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Application of System Identification Methods in Cost Estimating for Renewable Energy Projects

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Abstract: The article presents an analysis of the applicability of system identification methods in cost estimation for renewable energy projects. The study is based on an interdisciplinary approach that combines engineering sciences, reliability theory, and applied energy economics. Particular attention is given to the comparison of Bayesian reliability models for wind turbines, predictive monitoring architectures, evolutionary algorithms for parametric identification in photovoltaics, and optimization strategies for the operation of energy storage systems. Modern methods are considered that enable the integration of technical data into financial and economic calculations, including forecasting of operating expenses, capital costs, and key investment metrics. The study identifies key interdependencies between the accuracy of engineering models and the reliability of investment forecasts, which is especially relevant under conditions of high market volatility. A comparative analysis has shown that the application of advanced algorithms reduces uncertainty in cost estimation and increases the reliability of payback calculations. Special attention is paid to the problems of data scarcity for certain technologies, the sensitivity of metaheuristic methods to noise, and the necessity of institutional support for the implementation of identification procedures in energy planning practices. The article proposes an original classification of applied models and substantiates the need for a comprehensive approach that combines engineering and economic data. This work will be useful for researchers in the field of renewable energy, cost estimation experts, design engineers, and investors focused on the development of sustainable energy strategies.

Keywords: system identification, cost estimating, renewable energy, wind power, photovoltaics, battery storage, Bayesian modeling, investment analysis.

Introduction

Modern energy systems, in the context of the transition to a low-carbon economy, are undergoing fundamental changes related to the growing share of renewable sources, the increasing complexity of infrastructure systems, and the rising demands for accuracy in cost forecasting. Wind and solar power projects are characterized by high capital intensity, long payback periods, and significant uncertainty in operational parameters, which necessitate the implementation of system identification and modeling methods [3]. These approaches make it possible to account for the nonlinear behavior of installations, the variability of weather factors, and the stochastic nature of equipment failures, creating a basis for a more accurate assessment of costs and risks.

Against the backdrop of a rapid increase in global investment in renewable energy sources (RES) and the diversification of the energy market, the task of improving the reliability of cost calculation models is becoming particularly relevant. In scientific and applied literature, the question of how to account for the complex interrelationships between technical and economic parameters—from the reliability of wind turbines and the accuracy of photovoltaic model identification to the profitability of energy storage systems—is being raised with increasing frequency. The development of new methods that combine Bayesian reliability models, metaheuristic algorithms, and optimization strategies opens up opportunities for integrating technical data into financial and economic assessments, reducing the risk of underestimating operational and investment costs.

An example of a comprehensive approach to cost analysis can be found in studies that use Bayesian reliability analysis in wind installations, advanced parameter identification algorithms in solar energy, and strategies for optimizing the operation of battery systems. These tools demonstrate high accuracy in forecasting technical and economic indicators, but they require adaptation to industry and regional conditions.

The purpose of this study is to conduct a systematic analysis of system identification methods in the cost assessment of renewable energy projects, to classify existing approaches, to highlight their advantages and limitations, and to propose directions for integrating engineering and economic data to improve the accuracy of investment forecasts and the sustainability of energy strategies.

Materials and Methods

The methodological basis of this study is formed at the intersection of engineering sciences, reliability theory, and applied energy economics. The interdisciplinary nature of the topic necessitated the use of a comparative analysis of modern scientific works on system identification methods, failure prediction models, and parametric optimization algorithms in the field of renewable energy.

The study utilized sources covering both the technical and economic context of the application of system identification methods. A central place is occupied by the work of Anderson F. [1], in which a Bayesian reliability model for wind turbines was developed, taking into account seasonal factors, service history, and the position of the installation, which made it possible to identify an increase in the failure rate in the first days after maintenance. Additionally, the study by Bera B. [2] proposed a predictive monitoring architecture using Bayesian model updating and LSTM, which provided an increase in the accuracy of diagnosing imbalances in rotor-bearing systems. An important contribution to the methodological base was made by the analysis of Donnelly O. [3], where a comparison of operation and maintenance costs for direct-drive and medium-speed turbines was conducted, demonstrating the advantages of direct drive in OPEX assessment.

The class of probabilistic modeling methods is represented in the work of Farhan M. [4], where a Bayesian model for optimizing inspections of offshore wind turbine support structures was developed, taking into account uncertainties in weather conditions, logistics, and repairs. In the field of solar energy, the methodological basis was supplemented by a critical review by Li D. [5], which systematized modern approaches to the identification of solar cell parameters and identified the limitations of metaheuristic algorithms. This line of research is continued in the study by Yuan S. [10], which proposed an improved DODE algorithm that showed record-breaking results in terms of RMSE for single-, double-, and triple-diode models, as well as industrial modules.

A special place is occupied by the work of Marti-Puig P. [6], which presents a unique SCADA database of the operation of five turbines with a 5-minute interval, covering more than 300 variables and events, which allows for the testing of intelligent models for the early detection of failures. In the vein of dynamic analysis, the study by Palma G. [7] should be highlighted, which applied the dynamic modal decomposition method to identify the characteristics of a floating offshore turbine, opening up possibilities for integrating system identification with load forecasting.

A systematization of the accumulated experience was carried out by Santiago R. [8], which provides a review of AI models for the diagnosis and prediction of failures in turbines (from autoencoders to transformers), and identifies gaps related to the lack of data for direct-drive installations. Finally, an important economic perspective is provided by the work of Shabani M. [9], where an optimization strategy for the operation of battery energy storage systems in 25 European countries was developed, allowing for the assessment of NPV, PI, and PBP indicators in conditions of high price volatility.

Thus, the methodological strategy of the research is based on a comprehensive theoretical analysis of modern scientific sources, which made it possible to systematize existing system identification approaches, identify their strengths and weaknesses, and outline directions for integrating engineering and economic models for the purpose of accurate cost estimating in renewable energy projects.

Results

The application of system identification methods in wind energy is driven by the need to improve the accuracy of cost and risk assessment related to the operation and maintenance of installations. A feature of wind turbines is their high sensitivity to operating and maintenance conditions, which complicates cost forecasting using traditional models. In this regard, Bayesian and probabilistic approaches allow for the consideration of nonlinear and stochastic dependencies, integrating factors of seasonality, geographical location, and the technical condition of the equipment. This approach makes it possible to form more reliable models of the turbine life cycle cost, minimizing uncertainties in long-term planning.

The study by Anderson F. [1] proposes a Bayesian reliability model that integrates the annual maintenance history and seasonal effects. The use of the Weibull distribution and spline approximation made it possible to establish an increase in the failure rate in the first six days after scheduled maintenance, which directly affects the cost estimation. Bera B. [2] developed this methodology by proposing a predictive monitoring architecture using Bayesian model updating, supplemented by an LSTM algorithm. Donnelly O. [3] examined the problem through the prism of operating expenses, showing that direct-drive turbines provide higher availability and a reduction in OPEX compared to medium-speed machines. At the same time, the cost differences turned out to be significantly lower than previously assumed, which indicates the need to use more accurate identification methods in cost assessment.

An important contribution to the development of probabilistic models was made by Farhan M. [4], who developed a Bayesian scheme for estimating the costs of inspections and repairs for the support structures of offshore turbines. The use of PIPA-DA made it possible to model a wide range of uncertainties, including the type of vessel, the duration of operations, weather conditions, and the composition of personnel. Table 1 provides a comparison of approaches to identifying failures and costs in wind energy.

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Table 1: Comparison of system identification approaches for failure and cost modeling in wind energy (Compiled by the author based on sources: [1, 3, 4])

Methodology	**Key Focus**	**Main Findings**	**Cost/Failure Implications**
Bayesian reliability with Weibull models and B-splines	Scheduled maintenance & seasonal effects	Failure intensity increases in the first 6 days post-service	Higher short-term failure costs; importance of maintenance timing
Bayesian model updating + LSTM	Predictive monitoring of rotor–bearing faults	74.48% error reduction vs fixed parameters	Improved accuracy reduces unnecessary maintenance costs
StrathOW-OM O&M cost comparison	15 MW direct-drive vs medium-speed offshore turbines	Direct-drive yields lower OPEX; gap 1.58–5.78% (vs earlier 29.79%)	Direct-drive is more cost-efficient, but smaller margin than assumed
Probabilistic Bayesian cost modeling (PIPA-DA)	Inspection & maintenance of offshore support structures	Integration of vessel, weather, repair type & personnel	Enables cost-risk optimization for inspection schedules

The comparative analysis presented in the table allows for the identification of a general trend: modern system identification methods are increasingly focused on combining engineering and economic data into a single analytical loop. Bayesian models make it possible to account for hidden risk factors and operational dynamics, while architectures with real-time parameter updates provide an increase in prediction accuracy. Probabilistic approaches demonstrate their effectiveness in conditions of high uncertainty in offshore projects, where errors in estimating the cost of inspections or repairs can lead to significant financial losses.

The identification of parameters for photovoltaic models is a critical stage in assessing the efficiency and cost of projects based on solar energy. An incorrect determination of key parameters (photocurrent, resistances, and diode ideality) leads to a distortion of the cost and payback period calculations for projects. The study by Li D. [5] shows that metaheuristic methods, such as particle swarm algorithms, genetic algorithms, and flower pollination algorithms, have limitations: they are vulnerable to noise, prone to premature convergence, and can get stuck in local minima, which reduces the reliability of parameter identification under real operating conditions.

As an alternative, Yuan S. [10] proposed an improved DODE (Dual-strategy Oriented Differential Evolution) algorithm, which integrates a dual mutation mechanism and orientation-based control of population evolution. This method allows for a balance between global and local search, avoids premature convergence, and ensures high resistance to noise. Table 2 provides a comparison of the results of parameter identification accuracy for different models of photovoltaic systems.

Table 2: Accuracy of parameter identification in PV models (RMSE) using DODE (Compiled by the author based on [10])

PV Model	**DODE RMSE (optimal)**
Single Diode Model (SDM)	$9.86021877891317 \times 10^{-4}$
Double Diode Model (DDM)	$9.82484851784979 \times 10^{-4}$
Triple Diode Model (TDM)	$9.82484851784993 \times 10^{-4}$
Photowatt-PWP201 Module	$2.42507486809489 \times 10^{-3}$
STM6-40/36 Module	$1.72981370994064 \times 10^{-3}$
STP6-120/36 Module	$1.66006031250846 \times 10^{-2}$

The RMSE (Root Mean Square Error) indicators shown in the table reflect the root mean square deviation between the actual experimental data and the results obtained after identifying the model parameters. The lower the RMSE value, the higher the accuracy of the model's approximation to the measured data. For the basic models (SDM, DDM, TDM), RMSE values of the order of 10^{-4} demonstrate an almost perfect match between the calculated and experimental current and voltage curves. This means that the DODE algorithm is able to accurately reproduce the behavior of single cells under various operating conditions. For industrial modules (Photowatt-PWP201, STM6-40/36, STP6-120/36), the RMSE values increase to 10^{-3}–10^{-2}, which is due to the complexity of their architecture and a large number of internal factors (shunting, material inhomogeneity, temperature effects). Nevertheless, even under these conditions, the DODE algorithm demonstrates a noticeable superiority compared to traditional metaheuristics [5].

Discussion

A comparison of system identification methods in wind energy and photovoltaic systems reveals a common pattern: an increase in the accuracy of models leads to a reduction in uncertainty in cost estimation, although the technical implementation differs. In wind energy, one of the first examples was the study by Anderson F. [1], where the use of a Bayesian reliability model showed an increase in the failure rate of turbines in the first six days after maintenance, which significantly changes the structure of operating costs. The architecture of Bayesian model updating made it possible to reduce the monitoring error by 74.48% and to transition to predictive maintenance [2].

A further direction is related to the direct comparison of turbine configurations. Donnelly O. [3] established that 15 MW direct-drive installations provide lower operating costs compared to medium-speed ones, although the gap in OPEX turned out to be lower than expected, which corrects economic forecasts. At the same time, Farhan M. [4] developed a probabilistic model of the costs of inspections and repairs of support structures, showing that the uncertainty of external factors (weather, vessel availability, type of repair) requires optimization based on the criterion of failure risk.

A significant role in wind energy is played by the growth of data. Marti-Puig P. [6] presented a three-year SCADA database for five turbines. It allowed for the use of early failure detection algorithms, which increases the accuracy of calculating expected operating costs. Palma G. [7] added a new dimension by applying the dynamic modal decomposition (DMD) method to identify the parameters of a floating turbine, which demonstrated the potential of prognostic scenarios at the intersection of hydrodynamics and electrical engineering. In a systematic review, Santiago R. [8] emphasized that the deficit of failure data and the complexity of applying deep learning to electronic components, especially for direct-drive installations and permanent magnet generators, remains a key barrier.

In photovoltaic systems, parameter identification poses different challenges. Li D. [5] showed that metaheuristic algorithms applied to SDM, DDM, and TDM models are vulnerable to noise, local minima, and instability on real data, which limits their accuracy. However, Yuan S. [10] proposed the DODE algorithm, which demonstrated an RMSE at the level of 9.86×10^{-4} (SDM) and 1.66×10^{-2} (STP6-120/36), surpassing 10 competing algorithms.

Finally, it is important to note the connection between identification methods and the economic dimension. Shabani M. [9] proved that optimizing the operating strategies of energy storage systems in the wholesale markets of the EU can increase profitability to 38.4 thousand €/MWh/year. Although the work concerns battery systems, it illustrates a general effect: the more accurately physical processes and equipment parameters are reproduced, the more reliably the cost and revenue model is formed.

Considering the economic consequences of implementing system identification methods goes beyond purely engineering problems and is directly related to the investment attractiveness of projects in renewable energy. This relationship is particularly evident in the field of electricity storage, where the accuracy of calculating operating parameters affects the projected payback and the level of investment risks. The study by Shabani M. [9] proposes a strategy for optimizing the charging and discharging modes of batteries, taking into account the degradation factor and price volatility in the wholesale electricity market. Unlike traditional static models, such a solution allows for an increase in the reliability of forecasts and a correct accounting of long-term costs, forming a more realistic assessment of economic efficiency. Of particular importance is the fact that in European countries, the results of implementing such strategies differ significantly depending on the market situation. Table 3 shows how the application of optimization approaches affects the key financial metrics of electricity storage systems in different European countries.

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Table 3 – Financial metrics for grid-scale battery storage in Europe (Compiled by the author based on [9])

Country	PPEI (k€/MWh/yr)	PBP (years)	PI (%)	NPV (k€)
Romania	38.4	4.5	93.6	374.3
Latvia	37.9	4.6	95.8	383.0
Lithuania	37.7	4.7	94.8	379.5
Estonia	37.5	4.6	95.7	383.0
Spain	−5.5	None	−16.1	−645.7
Portugal	−5.9	None	−17.9	−71.4
Norway	−6.3	None	−20.9	−83.9

The data provided clearly demonstrates the differences in the investment attractiveness of battery projects depending on the country. The markets of Eastern Europe (Romania, Latvia, Lithuania, Estonia) show a profitability of around 38 thousand euros per megawatt-hour per year and an average payback period of about 4.5 years. At the same time, the profitability index exceeds 90%, which makes these regions leaders in the attractiveness of investments in energy storage. In contrast, in the countries of Western Europe (Spain, Portugal, Norway), the net present value indicators remain negative, and the payback period cannot be determined, which effectively rules out the economic feasibility of large-scale investments in this segment. A comparison of these results with the experience of wind and solar generation allows for the identification of a general trend: the higher the accuracy of identifying operational parameters, the more reliable the cost calculations become, which means the probability of a systematic underestimation of OPEX and CapEx decreases [1, 4, 5, 10].

Thus, the application of advanced models that combine probabilistic approaches and optimization algorithms provides investors with a more realistic understanding of project prospects. This is especially important in conditions of high market volatility and uncertainty, where an erroneous assessment of economic parameters can lead to the disruption of strategic energy development programs.

Conclusion

The conducted research has allowed for the establishment of a steady trend towards a transition from traditional cost estimation methods to integrated system identification models that combine engineering data with probabilistic and optimization approaches. It has been determined that the application of such solutions provides both an increase in the accuracy of cost calculations in wind energy and photovoltaic systems and a more reliable forecast of the investment efficiency of energy storage projects.

An analysis of the approaches, including Bayesian reliability models, predictive monitoring algorithms, dynamic modal decomposition, and evolutionary methods for parameter identification, has shown that the effectiveness of their application depends on the ability to account for the nonlinearity of operating conditions, the stochastic nature of failures, and market volatility. Empirical data have confirmed the significant superiority of improved algorithms (e.g., DODE for PV models) over traditional metaheuristics in terms of accuracy metrics, and have demonstrated that the implementation of architectures with real-time parameter updates reduces the uncertainty of cost estimation in wind energy.

It has been established that in the context of the high capital intensity of renewable energy projects, models that allow for the integration of the results of identifying technical parameters into financial and economic calculations are of particular value. This provides the opportunity for a more realistic assessment of payback periods, net present value, and the profitability index, which is especially important for substantiating investment decisions. A comparative analysis has shown that the markets of Eastern Europe provide a PPEI of around 38 thousand €/MWh/year and a PBP of about 4.5 years, whereas in certain countries of Western Europe, the economic efficiency of storage systems remains negative, which documents the regional specificity of investment risks.

The identified limitations, including the lack of data for direct-drive installations, the sensitivity of metaheuristic algorithms to noise, and the need for complex computational tools, outline the boundaries of the applicability of modern methods. These barriers confirm the need for further expansion of industry databases, the standardization of approaches, and institutional support for the implementation of system identification in energy projects.

Thus, the integration of system identification methods into the practice of cost estimation forms a new level of investment analysis in renewable energy. Prospects for further research are related to the development of multi-level models that combine Bayesian and evolutionary algorithms, the expansion of SCADA databases, and the adaptation of identification procedures to market dynamics, which will allow for an increase in the sustainability of energy strategies and a reduction in the risk of underestimating capital and operating costs.

References

[1]. Anderson, F., Dawid, R., McMillan, D., & García-Cava, D. (2023). A Bayesian reliability analysis exploring the effect of scheduled maintenance on wind turbine time to failure. Wind Energy. Advance online publication, 26(9), 879-899. https://doi.org/10.1002/we.2846

[2]. Bera, B., Huang, S.-C., Lin, P. T., Chiu, Y.-J., & Liang, J.-W. (2024). Bayesian architecture for predictive monitoring of unbalance faults in a turbine rotor–bearing system. Sensors, 24(24), 8123. https://doi.org/10.3390/s24248123

[3]. Donnelly, O., Anderson, F., & Carroll, J. (2024). Operation and maintenance cost comparison between 15 MW direct-drive and medium-speed offshore wind turbines. Wind Energy Science, 9(6), 1345–1362. https://doi.org/10.5194/wes-9-1345-2024

[4]. Farhan, M., Schneider, R., Thöns, S., & Gündel, M. (2025). Probabilistic cost modeling as a basis for optimizing inspection and maintenance of turbine support structures in offshore wind farms. Wind Energy Science, 10(2), 461–481. https://doi.org/10.5194/wes-10-461-2025

[5]. Li, D., Yang, B., Li, L., Li, Q., Deng, J., & Guo, C. (2022). Recent photovoltaic cell parameter identification approaches: A critical note. Frontiers in Energy Research, 10. https://doi.org/10.3389/fenrg.2022.902749

[6]. Marti-Puig, P., Blanco-M, A., Cusidó, J., & Solé-Casals, J. (2024). Wind turbine database for intelligent operation and maintenance strategies. Scientific Data, 11, 255. https://doi.org/10.1038/s41597-024-03067-9

[7]. Palma, G., Bardazzi, A., Lucarelli, A., Pilloton, C., Serani, A., Lugni, C., & Diez, M. (2025). Analysis, forecasting, and system identification of a floating offshore wind turbine using dynamic mode decomposition. Journal of Marine Science and Engineering, 13(4), 656. https://doi.org/10.3390/jmse13040656

[8]. Santiago, R. A. d. F., Barbosa, N. B., Mergulhão, H. G., Carvalho, T. F. d., Santos, A. A. B., Medrado, R. C., Filho, J. B. d. M., Pinheiro, O. R., & Nascimento, E. G. S. (2024). Data-driven models applied to predictive and prescriptive maintenance of wind turbine: A systematic review of approaches based on failure detection, diagnosis, and prognosis. Energies, 17(5), 1010. https://doi.org/10.3390/en17051010

[9]. Shabani, M., Shabani, M., & Yan, J. (2025). Techno-economic profitability of grid-scale battery storage allocation in European wholesale markets under a novel operation optimization strategy. Energy Conversion and Management: X, 26, 100936. https://doi.org/10.1016/j.ecmx.2025.100936

[10]. Yuan, S., Ji, Y., Chen, Y., Liu, X., & Zhang, W. (2023). An improved differential evolution for parameter identification of photovoltaic models. Sustainability, 15(18), 13916. https://doi.org/10.3390/su151813916