermal power plants in Tunisia using a two-stage DEA method enhanced with a double bootstrap approach. This method corrects for statistical bias, offering a clearer and more realistic picture of performance levels across different technologies and plant sizes. The results show that many Tunisian TPPs are underperforming, with efficiency scores suggesting considerable room for input reduction without compromising output.

From a managerial standpoint, the findings carry several actionable implications. First, the wide efficiency gap between newer, larger facilities and older, smaller plants suggests that plant managers and policymakers should consider targeted investments in modernization. By benchmarking against the most efficient plants, such as SOUSSE B or RADES A, managers can better identify specific areas where performance can be improved, whether through equipment upgrades, better maintenance routines, or operational process refinement.

The data also shows that larger power plants tend to be more efficient, likely due to scale advantages. For energy planners and utility executives, this supports the case for consolidating older, small-scale facilities into larger regional units. This move could help reduce fuel consumption, lower production costs, and improve grid reliability. From a management perspective, this transition would require careful planning, including risk assessments, resource reallocation, and community engagement.

Another key insight relates to plant aging and its negative effect on performance. For asset managers, this highlights the importance of long-term maintenance strategies and phased equipment replacement. Rather than reacting to breakdowns, plant leaders should adopt a more proactive maintenance schedule, especially for facilities built before 1990.

Furthermore, the consistent link between poor heat rate performance and low efficiency provides engineers and operations teams with a valuable performance indicator. Monitoring this metric closely can help guide decisions around combustion tuning, process optimization, and fuel management.

Looking beyond operations, the study also contributes to national policy objectives. Efficiency improvements in TPPs could help Tunisia meet its environmental commitments, especially if linked to mechanisms like emissions trading or carbon pricing. For managers, this means developing internal systems for tracking energy use, emissions, and performance trends. Digital tools and real-time monitoring systems would be valuable in this context and could become standard practice across the sector.

Finally, as plants shift toward more modern and automated systems, workforce readiness becomes crucial. Managers must anticipate the skills needed in a more technology-driven environment. Designing retraining programs and encouraging continuous learning can help smooth the transition, particularly in regions where the energy sector is a key employer.

In sum, this study not only reveals technical inefficiencies but also provides clear guidance for managers and decision-makers. The results can support smarter investments, more effective resource management, and better alignment between plant-level actions and national energy goals. Future research should explore how managerial capabilities, governance practices, and employee engagement influence operational performance in Tunisia's evolving energy landscape.

Uncited references

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CRediT authorship contribution statement

Mariam BELGAROUI: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Jalel EUCHI:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Conceptualization. **Olfa KAMMOUN:** Writing – review & editing, Resources, Project administration, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Algorithm 2 of [53]

1. Estimate the technical efficiency scores, θ_j, for all TPPs in the sample using input-oriented DEA model with VRS technology.

2. Preform a truncated maximum likelihood estimation to regress technical efficiency scores against a set of explanatory variablesZ_j, modeled as $\theta_j = Z_j\beta + \varepsilon_j$, where β is the coefficient vector and ε_j represent the residual errors. From this, estimate$\widehat{\beta}$, the coefficient vector, and $\widehat{\sigma_\varepsilon}$, the standard deviation of the residuals.

3. For each TPP, ($j = 1, \ldots ...., N$), repeat the following four steps (3.1–3.4) t_1 times to obtain a set of t_1 bootstrap estimates $\widehat{\theta_{jz}}$for $z = 1, \ldots ...., Z_1$.

3.1 Generate the residual error, ε_j, from the normal distribution $N\left(0, \widehat{\sigma_\varepsilon^2}\right)$.

3.2 Compute $\theta_j^* = Z_j\widehat{\beta} + \beta$.

3.3 Create a pseudo data set $\left(x_j^*, y_j^*\right)$where $y_j^* = y_j\left(\frac{\theta_j}{\theta_j^*}\right)$.

3.4 Using the pseudo data set $\left(x_j^*, y_j^*\right)$apply the DEA with VRS to calculate the pseudo efficiency estimates $\widehat{\theta}_J^*$.

4. Obtain the bias-corrected estimator, $\widehat{\theta}_j$, for each TTP$_\mathrm{j}$ by using the bootstrap estimator or the bias$\widehat{z}_j$, where $\widehat{\theta}_j = \theta_j - \widehat{z}_j$ and $\widehat{z}_j = \left(\frac{1}{Z_1}\sum_z^{z_1}\widehat{\theta}_{Jz}^*\right) - \theta_j$.

5. Reapply the truncated maximum likelihood estimation to regress$\widehat{\theta}_j$ on the explanatory variables zj, and yielding update estimate $\widehat{\beta}^*$for $\beta$and an estimate $\widehat{\sigma}^*$for σ_ε.

6. Repeat the following steps (6.1–6.3) t_2 times to obtain a set of t_2 pairs of bootstrap estimates $(\widehat{\beta}_j^{**}, \widehat{\sigma}_j^{**})$for $z = 1, \ldots ...., Z2$.

6.1 Generate residual error ε_j from the normal distribution $N\left(0, \widehat{\sigma_\varepsilon^2}\right)$.

6.2 Calculate$\widehat{\theta}_j^{**} = Z_j\widehat{\beta}^* + \varepsilon_j$.

6.3 Perform the truncated maximum likelihood estimation to regress $\widehat{\theta}_j^{**}$on the explanatory variables, Zj, and provide an estimate $\widehat{\beta}_j^{**}$for β and an estimate$\widehat{\sigma}^{**}$ for σ_ε.

7. Construct the estimated $(1-\alpha)\,\%$ confidence interval of the n-th element,β_n of the vector β.

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