# Research on Enhancing Power Generation Forecasts with Real-Time Machine Learning Models

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**Abstract**

Intelligent methods for optimizing energy use are rapidly gaining popularity as the world moves towards sustainable energy solutions. This study delves into enhancing the efficiency of alternative energy usage by improving of the forecasting model by integrating data collected in real time from local weather stations, leading to more accurate and localized forecasting of power generation. Significant focus is placed on the development and integration of cost-effective, custom-built measurement systems for wind speed and solar irradiation. By integrating real-time data from local meteorological stations with advanced machine learning methods, the study proposes a new approach that combines broad weather forecasts with precise local conditions to predict power generation more accurately. The research emphasizes the scientific novelty of the model, which combines real-time data from local meteorological stations with Long Short-Term Memory model. It also highlights the practical significance in improving the reliability and efficiency of alternative energy use in home automation systems.

**Keywords**

Home automation system, real-time machine learning, artificial neural networks, incremental learning, adaptive learning, power generation, forecasting, LSTM, OpenHAB

## 1. Introduction

In today's world, saving energy is becoming more and more important. Many people are looking for ways to use less electricity from the traditional power grid to save money and help the environment. One popular way to do this is by using alternative energy sources, like solar or wind power. However, the effective use of power from alternative sources requires advanced management strategies. There is a lot of discussion around this topic, so many authors have proposed their own methods for solving this problem. Existing works propose three main categories of energy optimization strategies: the optimization of electrical appliance usage schedule [1, 2, 3, 4, 5, 6, 7, 8], forecasting electricity consumption [9, 10, 11, 12, 13, 14, 15, 16, 17], and forecasting power generation [18, 19, 20]. Each of these approaches has its own advantages and limitations, which contribute to the overall goal of achieving energy efficiency from alternative sources.

The study [21] introduced a complex intelligent method for controlling energy consumption in home automation systems (HAS). This novel approach comprises two strategies: forecasting power generation and optimizing the schedule of electrical appliance usage. Consequently, houseowners can use energy more efficiently, saving money and reducing environmental impact. To facilitate this, an intelligent support subsystem was developed, providing residents with

CMIS-2024: Seventh International Workshop on Computer Modeling and Intelligent Systems, May 3, 2024, Zaporizhzhia, Ukraine
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recommendations for the efficient use of electrical appliances. While the developed Long Short-Term Memory (LSTM) model [21] showed good predictive capabilities in forecasting power generation, a significant limitation arises from its reliance on data from online weather services. The effectiveness of these forecasts is often compromised, as they may not accurately reflect the actual weather conditions where the HAS is located. This can cause issues for the developed intelligent support subsystem [21] while forecasting power generation and providing recommendations.

Therefore, the task of enhancing the accuracy of the forecasting model by incorporating real-time data is urgent.

The goal of the work is the research and practical implementation of methods and tools for real-time data collection, as well as methods for real-time machine learning.

# 2. Study of real-time data collection features for power generation forecasting

## 2.1. Analysis of management architectures for alternative energy sources

The initial phase of this study delves into how inverters are used within alternative energy sources, focusing on their architectural integration. By exploring different inverter architectures, the aim is to see how they can integrate with the power grid and other energy sources.

Inverters play a crucial role in integrating alternative energy, transforming the direct current (DC) produced by solar panels and wind turbines into the alternating current (AC) used in homes and the power grid. This transformation is key because it makes the generated electricity compatible with usual household appliances and the wider electrical system. But solar inverters do a lot more than just convert DC to AC. They also adjust the electricity to the right voltage and sine wave frequency, making sure it is safe for home use or to be sold out on the electricity grid. Furthermore, these inverters incorporate safety features, ensuring a secure energy supply [24].

It is also important to understand the different types of inverters in order to fully appreciate their role in adopting alternative energy. There are three main types: Stand-alone, Grid-tie and Hybrid inverters.

Stand-alone inverters are the heart of off-grid solar systems. They convert DC electricity from batteries, which get charged by the solar panels, into AC that can be used for a variety of needs (Fig. 1). This type is perfect for places without access to the traditional grid, providing a reliable source of power. They have features that protect batteries from overcharging and help keep the power supply steady, making them crucial for continuous energy in off-the-grid spots [24, 25].

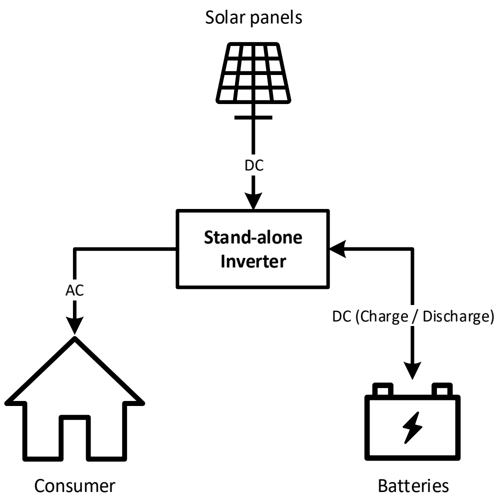


**Figure 1:** Stand-alone inverter configuration for off-grid scenarios

Grid-tie inverters connect solar systems to the utility grid. They transform the DC electricity from solar panels into AC that matches the external grid's requirements. A key function of these inverters is to synchronize the solar power with the grid's frequency and phase (Fig. 2). This not only lets homes use solar power but also lets them sell extra electricity back to the grid to get credits for this extra energy [24, 25].

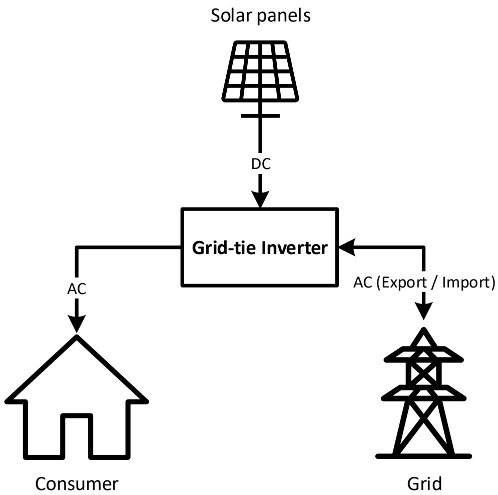


**Figure 2:** Grid-tie inverter integration with public electricity grid

Hybrid inverters combine the best features of both stand-alone and grid-tie inverters. They are capable of using power from solar panels, batteries and the external grid, supporting systems that aim for independence from the traditional grid while also ensuring efficient energy use (Fig. 3). These inverters allow homes to store excess solar energy for use during periods of high demand or when the grid is unavailable. This type of inverter is particularly useful in areas with unreliable grid service, as it makes energy use more efficient and reduces reliance on the grid.

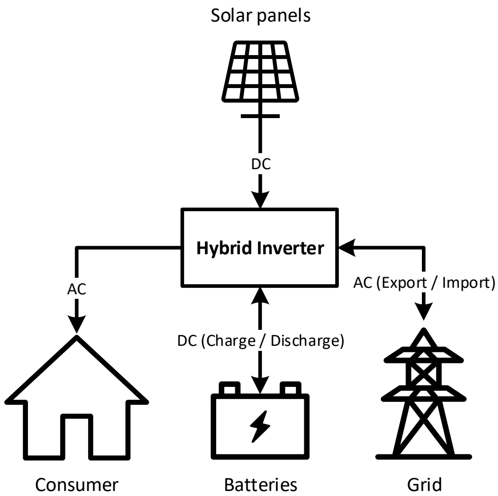


**Figure 3:** Hybrid inverter configuration for integrated energy management

In work [21], a real HAS was examined, with a focus on its integration with alternative energy sources and battery backup system. It has a hybrid setup, including a hybrid inverter connected to the external power grid, battery storage and renewable energy sources such as solar panels and wind turbines. These batteries play a critical role as a backup solution in scenarios where both self-generated electricity and the external grid are unavailable. Under normal conditions, they maintain a charged state, acting as a buffer and enabling efficient energy management within the system.

Additionally, this system incorporates Open Home Automation Bus (OpenHAB), a home automation software that allows homeowners to control a wide range of Internet of Things (IoT) devices. This means that people can easily control the environment in their home, making it more comfortable and able to respond to their needs more effectively.

## 2.2. Analysis and implementation of real-time data collection from meteorological stations

Recent study [21] has shown the correlation between weather data and power generation while implementing an LSTM forecasting model. Specifically, wind speed (measured in meters per second) and solar irradiation (measured in watts per square meter) have been identified as essential parameters for the forecasting model. To collect this data, it is necessary to install a meteorological station near the HAS. Such an installation not only ensures the availability of real-time data but also enhances the model's predictive accuracy by using local weather conditions.

A detailed review of various online stores offering meteorological stations was carried out to find the best solution. The research showed a strong preference for all-in-one weather stations. These stations can track a variety of weather information, such as wind speed and direction, temperature, solar irradiation, air pressure etc. Despite their capabilities, the primary drawback of these stations lies in their high cost, making them a less suitable option for budget limited projects. As a result, a more affordable alternative is to buy wind and solar irradiation sensors separately. Although this approach offers a smaller range of data, it still meets the essential requirements for the forecasting model.

There is a wide variety of wind sensors available on the market at affordable prices. They are designed to accurately measure wind speed and direction, making them an ideal choice for collecting the necessary wind data for a forecasting model.

To collect wind speed data in real-time, the wind speed sensor “CWT-SWC-C-RS485” was selected for its price and efficiency. This wind sensor uses the RS485 standard, which OpenHAB does not support. To resolve this, the data is sent to an ESP8266 microcontroller with “Tasmota” firmware installed, acting as a Modbus bridge. Subsequently, OpenHAB processes this information and stores it in a local MySQL database. This measurement system represents a seamless integration of the sensor with HAS, enabling advanced wind speed monitoring and data collection (Fig. 4).

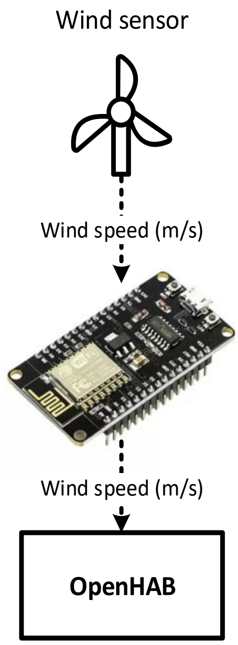


**Figure 4:** Architecture of custom wind measurement system

The custom wind speed measurement system has now been successfully implemented and is actively collecting local wind speed data for the database. On Figure 5, a sample of the data from the database is displayed.

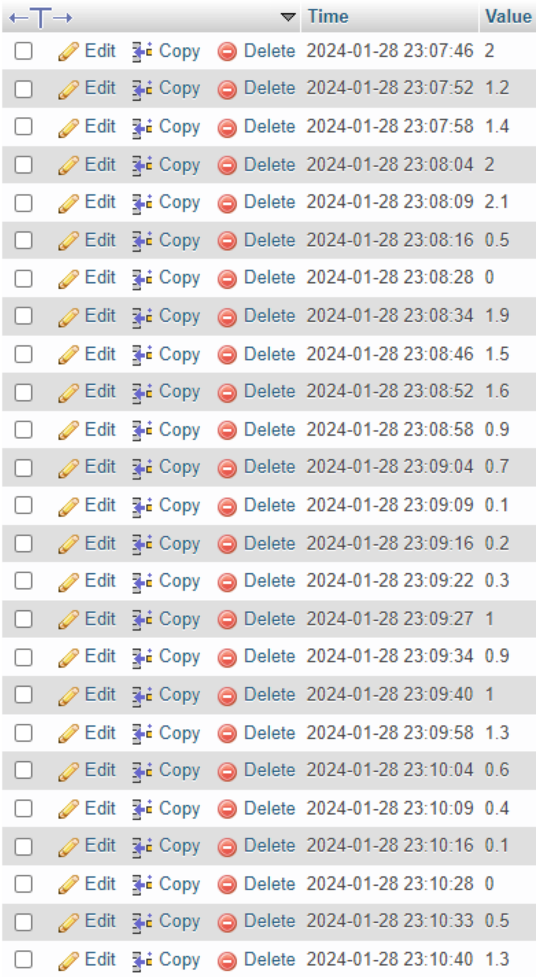

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**Figure 5:** Sample wind speed data collected from the local wind speed measurement system

The OpenHAB platform enables real-time monitoring of wind speed data (Fig. 6) and offers access to historical data charts (Fig. 7). This setup provides instant insights into current wind conditions and supports the analysis of wind speed trends over time. Additionally, OpenHAB collects wind speed data from online weather service OpenWeatherMap [23], which enables to compare the local weather data with online forecasts.

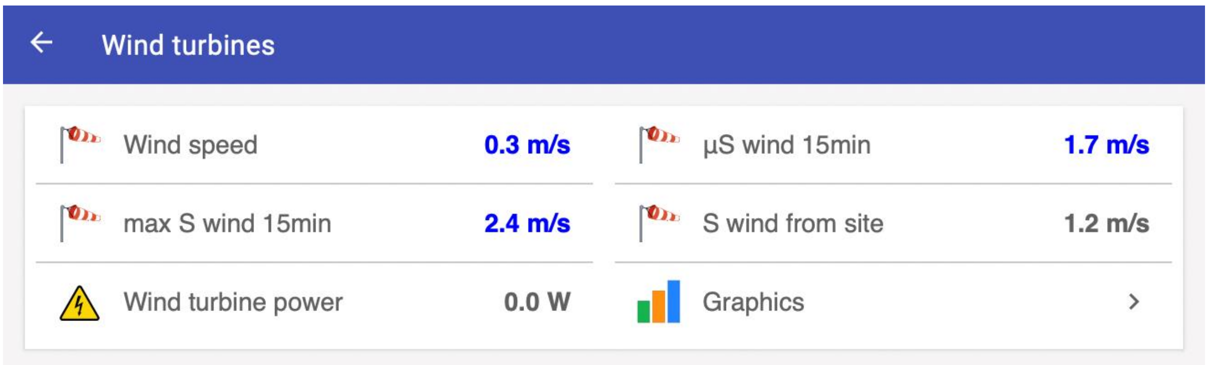


**Figure 6:** Real-time wind speed monitoring via the OpenHAB interface

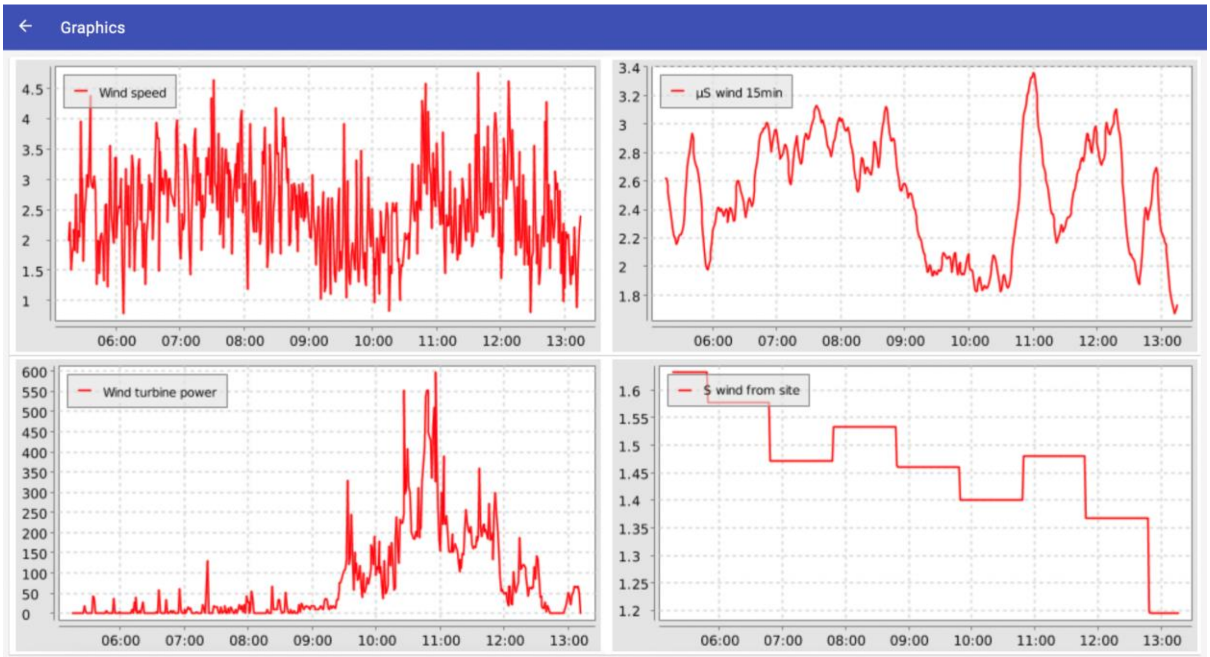


**Figure 7:** Historical wind speed data charts in the OpenHAB interface

Subsequent research involved analyzing data obtained from online weather service, which was used for forecasting power generation. In Figure 8, a chart shows a comparative analysis of historical wind speed data, derived from both a local meteorological station and online weather service. The local meteorological station data, denoted by the blue line with error bars, shows the mean wind speed for each hour along with the standard deviation, indicating variability within the hour. The error bars show how much the wind speed can vary over time. In contrast, the data from the online weather service OpenWeatherMap [23] is plotted as an orange line.

The comparative analysis between these two datasets revealed some major differences, suggesting that incorporating local meteorological station data could enhance the accuracy of power generation forecasts. This visual analysis not only highlights the temporal dynamics of wind speed but also serves as a crucial tool for evaluating the reliability of wind speed data from different sources. Such comparisons are essential for applications where accurate weather data is crucial for predicting power generation and providing recommendations.

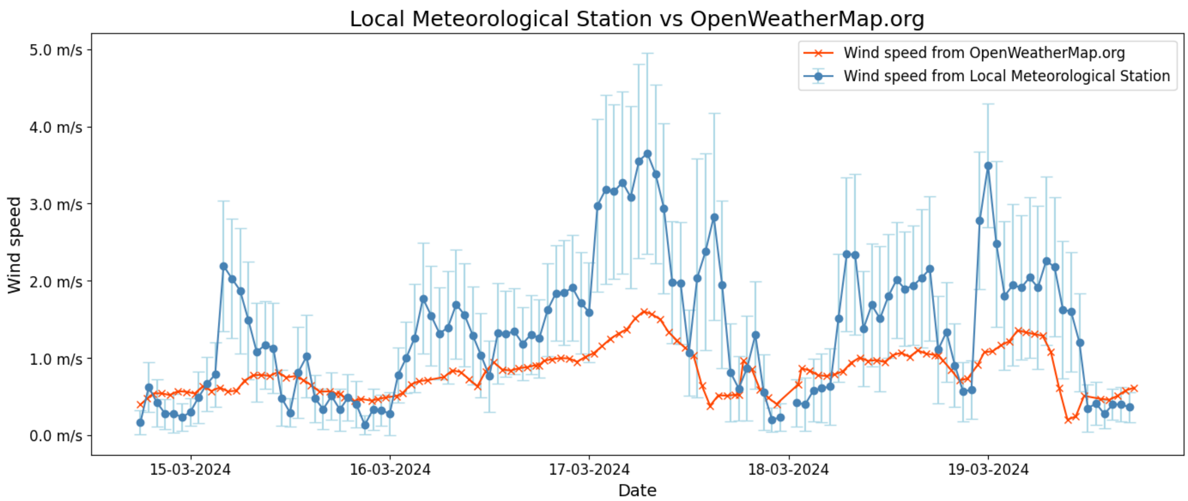


**Figure 8:** Comparative analysis of hourly historical wind speed data between a local meteorological station and an online weather service

During the search for a suitable solar irradiation sensor, it was discovered that the available sensors on the market are too expensive. This discovery suggested an idea for designing and building a custom solar irradiation measurement system that would meet the requirements of the study. This solution is expected to provide accurate data on solar irradiation at a lower cost than commercial sensors.

To calculate the level of solar irradiation, a measurement system was suggested that involves a solar controller charger with pulse width modulation (PWM) technology, a solar panel and a battery. By measuring the electrical output from the solar panel and considering the panel's surface area, the level of solar irradiation can be calculated (Fig. 9). The solar controller charger plays a crucial role in this process by managing the charging cycle and ensuring that the energy transfer to the battery remains within safe bounds.

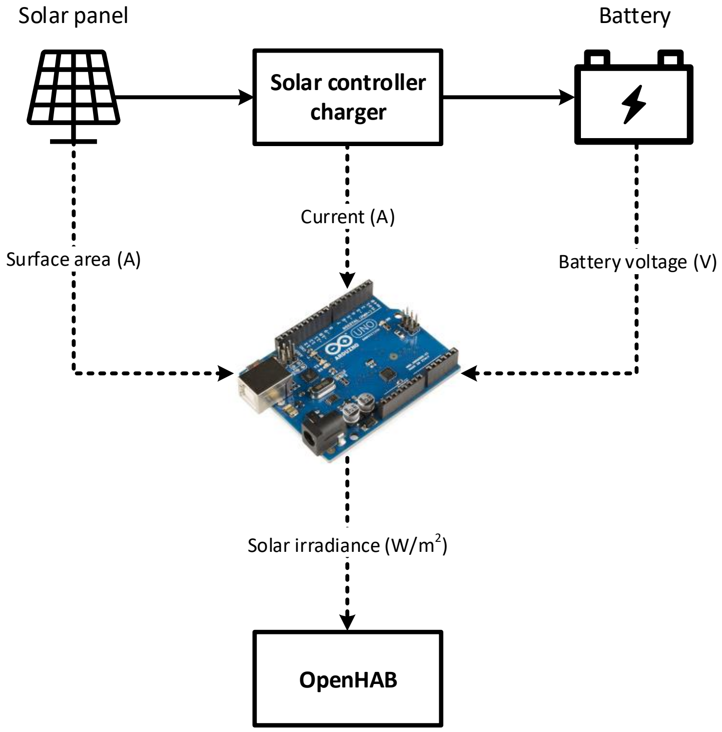


**Figure 9:** Architecture of custom solar irradiation measurement system

Initially, the chosen solar controller charger is connected to both the solar panel and a battery. An Arduino is used to monitor the battery's voltage, which helped to determine the solar panel's current power output using formula (1):

$$P = V \times I, \tag{1}$$

where *P* represents power in watts (W), *V* is the voltage in volts (V) and *I* stands for the current in amperes (A).

Subsequently, once the power output and the surface area of the panel are known, the level of solar irradiation can be calculated using formula (2):

$$I = \frac{P}{A}, \tag{2}$$

where *I* is the solar irradiance in watts per square meter (W/m$^2$).

This solution will provide real-time data on local solar irradiation, necessary for enhancing the accuracy of the forecasting model without the use of specialized meteorological stations.

## 3. Related works

To enhance the accuracy of power generation forecasting, the next step is to thoroughly review related works in this area. This includes examining different techniques and machine learning models, applied to a range of energy sources.

In the work [26], the authors introduced an online domain adaptive learning approach, enhanced with the AdaBoost algorithm, for solar power forecasting. This model is specially designed for its ability to adapt to changing weather conditions, thereby significantly enhancing the accuracy of solar energy output predictions. Unlike traditional batch learning models, which become static after training, this innovative approach allows for continuous adaptation to new data without the need for retraining. This makes it particularly suitable for the unpredictable nature of solar irradiation.

This adaptive learning model [26] demonstrates remarkable performance improvements over traditional forecasting methods, such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Extreme Learning Machines (ELM), Gaussian Mixture Regression (GMR) and the Persistence Model, across various datasets. For example, on one dataset, the proposed adaptive learning model achieved a Root Mean Square Error (RMSE) of 94.6843 W/m$^2$, far surpassing the RMSE values of GMR (106.7835 W/m$^2$) and ANN (126.6187 W/m$^2$). Furthermore, when tested on other datasets, the model's accuracy remained consistent. On another dataset, its RMSE measure of 44.21007 W/m$^2$ outperforms those of GMR (52.4752 W/m$^2$) and SVM (60.7089 W/m$^2$), underscoring an improvement of approximately 15% over GMR, which is the closest competitor. These findings highlight not only the model's enhanced accuracy but also its reliability in forecasting solar power output under varied meteorological conditions.

In the research [27], the Adaptive Learning Hybrid Model (ALHM) was introduced as a solution for solar intensity forecasting, crucial for the integration of renewable energy sources into smart grids. This model stands out for its ability to adaptively learn from new data over time, capturing both linear and nonlinear dynamics through its integration of Time-varying Multiple Linear Model (TMLM) and Genetic Algorithm Back Propagation Neural Network (GABPNN). Using an extensive dataset that includes various meteorological variables such as temperature, humidity, dew point, wind speed and precipitation, the model has demonstrated superior forecasting performance.

The proposed model [27] outperformed both ANN and SVM models in terms of Mean Absolute Percentage Error (MAPE) and RMSE. The proposed model achieved a MAPE of 13.68% and an RMSE of 16.95 W/m$^2$, indicating a higher forecasting accuracy and reliability. In contrast, ANN and SVM models reported higher MAPE values, demonstrating their lesser ability to forecast. One of the key advantages of the proposed model over ANN and SVM is its adaptive learning capability. It can adaptively learn from new data, improving its forecasting accuracy over time. This is particularly valuable in dynamic environments like solar intensity forecasting, where weather patterns and other influencing factors can change.

In the study [28], an innovative Adaptive Long Short-Term Memory (ALSTM) model was proposed to address the challenge of day-ahead forecasting of photovoltaic (PV) power generation. This model focuses particularly on overcoming the problem of concept drift, where the data distribution changes over time, making traditional models less effective. The main idea of the proposed is to enhance its adaptability by enabling it to continuously learn from new data as it arrives. This allows the model to maintain high forecasting accuracy even in the presence of concept drift.

The dataset used for evaluating the proposed model [28] included records from a PV plant over several months, incorporating both historical and newly-arrived data streams. Compared to other forecasting methods such as Persistence, Autoregressive Integrated Moving Average (ARIMA), k-Nearest Neighbors (k-NN) and the traditional offline LSTM model, the ALSTM demonstrated superior performance across various metrics. For example, when compared to the offline LSTM, the ALSTM showed an MSE reduction ranging from approximately 56.07% to 92.77%. This indicates a higher forecasting accuracy and its effectiveness in adapting to new data and mitigating the impacts of concept drift, offering a significant advancement over traditional forecasting approaches.

In the work [29], an innovative methodological framework that incorporates incremental learning to improve the accuracy in the field of energy forecasting was introduced. This approach is the adoption of incremental learning techniques applied to a Multi-Layer Perceptron (MLP). This approach effectively addresses the limitations associated with traditional batch learning models by facilitating continuous learning from real-time data, thus ensuring the model's relevance and accuracy are maintained over time.

The effectiveness of the proposed method [29] was evaluated using real-world data from a microgrid located in Italy, which includes a multi-story building and a PV system. A comparative analysis between the performance of the proposed model and the traditional learning model clearly demonstrates the benefits of the new approach. The results represent a significant improvement in forecasting accuracy. The incremental learning MLP model reduces the MAE by 7.93% and the RMSE by 7.52%, compared to the traditional MLP model. This numerical evidence strongly supports the superiority of the proposed method. It highlighting its enhanced adaptability to changing data patterns and its increased predictive performance, making it an optimal choice for real-time energy forecasting applications.

In the study [30], a novel solar PV power generation forecasting model was introduced that combines different weather information to compensate for the lack of real-time power generation data. This approach uses Deep Neural Networks (DNN) for data fitting and LSTM networks for temporal forecasting. The model was rigorously tested using datasets from six solar power plants in Taiwan, covering diverse environmental conditions. The results demonstrated an exceptional forecasting accuracy of over 97% compared to traditional models like LSTM, DNN, SVM and Back-Propagation Neural Network (BPNN). Among these traditional models, the DNN-LSTM model showed superior performance, as evidenced by its lower Normalized Root Mean Square Error (nRMSE) and Normalized Mean Absolute Error (nMAE). This underscores its robustness and reliability in comparison to conventional forecasting methodologies.

In the study presented in [31], a new approach using transfer learning for predicting day-ahead PV power is introduced. This methodology relies on the fundamental idea of leveraging the deep learning models trained on large historical datasets from existing PV power plants to enhance the prediction accuracy for newly installed PV systems. The transfer learning framework improves prediction accuracy by applying patterns and insights extracted from extensive historical data to new situations where the historical data is limited.

The datasets used in the study [31] include hourly historical data from two PV power farms that are located in close proximity to each other. The first provides a more extensive dataset, while the second farm provides more recent data. A comparative analysis of the developed models: linear, dense, Convolutional Neural Network (CNN) and LSTM reveals the superior performance of the transfer learning models over their new and untrained counterparts. For example, the trained transfer LSTM model consistently outperformed their counterparts, with improvements in MAE, MSE and RMSE reaching up to 41.42%, 69.45% and 45.91% respectively. This demonstrates the potential of transfer learning in renewable energy forecasting applications.

The results of the machine learning models and techniques reviewed in related works, along with their comparisons to traditional models, are presented in Table 1.

The survey of related works [26, 27, 28, 29, 30 31] consistently underscores the advantage of real-time adaptive learning methodologies over traditional forecasting models in enhancing the accuracy of power generation predictions. These studies demonstrate that integrating adaptive learning techniques can greatly improve the forecasting process by allowing models to continuously update and adjust to new data. Specifically, the work presented in [31] offers a strong foundation for developing an improved predictive model that takes into account the architecture of a real HAS [21]. By integrating real-time learning and transfer learning techniques, this model has the potential to significantly improve the accuracy of power generation forecasts. This approach not only enhances accuracy but also improves the operational efficiency of energy systems in constantly changing environmental conditions.

**Table 1**
**Comparative analysis of real-time learning models to traditional models**

| Model / Technique used | Core features | Comparative improvement |
|---|---|---|
| Domain Adaptive Learning with AdaBoost [26] | High adaptability to changing conditions | Outperforms ANN, SVM, ELM, GMR models |
| Adaptive Learning Hybrid Model (ALHM) [27] | Adaptively learns from new data | Superior to ANN and SVM models |
| Adaptive Long Short-Term Memory (ALSTM) [28] | Effectively handles concept drift | Better than traditional LSTM model |
| Incremental Multi-Layer Perceptron (MLP) [29] | Continuous learning from real-time data | Enhances accuracy over traditional MLP model |
| DNN-LSTM Hybrid [30] | Utilizes varied weather information | Superior to LSTM, DNN, SVM, BPNN models |
| Transfer Learning LSTM [31] | Applies historical insights to new setups | Outperforms traditional linear, dense, CNN and untrained LSTM models |

# 4. An improved two-stage predictive model for enhanced forecasting accuracy with real-time data

Following a detailed review of related works and considering the architecture of a real HAS [21], an improved two-stage predictive model has been proposed. This will enhance the accuracy of power generation predictions for solar panels and wind turbines using local weather data.

The first stage involves the development of a predictive model that aims to bridge the gap between general weather forecasts provided by online weather service and the specific local weather conditions in a given area. This stage uses a predictive model *f* to convert the general weather forecasts provided by an online service to local weather predictions. The general forecast serves as the input features while the local historical data serves as the targets, enabling a better understanding of how general weather forecasts correlate with local weather phenomena, that can be expressed as follows (3):

$$\hat{W}_l(t) = f(W_g(t);\theta), \quad (3)$$

where $W_g(t)$ represents the general weather data at time *t*, $\hat{W}_l(t)$ represents the predicted local weather conditions at time *t*, and $\theta$ are the parameters of the model. The model *f* is trained using historical data from both online service and local meteorological station. Once the model is trained, it can be used to generate forecasts for local weather conditions based on the input from an online service. This approach will provide more accurate predictions for specific areas where a real HAS is located.

The second stage involves the development of the LSTM model, which is trained exclusively on historical weather data collected from a local meteorological station. Using the accurate and relevant information provided by the local meteorological station, this model is specifically designed to predict power generation based on the predicted local weather conditions obtained from the first stage. The predictive model for power generation can be expressed as follows (4):

$$\hat{P}(t) = LSTM(\hat{W}_l(t);\phi), \quad (4)$$

where $\hat{P}(t)$ is the predicted power generation at time *t*, $\hat{W}_l(t)$ is the local weather prediction derived from formula (3), and $\phi$ represents the parameters of the LSTM model. This LSTM model is specifically designed to predict power generation from these local weather predictions, thus enabling more accurate forecasts of power generation and taking full advantage of the understanding of local weather patterns established in the first stage.

The architecture of the proposed predictive model is illustrated in Figure 10, providing a visual representation of the two-stage model and its integration with real-time data for enhancing the accuracy of power generation forecasts.

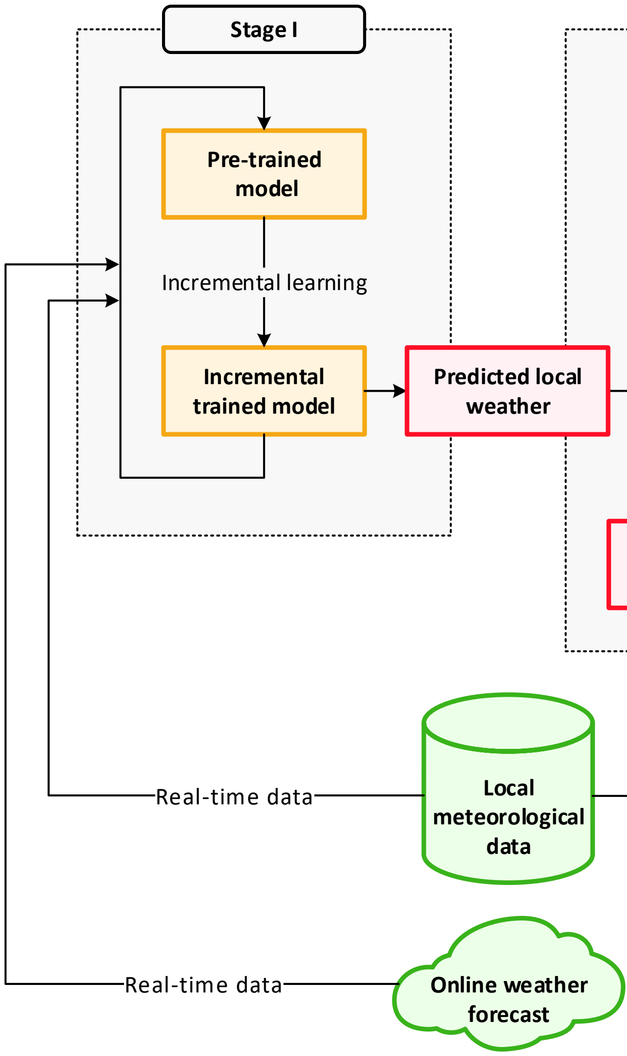


**Figure 10:** Architecture of the proposed two-stage predictive model incorporating real-time data for enhanced power generation forecasting

The data flow of the improved two-stage predictive model is illustrated in Figure 11, showing interactions between various components, including historical data from different sources and two predictive models. Significantly, it demonstrates the integration of historical weather and power generation data, which are crucial for training the first predictive model and the LSTM model, respectively, to accurately forecast power generation. The forecasted power generation is used to provide recommendations in the developed intelligent support subsystem [21].

Incorporating real-time data processing greatly enhances the accuracy of power generation forecasts. By updating the models in real-time with the latest data from the local meteorological station, the predictive models are guaranteed to adapt to the latest weather patterns. This real-time approach allows for continuous learning and adjustment, which will significantly improve the model's responsiveness to sudden weather changes and will enhance the accuracy of power generation predictions. The integration of real-time data will not only refine the models' predictive capabilities but will also ensure that the system remains relevant and accurate over time, despite the inherent variability and unpredictability of weather conditions. This approach provides a robust framework for reliably forecasting power generation from renewable energy sources, leveraging the synergy between localized data collection and advanced machine learning techniques.

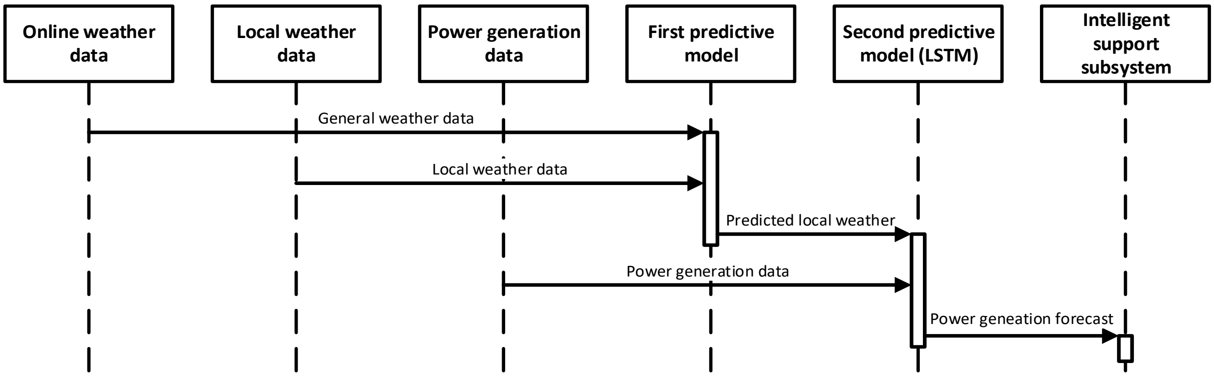


**Figure 11:** Sequence diagram of the improved two-stage predictive model incorporating real-time data for enhanced power generation forecasting

## 5. Conclusion

As a result of the conducted research, it has been demonstrated that integrating real-time local meteorological data with advanced machine learning techniques can significantly enhance the accuracy of power generation forecasts for alternative energy sources. The proposed two-stage predictive model, which combines general weather forecasts with specific local conditions, offers a more precise understanding of how weather impacts power generation. This approach not only overcomes the limitations of existing forecasting methods but also opens up the possibility for a more efficient and reliable use of alternative energy sources in HAS. By incorporating real-time data processing, the developed intelligent support subsystem [21] will be able to remain adaptable and responsive to sudden weather changes, thereby improving the sustainability and efficiency of energy use in HAS.

The scientific novelty of the work lies in the development of an improved two-stage predictive model that uses local weather data to improve forecasts of power generation from solar panels and wind turbines. The improved architecture of this model, which combines real-time data collection from local meteorological stations with advanced LSTM machine learning algorithms, represents a significant advancement in the field of alternative energy forecasting. Furthermore, the methodological approach of correlating general weather forecasts with local weather phenomena to enhance forecast accuracy introduces a new paradigm in predictive modeling for alternative energy sources.

The practical significance of this work is that it provides an effective way to improve the reliability and efficiency of using alternative energy sources, especially in HAS. With more accurate forecasts for power generation, homeowners can better manage their energy consumption, reducing their dependence on traditional power grids. This leads to cost savings and supports environmental sustainability by promoting the adoption of clean energy.

In future work, it is planned to implement the proposed two-stage model and then integrate it into a real HAS. This step will allow to evaluate and fine-tune the model within a real-world context, guaranteeing its effectiveness in optimizing energy management and forecasting capabilities. Additionally, exploring the potential of incorporating advanced artificial intelligence techniques to further improve the model's forecasting precision and operational performance is planned.

## Acknowledgements

This work is partly carried out with the support of Erasmus + KA2 project WORK4CE "Cross-domain competences for healthy and safe work in the 21st century" (619034-EPP-1-2020-1-UA-EPPKA2-CBHE-JP) and DAAD project ViMUk.

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