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A Decision Framework for Public-Private Partnership Selection in Sustainable Energy: Integration AROMAN and C5.0 Algorithm

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ABSTRACT

Public-private partnership (PPP) projects are a special form of project finance. The United Nations has supported PPP to be used as a tool for sustainable development, especially in emerging countries. Türkiye has an advantageous location for the generation of renewable energy. Sustainable energy investments ensure that the energy demand, which increases with population growth, is met more economically without harming nature. The aim of this study is twofold: First, to evaluate and rank past PPP electric generation projects in Türkiye based on seven decision criteria to identify which models have performed better under specific conditions. Second, leveraging these performance insights, to design a predictive decision-making model that will help public authorities and investors classify and select suitable PPP models for future projects. This study integrates Alternative Ranking Method by Computing Two-Step Normalization (AROMAN) for performance ranking and the C5.0 decision tree algorithm for classification, a novel approach for providing a holistic decision framework. The analysis reveals that while investment preferences lean towards sustainable technologies like wind and hydro, the highest-ranked projects have often been non-renewable, highlighting a critical governance challenge between ensuring financial bankability and achieving sustainability goals. In sustainable technology preferences, the focus was on wind energy and hydropower plants. Build, own, and operate (BOO), and build, rehabilitate, operate, and transfer (BROT) models were prominent in wind energy. In hydro energy, the highest intensities were the build, operate, transfer (BOT), Merchant, BROT, and BOO models, respectively. The study provides detailed deductions for project ranking and classification rules to guide future PPP structuring.

1. INTRODUCTION

Rising energy demand is a key indicator of economic development, creating significant challenges and opportunities for countries worldwide. Strategically situated at a crossroads between energy-rich regions and large consumer markets, Türkiye faces a constantly increasing energy need. To meet this demand sustainably and securely, Türkiye is increasingly prioritizing electricity generation projects, particularly focusing on harnessing its significant renewable energy potential. However, the scale of investment required for such infrastructure projects often exceeds the capacity of the public sector, necessitating innovative financing and operating models.

Project finance is an arrangement whereby a sponsor or group of sponsors incorporates a project as a legally separate entity, with project cash flow kept segregated for financing purposes from its sponsors [1]. Project finance provides a structure for off-balance-sheet financing of large-scale projects where the project's cash flow is the primary source of repayment. public-private partnerships (PPP) are a particular and widely adopted form of project finance. Following the UK's Private Finance Initiative (PFI) in 1992, PPPs have become a global instrument for the delivery of public services through long-term concession agreements between government and private organizations [2]. Recognizing their potential, the United Nations has supported PPPs as a mechanism for achieving the 2030 Sustainable Development Agenda, particularly in mobilizing private sector capital and expertise [3].

This study focuses on four commonly used PPP models in the energy sector: build, operate, transfer (BOT), build, own, and operate (BOO), and Merchant models, which are considered greenfield projects, while build, rehabilitate, operate, and transfer (BROT) is a brownfield model. Each model allocates risks and responsibilities differently. For example, in BOT, the private sector builds and operates a facility, then transfers it to the state, and the financial risk generally remains in the public sector. BOT is the first and most widely used PPP model in the energy sector in Türkiye. In contrast, the BOO model keeps ownership indefinitely with the private entity, while the Merchant model exposes the private sector to full market risk without a government revenue guarantee [4, 5].

Türkiye serves as an analytically important case study for several reasons. First, it has a long and diverse history of PPPs, having implemented the BOT model under Law No. 3096 in 1984. Second, the energy market was liberalized in 2001, creating a dynamic environment for private and foreign investment. Third, the country's rapidly increasing energy demand necessitates continuous new projects, making the selection of the right PPP model a critical policy issue. Finally, the existence of a strong drive towards renewable energy alongside reliance on fossil fuels creates a complex governance environment where sustainability, economic efficiency, and energy security are constantly being negotiated. This context makes Türkiye an ideal case study for analyzing how different PPP models perform and what factors drive their selection.

The existing literature on this subject can be broadly divided into three streams. The first stream focuses on PPP management and evaluation, investigating critical success factors, risk allocation, and the impact of PPPs on economic and environmental outcomes [6, 7]. The second stream focuses on the evaluation of sustainable energy projects, often using Multi-Criteria Decision Making (MCDM) techniques to rank renewable and non-renewable technologies or identify barriers to their adoption in developing countries [8-12]. These studies have used methods such as TOPSIS and fuzzy MCDM to prioritize energy sources and select sustainable project locations [13-15]. The third stream applies machine learning and intelligent algorithms to predict energy production and manage resources, demonstrating the potential of data-driven approaches in the sector [16, 17]. However, there are few studies that bridge these streams by integrating the performance evaluation of past PPP projects with a predictive model for future model selection.

This study aims to address this gap by developing a two-stage decision framework. First, it uses the Alternative Ranking Method by Computing Two-Step Normalization (AROMAN) MCDM method to rank the performance of 127 electricity generation PPP projects in Türkiye and identify the characteristics of successful models. Second, it uses the C5.0 decision tree algorithm to construct a classification model based on these findings.

The key contribution of this research is not only the novel integration of these two methods but also the tangible management insights this integration generates for the Turkish electricity sector. By combining a retrospective performance evaluation (AROMAN) with a prospective classification tool (C5.0), this study offers a data-driven framework that helps answer a critical management question: Under a given economic, political, and technical context, which PPP model is most likely to succeed and should therefore be chosen? The resulting decision tree serves as a practical, rule-based guide for policymakers and investors, transforming complex historical data into actionable recommendations for structuring future sustainable energy projects. This integrated approach fills a significant gap by moving beyond theoretical evaluation to offer a concrete decision-support system for PPP selection in Türkiye's energy sector.

2. METHODOLOGY

2.1 Data

An analysis was conducted for Türkiye for the period 1995-2023. This study examines four types of PPP models: (1) BOT, (2) BOO, (3) Merchant, and (4) BROT. The primary dataset consists of 127 PPP energy generation projects in Türkiye obtained from the World Bank's Private Participation in Infrastructure (PPI) database [18]. Only projects with accessible and complete information regarding the selected criteria were included. To construct the decision matrix, project-level data from the PPI database were combined with annual country-level indicators. The combination was performed by matching the country-level data for the specific year in which each project reached its financial close as recorded in the PPI database. This ensures that the macroeconomic and governance context at the time the investment decision was made is accurately captured for each project. The seven variables (criteria) used in the analysis are detailed in Table 1.

Table 1. Characteristics of variables

Variable	Definition	Data Source	Category
V1: CO_2 Emission	Per capita CO_2 emissions (Metric tonnes)	World Bank, World Development Indicators (WDI)	Sustainability
V2: Inflation GDP Deflator	(Annual%)	World Bank, World Development Indicators (WDI)	Economic
V3: Political Risk	Index score (0-1), categorized as High-Medium-Low	Political Risk Services (PRS) Group, ICRG	Government
V4: Regulatory Quality	Index score (0-1), categorized as High-Medium-Low	Political Risk Services (PRS) Group, ICRG	Government
V5: International Sponsor	Binary variable (1-Available, 0-Absent)	World Bank PPI Database	Technical
V6: Total Investment	Millions of US Dollars	World Bank PPI Database	Economic
V7: Capacity	Planned energy generation in MW	World Bank PPI Database	Technical

Note: Types of PPP Models: BOO, BROT, BOT, Merchant.

The selection of these seven variables is based on established literature on project finance and PPP evaluation. They were chosen to provide a comprehensive view through all four critical dimensions:

- Sustainability (V1): CO_2 emissions are a direct indicator of a project's environmental impact, which is the central theme of this study. It is expected to have a negative correlation since good performance of PPPs in sustainable energy projects should lead to reduced emissions.
- Economic (V2, V6): Inflation and Total Investment are key indicators of economic viability and risk. High inflation affects project costs and revenue streams, while investment size determines financial structuring and risk appetite, influencing the choice between models such as BOT (typically for very large projects) and Merchant.
- Government (V3, V4): Political Risk and Regulatory

Quality are crucial for long-term contracts such as PPPs. These factors, taken from the highly respected ICRG, measure the stability and predictability of the government framework, directly impacting investor confidence and the allocation of risk between public and private partners. Calculated index points were used for each year in the analysis. In the analysis, the 0-0.50 range was described as low, the 0.51-0.79 range was determined as medium, and the 0.80-1 range was determined as high.

- Technical (V5, V7): Having an international sponsor would indicate access to better technology and finances as well as technical know-how. One of the main technical indicators for a power plant is its Capacity (MW), which shows the scale of the plant and its function in the country's national grid.

Together, these criteria form a comprehensive set of indicators for evaluating the performance and contextual factors of PPP projects in the energy sector.

2.2 Model of the study

The study employs a two-stage model as illustrated in Figure 1. First, AROMAN is used to rank project performance. Second, the C5.0 algorithm is used to build a classification model.

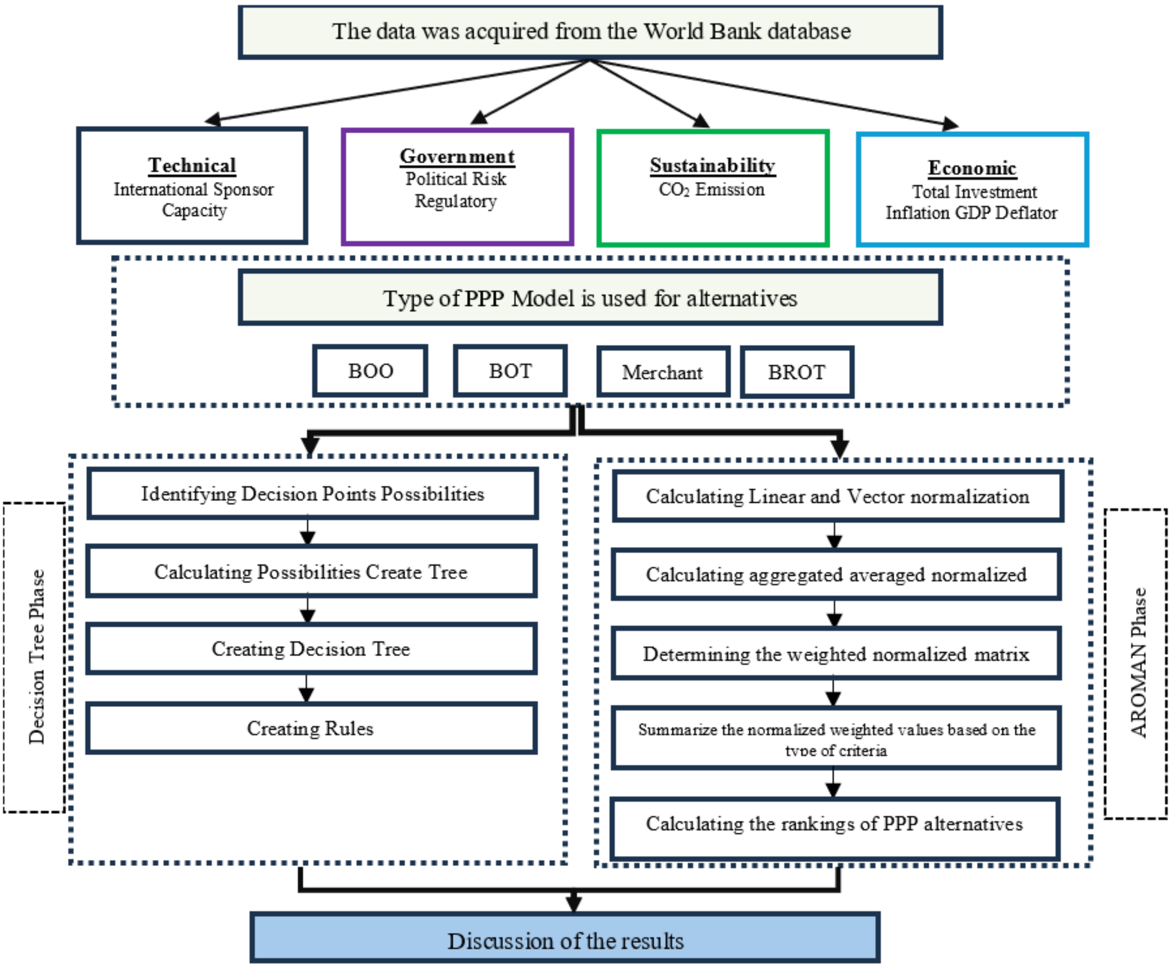

Figure 1. Model design process

AROMAN was chosen for the performance ranking phase for two specific reasons that are important for this study. First, its dual normalization process (combining linear and vector normalization) is particularly robust for handling decision matrices with criteria measured on very different scales, such as V6: Total Investment (million dollars) and V3: Political Risk (an index value between 0-1). This ensures that the outcome is not disproportionately affected by the scale of a single criterion [19, 20]. Second, it achieves this robust ranking with fewer computational steps compared to some other MCDM methods, making it an efficient tool for analyzing the 127 projects in our dataset [21].

Upon examining the latest literature, AROMAN has been effectively applied to rank various options, demonstrating its versatility across different domains, such as evaluating digital economic development [22], and assessing countries based on the macroeconomic performance indicators [23]. Table 2 outlines the procedure of the AROMAN method:

As shown in Table 2, before starting the decision-making process, a decision matrix should be created using existing input data. The second stage of the method involves normalizing the input data. During this stage, the data are scaled to a range from 0 to 1 to ensure comparability. Normalization is performed using two different methods: first, linear normalization, and then, vector-based normalization. After the normalization process, which is performed in two stages, the total average normalized matrix (t_{ij}^{norm}) values are calculated using Eq. (3). Here, t_{ij}^{norm} represents the combined and averaged normalized matrix, and the parameter β represents a weighting factor varying between 0 and 1. Multiplying each element in the total average normalized decision matrix by the corresponding weight values results in the creation of the weighted decision matrix. In the fifth step, the weighted normalized values for benefit and cost criteria are gathered using Eq. (5). The λ parameter in the formula indicates the degree of influence of the criterion type.

Table 2. Procedure of the AROMAN method

Step	Equation	
Step 1. Building the decision matrix	$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}$	(1)
Step 2: Normalization		
a) Linear normalization	$t_{ij} = \dfrac{x_{ij} - x_{ij}^{min}}{x_{ij}^{max} - x_{ij}^{min}} \quad if\ j \in B$ $t_{ij} = \dfrac{x_{ij}^{max} - x_{ij}}{x_{ij}^{max} - x_{ij}^{min}} \quad if\ j \in C$ *B represents benefit; C represents cost criteria.	(2)
b) Vector normalization	$t_{ij}^{*} = \dfrac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}}$	(3)
Step 3. Aggregating the normalized matrices	$t_{ij}^{norm} = \dfrac{\beta t_{ij} + (1-\beta) t_{ij}^{*}}{2}$	(4)
Step 4. Calculating the weighted averaged normalized matrix	$t_{ij}^{\wedge} = w_{ij} \cdot t_{ij}^{norm}$ $^{**}\beta$ is a weighting factor varying from 0 to 1.	(5)
Step 5. Summarizing the weighted normalized values based on the criteria type	$A_i = \sum_{j=1}^{n} t_{ij}^{max}$ $L_i = \sum_{j=1}^{n} t_{ij}^{min}$	(6)
Step 6. Calculating the final rankings	$R_i = L_i^{\lambda} \cdot A_i^{(1-\lambda)}$ $^{***}\lambda$ represents the coefficient degree of the criterion type between 0-1.	(7)

For the classification phase, the C5.0 algorithm was preferred over other decision tree algorithms due to its ability to generate clear, intuitive, and human-readable "if-then" rule sets. One of the main aims of this study is to create a practical decision support framework for policymakers who are not data scientists. C5.0 excels in this area by generating a transparent model that clearly shows which criteria (e.g., Capacity > 775 MW and Foreign Investor = Yes) lead to the selection of a particular PPP model (e.g., BOT). This interpretability is critical for translating analytical results into actionable management policy [24]. The formulation of the C5.0 algorithm is based on certain mathematical principles used in the process of constructing decision trees. The algorithm uses measures such as information gain or Gini index to determine the best splitting criterion at each node. These measures help in selecting the most appropriate features by reducing the uncertainty in the dataset.

3. RESULTS

3.1 General assessment

Our study presents a rule base to determine the most appropriate financing and operating models for different energy technologies. The success of energy projects depends greatly on the selection of the right financing and operating model. This rule base aims to support the decision-making process by considering various criteria such as technology type, capacity, investment amount, foreign investor participation, regulatory quality risk, inflation, GDP deflator, and CO_2 emission levels. The PPP project, which was used in the rule base, was the Merchant (commercial model), BOT, BOO, and BROT models. Which type of renewable energy will be chosen, and which criteria will be taken into account in decision making are important questions to be answered.

- Technology Type = Non-Renewable [Mode: Merchant]
  - Capacity MW <= 775 [Mode: BOT]
    - Foreign Investor <= 0 [Mode: Merchant] => Merchant
    - Foreign Investor > 0 [Mode: BOT] => BOT
  - Capacity MW > 775 [Mode: BOO]
    - Regulatory Quality Risk in ["high" "low"] [Mode: BOO] => BOO
    - Regulatory Quality Risk in ["medium"] [Mode: Merchant] => Merchant
- Technology Type = Renewable Other [Mode: BOO]
  - Inflation GDP Deflator <= 12.50 [Mode: BROT]
    - Capacity MW <= 55 [Mode: Merchant] => Merchant
    - Capacity MW > 55 [Mode: BROT] => BROT
  - Inflation GDP Deflator > 12.50 [Mode: BOO] => BOO
- Technology Type = Renewable Wind [Mode: BOO]
  - Total Investment Million Dollar <= 16.70 [Mode: BROT] => BROT
  - Total Investment Million Dollar > 16.70 [Mode: BOO] => BOO
- Technology Type = Renewable Hydro [Mode: BOT]
  - Inflation GDP Deflator <= 6.28 [Mode: BOO]
    - Capacity MW <= 47.40 [Mode: BOO] => BOO
    - Capacity MW > 47.40 [Mode: Merchant] => Merchant
  - Inflation GDP Deflator > 6.28 [Mode: BOT]
    - CO_2 Emission <= 355.69 [Mode: BOT]
      - CO_2 Emission <= 301.44 [Mode: Merchant] => Merchant
      - CO_2 Emission > 301.44 [Mode: BOT]
        - Capacity MW <= 15 [Mode: BROT] => BROT
        - Capacity MW > 15 [Mode: BOT]
          - CO_2 Emission <= 312.22 [Mode: BOT]
            - Capacity MW <= 33 [Mode: BOT] => BOT
            - Capacity MW > 33 [Mode: BOO] => BOO
          - CO_2 Emission > 312.22 [Mode: BOT] => BOT
    - CO_2 Emission > 355.69 [Mode: BOO] => BOO

Figure 2. Classification-based results in C5.0 algorithm

Table 3. Final ranking results of the past public-private partnership (PPP) models by Alternative Ranking Method by Computing Two-Step Normalization (AROMAN) method

No.	BOO		BROT	
	Project Name	Technology	Project Name	Technology
1	InterGen Gebze Adapazari Izmir	Non-Renewable	Hamitabat Combined Cycle Power Plant	Non-Renewable
2	Iskenderun Enerji Uretim ve Ticaret AS	Non-Renewable	Yavuz and Midilli Hydro Power Plant	Hydro
3	Zonguldak Coal Fired Power Plants	Non-Renewable	Bagistas Hydro Power Plant	Hydro
4	Niksar Hydropower Plant	Hydro	Zorlu Kizildere Geothermal Plant	Geothermal
5	GE Kirikkale Power Plant	Non-Renewable	Dares Datca Wind Farm Extension	Wind
No.	BOT		Merchant	
	Project Name	Technology	Project Name	Technology
1	Birecik Power Plant	Hydro	Enerjisa phases II	Non-Renewable
2	Denizli CCGT Power Project	Non-Renewable	Enerjisa phases I	Non-Renewable
3	Enerjisa Tufanbeyli Coal Plant	Non-Renewable	Boyabat Hydroelectric Power	Hydro
4	Uni-Mar Power Plant	Non-Renewable	Gebze CCGT Power Project	Non-Renewable

Note: BOO = Build, Own, and Operate; BOT = Build, Operate, Transfer; BROT = Build, Rehabilitate, Operate, and Transfer.

Decision trees are a widely used classification method in machine learning, and their accuracy plays a critical role in determining the model's success. According to the analysis results, the decision tree classification model's accuracy rate was determined as 80%. This rate was calculated by dividing the number of correctly classified samples by the total number of samples. 101 samples were correctly classified, and 26 were incorrectly classified out of a total of 127 examples. In this context, the accuracy of decision tree models stands out as an important measure for evaluating the performance of these models. The F1 score is calculated as the harmonic mean of precision and sensitivity. F1 score evaluates the performance of the model and is used to accurately represent its effectiveness of the model, especially in imbalanced datasets. The model's F1 score was found to be 0.77 (77%). If F1 score is closer to 1, the model's results will be more significant. Therefore, this model's F1 score is significant and valid. The text version of the decision tree results is shown in Figure 2.

In the second step of the analysis, once the decision matrix was created, the performance rankings of the projects were calculated independently following the steps of the AROMAN method. The rankings of the projects are presented in Table 3.

Examining Table 3, it is clear that various projects with different technological approaches emerge as leaders in the BOO, BROT, BOT, and Merchant models. Specifically, in the BOO model, all five projects demonstrating the highest performance are concentrated around non-renewable energy sources, exemplifying a significant trend towards conventional energy applications in this category. In the BROT model, while the leading project is also related to a non-renewable energy source, subsequent high-performing projects showcase a variety of technologies, particularly in the areas of hydro, geothermal, and wind energy. This diversity indicates a growing interest in integrating alternative energy sources alongside conventional energy sources.

In contrast, the BOT model exhibits a hydroelectric project that ranks first overall in terms of efficiency and sustainability, followed by four additional projects classified as non-renewable energy sources. This highlights a significant preference for hydroelectric energy as a viable and high-performing option within the BOT framework. Finally, in the Merchant model, a pattern similar to that seen in the BOO model emerges, where non-renewable energy projects dominate the top-performing rankings. Additionally, it is worth noting that two hydro projects have successfully secured positions within the top five rankings, suggesting that while non-renewable sources remain predominant, renewable energy projects are also making substantial strides in performance metrics.

3.2 Sensitivity analysis

The final ranking results of PPP models, according to their analysis criteria, can be affected by various parameters. Therefore, to assess the reliability of initial decisions and the effects of model parameters, the AROMAN model needs to be solved under different conditions. In this section of the study, the effects of varying criterion weights on ranking results were investigated through a sensitivity analysis. Accordingly, four different scenarios were developed, each emphasizing sustainability, economic, government, and technical criteria, respectively.

For each scenario where the criterion weights were adjusted, the solution was carried out using the AROMAN method. Spearman correlation coefficients (SCCs) were calculated to assess the relationship between rankings for each scenario and AROMAN rankings under equal weights; the results are shown in Table 4.

The SCC were calculated in Table 4 to compare the rankings of the proposed model with those from different weight change sets.

Figure 3 demonstrates that the similarity between the rankings obtained across different scenarios is significantly high.

Table 5 shows that, except for minor deviations, the final ranking results of the projects in the BOO and Merchant models are similar to the sensitivity analysis ranking results for the four scenarios according to AROMAN. In the BOT model, the sensitivity analysis rankings differ according to AROMAN for Scenario 2, where the "Economic" dimension is given more weight, and Scenario 3, where the "Government" dimension is more prominent. Similarly, in the BROT model, the sensitivity analysis rankings differ according to AROMAN for Scenario 3, where the "Government" dimension is more prominent, and Scenario 4, where the "Technical" dimension is given more weight.

One of the main reasons for the low sensitivity in the BOO and Merchant models is ownership rights. In the BOO model, the ownership of the project is permanently in the private sector. In the Merchant model, however, the investor assumes the market risk entirely, and since it is a model shaped by market conditions, changes in the criterion weights did not create very large deviations in the project rankings. BOT and BROT models are characterized by strong public sector ties, and after a specific period, these projects are transferred to the public sector. This makes the projects sensitive to the "Government (Scenario-3)" criteria. BOT projects are guaranteed by the public sector. Therefore, they will be highly sensitive to changes primarily related to "Economic (Scenario-2)" criteria. In the BROT model, since the rehabilitation of the facility is involved, the "Technical (Scenario-4)" criterion becomes important.

Table 4. Spearman correlation coefficients (SCCs) between the rankings of scenarios and the proposed model

		AROMAN Rankings (Equal Weights)			
Scenario	**Distribution of the Weights**	**BOO**	**BROT**	**BOT**	**Merchant**
1	Sustainability 50%- Others 50%	0.975975	0.978571	0.971383	0.990980
2	Economic 50% - Others 50%	0.967260	0.971429	0.975270	0.973541
3	Government 50% - Others 50%	0.881227	0.917857	0.949728	0.953096
4	Technical 50% - Others 50%	0.982578	0.817857	0.985305	0.974143

Note: AROMAN = Alternative Ranking Method by Computing Two-Step Normalization; BOO = Build, Own, and Operate; BOT = Build, Operate, Transfer; BROT = Build, Rehabilitate, Operate, and Transfer.

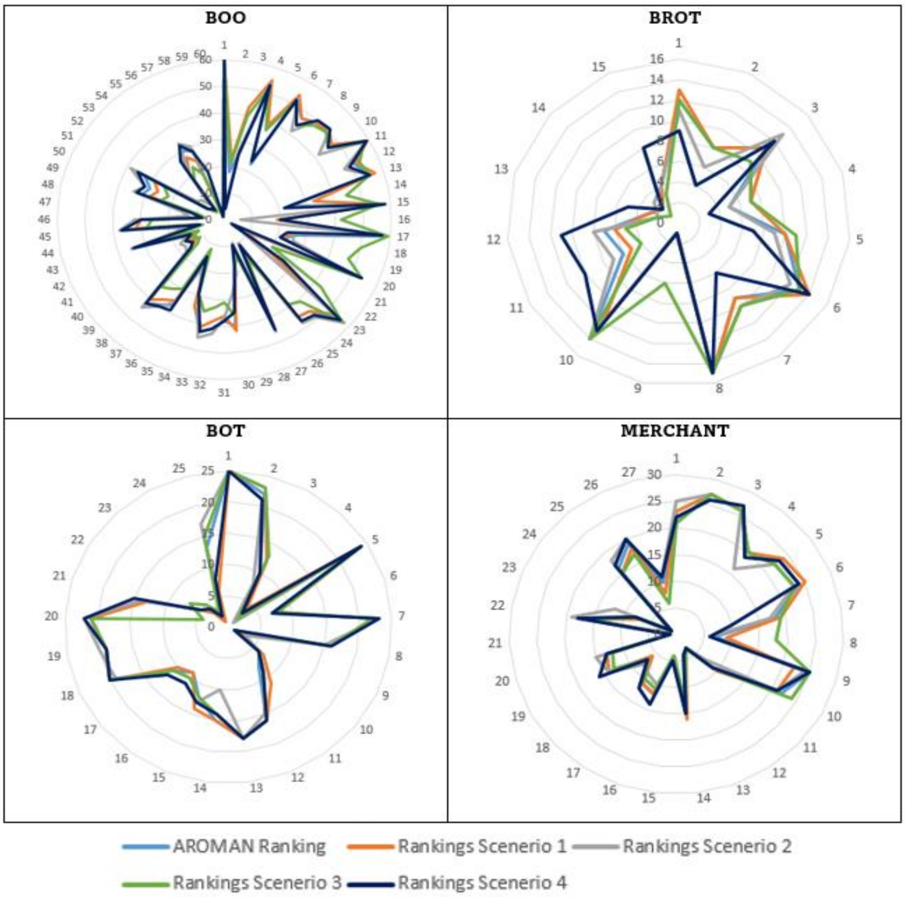

Figure 3. Radar chart based on rankings of past public-private partnership (PPP) models under different scenarios
Note: BOO = Build, Own, and Operate; BOT = Build, Operate, Transfer; BROT = Build, Rehabilitate, Operate, and Transfer.

Table 5. Rankings of the past public-private partnership (PPP) models after sensitivity

BOO Project	**A***	**S1**	**S2**	**S3**	**S4**	**BROT Project**	**A***	**S1**	**S2**	**S3**	**S4**	**BOT Project**	**A***	**S1**	**S2**	**S3**	**S4**	**Merchant Project**	**A***	**S1**	**S2**	**S3**	**S4**
InterGen Gebze	1	1	1	1	1	Hamitabat Combined	1	1	1	6	1	Birecik Power Plant	1	1	2	3	2	Enerjisa phases II	1	1	1	1	1
Iskenderun Enerji	2	2	2	2	2	Yavuz and Midilli Hydro	2	2	3	1	2	Denizli CCGT Power Project	2	2	3	1	1	Enerjisa phases I	1	1	1	1	1
Zonguldak Coal Fired	3	3	3	3	19	Bagistas Hydro	3	3	2	2	5	Enerjisa Tufanbeyli Coal Plant	3	4	1	2	3	Enerjisa phases II	3	3	3	3	3
Niksar Hydropower Plant	4	4	8	4	5	Zorlu Kizildere Geothermal	4	4	4	3	8	Uni-Mar Power Plant	4	3	4	5	4	Boyabat Hydroelectric	4	4	4	4	5
Kirikkale Power Plant	5	8	4	20	3	Dares Datca Wind Farm	5	7	5	7	3	Trakya Power Plant	5	5	5	7	5	Gebze CCGT Power Project	5	5	5	5	4

Note: * Alternative Ranking Method by Computing Two-Step Normalization (AROMAN) Rankings (Equal Weight). Note: BOO = Build, Own, and Operate; BOT = Build, Operate, Transfer; BROT = Build, Rehabilitate, Operate, and Transfer.

4. DISCUSSIONS

There is no single PPP model that can satisfy all requirements regarding a project's technical, financial, and locational conditions. The most suitable model should be selected considering the country's political and legal position, PPP market's development level, financial and technical features of the project, and sectors in question [25]. In a PPP model, the private sector takes risks and assumes the uncertainty of the profit-oriented return of the investment, while the public has concerns such as compliance with complex legislation, regulation and sharing of authority, political ideas, the democratic decision-making process, minimizing risk, and maximizing social benefit. These projects are used to benefit from the expertise and financing capacity of the private sector, without jeopardizing the quality of the services provided, amidst increasing financial constraints.

Natural gas and coal sources were added into the analysis to examine non-renewable technology. Türkiye's non-renewable energy resources are limited and inadequate; energy imports take the highest share of total imports. In non-renewable technologies, capacity and foreign investor participation have been identified as the determining factors in the selection of. Below 775 MW capacities, a Merchant model is suitable if there is no foreign investor, while BOT is preferred if there is a foreign investor. In capacities above 775 MW, the BOO model is effective. While the BOO model is applied in cases where regulatory quality risk is high or low, the Merchant model is suitable in cases of medium risk. This situation shows that in large-scale and risky projects; it is preferred to keep the ownership and operating responsibility under a single entity for the long term. The participation of foreign investors in projects creates an important dynamic in the energy sector in Türkiye.

Türkiye's long coastline and sea areas, especially in the Aegean and Mediterranean regions, have high wind potential. These regions can contribute to Türkiye's clean energy goals by providing favorable conditions for offshore wind renewable technology. The total investment amount in wind energy projects is a determining factor in selecting PPP models. The BROT model is preferred for investments below 16.70 million US dollars, and the BOO model is preferred for those above 16.70 million US dollars. The financial structure of wind energy projects plays a critical role in investors' decision-making processes. High initial costs and long payback periods are among the factors that affect investors' risk assessments. In this context, real option models used in wind energy investments help investors make more effective decisions under uncertainties [26]. In particular, the economic feasibility of wind energy projects increases the interest of investors in these projects, which contributes to the growth of the wind energy sector [27]. This situation shows that due to the high investment cost in large-scale wind energy projects, it is preferable that ownership and operating responsibilities remain with the investor in the long term.

Inflation GDP deflator, capacity, and CO_2 emission levels have a complex relationship that affects the selection of hydropower renewable technology. While the BOO model was preferred in low inflation periods (below 6.28%) and low capacities (below 47.40 MW), in contrast, the Merchant model was applied at high capacities. In high inflation periods (above 6.28%), different models are applied according to emission levels and capacity. While BROT and BOT models were applied at low CO_2 emission levels (below 355.69 tonnes and 301.44 tonnes) and low capacities (below 15 MW and 33 MW), respectively, the BOO model was preferred at high capacities and high CO_2 emission levels. Environmental impacts of hydroelectric projects, economic conditions, and perceptions of local people are also effective in model selection. This shows that environmental impacts and economic conditions of hydroelectric projects play an important role in model selection. Policymakers should be sensitive to cultural variation for creating green infrastructure PPPs [28].

In the study, other renewable technologies included waste, biomass, solar, geothermal and biogas alternatives. In other renewable technologies, GDP deflator and capacity were the main factors affecting model selection. In cases where the inflation GDP deflator was below 12.50%, the Merchant model was considered appropriate for capacities below 55 MW, and the BROT model was considered appropriate for capacities above 55 MW. In high inflation periods (above 12.50%), the BOO model is preferred. In high inflation periods, the preference for the BOO model stems from investors' desire to retain ownership and operational responsibility. Since high inflation increases investment risk, investors generally prefer less risky and more controllable models.

A central and perhaps contrary to common sense finding of this study is the high-performance ranking of non-renewable energy projects, despite the overall investment trend toward renewable energies. As seen in the AROMAN results (Table 3), the best-performing projects under the BOO and BOT models are predominantly based on non-renewable sources such as natural gas and coal. This raises a critical governance question: Does Türkiye's PPP framework implicitly reward financial bank lending eligibility over environmental sustainability, as observed in historical data? The analysis suggests this may be the case for several reasons. First, non-renewable projects, particularly large-scale thermal power plants, have historically offered more predictable and stable cash flows, making them highly attractive to private investors and lenders. Their established technologies and continuous operation (unlike intermittent renewable energies) reduce operational and market risks, making them more bankable. The high rankings of projects like InterGen Gebze Adapazarı İzmir and Enerjisa Tufanbeyli Coal Plant, known for their efficiency and reliability, support this view.

Secondly, these projects often benefit from strong state support mechanisms or strategic importance, further mitigating investment risk. For example, the success of the Zonguldak Coal-Fired Power Plant is dependent on the use of domestic coal reserves in line with national energy import dependency goals. This highlights a potential conflict within public policy itself: the goal of energy security through domestic fossil fuels may conflict with the goal of environmental sustainability.

This finding suggests that the governance framework may need to be adjusted for Türkiye to successfully steer its PPP program toward achieving sustainable development goals. Simply attracting private investment is not enough; the framework must be designed to make sustainable projects more or equally financeable than their fossil fuel counterparts. This could include establishing more robust and long-term price guarantees for renewable energies, developing risk mitigation tools specifically for green projects, or giving higher weight to sustainability criteria in the project selection and tendering process.

The sample included 127 projects in the analysis: sixty were BOO (47%), fifteen were BROT (12%), twenty-five were BOT (20%), and twenty-seven were Merchants (21%). In all PPP models, the investment preference focused on generating energy based on sustainable technology. In sustainable technology preferences, the intensity was also wind energy and hydropower plants. BOO and BROT models were prominent in the study of wind energy. In hydro energy, the highest intensity was BOT, Merchant, BROT, and BOO models. The prominent models in energy project investments with unsustainable technology content were the BOT (20%), Merchant (22%), and BOO (10%) models. AROMAN analysis' results can be discussed for PPP models in the following:

When the density distribution of sixty BOO model project was examined, forty-two (70%) were wind energy projects, ten (17%) were hydropower plants, three were coal (6%), two were natural gas (4%), one was solar (1%), one was geothermal (1%), and one was biomass (1%) energy project. In other words, 90% of BOO projects produce electricity with sustainable technology while 10% produce electricity with unsustainable technology. According to the order of success, the first three projects were BOO projects using unsustainable technology. Only one in the first five projects was using sustainable technology, four of the projects in the first ten were using unsustainable technology, and six of them were using sustainable technology. Two of the first three projects had foreign partners. Only one of the projects in the first ten was domestic, and two were 100% foreign investments. The project, which ranked first, achieved a 99.8% availability rate at the Adapazarı plant, which was seven points above the industry average and a world record for Class F gas turbine technology. Taking this performance into account, Power Magazine selected the Adapazarı plant as the power plant of the year among the world's natural gas power plants in 2011. The main source of the project, which ranks second, was imported coal. Over time, the project integrated sustainable technologies into its structure. The project, which ranks third, was Türkiye's first and only domestic coal power plant. Zonguldak is Türkiye's coal city. It is distinguished from its counterparts by being in a location with the richest coal reserves in Türkiye, such as Zonguldak, and by its location on the seashore. Thermal power plants contribute to the balance of production by providing energy in every month of the year. Since it provides electricity production according to renewable resources, it forms the backbone of the electricity system [29]. Therefore, although 90% of the BOO projects included in the analysis are based on sustainable technology, the top three in terms of success were projects that generate electricity from coal and natural gas-based power plants utilizing the country's unsustainable underground resources and were foreign capital-intensive.

Fifteen BROT model projects were used in the analysis. When the density distribution of the fifteen BROT projects was examined, six (40%) were wind energy projects, four (27%) were hydro power plants, four (27%) were geothermal, and one was natural gas (6%). In other words, 94% of the BROT projects generate electricity with sustainable technology, while 6% produce electricity with unsustainable technology. According to the ranking of success, only one project, which produces electricity with unsustainable technology (natural gas), with a share of 6% in the total project, was in the first place. All the remaining systems generate electricity with sustainable technology. While 53% of the projects were domestic projects, 47% consisted of projects in which foreign capital was a partner or entirely foreign capital. The first project is Türkiye's first natural gas combined cycle power plant. The second project is located on Yeşilırmak in Amasya. The third project is located on the Karasu/Fırat River in Erzincan. It is a local project. IC Enterra Renewable Energy, which began its work to enhance efficiency at the Bağıştaş-1 Dam and Hydroelectric Power Plant (HES), put into operation in 2015 in Erzincan, achieved a 25% reduction in domestic consumption, thereby increasing production efficiency. With steps such as the use of efficient equipment, LED conversion project in lighting, and transition to automation, the domestic consumption of the plant was reduced by 25%, and a significant efficiency increase was achieved in production [30].

Twenty-five BOT model projects were used in the analysis. When the density distribution in terms of project type of the twenty-five BOT projects was examined, seventeen (68%) were hydropower projects, two (8%) were wind energy, one was waste (4%), four were natural gas (16%), and one was coal (4%). In other words, 80% of the BOT projects produce electricity with sustainable technology, while 20% produce electricity with unsustainable technology. 52% of the projects were foreign-capital investments and 48% were domestic investments. In the ranking of success, it was observed that all the first thirteen projects were investments with foreign partners. One of the most important advantages of using this model is that advanced technology will enter the country if foreign investors realize projects requiring advanced technology. Through the model, the government will reduce the financial pressure required for realizing the infrastructure investments, and this will have positive effects on the budget. In total, 80% of BOT projects were based on sustainable technology, while two of the top three projects (67%) and four of the top five (80%) projects in the ranking of success, use unsustainable technology. Many developing economies are still dependent on fossil fuels, especially coal and oil, and more investment in renewable energy sources is needed to reach net zero emissions globally. In Türkiye, the share of fossil energy sources in energy generation is high, which contributes to economic growth. Fossil energy sources cause not only damage to the environment but also an increase in energy costs due to imports from abroad. In this context, it is important for Türkiye to choose renewable energy to achieve sustainable growth [31]. The first project was located in the Birecik district of Şanlıurfa on the Euphrates River. It is the 6th largest hydroelectric power plant in Türkiye. The second project is award-winning. In 2014, the power plant was awarded first place in the category of natural-gas-fired thermal power plants at the ICCI Energy Awards. In 2015, it received an award in the same category. The power plant has also won environmental awards. The Turkish Healthy Cities Association presented it with its Environmentally Friendly Facility Award in 2014. The third project generates electricity with coal. It is Türkiye's 16th largest lignite thermal power plant. Local coal is used in the facility.

Twenty-seven Merchant model projects were used in the analysis. When the density distribution of the twenty-seven Merchant projects was examined, nine (33%) were hydro projects, six (22%) were natural gas, seven (26%) were wind, two were geothermal (7%), one was solar (4%), one was biogas (4%), and one was biomass (4%) projects. In other words, 78% of Merchant projects produce electricity with sustainable technology, while 22% generate electricity with unsustainable technology. In the success ranking, two of the top three projects and three of the top five projects use sustainable technology. While 67% of the projects were domestic capital, 33% were financed by foreign investors. Although the number of projects involving foreign investors was low, the top five projects in the success ranking were foreign capital projects. Also, two of the projects in the first three were established as hydropower plants.

5. CONCLUSION

This study analyzes four PPP model alternatives and seven decision criteria to develop a decision framework for electricity generation projects in Türkiye. By integrating the AROMAN method for performance evaluation and the C5.0 algorithm for predictive classification, it offers a dual-purpose tool to guide investors and policymakers.

It has been determined that the BOO model is mostly applied in electricity generation projects in Türkiye. The study's main findings are that in all PPP models, the investment preference intensity focused on the energy generated using sustainable technology. In sustainable technology preferences, the intensity was also wind energy and hydropower plants. BOO and BROT models were prominent in wind energy in the study. Due to the high investment cost in large-scale wind energy projects, ownership and operating responsibility are preferred to remain with the investor in the long term. In hydro energy, the highest intensity was BOT, Merchant, BROT and BOO models, respectively. Environmental impacts of hydroelectric projects, economic conditions and perceptions of local people are also effective in model selection. The prominent models in energy project investments with unsustainable technology content were BOT (20%), Merchant (22%) and BOO (10%). In non-renewable technologies, capacity and foreign investor participation have been identified as the determining factors in PPP models selection. While the BOO model is applied in cases where regulatory quality risk is high or low, the Merchant model is suitable in cases of medium risk. The decision rules generated by the C5.0 algorithm reveal that the selection of a PPP model is highly sensitive to factors such as project capacity, total investment, inflation, and the presence of foreign investors. These rules offer a practical guide for structuring future projects.

The financing deficit for sustainable investments hinders the achievement of the required investment pace even in developed countries, while it prevents developing countries from abandoning fossil fuels. In Türkiye, the share of fossil energy sources in increasing energy generation with economic growth is high. While most new projects rely on renewable energy, the highest-ranking historical projects are often based on non-renewable energy. This situation points to a significant governance problem within the current PPP framework, where banking and operational reliability attributes, historically associated with fossil fuel power plants, outweigh environmental sustainability. This suggests that policymakers need to do more than simply promote renewable investment to achieve sustainable development goals; they need to actively shape the financial and regulatory environment to make sustainability a core component of bankability.

According to the results of sensitivity analysis, the fact that the BOO and Merchant models are not affected by external parameter changes proves that these models offer strategic stability. Investors seeking low risk and long-term stability may prefer the BOO and Merchant models. The fact that the ranking of the BOT and BROT models changes, especially when the weights of "Government (Scenario-3)" and "Technical (Scenario-4)" criterion increase, theoretically confirms the high-risk and/or high-dependent nature of these models. Those seeking government support and guarantees may prefer the BOT model. The BROT model may be preferred in investments where technical expertise is high.

In future studies, the criteria included in this analysis can be expanded to make decisions for PPP models in the energy sector. The proposed methods in the study can be compared with other MCDM methods, or if social variables are involved, fuzzy MCDM can be incorporated into the analysis.

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