

Optimizing the performance of photovoltaic systems with battery energy storage through forecasting-based energy management systems

Nikolay Kurtev

The increasing demand of integration of Photovoltaic (PV) systems with Battery Energy Storage Systems (BESS) requires advanced Energy Management System (EMS) strategies to optimize performance, maximize self-consumption and enhance economic profitability. This review explores state-of-the-art methods for optimizing PV installations with integrated BESS, focusing on forecasting techniques, market-driven optimization and control strategies. A comparative analysis of statistical, machine learning and hybrid forecasting methods highlights their advantages, limitations and applications in day-ahead energy trading. Additionally, the economic implications of energy scheduling are examined, emphasizing the role of data-driven decision-making in improving system efficiency. The paper identifies key challenges and future research directions, including AI-based adaptive control, cybersecurity and real-time optimization techniques, essential for the next generation of smart, decentralized energy systems.

Keywords – BESS, economic optimization, energy management system, forecasting, machine learning

Оптимизиране на производителността на фотоволтаични системи с батерийно съхранение на електрическа енергия посредством базирани на прогнози системи за управление на енергията (Николай Куртев). Нарастващото търсене на решения за интеграция на фотоволтаични (PV) системи със батерийни системи за съхранение на енергия (BESS) изисква сложни системи за управление на енергията (EMS), за да се оптимизира производителността, увеличи енергията за собственото потребление и увеличи икономическата печалба. Този обзор разглежда съвременни методи за оптимизиране на фотоволтаични инсталации с интегрирани батерийни системи за съхранение на енергията, с акцент върху техники за прогнозиране, пазарна оптимизация и стратегии на управление. Направен е сравнителен анализ на статистически, машинно обучителни и хибридни методи за прогнозиране, като се подчертават техните предимства, ограничения и приложения в търговията с енергия в сегмент „ден напред“. Допълнително са разгледани икономическите последици от енергийните прогнози, като се набляга на ролята на решенията, базирани на данни, за подобряване на ефективността на системата. Статията обсъжда основните предизвикателства и възможните аспекти на бъдещи разработки, включително адаптивно управление, базирано на изкуствен интелект, киберсигурност и техники за оптимизация в реално време, които са съществени за следващото поколение интелигентни, децентрализирани енергийни системи.

I. Introduction

The global transition toward renewable energy sources has significantly increased the deployment of Photovoltaic (PV) systems integrated with Battery Energy Storage Systems (BESS). The combination of solar energy generation with energy storage solutions offers enhanced grid reliability, energy security and cost savings. These hybrid systems are crucial in

enabling a more sustainable energy future, as they address the intermittency of solar power by storing excess generation for use during periods of low solar output or high demand [1]. However, to fully capitalize on the potential of PV systems with BESS integration, effective management and control of energy flows is critical. Energy Management Systems (EMS) have emerged as key solutions for optimizing the operation of these hybrid systems by balancing the

interaction between solar generation, storage and consumption. The primary goal of an EMS is to ensure that energy is used in the most cost-efficient manner possible, improving the overall system performance and economics [2]. Traditional EMSs operate based on real-time data, focusing on optimizing the current energy flow. However, with the increasing volatility in energy markets and the growing complexity of grid operations, integrating forecasting models into EMS frameworks is becoming essential for enhancing the economic performance and flexibility of PV with integrated BESS systems.

Forecasting energy prices and consumption patterns for the upcoming day or week allows the EMS to plan ahead, optimizing battery charge/discharge cycles and enabling more strategic decision-making. By integrating energy trade forecasts, EMS can anticipate market conditions and adjust the system's energy flow accordingly, ensuring that energy is traded or stored at the most favorable times. These predictive capabilities are especially important in markets where energy prices fluctuate throughout the day due to demand and supply dynamics [3]. As energy prices are subject to various factors such as weather patterns, grid demand and renewable energy supply, the accuracy of energy trade forecasts plays a crucial role in optimizing economic returns from the PV with integrated BESS system.

Incorporating forecasting models into EMS can have multiple benefits. By using predictive algorithms, such as machine learning or time-series forecasting models, EMS can reduce energy costs by managing the storage system efficiently based on predicted energy prices and demand [4]. This approach allows for energy arbitrage, where energy is stored when prices are low and used or sold when prices are high, improving the system's return on investment (ROI). Furthermore, predictive forecasting enables better participation in demand response programs and virtual power plants (VPPs), where the system can provide ancillary services to the grid, generating additional revenue streams for the owners [5]. Moreover, the integration of forecasting into EMS also aids in enhancing grid stability by optimizing the charging and discharging of batteries in response to forecasted grid demand. In addition, smart grid integration can further optimize system performance, enabling two-way communication between the EMS, the grid operator and electricity market participants, thus allowing for better coordination and reduced grid congestion [6].

This paper aims to explore the integration of forecasting-based control strategies into Energy

Management Systems (EMS) for PV with integrated BESS projects, with a specific focus on improving economic performance, system reliability and grid interactions. The study will analyze the potential of using next-day energy trade forecasts to enhance the operation of these hybrid systems, with an emphasis on battery storage optimization, cost savings and energy market integration. We will also review various forecasting models that are suitable for these applications, such as machine learning, time-series analysis and weather data correlation and assess their impact on the overall performance and profitability of PV installations integrated with BESS systems.

II. Background and Literature Review

Energy Management Systems (EMS) are designed to control and balance the flow of energy between various components, ensuring that energy production, storage and consumption are optimized. Several control strategies are employed in EMS, such as rule-based control, model predictive control (MPC) and fuzzy logic approaches. Rule-based control is the simplest and relies on predefined rules, typically aimed at reducing battery degradation and managing energy flows according to specific thresholds. On the other hand, MPC allows for optimization over a defined prediction horizon by solving a mathematical optimization problem, considering the future behavior of the system. This strategy has gained significant traction due to its ability to forecast energy demands and adjust accordingly [4]. Furthermore, fuzzy logic control enables more flexible and adaptive decision-making processes by utilizing linguistic variables, which are particularly useful in systems with a high degree of uncertainty [2].

Accurate forecasting is key to improving the performance of EMS in PV with integrated BESS systems. Forecasting can be applied to predict energy demand, solar generation, battery state of charge and energy market prices. By incorporating forecasting models, the EMS can make informed decisions regarding charging or discharging the battery, which minimizes costs and maximizes the return on investment. In energy trading, forecasting energy prices is one of the most critical aspects, as it enables energy arbitrage, a process where energy is stored when prices are low and used or sold when prices are high. Different methods are used for energy price forecasting, including statistical time-series models like Autoregressive Integrated Moving Average (ARIMA), as well as more sophisticated methods based on machine learning (ML) techniques [4]. These models take historical price data and external

factors, such as weather patterns and grid demand, to predict energy price fluctuations over short and long-term horizons. Machine learning techniques, such as artificial neural networks (ANN) and support vector machines (SVM), have been applied to improve the accuracy of energy price forecasts, showing promising results in both real-time and day-ahead predictions [3].

For load forecasting, historical consumption patterns, along with external factors such as weather conditions and public holidays, are often used to predict future demand. Time-series analysis, coupled with statistical learning models, is commonly employed for short-term load forecasting (STLF), with methods like ARIMA, exponential smoothing and long short-term memory (LSTM) networks showing strong performance in predicting load fluctuations [2].

Optimization is the backbone of EMS, enabling the efficient operation of PV and BESS systems. In a typical EMS, the optimization problem involves determining the best strategy for battery operation, such as when to charge and discharge the battery and at what rates, considering the forecasted energy demand and market prices. Various optimization techniques have been explored in the literature, including linear programming, dynamic programming and genetic algorithms. Linear programming is often used for real-time decision-making due to its simplicity and fast computation, making it suitable for large-scale systems [5]. Dynamic programming is more effective when the optimization problem involves multi-stage decision-making over a specific horizon, as it can handle the system's temporal dynamics. Genetic algorithms, inspired by natural selection, are used for complex, non-linear optimization problems, where the system's decision-making is influenced by many interdependent variables.

A promising area of research is the integration of multi-objective optimization, where the EMS seeks to balance multiple conflicting objectives, such as minimizing both battery degradation and energy costs. This is particularly important in PV with integrated BESS systems, where trade-offs between long-term battery health and short-term economic benefits must be carefully managed [6]. Despite the advancements in EMS, several challenges remain. First, the uncertainty associated with solar energy generation and market price fluctuations makes accurate forecasting a difficult task. Moreover, the integration of real-time data with forecasting models requires substantial computational power and the ability to

process large datasets. Future research will likely focus on improving the accuracy of forecasting models, utilizing techniques such as deep learning and big data analytics to enhance the performance of EMS. Moreover, grid integration presents a challenge as well, particularly in regions with high penetration of renewables. Effective coordination between distributed energy resources (DERs), EMS and grid operators is needed to maintain grid stability while maximizing the utilization of renewable energy [4]. Furthermore, the advent of smart grids offers new opportunities for improving demand response and enabling more efficient energy trading. The application of artificial intelligence (AI) in EMS for predictive maintenance and real-time optimization is a promising direction for future research.

III. Control strategies in EMS for PV generators with BESS systems

The control strategies for Energy Management Systems (EMS) in Photovoltaic (PV) and Battery Energy Storage Systems (BESS) are central to the successful integration and optimization of these systems. These strategies govern the interaction between various components, including the PV array, battery storage, grid and load, to ensure that the system operates optimally under different conditions. The control mechanisms are primarily focused on managing energy flows, maximizing self-consumption, minimizing energy costs and reducing battery degradation. Several control strategies have been proposed in the literature, including rule-based, model predictive control (MPC), fuzzy logic and neural network-based control [7].

A. Rule-Based Control Strategies

Rule-based control is one of the simplest and most commonly used strategies in EMS for PV installations with storage. It uses a set of predefined rules to decide when to charge or discharge the battery based on observed system states, such as battery state of charge (SoC), solar generation and energy consumption patterns. For example, a rule-based controller may discharge the battery when the grid electricity price is high and charge it when the price is low. This strategy does not require complex modelling or real-time optimization, making it suitable for small to medium-sized systems [8]. Although rule-based controllers are computationally efficient, they have limitations, particularly in handling system uncertainties such as unpredictable fluctuations in energy generation and load. The lack of dynamic optimization leads to suboptimal performance in some cases, especially

under varying grid prices or when there are significant discrepancies between forecasted and actual solar production [9].

B. Model Predictive Control (MPC)

Model Predictive Control (MPC) has become increasingly popular in PV and storage systems due to its ability to account for dynamic changes in both generation and demand. MPC optimizes the system performance by using a mathematical model to predict future system states (e.g., battery SoC, energy demand and solar power generation) and solve an optimization problem over a future prediction horizon. This method considers system dynamics, forecasting errors and constraints, such as battery limits and grid connection parameters, to provide optimal control actions. MPC has been successfully applied in PV with integrated BESS systems to maximize self-consumption of solar energy, improve economic performance and minimize battery degradation [10]. A significant advantage of MPC is its ability to adjust the control actions based on real-time forecasts, making it highly adaptive to fluctuating conditions. However, MPC often involves high computational complexity, especially for large systems or systems with multiple objectives, requiring efficient algorithms and real-time data processing [11].

C. Fuzzy Logic Control

Fuzzy Logic Control (FLC) is another widely used control approach in EMS for PV installations integrated with battery systems, particularly in situations where there is system uncertainty and non-linearity. FLC models the system using linguistic variables (e.g., low, medium and high) to describe the states of the system and define rules for decision-making. FLC is often used in conjunction with other techniques, such as optimization algorithms or neural networks, to enhance the robustness and adaptability of EMS. One of the key benefits of FLC is its ability to handle imprecise inputs, such as weather forecasts and fluctuating load demands, without the need for precise mathematical models. This makes it a versatile and flexible strategy, particularly in environments with unpredictable changes. In PV with integrated BESS systems, FLC can manage the battery charging and discharging cycles effectively, taking into account external conditions such as solar irradiation and grid energy prices [12]. While FLC can handle uncertainties well, it may still suffer from a lack of optimization, which is why it is often combined with optimization techniques [13].

D. Neural Network-Based Control

Artificial Neural Networks (ANNs) have gained significant attention in EMS for BESS systems due to their ability to model complex non-linear relationships between various system variables. ANNs are used for forecasting, control and optimization, as they can learn from historical data and improve their performance over time. For example, ANNs can predict solar power generation, load consumption and battery performance, which are then used to optimize control actions [14]. ANN-based control systems can be integrated with other techniques, such as MPC, to enhance their forecasting and decision-making capabilities. By incorporating backpropagation algorithms, ANNs can continuously update their parameters and improve the accuracy of predictions, making them suitable for real-time control in dynamic systems. However, training ANNs requires large datasets and they can be computationally intensive, which may be a limitation in smaller systems or applications requiring fast response times [4].

E. Hybrid Control Approaches

In many PV with integrated BESS applications, hybrid control strategies have been proposed, combining two or more control techniques to leverage their respective strengths. For example, rule-based control can be combined with MPC or fuzzy logic to create a more robust EMS that adapts to different operating conditions while maintaining low computational complexity. Hybrid systems can improve the overall efficiency, robustness and scalability of the EMS, enabling them to meet the varying needs of different users [6]. Moreover, multi-agent systems (MAS) have been introduced in EMS to coordinate between different components, such as the PV array, BESS and the grid. In MAS, each component operates autonomously but communicates with others to optimize energy flows and improve system reliability. This approach is especially beneficial in systems with large numbers of distributed components, where centralized control would be too complex [15].

IV. Forecasting techniques for energy management in PV with BESS systems

Effective energy management in PV installations coupled with Battery Energy Storage Systems (BESS) relies heavily on accurate forecasting techniques. These techniques help predict solar energy generation, electricity demand and market prices, allowing the Energy Management System (EMS) to optimize energy flows, maximize efficiency and reduce

operational costs. Forecasting is particularly crucial in systems participating in day-ahead energy markets, where optimal scheduling of power generation and storage relies on anticipated conditions [16]. Forecasting techniques can be broadly classified into statistical methods, machine learning (ML) approaches and hybrid models that combine both paradigms. Each approach has advantages and limitations, depending on factors such as data availability, forecasting horizon and computational complexity [17].

A. Statistical Forecasting Methods

Statistical forecasting models have been traditionally used in energy systems due to their mathematical simplicity and interpretability. Common statistical methods include Auto-Regressive Integrated Moving Average (ARIMA), Exponential Smoothing (ES) and Multiple Linear Regression (MLR). The ARIMA model is a widely used time series forecasting technique for energy applications. It works by identifying trends and seasonality in historical data and extrapolating them into the future. ARIMA has been effectively applied to forecast solar power generation, electricity demand and market prices [18]. However, its performance degrades in highly volatile and non-linear environments, making it less suitable for complex solar radiation patterns influenced by weather fluctuations [19].

Exponential Smoothing (ES) is another classical method used for short-term load forecasting. It assigns exponentially decreasing weights to past observations, making it effective for handling trends. Similarly, Multiple Linear Regression (MLR) models the relationship between multiple predictors (e.g., temperature, cloud cover) and energy output, helping to forecast solar power generation with reasonable accuracy [20]. However, both methods struggle to capture sudden changes caused by unpredictable weather conditions.

B. Machine Learning-Based Forecasting Approaches

Machine learning techniques have emerged as powerful tools for forecasting in PV with integrated

BESS applications due to their ability to learn complex, non-linear relationships from large datasets. Common ML approaches include Artificial Neural Networks (ANNs), Support Vector Machines (SVMs) and Long Short-Term Memory (LSTM) Networks.

The ANNs have been widely applied in solar power forecasting due to their capacity to capture complex relationships in time series data. ANNs can process multiple input variables such as solar irradiance, temperature, humidity and historical generation patterns, making them highly effective for short- and medium-term predictions [4]. However, their accuracy depends on the availability of large datasets and careful hyperparameter tuning.

LSTM, a type of recurrent neural network (RNN), has shown superior performance in time-series forecasting for PV generation and energy prices. Unlike standard ANNs, LSTM networks can retain past information for longer periods, allowing them to capture temporal dependencies in solar radiation patterns [21]. LSTM models have been successfully used to optimize day-ahead scheduling in PV with integrated BESS systems, reducing errors in solar generation forecasts by up to 30% compared to ARIMA models [22].

SVMs are another effective machine learning technique used in solar energy forecasting. SVMs are particularly useful for short-term forecasting when datasets are small or contain noise. They have been applied to forecast electricity prices and solar power fluctuations, outperforming traditional regression models in scenarios with high uncertainty [23]. However, SVMs require careful selection of kernel functions to achieve optimal performance.

C. Hybrid Forecasting Models

Hybrid models combine statistical methods and machine learning algorithms to enhance forecasting accuracy. For example, ARIMA-ANN and LSTM-SVM hybrids leverage ARIMA's ability to capture linear patterns while utilizing ML models to handle non-linearity [16]. Hybrid models have demonstrated higher robustness in PV forecasting, especially under unpredictable weather conditions.

Criteria	ARIMA	Exponential Smoothing (ES)	Multiple Linear Regression (MLR)	Artificial Neural Networks (ANNs)	Long Short-Term Memory (LSTM) Networks	Support Vector Machines (SVMs)	Hybrid Models
Type	Statistical	Statistical	Statistical	Machine Learning	Deep Learning	Machine Learning	Hybrid
Advantages	Good for trends	Simple, fast	Handles multiple variables	Captures non-linear patterns	Retains long-term dependencies	Works with small datasets	High accuracy, robust
Limitations	Struggles with non-linearity	Poor for long-term	Assumes linearity	Needs large training data	High computation demand	Kernel selection is critical	Complex, needs integration
Common Applications	Short-term PV forecasting	Load forecasting	Solar generation prediction	Solar/load forecasting	Day-ahead market prediction	Price/load forecasting	EMS optimization
Complexity	Low	Low	Low-Medium	Medium-High	High	Medium	High

Tabl.1. Comparative representation of different forecasting techniques

Comparison of forecasting techniques is presented in Table 1. Statistical models such as ARIMA, Exponential Smoothing (ES), and Multiple Linear Regression (MLR) are computationally efficient and suitable for short-term forecasting but struggle with complex, non-linear patterns. In contrast, machine learning (ML) techniques like Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) provide greater accuracy by capturing intricate relationships within the data, though they require substantial training datasets. Deep learning models, particularly Long Short-Term Memory (LSTM) networks, are highly effective for time-series forecasting but demand high computational power and large amounts of historical data. Hybrid models, which combine statistical and ML approaches, offer the highest accuracy and adaptability, making them ideal for day-ahead energy trading and EMS optimization. However, their increased complexity necessitates careful model integration and higher processing resources.

The accuracy of forecasting directly impacts EMS control strategies in PV and BESS systems. A poor forecast can lead to suboptimal battery scheduling, increased energy costs and reduced system efficiency. In contrast, an accurate forecast enables EMS to: 1) Optimize charging/discharging cycles to align with energy prices; 2) Minimize curtailment of solar energy by improving self-consumption; 3) Reduce reliance on grid imports, leading to financial savings; 4) Improve battery lifespan by preventing unnecessary charge-discharge cycles.

Advanced forecasting techniques, when integrated with Model Predictive Control (MPC) and real-time optimization, have been shown to improve energy savings by up to 15% in PV with integrated BESS systems [24]. This highlights the necessity of

integrating state-of-the-art forecasting models into EMS design.

V. Conclusion

The integration of Photovoltaic (PV) systems with Battery Energy Storage Systems (BESS) has become a crucial solution for achieving efficient energy management and grid stability in renewable energy applications. This paper has provided a comprehensive review of computer-aided tools and control strategies for optimizing PV with integrated BESS systems, focusing on forecasting techniques, economic analysis and energy management strategies.

One of the key aspects of an effective Energy Management System (EMS) is its ability to accurately predict solar generation, energy demand and electricity prices. The comparative study of forecasting methods highlights that while traditional statistical models (e.g., ARIMA, Exponential Smoothing) remain widely used due to their simplicity, they struggle with non-linearity and uncertainty. In contrast, machine learning (ML) and deep learning (DL) models (e.g., Artificial Neural Networks, Long Short-Term Memory networks) significantly improve forecasting accuracy, making them ideal for day-ahead market participation and real-time energy scheduling. Furthermore, hybrid models, which combine statistical and ML/DL approaches, offer the highest accuracy and adaptability at the cost of increased computational complexity.

The economic viability of PV projects with BESS is highly dependent on efficient scheduling and trading strategies. The ability to incorporate day-ahead market price forecasts into EMS optimization allows for cost-effective energy dispatching, increasing

profitability and grid flexibility. Advanced forecasting techniques, combined with optimization algorithms, enable energy systems to maximize self-consumption, minimize curtailment and enhance revenues from electricity trading.

Despite recent advancements, several challenges and research gaps remain. The increasing integration of AI-driven forecasting, real-time data analytics and adaptive control algorithms will play a pivotal role in future EMS developments. Future research should focus on further enhancing hybrid forecasting models, improving real-time EMS adaptability and developing market-driven optimization strategies for PV with integrated BESS systems. Additionally, cybersecurity and data privacy concerns must be addressed as digitalization and IoT-enabled platforms become more prevalent in energy management and forecasting applications.

In conclusion, the combination of advanced forecasting models, intelligent EMS control strategies and economic optimization techniques can significantly improve the performance, reliability and profitability of PV installations incorporating BESS solutions. The adoption of AI-driven decision-making processes will pave the way for smarter, more resilient energy systems, ultimately accelerating the transition toward a sustainable and decentralized energy future.

Acknowledgements

The author would like to acknowledge the financial support received from HYPOTEC Ltd. for publishing this paper.

REFERENCES

- [1] J. Hong, J. Yin, Y. Liu, J. Peng, H. Jiang, "Energy Management and Control Strategy of Photovoltaic/Battery Hybrid Distributed Power Generation Systems With an Integrated Three-Port Power Converter", *IEEE Access*, vol. 7, pp. 82838-82847, 2019.
- [2] Y. Yang, S. Bremner, C. Menictas, M. Kay, "Modelling and optimal energy management for battery energy storage systems in renewable energy systems: A review", *Renewable and Sustainable Energy Reviews*, Vol. 167, pp. 112671, 2022.
- [3] F. Durán, W. Pavón, L. I. Minchala, "Forecast-Based Energy Management for Optimal Energy Dispatch in a Microgrid", *Energies*, 17, 486, 2024.
- [4] Y. Gao, J. Li, M. Hong, "Machine Learning Based Optimization Model for Energy Management of Energy Storage System for Large Industrial Park", *Processes*, 9, 825, 2021.
- [5] S. Garip, S. Ozdemir, "Optimization of PV and Battery Energy Storage Size in Grid-Connected Microgrid" *Applied Sciences* 12(16):8247, 2022.
- [6] Y. Zhang, T. Ma, H. Yang, "Grid-connected photovoltaic battery systems: A comprehensive review and perspectives" *Applied Energy*, Vol. 328, No. 15, pp. 120182, 2021
- [7] A. C. Real, G. P. Luz, J.M.C. Sousa, M.C. Brito, S.M. Vieira, "Optimization of a photovoltaic-battery system using deep reinforcement learning and load forecasting", *Energy and AI*, Vol. 150, p. 111559, 2022.
- [8] H. Camblong, I. Zapirain, O. Curea, J. Ugartemendia, Z. Boussaada, R. Zamora, "Rule-Based Energy Management System to Enhance PV Self-Consumption in a Building: A Real Case" *Energies*, 17, 6099, 2024.
- [9] Y. Triki, A. Bechouche, H. Seddiki, D. Abdeslam, "A Rule-Based Energy Management Strategy for a Standalone Photovoltaic/Wind/Battery Hybrid Renewable Energy System", *The First International Conference on Renewable Energy Advanced Technologies and Applications - ICREATA 2021* p. 208, 2021.
- [10] F. Guan, L. Zhang and Z. Wu, "Optimal model predictive control of energy storage devices for frequency stability of modern power systems", *Journal of Energy Storage*, Vol. 57, p. 106310, 2023.
- [11] N. T. Mbungu et al., "Predictive control technique for solar photovoltaic power forecasting", *Energy Conversion and Management: X*, Vol. 24, p. 100768, 2024.
- [12] T. Nguyen, K. B. Lee and D. L. Lee, "Fuzzy logic based energy management for grid connected hybrid PV system", *Energy Reports*, Vol. 8(10), pp.751-758, 2022.
- [13] A. Alankrita, A. Pati, N. Adhikary, S.K. Mishra, B. Appasani, T. S. Ustun, "Fuzzy logic-based energy management system for hybrid photovoltaic-battery systems," *Energy Reports*, Vol. 6, 2020, pp. 531-537, DOI: 10.1016/j.egyr.2019.10.014.
- [14] Y. Gupta, M. Amin, "A Neural Network-Based Energy Management System for PV-Battery Based Microgrids", <https://doi.org/10.48550/arXiv.2206.06716> 2022.
- [15] D. Hafiane, A. Magri, H. Chakir, R. Lajouad, S. Boudoudouh, "A multi-agent system approach for real-time energy management and control in hybrid low-voltage microgrids", *Results in Engineering*, Vol. 24, p. 103035, 2024.
- [16] X. Pan, J. Zhou, X. Sun, Y. Cao, X. Cheng, H. Farahmand "A hybrid method for day-ahead photovoltaic power forecasting based on generative adversarial network combined with convolutional autoencoder," *IET Renewable Power Generation*, Vol. 17, Issue 3, pp. 644-658 24, 2023.
- [17] R. Gaamouche, M. Chinnici, M. LahbyMohamed, Y. Abakarim, A. Hasnaoui, "Machine Learning Techniques for Renewable Energy Forecasting: A Comprehensive Review", DOI: 10.1007/978-3-030-96429-0_1 2022.
- [18] S. Atique, S. Noureen, V. Roy, S. Bayne, "Forecasting of total daily solar energy generation using ARIMA: A case study", *IEEE 9th Annual Computing and*

Communication Workshop and Conference (CCWC), Las Vegas, NV, USA, pp. 0114-0119, 2019.

[19] J. Thaker, R. Holler, "A Comparative Study of Time Series Forecasting of Solar Energy Based on Irradiance Classification", *Energies*, Vol. 15(8), p. 2837, 2022.

[20] Z. Dong, D. Yang, T. Reindl, W. Walsh, "Short-term solar irradiance forecasting using exponential smoothing state space model", *Energy* Vol. 55, pp. 1104-1113, 2013.

[21] W. Lee, K. Kim, J. Park, J. Kim, Y. Kim "Forecasting Solar Power Using Long-Short Term Memory and Convolutional Neural Networks", *IEEE Access*, Vol. 6, pp. 73068-73080, 2018.

[22] J. Qu, Z. Qian, Y. Pei, "Day-ahead hourly photovoltaic power forecasting using attention-based CNN-LSTM neural network embedded with multiple relevant and

target variables prediction pattern," *Energy*, Vol. 232, p. 120996, 2021.

[23] T. Papadimitriou, P. Gogas, E. Stathakis, Forecasting energy markets using support vector machines", *Energy Economics*, Vol. 44, pp. 135-142, 2014.

[24] J. F. L. de Oliveira et al. "Forecasting Methods for Photovoltaic Energy in the Scenario of Battery Energy Storage Systems: A Comprehensive Review", *Energies*, 16, 6638, 2023.

Dr. Nikolay Kurtev – Assistant professor at Faculty of Electronic Engineering and Technology, Technical University of Sofia, Bulgaria.

e-mail: n.kurtev@tu-sofia.bg

Received on: 17.02.2025

THE FEDERATION OF THE SCIENTIFIC-ENGINEERING UNIONS IN BULGARIA /FNTS/

is a professional, scientific - educational, nongovernmental, nonpolitical, nonprofit association of legal entities - professional organizations registered under the Law on non-profit legal entities, and their members are engineers, economists and other specialists in the fields of science, technology, economy and agriculture.

FNTS has bilateral cooperation treaties with similar organizations in multiple countries.

FNTS brings together 19 national associations – Scientific and Technical Unions (STU), 31 territorial associations, which have more than 15 000 professionals across the country.

FNTS is a co-founder and member of the World Federation of Engineering Organizations (WFEO).

FNTS is a member of the Engineers Europe (EE), and a member of the Standing Conference of engineering organizations from Southeast Europe (COPISEE), UN Global Compact, European Young Engineers (EYE). The Federation has the exclusive right to give nominations for the European Engineer (EUR ING) title.

Contacts: 108 Rakovsky St., Sofia 1000, Bulgaria

WEB: <http://www.fnts.bg>

E-mail: info@fnts.bg