energies

MDPI

Article

Predictive Modeling of Renewable Energy Purchase Prices Using Deep Learning Based on Polish Power Grid Data for Small Hybrid PV Microinstallations

Michał Pikus * and Jarosław Wąs

Department of Applied Computer Science, Faculty of Electrical Engineering, Automatics, Computer Science and Biomedical Engineering, AGH University of Krakow, al. Mickiewicza 30, 30-059 Krakow, Poland; jaroslaw.was@agh.edu.pl

* Correspondence: mpikus@agh.edu.pl

Abstract: In the quest for sustainable energy solutions, predicting electricity prices for renewable energy sources plays a pivotal role in efficient resource allocation and decision making. This article presents a novel approach to forecasting electricity prices for renewable energy sources using deep learning models, leveraging historical data from the power system operator (PSE). The proposed methodology encompasses data collection, preprocessing, feature engineering, model selection, training, and evaluation. By harnessing the power of recurrent neural networks (RNNs) and other advanced deep learning architectures, the model captures intricate temporal relationships, weather patterns, and demand fluctuations that impact renewable energy prices. The study demonstrates the applicability of this approach through empirical analysis, showcasing its potential to enhance energy market predictions and aid in the transition to more sustainable energy systems. The outcomes underscore the importance of accurate renewable energy price predictions in fostering informed decision making and facilitating the integration of renewable sources into the energy landscape. As governments worldwide prioritize renewable energy adoption, this research contributes to the arsenal of tools driving the evolution towards a cleaner and more resilient energy future.

Keywords: AI; energy price forecasting; LSTM; DNN

Citation: Pikus, M.; Wąs, J. Predictive Modeling of Renewable Energy Purchase Prices Using Deep Learning Based on Polish Power Grid Data for Small Hybrid PV Microinstallations. *Energies* **2024**, *17*, 628. https://doi.org/10.3390/en17030628

Academic Editor: Ramiro Barbosa

Received: 17 December 2023
Revised: 21 January 2024
Accepted: 26 January 2024
Published: 28 January 2024

1. Introduction

The realm of renewable energy in Poland, particularly within the domain of photovoltaics (PV), is experiencing a notable surge. Various elements are driving the progress of PV technology in the country, mirroring trends across various European Union (EU) member nations [1,2]. Poland, like its counterparts, has set ambitious targets for integrating renewables into its energy matrix [3], igniting substantial interest and investments in solar energy and PV advancements [4]. To galvanize the growth of these initiatives, the government has strategically implemented an array of support mechanisms including feed-in tariffs, auctions, and subsidies, specifically tailored to nurture renewable energy ventures, especially in the PV sector. As a participant in EU programs dedicated to renewable energy adoption, Poland is harnessing financial aids that expedite the transition to sustainable energy sources, further catalyzing PV projects nationwide.

Remarkably, the cost of PV technology has been progressively diminishing, enhancing the economic viability of solar energy. This reduction in costs has amplified the allure of solar investments for both financial backers and consumers, aligning with the broader goal of diminishing reliance on imported fossil fuels. Noteworthy emphasis has been placed on bolstering domestic renewable energy capacities, exemplified by the focus on solar power. The resilience and security of Poland's energy landscape have been augmented as PV technology diversifies the energy portfolio. An impressive milestone achieved between 2019 and 2022 involved the establishment of over one million PV micro-installations, predominantly targeting individual households. These micro-installations are thoughtfully customized to harmonize with distinct energy consumption patterns over varying periods, meticulously complying with Poland's regulatory guidelines for prosumers.

Approaches in the field of predicting electricity prices for renewable energy sources exhibit variations across several dimensions. The choice of data sources can range from studies concentrating on national power grid data to those utilizing regional or local datasets. The granularity and availability of the data play a pivotal role in influencing the accuracy of the predictive model. Diverse deep learning architectures, such as recurrent neural networks (RNNs), long short-term memory (LSTM) networks, or hybrid models, are applied based on the intricacies of the data and the necessity to capture temporal dependencies. Feature engineering strategies differ between approaches, with considerations encompassing historical electricity prices, patterns of renewable energy generation, weather data, and grid demand. Methodologies for training and validation exhibit variability, ranging from traditional train–test splits to more sophisticated techniques like cross-validation. The approaches to hyperparameter tuning can also diverge. Evaluation metrics utilized in assessing model performance may include mean absolute error (MAE), root mean square error (RMSE), and correlation coefficients, with the specific metric chosen to align with the unique goals of each study. Integration with control systems diverges across approaches, with some emphasizing real-time decision making and the control of renewable energy installations based on predicted prices, while others prioritize long-term planning. The real-world applications of these models showcase varying degrees of success, with some approaches demonstrating tangible benefits such as cost savings, efficient energy management, or improved grid stability in practical scenarios. Finally, the innovations and contributions of each approach are distinct, with some studies introducing novel methodologies and others focusing on the refinement of existing techniques within the realm of predicting electricity prices for renewable energy sources.

The core objective of this investigation revolves around assessing the viability and precision of PV energy production calculations tailored to Poland's conditions. Researchers have identified existing energy production estimation methods as potentially flawed due to inadequacies in accounting for geographical features, local conditions, wind dynamics, and the inherent characteristics of PV panels. In this pursuit, deep neural network (DNN) methodologies are at the forefront, particularly focusing on hybrid architectures that incorporate long short-term memory (LSTM) elements [5–8]. These advanced models are poised to revolutionize energy pricing predictions, providing a more accurate and effective framework for this evaluation.

The study published in [8] delves into the critical task of forecasting electricity demand, with a primary emphasis on ensuring stability within the energy sector. It explores the efficacy of deep learning models, specifically recursive neural networks (RNNs) based on LSTM and combined architectures. The dataset, obtained from a SolarEdge designer, comprises daily records from a solar farm in Central Europe (Poland's Swietokrzyskie Voivodeship) over the past year. This work concludes that the LSTM models demonstrate superior forecasting accuracy compared to other models, with specific measurable results provided.

The current approach focuses on predicting electricity prices for renewable energy sources, aligning with the quest for sustainable energy solutions. It introduces a novel approach that leverages deep learning models, including recurrent neural networks (RNNs) and other advanced architectures [9–11]. The data used comes from the power system operator (PSE), emphasizing historical data for renewable energy sources. This work covers various aspects of the methodology, including data collection, preprocessing, feature engineering, model selection, training, and evaluation. The outcomes of empirical analysis showcase the potential of the approach to enhance energy market predictions and contribute to a cleaner and more resilient energy future. Additionally, the study underlines the importance of accurate renewable energy price predictions in supporting informed decision making and facilitating the integration of renewable sources into the global energy landscape.

The research introduces a novel perspective on addressing the challenges associated with renewable energy purchases, particularly in the context of off-grid systems. The existing literature often focuses on traditional aspects of the energy trilemma and may not adequately explore the potential of deep neural network (DNN) models for controlling off-grid energy systems based on energy prices.

The discussion on clean energy systems [12], resilience, and the need for predictable demand for energy technologies resonates with the essence of forecasting renewable energy purchases. The mention of reliable affordability, system security, and the emerging objective of reliable speed also connects with the challenges and objectives often associated with forecasting in the renewable energy sector.

A similar approach was introduced in [13], which describes real-time energy management in off-grid smart homes, particularly nanogrids, employing various renewable energy sources (RESs) and energy storage systems. This work introduces the concept of home energy management systems (HEMSs) for optimal performance, aiming to balance energy production and consumption. The manuscript highlights the integration of fuel cell (FC) systems as environmentally friendly energy sources and discusses challenges associated with FCs under rapid load demand variations. The importance of combining FCs with other energy sources, such as batteries and RESs, and implementing demand-side management (DSM) for improved efficiency and system lifetime is emphasized. The literature review provides an overview on existing home energy management systems for both grid-connected and off-grid microgrid systems, showcasing various approaches to improve reliability, resilience, and cost-effectiveness while ensuring user comfort. In comparison to our approach, both of the above contribute valuable insights to the field of renewable energy and energy management, albeit in different contexts and with different methodological approaches. Whereas authors of [13] primarily focus on real-time energy management in off-grid smart homes, emphasizing the role of home energy management systems and the integration of fuel cell systems, our idea is to primarily focus on predicting electricity prices for small hybrid PV micro-installations using deep learning and then try to optimize cost of energy. In our approach, we try to emphasize predictive modeling, encompassing data processing, feature engineering, and the use of deep learning models in combination with statistical data and forecasting in energy management, especially in the context of demand-side control and the challenges associated with fuel cell systems.

In the ensuing sections, we shall elucidate upon several key facets, commencing with a detailed exposition of the employed deep neural network (DNN) model, succeeded by an exhaustive delineation of the utilized dataset, and ending with an explication of its connection to the domain of energy management.

The initial segment entails a meticulous portrayal of the hybrid DNN-long short-term memory (LSTM) model, encompassing a thorough explication of its constituent layers, units, and activation functions. Particular emphasis is placed upon the model's intrinsic capacity to adeptly manage sequential data, substantiated by a comprehensive visual representation of its architectural framework.

Subsequently, the elucidation delves into the intricacies of the dataset, derived from the Polish Power Company (PSE) data repository. A comprehensive exposition unfolds, elucidating the pivotal parameters integral to the nuanced task of electricity price forecasting. This includes a meticulous discussion of the organizational structure of the time-series data, accentuating the imperative nature of various preprocessing steps such as the adept handling of missing values and the normalization process.

The discourse then seamlessly transitions to the domain of autonomous energy management via DNN-projected pricing, wherein the components of an innovative energy management system are introduced. An in-depth examination ensues, elucidating the pivotal role of the DNN LSTM model in forecasting energy prices, coupled with optimization strategies tailored for both grid-linked and autonomous off-grid subsystems. The latter, notably reliant on renewable energy sources, is expounded upon in detail, underscoring the intricate fusion of DNN model projections within both control paradigms. Implementation intricacies about intelligent residence infrastructure are subsequently unveiled.

The subsequent focal point of our discourse revolves around the meticulous emphasis on model development and training. This phase encapsulates a systematic optimization of key parameters, including but not limited to LSTM units, fully connected layer size, and activation functions. A comprehensive exposition follows, detailing the intricate facets of the training and validation processes, ensuring the model's adaptability and generalization to hitherto unseen data. Various loss functions are scrutinized to gauge the divergence between the model's prognostications and actual values. Quantitative assessments are underpinned by metrics such as mean squared error, accuracy, and R-squared.

The Results section serves as the conduit for presenting the outcomes of model training and validation, meticulously elucidating upon the predictive capabilities of the model. A nuanced discussion unfolds, delving into the ramifications of hyperparameter tuning on overall performance. The subsequent Discussion section undertakes the scholarly interpretation of the results within the intricate domain of electricity price prediction. Comparative analyses are conducted vis-à-vis existing models and methodologies, fostering insights into the overarching significance of the hybrid DNN-LSTM model. The Conclusion section serves as a comprehensive recapitulation of key findings, affording a platform to deliberate upon the broader implications for renewable energy applications. Furthermore, it proffers nuanced suggestions for potential avenues that merit exploration in future research endeavors. The References segment encapsulates meticulous citations of pertinent literature and sources that have significantly contributed to the underpinning of this scholarly endeavor.

2. Materials and Methods

2.1. DNN Model Architecture

A hybrid DNN-LSTM model combines the strengths of deep neural networks (DNNs) and long short-term memory (LSTM) networks to tackle complex problems involving sequential data. In the described model, we integrate the capabilities of DNNs for capturing high-level patterns from data with the sequence modeling capabilities of LSTMs. This amalgamation proves particularly advantageous when confronted with the necessity to manage both the inherent sequential nature and intricate relationships present within the dataset. The architectural representation is delineated below Figure 1.

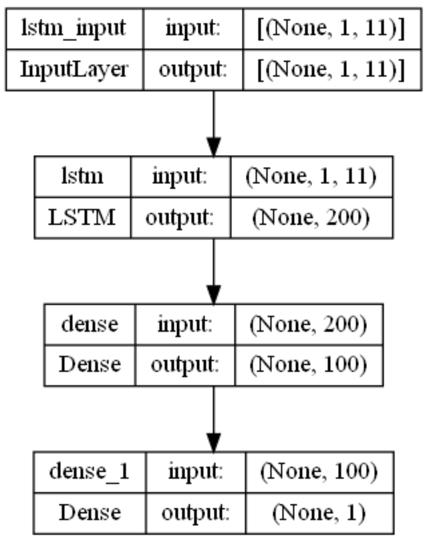


Figure 1. Multi-LSTM DNN model architecture.

The first layer is an LSTM (long short-term memory) layer. In this model, the LSTM layer has 200 units (also called cells or neurons). The activation function used within each LSTM unit is the Rectified Linear Unit (ReLU), which introduces non-linearity to the network. Following the LSTM layer is a dense fully connected layer. This layer contains 100 units and employs the ReLU activation function. The purpose of this layer is to learn higher-level features and patterns from the output of the LSTM layer. It adds a level of non-linearity and abstraction to the model's representation. The final layer is the output layer and produces the final predictions of the model.

The hybrid DNN-LSTM model described in this study represents a sophisticated fusion of deep neural networks (DNNs) and long short-term memory (LSTM) networks. This integration aims to leverage the unique strengths of each, enabling the model to effectively handle complex challenges associated with sequential data. By combining the pattern recognition capabilities of DNNs with the sequence modeling capabilities of LSTMs, the proposed architecture emerges as a robust solution capable of addressing the inherent sequential nature and intricate relationships within the data.

The architectural details of the hybrid model unfold in a layered structure. The initial layer comprises an LSTM layer featuring 200 units, each incorporating the Rectified Linear Unit (ReLU) as the activation function. This choice introduces non-linearity to the network, enhancing its capacity to capture complex patterns. After the LSTM layer, a dense fully connected layer follows suit, housing 100 units and applying the ReLU activation function. This layer serves the purpose of extracting higher-level features and patterns from the LSTM layer's output, thereby contributing an additional layer of non-linearity and abstraction. The concluding layer in the model is the output layer, responsible for generating the final predictions.

Technical investigations underpin the model's development and assessment. These investigations involved meticulous hyperparameter tuning, where parameters such as the number of LSTM units, the size of the fully connected layer, and the choice of activation functions were systematically optimized. The training and validation processes were executed rigorously, ensuring the model's adaptability and generalization to unseen data. Different loss functions were explored to gauge the disparity between the model's predictions and actual values, and various evaluation metrics, including mean squared error, accuracy, and R-squared, were employed to quantitatively assess predictive capabilities. The study also delved into considerations of computational efficiency, emphasizing the optimization of training and prediction speed without compromising accuracy.

This comprehensive exploration not only unveils the intricacies of the hybrid DNN-LSTM architecture but also establishes the model's robustness and reliability across diverse applications. From electricity demand forecasting to renewable energy price predictions, the technical investigations presented herein contribute valuable insights to the broader field of deep learning and sequential data modeling, enhancing our understanding of complex data patterns and their applications in real-world scenarios.

2.2. Prepared Dataset

The dataset created based on published data from the PSE (Polish Power Company) for predicting the market price of electricity contains various parameters related to electricity pricing and deviations. These parameters are crucial for building a predictive model for electricity price forecasting. Each parameter contributes to the model's ability to capture the intricate dynamics of the electricity market.

Below is a description of the dataset and its parameters:

1. CRO + (Deviation Settlement Price − Higher Demand): The deviation settlement price determined on day $n - 1$ for information purposes when the national power system (NPS) demand is higher by 5% than assumed in the NPS work plan.
2. CRO − (Deviation Settlement Price − Lower Demand): The deviation settlement price is determined on day $n - 1$ for information purposes when the NPS demand is lower by 5% than assumed in the key schedule (KS) work plan.

3. CRO (Deviation Settlement Price): The general deviation settlement price determined on day n − 1 for deviations from the expected demand levels.
4. CROs (Settlement Price of Sales Deviation): The settlement price associated with the sales deviation, reflecting the financial impact of deviations from planned sales levels.
5. CROz (Purchase Variance Settlement Price): The settlement price is related to the purchase variance, indicating the financial consequences of deviations from planned purchase levels.
6. CEBPRw (Weighted Average Price of Planned Forced Balancing Energy Received): The weighted average price of the planned forced balancing energy received, which is part of the balancing mechanism to ensure stability in the power system.
7. CEBPPw (Weighted Average Price of Planned Forced Balancing Energy Delivered): The weighted average price of the planned forced balancing energy delivered, also contributes to maintaining the power system's stability.
8. CEBPR (Weighted Average Price of Planned Balancing Energy Received): The weighted average price of the planned balancing energy received, reflecting the cost of maintaining a balanced power supply–demand relationship.
9. CEBPP (Weighted Average Price of Planned Balancing Energy Delivered): The weighted average price of the planned balancing energy delivered, representing the compensation for supplying balancing energy to the grid.

The dataset is likely organized with time series data from the beginning of 2020 to July 2023, where each parameter's values are recorded hourly. The historical values of these parameters, along with the corresponding electricity market prices, form the basis for training and evaluating predictive models, such as the hybrid DNN LSTM model described earlier. To ensure that the dataset is ready for model training, there were a few steps before usage such as handling missing values, normalization, and possibly feature engineering. The richness and complexity of the parameters in this dataset provide a solid foundation for developing accurate electricity price prediction models tailored to the micro-installation context.

2.3. Innovative Grid-Connected and Autonomous Energy Management via DNN-Projected Pricing

The notion of employing "grid-linked" and "off-grid" management grounded in the insights of a predictive deep neural network (DNN) model for energy costs revolves around the astute management and enhancement of energy consumption, taking into account the ever-fluctuating electricity prices prevalent in the energy market.

The central components of this pioneering system include the following:

1. DNN LSTM-Based Energy Price Prediction Model At the heart of this initiative lies a deep neural network (DNN) powered by long short-term memory (LSTM) architecture. This advanced machine learning model is capable of being trained to forecast forthcoming energy prices by dissecting historical data and deciphering the intricate trends governing energy market pricing. By assimilating diverse input parameters expounded upon in the preceding section, this model generates predictions of impending energy prices, pivotal for informed decision making.
2. Grid-Linked Subsystem The grid-linked control facet concentrates on judiciously orchestrating energy consumption within an edifice or establishment interlinked with the primary electricity grid. Contextualized within the framework of energy price prediction, grid-linked control entails the calibration of energy utilization by the facility's systems (ranging from HVAC and lighting to appliances) by the anticipated energy price fluctuations. The ultimate objective is to amplify energy consumption during phases of subdued pricing while curtailing consumption during peak-cost periods.
3. Autonomous Off-Grid Subsystem Autonomous off-grid control predominantly applies to scenarios where an edifice or facility functions autonomously, disengaged from the principal electricity grid. Frequently, such setups harness renewable energy resources (such as solar panels) and energy reservoir systems (like batteries). In this scenario, the energy price projections sourced from the DNN model serve as a

compass for discerning when to stockpile surplus energy from sustainable sources and when to deploy accumulated energy in consonance with price projections. This optimization guarantees that the facility trims energy expenses, all while sustaining a dependable power supply.

4. Fusion of DNN Model Projections The DNN model's prognostications wield a pivotal role within both grid-linked and off-grid control paradigms. For grid-linked control, these predictions underpin determinations about the optimal transfer of energy-intensive operations to non-peak hours. For off-grid control, these predictions underlie the orchestration of energy reservoir system charging and discharging, impeccably aligned with projected price oscillations.
5. Implementation of Intelligent Residence Infrastructure The practical realization of grid-linked and off-grid control predicated on energy price predictions often entails a measure of automation. Intelligent energy management frameworks can be tailored to obtain real-time price updates from the DNN model and subsequently effectuate automated adjustments in energy consumption or reservoir operations. This synergy can be realized through a constellation of Internet of Things (IoT) devices, interconnected appliances, and energy management software.

It is imperative to acknowledge that the efficacy of such a system hinges on the precision of the DNN model's predictions, the nimbleness of the control systems, and the adaptability of the facility's energy consumption and storage competencies. Furthermore, real-world execution might necessitate tackling hurdles such as system latency, hardware compatibility, and user predilections.

In summation, this concept embodies a progressive strategy for optimizing energy utilization and expenditure, particularly within the context of an increasingly dynamic and price-conscious energy domain.

3. Results

Accuracy of Designed DNN Model

Below, we present our comparison between values reported by RCE simulations from PSE and our DNN model Figure 2 and Table 1.

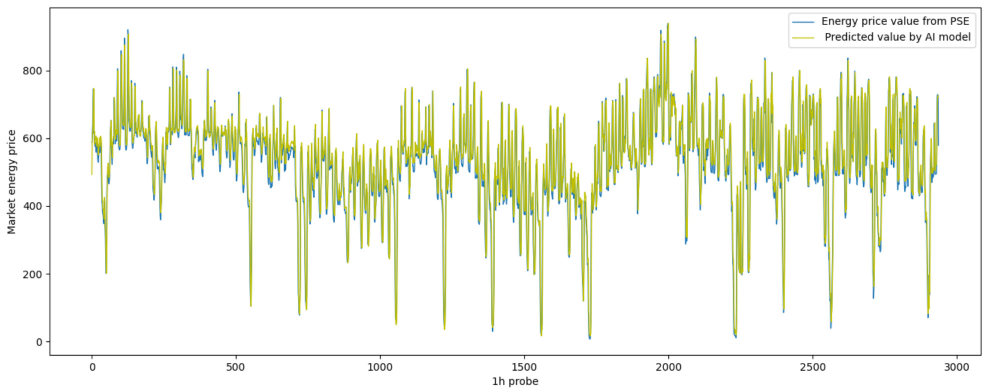


Figure 2. Multi-LSTM price prediction results.

Table 1. Multi-LSTM metrics.

MAE: 35.863	NMAE: 0.038	MPL: 17.931
MAPE: 0.088	MSE: 2492.210	
EVS: 0.887	R2: 0.876	RMSE: 49.922

The results provided by the deep neural network (DNN) model are as follows:

In evaluating the performance of the predictive model, several key scientific metrics were employed. The mean absolute error (MAE), calculated as the average absolute difference (35.86) between predicted values and actual values, serves as a quantitative measure of the magnitude of errors, irrespective of their direction. The normalized mean absolute error (NMAE), represented as 0.0382, is a normalized version of the MAE, expressed as a fraction of the range of the actual values. This normalization facilitates comparisons across diverse datasets.

The mean percentage error (MPL), denoting the mean percentage difference (17.93 percent) between predicted and actual values, provides insights into the relative magnitude of errors as a percentage of the actual values. The mean absolute percentage error (MAPE), computed as the average percentage difference (0.0886 percent) between predicted and actual values, contributes to understanding the overall accuracy of predictions in terms of percentage errors.

The mean squared error (MSE), averaging the squared differences (2492.21) between the predicted and actual values, penalizes larger errors more heavily than smaller ones. The mean error absolute error (MEAE), measured at 25.13, signifies the average absolute difference between the predicted mean and the actual mean, serving as an indicator of the overall bias in the predictions.

The explained variance score (EVS), quantifying the proportion of variance in the dependent variable explained by the model (0.8877), assesses the goodness of fit, with higher values indicative of a better fit. The coefficient of determination (R2), measuring the proportion (0.8770) of the variance in the dependent variable predictable from the independent variables, elucidates the model's ability to explain variability.

Lastly, the root mean squared error (RMSE), represented as 49.92, is the square root of the average of the squared differences between predicted and actual values. This metric, akin to the MSE but in the same unit as the original data, enhances interpretability. Collectively, these metrics offer a comprehensive assessment of the model's predictive performance across various dimensions.

4. Discussion

Proposed Off-Grid Subsystem

A proposed off-grid energy system is a combination of advanced engineering and self-reliance. The backbone of this autonomous power grid is a set of three powerful Victron Quattro inverters, each with an impressive 15 kW of power Figure 3. Their presence symbolizes the key role they play in orchestrating the conversion of stored DC battery energy into usable AC power, covering a spectrum of energy needs.

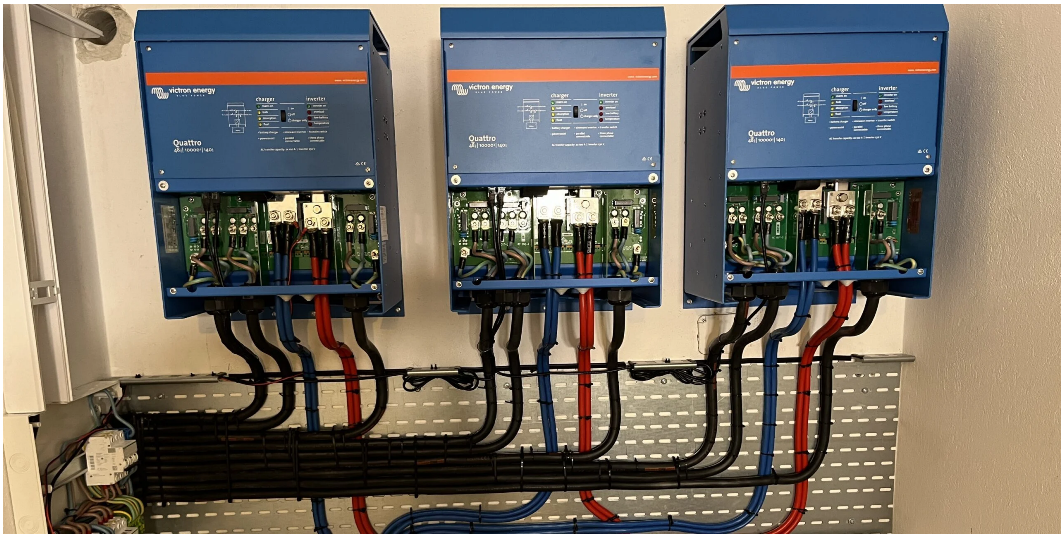
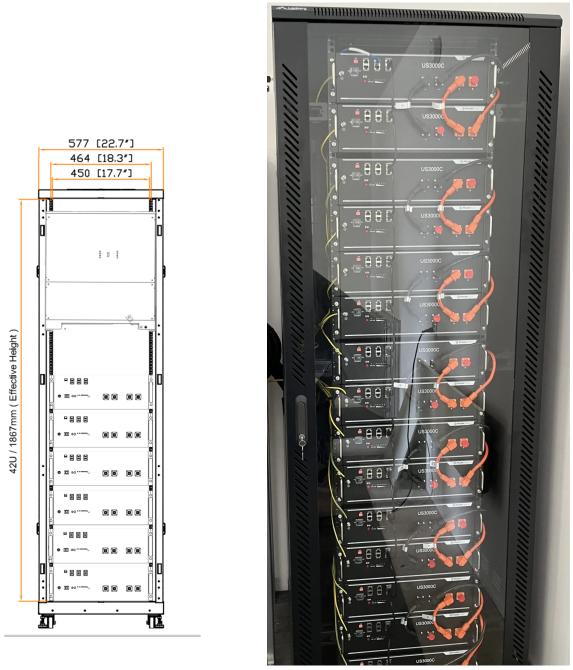


Figure 3. Triple Victron Quattro inverters (source https://enerp.pl/project/victron-ess-kamienica-30kva-404kwh), accessed on 2 January 2023.

A precisely arranged set of Pylontech batteries deployed in a safe and well-ventilated area is used as an energy store Figure 4. Through a careful combination of series and parallel connections, these batteries combine to form a powerful energy storage system. Their combined capacity can provide a sustainable power supply, ensuring system resilience when external energy sources are scarce.



(a) (b)

Figure 4. Example of batteries and inverter installation: (**a**) one-phase installation including 1 inverter and 6 batteries; (**b**) separate batteries mounted on a rack (source https://enerp.pl/project/victron-ess-kalisz-45kva-50kwh), accessed on 2 January 2023.

An array of solar panels with a total capacity of 25 kWp is studied Figure 5. Their calculated orientation maximizes solar exposure by collecting photons with remarkable efficiency. Directing the DC power output, the grid-connected 25 kW SolarEdge inverter takes over the power conversion function Figure 6. It balances domestic consumption demand by seamlessly exporting surplus energy back to the grid, in line with net billing regulations.

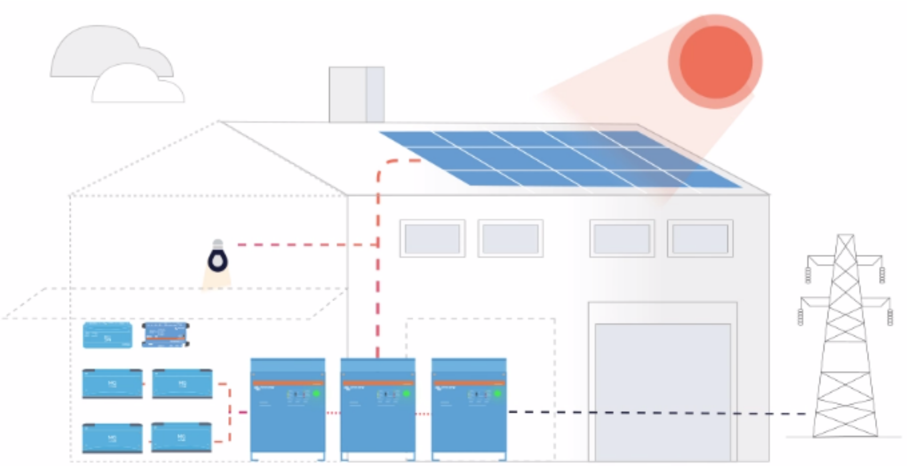


Figure 5. Example installation (source https://enerp.pl), accessed on 2 January 2023.

Figure 6. PV panel installation.

The Cerbo GX control unit stands as a pinnacle of integration, seamlessly merging a myriad of disparate components into a unified and harmonious whole. This sophisticated controller, with its comprehensive capabilities, plays a pivotal role in facilitating remote accessibility and control, providing stakeholders with a transparent window into the dynamic performance of the entire system. Its multifaceted functionality extends beyond mere oversight, offering a platform for efficient and responsive management of various processes within the connected ecosystem.

An intriguing application of the Cerbo GX control unit lies in its ability to harness the latest technological advancements, particularly in the realm of energy management. The integration of deep neural networks (DNNs) for energy price forecasting marks a significant leap forward in the unit's capabilities. By employing DNNs, the Cerbo GX can be intelligently controlled through an external application programming interface (API), enabling seamless transitions between on-grid and off-grid modes based on the results of sophisticated energy price forecasting algorithms.

The process of orchestrating the control of a device like Cerberus GX using an external API for dynamic mode switching involves a series of intricate steps. It necessitates a nuanced understanding of the interplay between the controller's capabilities, the DNN-driven forecasting outcomes, and the external API's functionality. In this context, we propose the utilization of the VRM (Victron Remote Management) API as the linchpin for orchestrating the seamless shift between on-grid and off-grid modes. The VRM API, with its robust features, provides an effective means of interfacing with the Cerbo GX, allowing for responsive and intelligent adjustments based on real-time energy forecasting results.

The proposed methodology not only exemplifies the adaptability and sophistication of the Cerbo GX control unit but also underscores the critical role of innovative technologies in shaping the future of energy management. By marrying the power of DNNs for accurate forecasting with the versatility of the VRM API, the Cerbo GX positions itself at the forefront of intelligent and dynamic energy control systems.

Looking ahead, this integration of advanced technologies within control units like the Cerbo GX lays the foundation for a more resilient and sustainable energy landscape. The ongoing synergy between cutting-edge control capabilities and emerging technologies promises to usher in an era of unprecedented efficiency and responsiveness in energy management, ultimately contributing to a more sustainable and intelligent future.

5. Conclusions

The holistic architecture of the designed DNN exhibits a commendable capability to generate remarkably precise predictions. This assertion finds its basis in the discernibly low error metrics such as mean absolute error (MAE), normalized mean absolute error (NMAE), and mean absolute percentage error (MAPE). Additionally, the DNN garners remarkable scores in terms of prediction quality, as evidenced by the elevated values of the explained variance score (EVS) and the coefficient of determination (R2). These credentials collectively underscore the potential usability of the model in practical applications.

However, it is essential to underscore that the effectiveness of such a system hinges upon several pivotal factors. Foremost among these is the degree of precision embedded within the predictions furnished by the DNN model. Equally critical is the agility of the control systems orchestrating the model's functioning. Moreover, the adaptability of the facility's energy consumption and storage proficiency plays a nontrivial role in the overall efficacy of the system. This intricate interplay of components necessitates a holistic approach to ensure optimal performance.

Looking beyond the theoretical construct, the real-world implementation of this concept is bound to encounter its own set of challenges. Among these, the issue of system latency takes prominence, warranting a robust strategy to mitigate any undue delays in prediction and response. The facet of hardware compatibility also emerges as a potential hurdle, demanding meticulous attention to ensure seamless integration. Additionally, accommodating diverse user preferences and predispositions adds a layer of complexity that must be accounted for during the system's deployment.

In the grand scheme of things, this innovative concept encapsulates a forward-looking approach to revolutionizing the landscape of energy utilization and expenditure. Its significance is particularly pronounced within the framework of an energy domain characterized by escalating dynamism and an ever-heightening emphasis on cost-consciousness. By navigating the intricate web of challenges and intricacies, this concept stands poised to contribute significantly to the ongoing pursuit of energy optimization, offering a beacon of promise for a more sustainable and efficient future.

In conclusion, the designed deep neural network (DNN) exhibits impressive predictive capabilities but faces key limitations. Precision improvement, system agility enhancement, and seamless integration with existing infrastructure are crucial for practical viability. Challenges include system latency, hardware compatibility, and accommodating diverse user preferences.

The future agenda involves proactive strategies for precision enhancement, minimizing system latency, ensuring hardware compatibility, and adopting a user-centric deployment approach. Despite the challenges, the concept holds promise for revolutionizing energy utilization, contributing to the ongoing pursuit of energy optimization for a sustainable future.

Author Contributions: Methodology, M.P. and J.W.; Software, M.P.; Validation, M.P.; Investigation, M.P.; Resources, M.P.; Writing—original draft, M.P.; Writing—review & editing, J.W.; Supervision, J.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Publicly available datasets were analyzed in this study. This data can be found here: [https://www.pse.pl/dane-systemowe/funkcjonowanie-rb/raporty-dobowe-z-funkcjonowania-rb/podstawowe-wskazniki-cenowe-i-kosztowe/rynkowa-cena-energii-elektrycznej-rce], accessed on 2 January 2023.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Gołebiewski, D.; Barszcz, T.; Skrodzka, W.; Wojnicki, I.; Bielecki, A. A New Approach to Risk Management in the Power Industry Based on Systems Theory. *Energies* **2022**, *15*, 9003. [CrossRef]
2. Wąs, K.; Radoń, J.; Sadłowska-Sałęga, A. Thermal Comfort—Case Study in a Lightweight Passive House. *Energies* **2022**, *15*, 4687. [CrossRef]
3. Wąs, J. *Modeling and Simulation of Complex Collective Systems*, 1st ed.; CRC Press: Boca Raton, FL, USA, 2023. . [CrossRef]
4. Alkhayat, G.; Mehmood, R. A review and taxonomy of wind and solar energy forecasting methods based on deep learning. *Energy AI* **2021**, *4*, 100060. [CrossRef]
5. Bilski, J.; Rutkowski, L.; Smolag, J.; Tao, D. A novel method for speed training acceleration of recurrent neural networks. *Inf. Sci.* **2021**, *553*, 266–279. [CrossRef]

6. Bo, W.; Xiaokang, W.; Ning, W.; Zahra, J.; Navid, M.; Mahyar, A. Machine learning optimization model for reducing the electricity loads in residential energy forecasting. *Sustain. Comput. Inform. Syst.* **2023**, *38*, 100876 [CrossRef]
7. Huanjian, M.; Lijuan, X.; Zahra, J.; Navid, M.; Mahyar, A. Reducing the consumption of household systems using hybrid deep learning techniques. *Sustain. Comput. Inform. Syst.* **2023**, *38*, 100874. [CrossRef]
8. Pikus, M.; Wąs, J. Using Deep Neural Network Methods for Forecasting Energy Productivity Based on Comparison of Simulation and DNN Results for Central Poland—Swietokrzyskie Voivodeship. *Energies* **2023**, *16*, 6632. [CrossRef]
9. Lee, D.; Kim, K. PV power prediction in a peak zone using recurrent neural networks in the absence of future meteorological information. *Renew. Energy* **2021**, *173*, 1098–1110. [CrossRef]
10. Lago, J.; Ridder, F.D.; Schutter, B.D. Forecasting spot electricity prices: Deep learning approaches and empirical comparison of traditional algorithms. *Appl. Energy* **2018**, *221*, 386–405. [CrossRef]
11. Małek, A.; Marciniak, A. The use of deep recurrent neural networks to predict performance of photovoltaic system for charging electric vehicles. *Open Eng.* **2021**, *11*, 377–389. [CrossRef]
12. Neuhoff, K.; Richstein, J.C.; Kröger, M. Reacting to changing paradigms: How and why to reform electricity markets. *Energy Policy* **2023**, *180*, 113691. [CrossRef]
13. Boynuegri, R.; Tekgun, B. Real-time energy management in an off-grid smart home: Flexible demand side control with electric vehicle and green hydrogen production. *Int. J. Hydrogen Energy* **2023**, *48*, 23146–23155. [CrossRef]