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APPLICATION OF ARTIFICIAL INTELLIGENCE IN BUSINESS PROCESS OPTIMISATION ON THE EXAMPLE OF INTELLIGENT ENERGY PRICE FORECASTING FOR PHOTOVOLTAIC FARMS

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ABSTRACT

Purpose: *The purpose of this paper is to evaluate the application of advanced artificial intelligence methods in the forecasting of photovoltaic farm electricity prices and to analyse their impact on the optimisation of business decisions and operational processes.*

Need for the study: *With the increasing volatility of energy markets due to unstable weather conditions, dynamic regulatory changes and financial risks associated with long-term PPAs, traditional forecasting methods are proving insufficient. It is necessary to develop state-of-the-art solutions that, through the integration of Big Data and advanced machine learning algorithms, enable accurate energy price forecasting.*

Methodology: *The study is based on a two-stage analysis: a literature review and a conceptual analysis, leading to the formulation of the concept of an intelligent energy price forecasting system. This system integrates data from multiple sources, which are subjected to processes of cleaning, transformation and feature extraction. The resulting hybrid predictive model, based on the LSTM-Transformer architecture, is enriched with adaptation mechanisms that enable continuous updating of the models in the context of optimising business and operational decisions. The approach is validated through an empirical case study on a 1 MW PV farm, using historical data to train the model and evaluate its performance.*

Findings: *The literature analysis and the conceptual analysis conducted show that the implementation of a system based on a hybrid AI model allows for a reduction in energy price forecast errors compared to traditional methods. Adaptive mechanisms allow the model to adapt to changing market conditions on an ongoing basis, resulting in higher forecast accuracy and more effective financial risk management. Furthermore, the case study results confirmed improvements in forecast accuracy, which in turn enhances operational decision-making for the PV farm.*

Practical Implications: *The proposed AI system enables PV farm operators to make data-driven decisions based on reliable data, resulting in optimised sales strategies, energy storage management and stabilised financial flows, thus providing a competitive advantage in the renewables market.*

Keywords: artificial intelligence, machine learning algorithms, management systems, decision support systems, decision optimisation, energy pricing, photovoltaic farms, renewable energy sources, energy price forecasting, economic sustainability

JEL classifications: C53, D81, Q41, Q42, Q48, A1

1. INTRODUCTION

In an era of rapid technology development and the growing need for efficient management of energy resources, renewable energy systems, and photovoltaic (PV) farms in particular, are becoming a strategic component of the energy transition. The deployment of renewable energy solutions enables the creation of sustainable electricity systems that provide a stable energy supply despite changing weather conditions and market fluctuations (Kanase Patil et al., 2020). However, the efficient operation of PV farms requires not only accurate forecasting of energy production, but also dynamic management of energy prices, which has a direct impact on business decision-making. Traditional mathematical models often cannot cope with the increasing complexity of energy markets, so artificial intelligence (AI) algorithms are increasingly being used for advanced data analysis, system parameter optimisation and energy price forecasting (Lokhande et al., 2022). The use of AI algorithms, such as neural networks, evolutionary algorithms and hybrid deep learning models, allows for accurate forecasting of energy production and market prices, enabling companies to make more accurate operational and business decisions (Kanase-Patil et al., 2020). As a result, PV farm operators can dynamically adjust energy sales strategies, minimising financial risk and increasing operational efficiency of the systems.

In addition, recent research indicates that the integration of hybrid models, combining deep learning with evolutionary algorithms, enables even more accurate energy price forecasting, which is crucial in rapidly changing market conditions (Zhang et al., 2020). The integration of meteorological data with neural network-based predictive models allows for the ongoing adjustment of management strategies, resulting in optimised business decisions (Hou et al., 2024). Furthermore, hybrid optimisation algorithms support decision-making processes by minimising the risk of prediction errors and improving the operational efficiency of energy systems (Krishna Prakash & Singh, 2023).

The aim of this paper is to provide a theoretical analysis of the challenges of forecasting energy prices on PV farms and to assess the role of intelligent management systems based on artificial intelligence technologies in optimising business decisions and operational processes. Forecasting energy prices in the context of PV farms is an extremely complex task due to dynamic changes in weather conditions, fluctuations in demand and market instability. Traditional statistical methods, based mainly on the analysis of historical data, are not able to fully take into account the multidimensionality and complexity of factors influencing energy prices, leading to the generation of forecasts with a high degree of uncertainty. Therefore, it becomes necessary to apply advanced technologies such as machine learning algorithms and neural networks, which, thanks to their adaptability and ability to analyse large data sets, enable the accuracy of forecasts to be improved. The article undertakes a critical analysis of the limitations of traditional forecasting methods and presents a theoretical conceptual framework for intelligent energy price forecasting systems. The proposed model integrates a variety of analytical techniques, including both hybrid approaches based on LSTM-Transformer architectures and adaptive mechanisms to dynamically adjust models to changing operational conditions. This theoretical framework is further validated by a single-case study, which demonstrates the potential implications of AI for optimizing business strategies and operational workflows in a real-world PV-farm setting. The solutions presented have important practical implications – enabling the optimisation of decision-making processes, reduction of operational risks and increased profitability of PV farms. In an era of increasing competitiveness in the renewable energy sector, the implementation of intelligent forecasting systems is becoming a key element in building competitive advantage, providing operators with tools to make decisions based on reliable and up-to-date data.

2. LITERATURE REVIEW

Forecasting electricity prices for PV farms is currently a significant challenge due to increasing market volatility and a number of external factors affecting price levels. The high penetration of renewables in the energy mix leads to increased uncertainty and price volatility, making it difficult to accurately predict future revenues from PV farms (Uniejewski & Ziel, 2025), (Poggi, Di Persio, & Ehrhardt, 2023). The following is an analysis of the scientific literature on key aspects of this issue, including the impact of price volatility and external factors, the risks of long-term PPAs, and the need for improved forecasting methods.

Electricity prices on wholesale markets are characterised by high volatility, which in the case of PV farms is strongly linked to weather factors and market and regulatory conditions. Solar generation depends on weather conditions (insolation, cloud cover), which translates into PV power supply and consequently the spot market price level. Research indicates that the volatility of renewable generation (such as solar or wind) can lead to higher price fluctuations and system balance challenges (Uniejewski & Ziel, 2025). In addition, prices are influenced by macroeconomic and political factors - e.g. increased demand after a pandemic, commodity crises or political decisions. Poggi et al. emphasise that energy prices are influenced by economic activity, political changes, weather conditions and the dynamics of related markets (Poggi, Di Persio, & Ehrhardt, 2023). Also, regulatory interventions, such as the introduction of price caps or changes to the RES support scheme, can significantly alter price formation mechanisms. The complexity of these interdependencies makes price forecasts subject to considerable uncertainty, especially in systems with increasing solar PV.

The regulatory environment and political decisions have a strong influence on energy price formation mechanisms. The rules governing the energy market - such as the market structure (e.g. the existence of a capacity market, RES support mechanisms), the level of price regulation, taxes and subsidies – set the framework within which supply and demand mechanisms operate. Regulatory changes can therefore significantly alter the boundary conditions for price forecasts. For example, the introduction or removal of government subsidies for either energy producers or consumers can change the effective cost of generation or the price paid by consumers, which in turn alters market behaviour (Kojima et al., 2016). In countries where the government keeps tariffs artificially low through subsidies (often at the expense of not compensating state-owned energy companies for generation costs), market prices do not fully reflect production costs (Kojima et al., 2016). Forecasting under such conditions requires tracking government policies and possible adjustments to these support mechanisms.

Another example of the impact of policies on energy prices is climate and environmental regulation. The introduction of emissions trading schemes (such as the EU ETS in Europe) has imposed the cost of CO_2 allowances on power plants, which has gradually raised wholesale energy prices, especially from conventional sources. When policies tighten emission standards or reduce the supply of free allowances, the cost of producing energy from coal or gas rises – and forecasting models need to take these trends into account. As mentioned, in the EU, allowance prices have risen sharply, doubling in the short term, significantly affecting energy price levels (Kojima et al., 2016). Also, energy policy goals, e.g. energy transition (decarbonisation) strategies, indirectly influence the market: announcements of coal plant shutdowns, the development of nuclear power or accelerated investment in RES give signals on how the future supply and cost of energy may evolve. Long-term price forecasts must therefore take into account policy scenarios, such as the implementation of RES share targets, the introduction of a carbon tax, changes in market regulation (e.g. balancing market reforms) (Baird, 2024).

Long-term power purchase agreements (PPAs) are commonly used by PV farm investors to ensure stable revenues, but they come with a number of risks. A key concern is price risk - over the long horizon, market prices may be lower than those agreed in the contract, leading to consumers paying more and producers losing potential profits. In addition, the volatility of RES generation, due to weather variability, results in increased balancing costs and cannibalisation phenomena when oversupply lowers market prices. Regulatory and contractual risks are also important – government interventions, such as temporary price caps, and an increase in the likelihood of parties defaulting on their contracts, further complicate PPA negotiations. Price volatility in the futures market, resulting from backwardation, leads producers to prefer shorter contracts or hedging strategies to long-term contracts. Despite these challenges, PPAs remain an attractive hedging tool, provided they are supported by careful risk analysis and the use of appropriate protection mechanisms (Kapral, Soetaert, & Castro, 2024).

Technological advances and changes in energy generation and consumption patterns introduce dynamic modifications to the market, making price forecasting difficult. The growth of renewables such as solar and wind power is making energy supply highly weather-dependent, resulting in rapid fluctuations - prices fall during periods of oversupply and rise sharply when production declines. Forecasting models must therefore take into account the effect of the so-called 'duck curve', illustrating the oversupply of solar at midday and the shortage of capacity during the evening peak (U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy, 2017; Nowotarski & Veron, 2018).

Additionally, although the development of energy storage technologies and demand response systems may contribute to market stabilisation in the future, their current impact remains limited.

Changes in demand patterns due to the electrification of transport and increased efficiency of domestic appliances modify the energy consumption profile, which particularly affects prices during night periods (Baird, 2024). Scenario analyses, based on indicators such as the growth rate of electric vehicles and smart home penetration, are a key element in forecasting medium- and long-term price trends. An important group of factors affecting energy price forecasts are sudden, unpredictable external events, known as market shocks. These events, such as geopolitical crises, natural disasters or sudden economic downturns, go beyond typical market volatility and can quickly change supply and demand relationships, causing prices to deviate significantly from historical trends. An example is the armed conflict in Ukraine in 2022, which caused a disruption in energy commodity trade, resulting in unprecedented increases in gas and electricity prices in Europe. As a result of such shocks, forecasting models based on pre-event data often generate erroneous results, highlighting the difficulty of incorporating extreme, rare events into medium- and long-term forecasts (Baird, 2024).

In view of the described unpredictability of prices and market risks, the literature highlights the need to improve energy price forecasting methods for PV farms. Traditional forecasting models, based on historical data and simple statistical assumptions, are increasingly failing in today's highly volatile market (Uniejewski & Ziel, 2025). Hong et al. previously noted that the accuracy of energy price forecasts is limited by the occurrence of abnormal events and rapid market changes, necessitating continuous model refinement. More recent studies confirm that including more inputs (e.g. demand forecasts, RES production, weather) and the uncertainty of these variables can significantly improve the accuracy of price forecasts (Hong et al., 2020). Uniejewski and Ziel showed that integrating probabilistic forecasts of solar and wind generation (rather than just point values) can reduce price forecast error by up to several per cent compared to the traditional approach (Uniejewski & Ziel, 2025). Importantly, more accurate forecasts translate directly into reduced operational and financial risks for PV farms. Better prediction of production and prices enables farm operators to optimally plan energy sales in day-ahead and intra-day markets, reducing costly schedule deviations. It has been estimated that forecasting errors can cause significant revenue losses – Karimi-Arpanahi and colleagues estimated that a 100 MW PV farm can lose up to about 9% of potential annual revenue precisely because of generation unpredictability (Karimi-Arpanahi, Pourmousavi, & Mahdavi, 2023). This is due to the need to buy back the missing energy at high prices or to miss sales opportunities during peak periods.

3. METHODOLOGY

The issue of energy price forecasting for photovoltaic (PV) farms is complex and interdisciplinary – combining elements of economics, energy and management including advanced data analysis methods. Knowledge in this area is developing very dynamically and is sometimes dispersed between different disciplines, making it difficult to keep up to date with the latest developments and to assess the state of the art holistically (Snyder, 2019). Under such conditions, the use of a literature review as the main research method is fully justified. A literature review allows the collection and systematisation of existing knowledge, providing a cross-sectional view of existing research findings and approaches used. This is particularly important for identifying key concepts, trends and possible research gaps in energy price forecasting methods. Furthermore, adopting a formal, rigorous review methodology – rather than an ad hoc approach - increases the quality and credibility of the conclusions obtained (Snyder, 2019).

In addition, in order to provide a theoretical conceptual framework for an intelligent energy price forecasting system, the literature review will be complemented by a conceptual analysis of the collected material. Conceptual analysis is a research approach that involves the precise definition and clarification of key concepts and their interrelationships on theoretical grounds (Furner, 2004). This technique treats concepts as classes of objects or phenomena and indicates the conditions under which a phenomenon can be classified into a given concept. The purpose of applying conceptual analysis in the present context is to better understand how particular concepts related to energy price forecasting are used and defined in the literature (Furner, 2004). Based on this combined framework, a single-case study was undertaken to demonstrate the potential implications of artificial-intelligence methods in optimizing operational workflows and guiding business-strategy decisions. Case study research is widely endorsed as a valid method for examining contemporary phenomena within their real-world context – especially in applied settings where the phenomenon and its context are deeply intertwined. This makes it an appropriate strategy for studying operational applications of AI in businesses, where technology and organizational context cannot be meaningfully separated (Yin, 2018).

It is worth emphasising that the research strategy adopted (i.e. a combination of literature review and conceptual analysis) is grounded in scientific best practice. In rapidly evolving research areas, the literature review is a recognised method for keeping up with the state of the art and evaluating the collective evidence (Snyder, 2019).

It should be noted that the literature review methodology has several limitations that need to be taken into account when interpreting the results. Firstly, the temporal scope only includes publications available up to 2024, which means that the most recent research may not be included, especially in rapidly developing areas such as AI methods and the energy market. Secondly, publication bias may result in an overestimation of the effectiveness of methods, as papers with positive results are published more often, which may distort the overall picture of achievements. In addition, the heterogeneity of studies, due to differences in assumptions, models, time horizons and error measures, makes direct comparisons of results between studies difficult and requires some simplification when making generalised conclusions.

3.1. Methodological Framework: AI-Based Energy Price Forecasting Models

To meet the challenges of energy price forecasting, researchers are intensively developing advanced artificial intelligence algorithms for energy price forecasting. The trend in the literature in recent years has been to move away from simple regression models towards machine learning and deep learning methods. Neural networks (including deep recurrent LSTMs, GRUs and convolutional CNNs) can capture non-linear relationships between multiple variables (e.g. PV production, demand, weather) and thus often outperform traditional statistical models in accuracy. Chatterjee et al. compared different deep grid architectures (LSTMs, CNNs, CNN-LSTM hybrids) for daily price forecasts and showed significant improvements in accuracy compared to classical methods (Chatterjee et al., 2023). Similarly, other works propose hybrid models that combine signal processing techniques (wavelet transform, feature decomposition) with neural networks to extract hidden temporal patterns. For example, a sequential LSTM model supported by signal decomposition can better represent price spikes than a single network without such preprocessing (Laitsos et al., 2024).

In addition to neural networks, other machine learning algorithms such as vector machines (SVMs), decision trees or ensemble learning methods have been successfully used. The combination of multiple methods in the form of ensembles or model committees has been shown to produce more stable and accurate predictions than single models (Zhou et al., 2019), (Shi et al., 2021). Laitsos et al. (2024) presented a model combining a CNN, a GRU and an attention mechanism that achieved an average MAPE error of ~6.3%, outperforming the accuracy of classical neural models not using an attention mechanism (Laitsos et al., 2024).

In contrast, other studies explore probabilistic forecasting using Bayesian methods and generative networks, providing confidence intervals for prices. This approach helps market participants to assess not only the most likely price scenario, but also the risk of deviation from this forecast, which is particularly important when planning PV farm energy sales strategies.

Three main approaches using AI for energy price forecasting are presented below: machine learning models, neural networks and optimisation algorithms. Their application to the RES market (especially in the context of photovoltaic farms) and the concept of intelligent adaptive predictive systems are also discussed.

Machine learning (ML) covers a wide range of statistical and algorithmic methods that learn relationships from data. Among others, regression models, decision trees (e.g. random forests) or gradient boosting-style ensemble models (Future Bridge, 2024) are successfully used in energy price forecasting. Their task is to look for patterns between variables affecting the price - e.g. energy demand, supply from RES, fuel prices or weather conditions - and predict future price fluctuations on this basis. ML models are able to take into account multiple features (feature vectors) simultaneously and thus capture non-linear relationships better than traditional methods. For example, machine learning algorithms can analyse correlations between various market factors and automatically adapt their models to changing market conditions, which is crucial in a volatile energy market (Pragmile, 2024). This means that when relationships change (e.g. the introduction of new subsidies, changes in weather or consumer behaviour), the ML model can be re- learned on new data or adjusted to still accurately reflect the current situation. As a result, machine learning techniques provide greater flexibility and accuracy in energy price forecasts compared to the rigid statistical models of the past.

Artificial neural networks (ANNs) are a special class of machine learning models inspired by the structure of the human brain. They consist of multiple interconnected layers of neurons (input, hidden and output), which allows them to model highly complex non-linear relationships between data (Future Bridge, 2024). Deep neural networks, including Recurrent Neural Networks (RNN) architectures and their variations such as Long Short-Term Memory (LSTM), are increasingly used in energy price forecasting. These models are suited to time series analysis - they can remember relevant information from the past and thus capture temporal relationships in price data. Neural networks excel at detecting subtle patterns that are difficult to spot with traditional statistical methods (Pragmile, 2024). For example, they can forecast energy prices based on predicted RES generation (e.g. solar insolation and PV farm production) or predict the impact of weather conditions on this generation - allowing operators to better plan system operation (Pragmile, 2024). Compared to simpler models, deep grids are able to analyse huge datasets from multiple sources (e.g. price history, weather forecasts, demand, sensor data on the grid) and learn from them representations of phenomena affecting price. As a result, they often achieve higher forecast accuracy. The disadvantage can be a 'black box' - the difficulty of interpreting internal weights - but in the context of energy price prediction accuracy, the advantage of neural networks is well documented (Pikus & Wąs, 2024).

The third group of approaches are optimisation algorithms, which support the forecasting process by finding solutions that minimise forecast error or maximise a specific profit. This category includes evolutionary algorithms (e.g. genetic algorithm, GA) and algorithms inspired by natural behaviour (e.g. particle swarm optimisation, PSO). These algorithms are sometimes combined with learning models - e.g. for tuning the hyperparameters of ML/ANN models. For example, the use of a genetic algorithm to optimise the parameters of an LSTM network can improve its price prediction ability through better selection of training settings (Future Bridge, 2024). Another application is the creation of hybrid models: optimisation algorithms can help divide the prediction task into simpler components (e.g. using signal decomposition) or dynamically select a combination of different prediction models to minimise error. For example, the literature describes the use of swarm optimisation (Grey Wolf Optimizer) to tune a random forest model, which significantly improved the accuracy of short-term energy market price forecasts (Zhang et al., 2022). Moreover, the optimisation algorithms are indirectly applicable - the results of the forecasting models can serve as inputs to decision-making algorithms that optimise the operation of the energy system (e.g. planning the use of energy storage, as discussed below). This machine learning and optimisation approach allows not only to predict prices, but also to make the best decisions in response to forecasts.

3.2. Research Instruments: Design of the Intelligent Energy Price Forecasting System

Given the widespread use of AI to optimise business decisions and operational processes in support of PV farm energy price forecasting, the following chapter proposes a system for energy price forecasting to support the optimisation of business decisions of photovoltaic (PV) farm operators, allowing decision makers to support and optimise business decisions and operational processes. The system consists of modules corresponding to the successive stages of information processing – from data acquisition, through data preparation and analysis using artificial intelligence, to adaptive model refinement, application of forecasts to operational decisions and presentation of results to users. Figure 1 shows the designed system, which integrates a variety of approaches and innovative solutions to ensure high forecast accuracy and flexibility in dynamic market conditions.

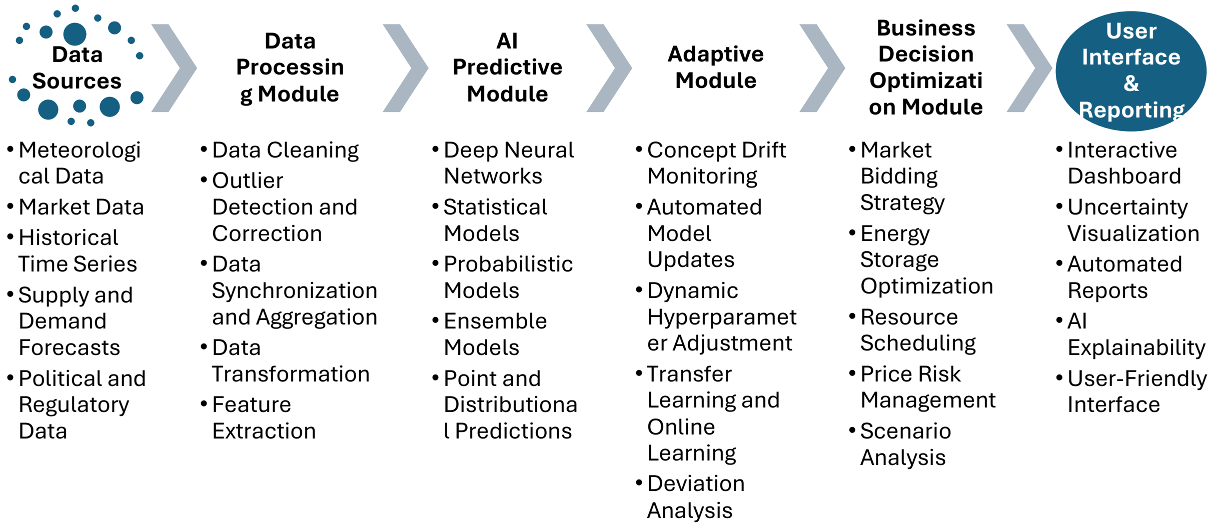

Figure 1. Intelligent energy price forecasting system for PV farms
Source: own elaboration.

Data sources

The energy price forecasting system is based on the integration of data from a wide variety of sources, capturing all the key factors that influence price formation. Among the data used is meteorological information such as sunshine, temperature and wind speed, which affect both renewable energy production and energy demand. Market data, including, among other things, wholesale prices, futures quotes and fuel prices, allow the impact of economic factors on energy prices to be assessed. Equally important are archived time series of prices, trading volumes, generation and past values of weather and macroeconomic variables, which provide a basis for identifying repeatable trends. In addition, supply and demand data – both current and forecast – allow for the identification of the system's ability to meet demand, which has a direct impact on price levels, especially when capacity reserves are insufficient. The inclusion of political and regulatory factors, such as regulators' decisions, legal changes or geopolitical events, on the other hand, allows to reflect the impact of unforeseen events on price dynamics (Singh & Mohanty, 2015; Poggi, Di Persio, & Ehrhardt, 2023). This rich set of data sources allows the forecasting model to learn the complex relationships between weather conditions, demand, fuel prices, and market events, resulting in more objective forecasts based on a broad context.

Data processing module

In the process of preparing data for energy price forecasting, it is crucial to carry out a comprehensive ETL (extract- transform-load) step, which ensures that the input data to the AI modules is reliable, consistent and properly formatted. At the outset, the raw data, extracted from many disparate sources, undergoes cleaning, which involves eliminating errors, gaps and duplicates. Missing observations are filled by imputation methods such as interpolation or moving average, and outliers, detected e.g. by the z-score method, are verified and, if necessary, corrected or removed so that they do not introduce disruptive noise into the model (Mancha Gonzales, Iftikhar, & López-Gonzales, 2024; Khalid et al., 2019). This is followed by data validation and aggregation, which involves synchronising information from different sources that may differ in measurement frequency and time lag. This creates a unified set of features where, for each time interval, demand data, PV and wind generation, reserve status, fuel prices, weather conditions and calendar information, among others, are recorded. The next step is feature transformation and extraction, where the data are normalised or standardised, allowing variables to be scaled to a uniform range and variances to be stabilised. In addition, seasonal components and long-term trends are removed through differentiation or filtering, bringing the time series closer to stationarity. This process results in advanced indicators such as moving averages or rates of change, which enhance the model's ability to detect hidden patterns. Taken as a whole, the implementation of these steps - cleaning, validation, aggregation, transformation and feature extraction - significantly improves the quality of the data, which is key to the effectiveness of further analysis and forecasting steps using advanced machine learning algorithms.

Predictive AI module

The AI prediction module is at the heart of the energy price forecasting system, responsible for generating forecasts for a set time horizon using advanced artificial intelligence algorithms. Within this module, hybrid strategies for combining different machine learning techniques are used to improve forecast accuracy by synergistically exploiting the strengths of the different methods. On the one hand, deep neural networks such as LSTM, CNN and transformer architectures enable the model to capture complex, non-linear relationships in serial data. LSTM, with its built-in memory mechanism, can effectively model long-term dependencies and trends, which are essential for energy price forecasting, where current values are strongly correlated with historical patterns (Poggi, Di Persio, & Ehrhardt, 2023). CNNs, when used to analyse sequential data, automatically identify characteristic shapes and patterns in the price signal, and a weight- sharing mechanism promotes the generalisation of detected features. Recent solutions based on transformer architectures derived from the field of natural language processing enable parallel processing of entire data sequences, which significantly improves the accuracy of modelling both short-term fluctuations and long-term price cycles (Poggi, Di Persio, & Ehrhardt, 2023).

In addition to deep networks, the prediction module integrates traditional statistical and machine learning models such as ARIMA/SARIMA and GARCH models, which are particularly effective in capturing seasonal components and linear trends. When used in parallel as ensembles, these methods enable the use of different perspectives of data analysis, which allows the reduction of prediction error by combining the results obtained with linear and non-linear models (Poggi, Di Persio, & Ehrhardt, 2023; Lee et al., 2024).

Another important element of the prediction module is the use of probabilistic approaches that go beyond traditional point forecasts. These models generate forecasts in the form of complete distributions, representing confidence intervals, which enables accurate risk assessment and identification of potential price extremes. For example, the distributional forecasting technique, which uses neural networks that learn the price distribution, allows modelling not only the expected value, but also the higher moments of the distribution, which is crucial for managing risk in volatile market conditions (Marcjasz et al., 2023).

By integrating these advanced techniques – a hybrid combination of deep networks, traditional statistical models and probabilistic approaches – the AI prediction module processes the prepared input data and generates forecasts that have high accuracy and reliability. Such a system enables energy companies to make better operational decisions by offering comprehensive insights into possible market scenarios and providing reliable tools for risk management. As a result, the predictive module, through the use of the latest developments in artificial intelligence, provides the foundation for an effective energy price forecasting system, which translates into increased competitiveness and operational stability for companies operating in a dynamic energy market.

Adaptation module

The adaptation module is a key component of the forecasting system, enabling the models to continuously adapt to dynamically changing market conditions. Two main mechanisms are implemented within this module: data drift monitoring and automatic model updating. The first of these, concept drift detection, involves constant surveillance of incoming data, including comparison of actual values with forecasts, in order to detect signals that the statistical properties of the data are changing, which may result in a loss of accuracy of the model trained so far. The system uses advanced detection algorithms that analyse forecast residuals and statistical changes to quickly identify significant deviations, while minimising the risk of false alarms. The second mechanism, automatic model updating, allows the system to adapt through periodic re-learning or incremental learning, allowing hyperparameters and network structure to be dynamically adjusted without full retraining. More advanced solutions use online learning and transfer learning techniques that allow the model to adapt immediately to new trends and changes in the input data. Such continuous feedback, based on analysis of forecast errors and comparison with current observations, allows the system's learning loop to be closed, so that the model maintains high accuracy and validity even in highly changing energy markets. As a result, the adaptive module provides flexibility and resilience to the system, enabling PV farm operators to benefit from forecasts that reflect the latest developments, such as current fuel prices, new regulations or weather changes, which is key to maintaining a competitive edge in a dynamic environment. (Xiang, Zi, Cong, & Wang, 2023)

Business decision optimisation module

The Business Decision Optimisation module is an integral layer of the system that transforms energy price forecasts into concrete operational actions, enabling efficient asset management and risk minimisation. On the basis of the forecasts generated by the prediction module, which take into account uncertainty expressed in terms of confidence intervals, the module develops bidding strategies, adjusting the amount of energy to be sold on the day-ahead market, the spot market or under long-term contracts. In situations where forecasts indicate an increase in prices, the system recommends selling larger volumes during peak periods and, when prices are low, using energy storage recharge opportunities to sell later at a higher price. In addition, the module enables the scheduling of maintenance work and the coordination of different energy sources within the portfolio, which allows production to be optimised even in a virtual power plant environment. Another important aspect is the use of scenario simulations, which, through what-if analysis, allow the resistance of adopted strategies to forecast deviations to be assessed and recommendations to hedge against price risk to be developed. The results of such analyses, supported by advanced algorithms, make it possible to precisely determine how much energy to offer at auction and how much to leave in storage, which translates into real savings and increased profitability. Such an integrated system, combining forecasting with decision optimisation, allows PV farm operators to make informed, data-driven decisions, respond to changing market conditions and effectively manage risk, a key element in achieving competitive advantage in a dynamic energy environment (Wu et al., 2024; Lee et al., 2024).

User interface and reporting

The user interface and reporting module is the final but key component of the system, allowing PV farm operators to interact with the system, monitor forecasts and receive recommendations and business reports. Through an intuitive dashboard, users have access to interactive charts showing the forecast price curve for the coming hours or days, complemented by visualisations of uncertainty ranges, allowing them to quickly understand trends and assess the reliability of forecasts. In addition, the module presents operational recommendations, such as optimising energy sales or managing storage, in the form of clear messages that enable specific actions to be taken. Reporting takes place both on an ongoing and periodic basis, generating comprehensive summaries of the effectiveness of forecasts and an analysis of savings achieved, which promotes continuous optimisation of operational strategies. A key aspect is also to ensure that the interface is user-friendly even for non-technical people – with responsive visualisations such as charts, icons and clear colours, decision-makers can easily interpret complex data and focus on key information, facilitating both individual and group decision-making. As a result, the module translates the advanced intelligence of the system into added value for the user, enabling effective analysis, communication of results and rapid response to market changes.

The energy price forecasting system presented in this study is characterised by a comprehensive integration of modules that together form an advanced platform for operational decision-making in a dynamic energy market. At the outset, the system collects data from a variety of sources, which are then subjected to rigorous processing – including data cleaning, validation, aggregation and transformation – to guarantee high quality input information. The prediction module, the heart of the system, uses a hybrid architecture that combines deep neural networks (such as LSTMs, CNNs and transformers) with traditional statistical methods to capture complex, non-linear relationships and account for variability in historical and current data. Probabilistic approaches are also used within this module, generating full distributions of forecasts to assess the uncertainty and risk associated with the predictions. Another key element is the decision-making module, which transforms price forecasts into specific operational strategies, such as sales optimisation, energy storage management or maintenance scheduling. The entire system is complemented by a user interface that offers intuitive visualisations and report generation, enabling decision-makers to make decisions quickly and efficiently. A system structured in this way, using approaches ranging from Big Data to advanced AI techniques to decision optimisation, provides a robust tool to support the operations of energy companies, as evidenced by the results of a study (Wu et al., 2024).

3.3. Case Study: Application of the Forecasting System

Installation Description and Data

A ground-mounted photovoltaic farm with a 1 MW installed capacity, located in southern Poland, is analyzed. The installation comprises PV modules fixed at a constant tilt, producing approximately 1 100 – 1 300 MWh annually (peak in summer, lower in winter). Historical data from 2020 – 2024 were employed, including the PV production profile (measured power/energy in hourly intervals), corresponding meteorological measurements (irradiance, temperature, cloud cover), day-ahead electricity market prices (TGE), and calendar features capturing diurnal and seasonal cycles (hour, time of day, day of week, month, season). Incorporating multiple input variables allows the model to learn complex dependencies – this approach aligns with industry practice, where LSTM networks are trained on a suite of weather and generation variables.

Data Preprocessing

Raw data underwent cleansing: missing values were removed or imputed, and obvious anomalies (e.g., zero generation on a sunny day due to equipment failure) were corrected. Feature engineering then added seasonal indicators (e.g., week number; sine/cosine transforms of day-of-year) and lagged generation and price values to inform the model of short-term trends. All numeric features were normalized (min–max scaling), a standard practice that stabilizes LSTM training. The dataset was split chronologically into training (2020 – 2023) and validation/test (2024) sets, preventing look-ahead bias and reflecting real forecasting conditions.

Forecast Horizon

A 24-hour-ahead horizon was adopted, so the model predicts generation and prices one day in advance, as required by the day-ahead market. This horizon is critical for the operator's planning of SPOT market participation, network load management, and maintenance scheduling.

AI System Implementation

The case study implements an AI system to forecast PV generation and electricity prices using a hybrid LSTM – Transformer architecture. The model ingests past outputs (historical generation), meteorological inputs (irradiance, temperature) and historical price data to capture both temporal patterns and weather impacts on yield. A multi-layer LSTM processes recent observations and extracts hidden trend representations; these are then analyzed by a Transformer encoder with several self-attention blocks, enabling the model to dynamically weight salient features (e.g., morning cloud cover's effect on afternoon output or time-of-day price patterns). Encoder outputs are concatenated and passed through dense layers to produce 24 hourly forecasts of both farm power and price. This multivariate approach supports simultaneous supply-side and market condition forecasting, facilitating operational optimization. The model was implemented in Python with TensorFlow/Keras and trained on GPU hardware. Training minimized mean squared error (MSE) between predictions and actual values while monitoring mean absolute error (MAE) and mean absolute percentage error (MAPE). An early-stopping criterion halted training when validation loss ceased improving, and the model with lowest validation error was selected. Due to its implementation as a simplified case study no parallel ARIMA/SARIMA, GARCH, or CNN models were included – forecasting relies solely on the LSTM – Transformer hybrid. Future work might extend the system with ARIMA or GARCH ensembles (e.g., weighted forecast averaging) and incorporate probabilistic forecasting (Bayesian LSTM or distributional-forecasting networks) to generate confidence intervals alongside point estimates.

4. RESULTS

Within the case study framework, the AI model demonstrated the MAPE of approximately 5 % for daily PV generation forecasts – comparable to leading commercial benchmarks (EPRI reports of 5 – 5.4 % MAPE). Price forecasts attained MAPE of approximately 12 %, within the typical 5 – 14 %

range for day-ahead electricity markets. Given price volatility, this represents a significant improvement over persistence and simple regression baselines.

Projections for 2025 preserve strong seasonality – summer daily maxima near installed capacity on clear days and several-fold lower winter output. Total annual generation is forecast at ~1120 MWh under standard weather assumptions, matching historical performance. Price forecasts foresee continued volatility, including midday negative-price events in spring/summer (–5 to –123 PLN/MWh) on low-demand sunny days, especially on late-spring weekends. Average daily prices are expected between 200 – 300 PLN/MWh, peaking during morning and evening demand surges and dipping overnight and midday.

Based on the generated forecasts, a simulation of the PV farm's operation in 2025 was performed to evaluate three distinct operational strategies (see Table 1).

Table 1. Operational Strategy Simulation

Strategy	Description
SPOT-Only Sales	All generation offered on the day-ahead market. Moderate revenues but high risk from negative prices, which can lead to operator payments to the grid.
AI-Driven BESS Optimization	Utilization of the forecasting model to intelligently control an on-site battery energy storage system.
Fixed-Price PPA	Sale of energy at a predetermined rate under a long-term Power Purchase Agreement.

Source: own elaboration.

Spot-Only Sales ('Merchant' Strategy) involves the farm offering all generated energy on the day-ahead market at prevailing spot prices without any adjustment to its generation profile. The simulation revealed that, while moderate and high prices yield revenues close to market averages, this strategy carries significant risk during periods of energy oversupply. Negative prices pose a serious threat—under extreme conditions, the operator might have to pay for energy injection. The 2025 forecast likewise predicts intermittent negative-price episodes, making a purely spot-market approach potentially less profitable and more volatile in terms of revenue stability. Market evidence shows that merchant projects become less viable without safeguards against price swings.

AI-Driven BESS Optimization Strategy involves equipping the farm with a battery energy storage system (BESS) and using the AI forecasting model to govern its charging and discharging decisions. The model anticipates periods of oversupply and low prices, allowing energy to be stored when sales would be unprofitable and dispatched when prices rise. A simulation using an optimization algorithm (e.g., reinforcement learning) demonstrated a substantial improvement in the farm's financial performance, with annual revenue increasing by approximately 15–20 % compared to the spot-only strategy. This finding aligns with literature reporting up to 20 % profit gains from intelligent storage management. The model avoids selling during negative-price hours—storing excess energy instead—and releases it once prices exceed a predefined threshold. This strategy proved the most financially effective and also reduced revenue volatility, yielding a more even profit distribution and greater resilience to extreme price fluctuations.

Fixed-Price PPA Strategy involves selling all 2025 generation under a long-term Power Purchase Agreement at a predetermined price. This strategy eliminates market risk – revenues remain stable regardless of spot price volatility. The simulation assumed a contract price close to the average forecast market price. Consequently, annual revenue was slightly lower than under the AI+BESS strategy (foregoing high-price gains) but higher than in the pure spot scenario, which suffers during negative-price intervals. The PPA arrangement completely removes negative-price exposure – the operator receives a fixed payment per MWh, avoiding charges for generation. This benefit is underscored by the growing popularity of long-term contracts among PV investors facing market unpredictability. In practice, securing an attractive PPA requires identifying a reliable off-taker and accepting a somewhat lower margin in exchange for reduced risk.

Implementing the AI system enhanced decision-making at several levels. First, BESS management became forecast-driven: precise generation and price predictions allow pre-planning of charge/discharge cycles – storing energy overnight or during anticipated negative-price periods and selling at evening peaks to maximize profit. Second, the model enables proactive curtailment or storage to avoid negative-price sales, protecting revenue and aiding local grid stability by reducing feed-in during critical periods. Third, continuous comparison of forecasted versus actual generation supports predictive maintenance: systematic under-performance under similar weather conditions signals potential faults (soiling, string failures), enabling timely service interventions before significant losses. Furthermore, knowledge of expected generation guides scheduling of inspections and maintenance on low-generation days, minimizing lost production. Overall, AI integration improved resource utilization (panels, battery, maintenance personnel) and illustrates the added value of advanced forecasting and decision-support algorithms in reducing uncertainty and enabling data-driven operations. As industry analyses note, AI applications in renewables – from forecasting to predictive maintenance – enhance operational efficiency and reliability in variable conditions (delfos.energy). In summary, the AI system delivered measurable economic benefits, reduced operational risk, and facilitated integration of the 1 MW PV asset into the dynamic energy market and grid, thereby increasing project competitiveness.

5. DISCUSSION

Photovoltaic (PV) farms operate in a highly volatile energy production and price environment, driven by weather conditions and a dynamic energy market. The use of artificial intelligence (AI) to forecast energy prices offers a promising solution to these challenges. Accurate AI-based forecasts enable PV farm operators to better plan and make business decisions in real time, resulting in more efficient use of the energy produced and improved profitability (World Economic Forum, 2024). In the context of limited data availability and variability of climatic conditions, it is important to discuss the scope of the model's generalization.

In the following, the key application areas of intelligent price forecasting systems - from production management, sales strategies and risk management to operational cost optimisation and integration with energy storage - will be discussed.

Energy production management

The variability of insolation makes PV energy production intermittent and difficult to control. Although insolation itself cannot be controlled, intelligent forecasting of both PV generation and energy prices can optimally manage the production schedule of PV farms. AI algorithms analysing meteorological data can predict solar production and future market prices with high accuracy (World Economic Forum, 2024). It is worthwhile to emphasize the need for validation of forecasts under varying local conditions and taking into account concept drift. This allows operators to plan operational activities in advance to maximise the use of the energy produced during periods of high prices and reduce losses during periods of low prices. For example, accurate production forecasts make it possible to predict energy surpluses and plan the use of loads or storage during peak generation hours, as well as estimate how much generation will be available for sale under given weather conditions (Rocha et al., 2024). AI thus enables more efficient use of the generated energy and optimisation of plant operating costs, resulting in better farm and grid performance (Rocha et al., 2024). In addition, smart systems can dynamically adapt the generation profile to market conditions, if the flexibility exists. In practice, with forecasts of very low or negative energy prices at certain times, PV farms may consider deliberate curtailment during these periods to avoid selling energy at a loss. However, such decisions require reliable price forecasts - the AI system is able to identify in advance the time intervals when prices will fall below zero and recommend temporarily shutting down some generation Feenstra, 2024). It is necessary to discuss the risks of over-reliance on forecasts and their impact on supply continuity. For example, European spot market conditions have seen an increasing incidence of negative prices during midday hours when there is ample supply from RES. Intelligent algorithms can issue a signal to reduce capacity during such a period, avoiding the costs associated with surrendering energy at a negative price (Feenstra, 2024). Importantly, this type of action should be seen as a last resort – the ultimate goal of price forecasting is to minimise the need to reduce production by better balancing supply and demand. However, the ability to schedule maintenance or technical outages during periods of predicted low prices (e.g. cloudy days with low demand) is also part of optimising the production schedule. AI makes it possible to postpone unavoidable outages to periods with minimal impact on revenue, so that the farm is fully ready at times of peak market prices. Managing energy production in PV farms becomes much more efficient with AI forecasts. They facilitate generation planning in correlation with prices, ensuring efficient use of resources and optimisation of financial returns even when supply is variable (World Economic Forum, 2024). As a result, the farm can react proactively to changing market conditions, instead of acting reactively ex post.

Sales strategies and energy trading

Intelligent electricity price forecasting is a key support in the development of PV farm power sales strategies. This includes day-ahead and spot market participation, as well as the management of long-term Power Purchase Agreements (PPAs). Having reliable price forecasts for the following days and hours enables PV farm operators to make better decisions on the volume and price of energy offered in day-ahead market auctions, resulting in higher sales efficiency and revenue stability. Trading on the day-ahead market. Traditionally, many RES operators sold energy mainly on the spot market (balancing market), accepting the risk of low prices during periods of oversupply. With AI, however, a change in approach is possible - learning algorithms based on historical price and weather data can predict price profiles in the day-ahead market with a high degree of accuracy, allowing sales bids to be made in advance and a fixed sales price to be secured against adverse conditions (Vinyard, 2024). However, the long-term robustness of these predictions under evolving market regulations and atypical weather patterns warrants further investigation. According to industry analysis, using AI-based recommendations to participate in the day-ahead market can increase a PV project's revenue, as it enables it to hedge against low prices in real time (hedging), while not taking away the opportunity to benefit from potential price spikes (Vinyard, 2024). In other words, the farm, thanks to forecasting, can sell part of the energy in advance at a predetermined price (if oversupply and the threat of falling prices are announced) and sell the remaining part on the spot market when favourable short-term price increases occur. This hybrid approach minimises the risk of revenue loss during periods of price downturns, while at the same time exploiting market opportunities to maximise profits. The trade-off between forecasting accuracy and model complexity should be evaluated to understand the cost-benefit balance of deploying such systems. However, high forecast accuracy is a prerequisite for effectiveness - day-ahead trading becomes virtually impossible without accurate generation and price predictions, as incorrect forecasts can result in penalties for contract defaults or lost profits. AI systems simultaneously integrate forecasts of production (e.g. from weather models) and prices, providing comprehensive recommendations on the optimal sales plan for the next day-ahead. Future research should examine the resilience of automated bidding algorithms to extreme market volatility and data anomalies. As the McKinsey report notes, advanced data analytics in volatile conditions (e.g. the intraday market) can be the deciding factor in making a profit or incurring a loss - the information advantage through AI is key here (Vinyard, 2024). In addition, AI-based trading algorithms can automatically adjust bids and execute trades in a fraction of a second, increasing the speed and efficiency of energy trading and exploiting short-term price fluctuations better than is possible with traditional methods (Montel, 2024a). It remains to be discussed whether reliance on microsecond execution could amplify systemic risks through algorithmic feedback loops.

PPA Management

Many PV farm owners enter into long-term PPAs, selling energy directly to consumers at a fixed price. Intelligent energy price forecasts play an important role in the negotiation and management of such contracts. Firstly, by forecasting price trends in the wholesale market, the investor can better assess the profitability of the proposed rate in the PPA against future market prices. AI analyses huge datasets – historical prices, demand projections, regulatory scenarios - to help estimate whether a given guaranteed price will provide the expected return on investment over the life of the contract, or whether there is a risk of opportunity cost in the event of a sudden increase in market prices. However, the sensitivity of these estimates to abrupt regulatory changes or unanticipated market shocks merits further examination. Secondly, modern business models introduce flexible PPAs in which volumes or prices can be partially indexed to the market. In such cases, AI predictions are essential for deciding when it is more advantageous to deliver energy under a PPA and when to direct it to the spot market. With price and production prediction, a farm owner can, for example, decide to divert surplus (over the agreed PPA volume) to the day-ahead market if forecast prices are higher than the PPA rate, or conversely, increase the volume sold under the PPA when expected market prices are lower. AI also enables ongoing monitoring of contract execution risks, such as the likelihood of defaulting on deliveries during periods of weaker generation. By integrating weather, satellite and market data, the forecasting system can warn the operator of impending periods of potential undersupply and suggest countermeasures (purchase of missing energy on the wholesale market in advance or activation of reserves) (Montel, 2024a).

It is worth noting that advanced data analytics and AI also improve PPA pricing and management by reducing risk and uncertainty. As studies show, the vast amounts of data generated by RES farms are worthless without proper analysis - AI transforms this data into actionable information, allowing both energy production and prices to be forecast with greater accuracy (Montel, 2024a). This enables farm owners to make informed decisions about future PPAs, choosing their length and price structure, and even renegotiating terms based on hard data rather than intuition. For example, analysis of weather and pricing patterns by machine learning can reveal periods of recurring shortages or surpluses (e.g. cyclical production 'bottoms' in winter and 'tops' in summer) and suggest contract mechanisms to mitigate their impact (such as volume flexibility clauses). In addition, AI supports PPA compliance - continuous monitoring of contract performance and anticipation of potential deviations helps avoid penalties and build a reputation as a reliable partner.

Intelligent forecasting systems significantly improve the trading of energy from PV farms. Both in the short term (day- ahead and intraday markets) and in the long term (PPAs), they provide the data needed to optimise sales strategies and maximise revenues with a controlled level of risk (Montel, 2024a), (Vinyard, 2024). Nonetheless, the comparative effectiveness of AI-driven PPA management versus traditional expert judgment under extreme market conditions remains an open question. The result is a more predictable and stable PV farm business model.

Financial risk management

Entering the energy market involves significant financial risks for PV farm operators, mainly due to high energy price volatility and regulatory uncertainty. Artificial intelligence, through advanced forecasting and data analysis, has become a valuable tool to identify, quantify and mitigate these risks.

Electricity prices on wholesale markets are subject to constant fluctuations depending on weather, demand, availability of other sources (e.g. failures of conventional power plants) or geopolitical factors. For RES generators, this means that revenues are unpredictable – periods of very low prices (or even negative prices) can significantly reduce the profitability of a PV farm. The use of AI reduces this uncertainty by providing more accurate predictions of price trends and market extremes, which in turn allows for pre-emptive hedging actions. For example, with a reliable prediction of a price drop in the coming weeks, a company can enter into forward/futures transactions earlier or increase sales volumes in fixed- price contracts to minimise the impact of a price drop on revenues. AI therefore supports the implementation of hedging strategies - by improving the accuracy and timeliness of price forecasts, it facilitates decisions on when and to what extent to use derivatives (futures, options, swap agreements) to stabilise farm cash flows. The literature shows that advanced analytics and AI improve the effectiveness of hedging strategies, increasing the relevance and efficiency of energy price hedging (Montel, 2024a). Figuratively speaking, AI gives visibility into future volatility – and the lack of such visibility makes volatility particularly threatening to corporate finances (Vinyard, 2024). With better insight into potential price fluctuations (volatility), PV farm management can adjust the financial and operational plan, e.g. maintain cash reserves for periods of expected downturn or, conversely, plan for investment expansion during periods of expected high prices. The implications of delayed data updates on operational decisions should also be critically assessed.

The energy sector is subject to constant regulatory changes (e.g. reforms of RES support schemes, introduction of marginal prices, capacity charges or emission regulation). Such changes can indirectly affect the market price level and the business model of a PV farm. Intelligent forecasting systems can support ‘what-if’ scenario analysis in the context of regulation – for example, simulating the impact of announced regulations on future energy prices and project profitability. In addition, AI facilitates the tracking of political and economic trends and their correlation with the energy market, allowing companies to more quickly adjust trading and hedging strategies in response to new regulations. While predicting policy decisions alone remains difficult, the system can adjust forecasting models on the fly whenever new data becomes available (e.g. the announcement of a change in the CO_2 levy rate or the introduction of price caps) – as a result, price forecasts take into account the most recent regulatory environment, giving managers a better basis for decisions. Moreover, some AI-based platforms emphasise transparency regulatory – they provide users with information about the regulatory assumptions made in the forecasts, which increases confidence in the models and allows for an assessment of potential risks (e.g. how much performance depends on maintaining a given tax break). According to vendors of such solutions, modern AI tools can improve transparency and understanding of the impact of the regulatory environment on forecast outcomes, enabling more informed management of compliance and market risks (Gupta, 2024). User comprehension of embedded regulatory assumptions and their implications should be empirically studied.

Integration with energy storage

Combining photovoltaic farms with energy storage (e.g. lithium-ion batteries) opens up new opportunities for increased profitability and stability of supply, but fully exploiting the potential of such integration requires intelligent, forecast - based control. AI systems forecasting energy prices play a key role in decision-making: when to store energy and when to release it to the grid. The aim, of course, is to buy (or store one's own energy) cheaply and sell expensively, which, in a competitive market, can significantly increase a PV farm's revenues.

In practice, there are often periods of oversupply of solar energy during the day (e.g. the midday hours of a sunny day), when prices in the market fall, and periods of scarcity (the evening peak of demand, after sunset), when prices rise. An intelligent price forecasting system can identify these periods and their expected prices in advance, so that energy storage can be managed in a way that maximises price arbitrage. This means that when the AI predicts low prices (or even negative prices) in the coming hours, the farm controller switches the system into storage charging mode - the energy produced by the panels is then not sold on the market immediately, but stored in batteries. Then, when forecasts indicate the arrival of high-priced hours (e.g. late afternoon, when the PV is no longer generating and grid demand is high), the system automatically orders the storage to be discharged and the stored energy to be sold. This gives the PV farm higher revenues for the same energy, compared to a scenario without storage, where it would have to sell everything immediately after generation at spot prices (World Economic Forum, 2024). AI can also take into account the technical limitations of the storage (capacity, cycle efficiency, degradation) and optimise its use on this basis – e.g. do not overcharge the battery if the price benefit is small compared to the lifecycle consumption of the battery. Questions remain on how forecast errors propagate through storage dispatch decisions and impact overall profitability.

Integrating AI with a storage system makes it possible to implement fully automated, dynamic energy trading over multiple time horizons. This is described in the literature as AI-enabled trading with storage – the algorithm continuously tracks price changes in intraday markets and signals from the grid, making near-real-time decisions to move energy (World Economic Forum, 2024). The suitability of such high-frequency dispatch in terms of regulatory compliance, market participation rules, and grid service obligations should be critically assessed. This ability to react on a scale of minutes or seconds is crucial, especially in fast-moving local markets or when participating in regulatory services. For example, if a sudden price peak occurs during the day (e.g. due to the failure of a large conventional power plant), the smart system may decide to liquidate some energy from storage immediately, even if the base plan was to sell later - to capture this short-term opportunity. Conversely, in the event of a sudden price collapse (e.g. due to an unexpected increase in wind), the system can pause the current sale and divert energy to storage or leave it for later use. Such flexible, real-time management using AI increases the use of stored energy and maximises profits, while helping to balance supply and demand in the energy system (World Economic Forum, 2024). Indeed, PV farms with AI-controlled storage can act as active participants in the market, providing energy when it is most needed and valuable, and holding back when the market is in surplus – benefiting both themselves and grid stability. However, the broader impact of aggregated AI-driven storage dispatch on system-wide volatility and market dynamics remains an open question.

6. CONCLUSION

Real-world applications of intelligent energy price forecasting systems for photovoltaic farms clearly demonstrate that the implementation of advanced AI technologies brings multidimensional benefits, both operationally, financially and strategically. Accurate price and production forecasts enable operators to make data-driven decisions to dynamically optimise sales strategies by selecting the most favourable markets and sales moments, negotiating better contract terms and effectively hedging financial risks. By integrating the forecasting system with the management of resources, both generated and stored, efficient use of energy is possible, which contributes to the optimisation of network supply, load reduction during peak periods and the minimisation of operational losses.

In addition, the use of advanced artificial intelligence algorithms, including hybrid models combining deep neural networks with traditional statistical methods, makes it possible to capture the complex, non-linear relationships found in historical and current data. Using techniques such as LSTMs, CNNs and transforms, these models can identify subtle patterns and predict future energy price fluctuations, which is particularly important in the volatile environment of energy markets. As a result, these systems provide operators with the tools to analyse trends quickly and accurately, helping to stabilise cash flows and protect operating margins.

As demonstrated in the case study, the deployment of AI-driven forecasting yielded marked improvements in forecast accuracy. This enhanced precision in predicting solar output, in turn, led to significant financial gains through AI-optimized energy trading and resource management strategies. Furthermore, intelligent decision-making enabled by these advanced forecasts delivered notable operational benefits – from more efficient asset utilization to enhanced grid reliability, ultimately streamlining overall plant performance.

The integration of AI algorithms into energy management systems also opens up new perspectives in operational optimisation – making it possible to link price forecasts to the operational control of energy storage and photovoltaic farms in real time. This approach enables optimal charging and discharging of batteries and flexible adjustment of production to current market conditions, which minimises losses and maximises profits. Further development of AI technologies, including explanatory artificial intelligence (XAI) methods and adaptive model updating mechanisms, will allow for an even better understanding of price drivers and a faster response to dynamic regulatory and market changes.

In the area of energy price forecasting algorithms, future research should focus on the implementation of increasingly sophisticated artificial intelligence techniques that will enable more accurate and stable forecasts. Modern deep learning models such as LSTM networks and transformer architectures, combined with hybrid approaches combining statistical methods with domain knowledge, have the potential to significantly improve forecast accuracy. The development of explanatory artificial intelligence (XAI) methods is equally important, as it increases the transparency of models and facilitates the understanding of the factors influencing forecast prices. Additionally, the standardisation and accessibility of data through the creation of open sets and benchmarking frameworks is a key element in accelerating progress in this field.

In summary, the development of AI in PV farm energy price forecasting will move towards the creation of more accurate and resilient models and closer integration with energy infrastructure, while increasing the transparency of these algorithms. Achieving this, however, requires overcoming a number of challenges - from ensuring high data quality to adapting models to rapidly changing market and regulatory conditions. Interdisciplinary research work (combining machine learning, energy, management and economics) and pilot implementations of new solutions in real-world settings will be key to fully realising the potential of artificial intelligence in energy price forecasting in the PV sector.

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REFERENCES

Altexsoft (2019). Price forecasting: Applying machine learning approaches to electricity, flights, hotels, real estate, and stock pricing. Altexsoft.

Baird, R. (2024, October 21). Energy price forecasts – The ultimate guide: What will energy prices look like in 2030? What are energy price forecasts and how do they work? DBSNE.

Chatterjee, P., Yazdani, M., Fernández-Navarro, F., & Pérez-Rodríguez, J. (2023). Machine learning algorithms and applications in engineering. CRC Press.

Dombi, G., & Dulai, T. (2022). Hourly electricity price forecast for short- and long-term, using deep neural networks. Acta Universitatis Sapientiae Informatica, 14(2), 208-222. https://doi.org/10.2478/ausi-2022-0013.

Feenstra, T. (2024). How to prevent negative returns in renewable energy and solar. Helin.

Furner, J. (2004). Conceptual analysis: A method for understanding information as evidence, and evidence as information. Archival Science, 4. https://doi.org/10.1007/s10502-005-2594-8

Future Bridge (2024). The role of AI and machine learning in power price forecasting.

Gupta, U. (2024). Hitachi Energy unveils AI-based solar forecasting solution. pv magazine.

Hong, T., Pinson, P., Wang, Y., Weron, R., Yang, D., & Zareipour, H. (2020). Energy forecasting: A review and outlook. IEEE Open Access Journal of Power and Energy, 7, 376–388.

Hou, Z., Zhang, Y., Liu, Q., & Ye, X. (2024). A hybrid machine learning forecasting model for photovoltaic power. Energy Generation, Advance online publication. https://doi.org/10.1016/j.egyr.2024.04.065.

Kanase-Patil, A. B., Kaldate, A. P., Lokhande, S. D., Panchal, H., Suresh, M., & Priya, V. (2020). A review of artificial intelligence-based optimization techniques for the sizing of integrated renewable energy systems in smart cities. Environmental Technology Reviews, 9(2), 111–136. https://doi.org/ 10.1080/21622515.2020.1836035.

Kapral, K., Soetaert, K., & Castro, R. (2024). An off-site power purchase agreement (PPA) as a tool to protect against electricity price spikes: Developing a framework for risk assessment and mitigation. Energies, 17(9), 2161. https://doi.org/10.3390/en17092161.

Karimi-Arpanahi, S., Pourmousavi, S. A., & Mahdavi, N. (2023). Quantifying the predictability of renewable energy data for improving power systems decision-making. Patterns, 4(4), 100708. https://doi.org/10.1016/j.patter.2023.100708.

Khalid, R., Javaid, N., Al-Zahrani, F. A., Aurangzeb, K., Qazi, E.-u. H., & Ashfaq, T. (2019). Electricity load and price forecasting using Jaya–long short term memory (JLSTM) in smart grids. Entropy, 22(1), 10. https://doi.org/10.3390/e22010010.

Kojima, M., Trimble, C., Perez Arroyo, I., & Mohammadzadeh, F. (2016, August). Financial viability of electricity sectors in Sub-Saharan Africa: Quasi-fiscal deficits and hidden costs (Policy Research Working Paper No. 7788). World Bank.

Laitsos, V., Vontzos, G., Bargiotas, D., Daskalopulu, A., & Tsoukalas, L. H. (2024). Data-driven techniques for short-term electricity price forecasting through novel deep learning approaches with attention mechanisms. Energies, 17(7), 1625. https://doi.org/10.3390/en17071625.

Lee, M. H. L., Ser, Y. C., Selvachandran, G., Thong, P. H., Cuong, L., Hoang Son, L., Tuan, N. T., & Gerogiannis, V. C. (2024). A comparative study of forecasting electricity consumption using machine learning models. Mathematics, 12(4), 789–812.

Lokhande, S. D., Kaldate, A. P., & Kanase Patil, A. B. (2022). Artificial intelligence based integrated renewable energy management in smart city. In Energy Storage Systems (pp. 1–20). Springer. https://doi.org/10.1007/978-981-19-4502-1_1.

Mancha Gonzales, S., Iftikhar, H., & López-Gonzales, J. L. (2024). Analysis and forecasting of electricity prices using an improved time series ensemble approach: An application to the Peruvian electricity market. AIMS Mathematics, 9(8), 21952–21971. https://doi.org/10.3934/math.20241067.

Marcjasz, G., Narajewski, M., Weron, R., & Ziel, F. (2023). Distributional neural networks for electricity price forecasting. Energy Economics, 125, 106843. https://doi.org/10.1016/j.eneco.2023.106843.

Montel (2024a). How is AI Transforming Renewable Energy Trading? Montel.

Montel (2024b). Data analytics in PPA management: Optimising pricing, forecasting, and risk. Montel.

Montel Energy (2024). Predicting energy prices: The role of weather forecasts. Montel.

N., K. P., & Singh, J. G. (2023). Electricity price forecasting using hybrid deep learned networks. Journal of Forecasting, 42(7), 1750–1771. https://doi.org/10.1002/for.2981.

Nowotarski, J., & Weron, R. (2018). Recent advances in electricity price forecasting: A review of probabilistic forecasting. Renewable and Sustainable Energy Reviews, 81, 1548–1568. https://doi.org/10.1016/j.rser.2017.05.234.

Pikus, M., & Wąs, J. (2024). Predictive modeling of renewable energy purchase prices using deep learning based on Polish power grid data for small hybrid PV microinstallations. Energies, 17(3), 628. https://doi.org/10.3390/en17030628.

Poggi, A., Di Persio, L., & Ehrhardt, M. (2023). Electricity price forecasting via statistical and deep learning approaches: The German case. AppliedMath, 3(2), 316–342. https://doi.org/10.3390/ appliedmath3020018.

Pragmile. (2024). Energy prices forecasting on the SPOT market using AI.

Rocha, H. R. O., Fiorotti, R., Fardin, J. F., Garcia-Pereira, H., Bouvier, Y. E., Rodríguez-Lorente, A., & Yahyaoui, I. (2024). Application of AI for short-term PV generation forecast. Sensors, 24(1), 85.

https://doi.org/10.3390/s24010085.
Shi, H., Wang, L., Scherer, R., Woźniak, M., Zhang, P., & Wei, W. (2021). Short-term load forecasting based on Adabelief optimized temporal convolutional network and gated recurrent unit hybrid neural network. IEEE Access, 9, 66965–66981. https://doi.org/10.1109/ACCESS.2021.3089891.
Singh, N., & Mohanty, S. R. (2015). A review of price forecasting problem and techniques in deregulated electricity markets. Journal of Power and Energy Engineering, 3(9), Article 001. https://doi.org/10.4236/jpee.2015.39001.
Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. Journal of Business Research, 104, 333–339.
U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy. (2017, October 12). Confronting the duck curve: How to address over-generation of solar energy. Energy.gov.
Uniejewski, B., & Ziel, F. (2025). Probabilistic forecasts of load, solar and wind for electricity price forecasting. arXiv.
Vinyard, J. (2024). How artificial intelligence (AI) and machine learning (ML) streamlines renewable energy trading. GE Vernova.
World Economic Forum. (2024). Sun, sensors and silicon: How AI is revolutionizing solar farms.
Wu, H., Feng, B., Yang, P., Shen, H., Ma, H., Kong, W., & Peng, X. (2024). Optimal schedule for virtual power plants based on price forecasting and secant line search aided sparrow searching algorithm. Frontiers in Energy Research, 12. https://doi.org/10.3389/fenrg.2024.1427614.
Xiang, Q., Zi, L., Cong, X., & Wang, Y. (2023). Concept drift adaptation methods under the deep learning framework: A literature review. Applied Sciences, 13(11), 6515. https://doi.org/10.3390/app13116515.
Yin, R. K. (2018). Case study research and applications: Design and methods (6th ed.). SAGE Publications.
Zhang, C., Li, R., Shi, H., & Li, F. (2020). Deep learning for day-ahead electricity price forecasting. IET Smart Grid, Special Issue: Machine Learning in Power Systems. https://doi.org/10.1049/iet-stg.2019.0258.
Zhang, J., Lei, Z., Cheng, R., & Zhang, H. (2022). Short-term electricity price forecasting using random forest model with parameters tuned by grey wolf algorithm optimization. Journal of System Science and Information, 10(2), 167–180. https://doi.org/10.21078/JSSI-2022-167-14.
Zhou, S., Zhou, L., Mao, M., Tai, H. M., & Wan, Y. (2019). An optimized heterogeneous structure LSTM network for electricity price forecasting. IEEE Access, 7, 108161–108173. https://doi.org/10.1109/ACCESS.2019.2936762