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PHOTOVOLTAIC GENERATION FORECASTING MODELS: CONCEPTUAL ENSEMBLE ARCHITECTURES

Abstract. *The decisions regarding power regulation, energy resource planning, and integrating "green" energy into the electrical grid hinge on precise probabilistic forecasts. One of the potential strategies to enhance forecast accuracy is the utilization of ensemble forecasting methods. They represent an approach where multiple models collaborate to achieve superior results compared to what a single model could produce independently. These methods can be categorized into two main categories: competitive and collaborative ensembles. Competitive ensembles harness the diversity of parameters and data to create a rich pool of base models. This approach may encompass statistical analysis, noise filtering, and anomaly elimination. On the other hand, collaborative ensembles rely on the interaction among models to achieve better outcomes. These methods encompass strategies such as weighted predictions, voting, aggregation, and a combination of model results. The research of ensemble forecasting methods in the context of photovoltaic generation is highly relevant, as solar energy represents a crucial source of renewable energy. Accurate predictions of solar energy production address the challenges related to the efficient utilization of photovoltaic panels and their integration into the overall energy system. This paper investigates conceptual ensemble architectures for photovoltaic energy forecasting. These architectures encompass various methods of aggregating base models within an ensemble, allowing for the consideration of different aspects and peculiarities of solar data, such as solar irradiation intensity, meteorological conditions, geographic factors, and more. These conceptual models are developed based on well-established statistical, machine learning, and artificial intelligence methods. Therefore, this paper provides an overview of ensemble forecasting methods for renewable energy, covering competitive and collaborative ensembles, as well as developing conceptual models for solar energy forecasting. This work aims to elevate the accuracy and efficiency of forecasts in the realm of renewable energy, representing a significant step in the advancement of sustainable and environmentally friendly energy production.*

Keywords: probabilistic solar forecasting, ensemble model, forecast combination, competitive ensembles, collaborative ensembles, conceptual models.

1. Introduction

The growing global demand for energy poses challenges such as excessive strain on supply [1], significant adverse environmental impacts [2] (rising temperatures [3], ozone layer depletion, climate issues, etc.) [4], and the depletion of energy resources [5]. Over the past decades, new resilient energy systems and methods for integrating renewable energy sources and energy storage systems into the electrical grid have been researched and discussed extensively [6, 7].

The impact of new approaches to designing, developing, and managing energy systems focusing on their resilience throughout their entire life cycle presents a significant challenge [8]. Key terms like "Smart Grids" and "Nearly Zero-Energy Buildings" are frequently used in the context of various energy system subfields. Still, it's essential to consider them within the framework of the overall energy system [9, 10]. An example of this is the concept of intelligent energy systems, commonly referred to as "Smart Energy Systems" [9, 11].

The full potential of managing energy systems using computational resources has not been fully realized, remaining a relevant topic for further research and development [12]. However, a crucial requirement is the integration of all subsystems of energy systems on a global scale [10].

The formal definition of a smart energy system, as stated in [11, 13], is that it comprises "new technologies and infrastructure that create new forms of flexibility, primarily in the energy system conversion stage" [14]. Various sectors, including electricity and transportation, collaborate to compensate for the lack of flexibility resulting from using renewable energy sources [15–17]. The smartness of energy systems is closely tied to the ability to predict their behavior in the future, making modeling, simulation, and forecasting essential.

Literature on forecasting in energy systems varies in terms of methods used, as noted in comparative reviews [3, 15, 18]. These reviews demonstrate that there is no one universal method that outperforms all others in all aspects. Primary research has focused on point forecasts, for which methods such as Artificial Neural Networks (ANN) [19, 20], K-Nearest Neighbors (KNN) [21], Support Vector Regression [22], Random Forests [23], and multi-factor linear regression models [24] are often considered optimal solutions. Traditional statistical methods like Autoregressive Integrated Moving Average (ARIMA) [25] and Seasonal ARIMA (SARIMA) are popular due to their simplicity, with the Box-Jenkins methodology often used for model configuration selection. However, it's essential to consider that ARIMA models assume a linear correlation structure between forecasts and past data, which may lead to poorer results in the presence of nonlinear patterns. As real data often contain a combination of linear and nonlinear patterns [26], and solar irradiation data exhibit intermittency and variability, ARIMA models may perform worse compared to other methods used in the literature [27, 28].

Recent trends in probabilistic solar forecasting advocate for the use of probabilistic combinations of individual forecasts as a viable approach to improve accuracy [18, 29, 30]. However, combining probabilistic forecasts is significantly more complex than combining point forecasts, where simple weighted averaging is often acceptable. When combining probabilistic forecasts, reliability and accuracy requirements must be met, and it's crucial to preserve the essential characteristics of the probabilistic forecast in the combined forecasts.

The purpose of this article is to elucidate the essence and content of the concept of “ensemble forecasting” while investigating the principles and providing conceptual models for ensemble solar forecasting.

2. Global Ensemble Concept

The concept of ensemble modeling is a powerful approach in machine learning (ML) and statistics that involves combining predictions or outputs from multiple individual models to create a more accurate and robust overall forecast. Ensemble modeling is based on the idea that by aggregating the results of several models, the variability and impact of deviations in predictions can be reduced, leading to improved overall performance. This approach is widely used in various fields, including data science, predictive analytics, and ML, to enhance the accuracy and reliability of forecasts and classifications.

An ensemble can be seen as the collaboration of a group of models. The process of modeling a problem is quite complex, as it involves many entities working together. One of the main challenges is the constant change in the state of entities. They can become part of the collaboration or leave it, as well as change their state and adapt to new conditions. Despite various methods that can be used for ensemble modeling, it is essential to combine them to achieve better results.

One approach to ensemble modeling is the HELENA approach proposed in [31]. Here, ensemble modeling is defined in terms of roles and their interactions for the shared achievement of a specific goal, which can be used as a basis for the system development process. In each system, there is a set of different states that allow us to define the components – ensemble participants and the role they play. The state of both is determined by the values of their attributes.

In the context of the task, ensembles are combinations of several models, and the individual forecasts are combined in a certain way to create the final forecast.

An ensemble consists of a set of individually trained classifiers, such as neural networks or decision trees, whose predictions are combined when classifying new instances. Each ensemble member is expected to work collaboratively and complement each other. If the ensemble models used are complementary, the probability of detecting an error in the prediction increases, as well as the possibility of correcting it with other models. Instead of many traditional ML algorithms that create a single model, ensemble learning methods generate multiple models. The ensemble passes a new example to each included model, receives their predictions, and combines them accordingly.

Fig. 1 illustrates the overall architecture of the ensemble.

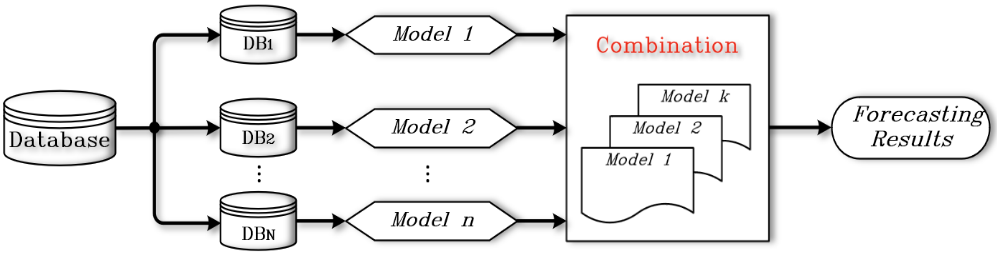

Fig. 1. The common ensemble architecture

As can be observed in Fig. 1, initially, the training data is divided into multiple datasets, and then several base models are created, which can be executed sequentially or in parallel. Finally, the models are combined on the base models [32, 33].

In general, the process of building an ensemble also involves several other steps:

1. Choosing a method by which variety is introduced into the basic models.
2. Choosing a method for combining models.
3. Selecting the type of base model.

Key concepts and components of ensemble modeling include:

Base (underlying) Models: Ensemble modeling starts with selecting base models or individual predictive models. These base models can be of different types or variations of the same model with different hyperparameters.

Aggregation: Ensemble methods employ various strategies to combine the predictions of base models. There are two primary types of aggregation:

- **averaging (pooling)**: Calculating the average (for regression tasks) or majority (for classification tasks) of predictions made by individual models;
- **weighted averaging (voting)**: Weighting the predictions of each model based on its effectiveness or expertise, giving more weight to better-performing models.

Pooling is primarily used for combining numerical outputs, while voting is used for combining nominal outputs [34]. “Voting” is the most popular method, where each base classifier votes for a specific class, and the class with the most votes is the ensemble's prediction.

The majority voting falls into the category of ensemble combination methods, whereas ensemble selection methods try to choose the best base models from the available set [35].

Diversity: The effectiveness of an ensemble often depends on the diversity of the base models. Different models tend to make different types of errors, and when combined, these errors can compensate for each other, leading to more accurate predictions. Diversity can be achieved through different model architectures, subsets of training data, or subsets of features.

Ensemble Methods: There are several popular ensemble methods, including:

- **bagging (Bootstrap Aggregating)**: Training multiple instances of the same base model on different data samples;
- **boosting**: Boosting algorithms such as AdaBoost and Gradient Boosting combine predictions from several weak models to create a “stronger” model;
- **random forest**: It combines bagging with random feature variation to create an ensemble of decision trees;
- **stacking**: Combining predictions from multiple models by training a meta-model (the final ensemble model) that learns to optimally combine their outputs.

Cross-Validation: To ensure that ensemble models generalize well to new data, cross-validation is often used to assess their performance. Cross-validation helps prevent overfitting, especially when there are many base models in the ensemble.

Hyperparameter Tuning: Ensemble models may have hyperparameters that require tuning to optimize their performance. “Grid search” or “random search” is used to find the optimal hyperparameter settings for both base models and the entire ensemble.

The ensemble development process involves two main stages: model training and model combination. During the training process, each model is trained using the same training examples but with different subsets of input features.

3. Proposed conceptual architectures of ensemble models

3.1. Architecture with voting-based aggregation

The first architecture developed by the authors and described in [9] is shown in Fig. 2.

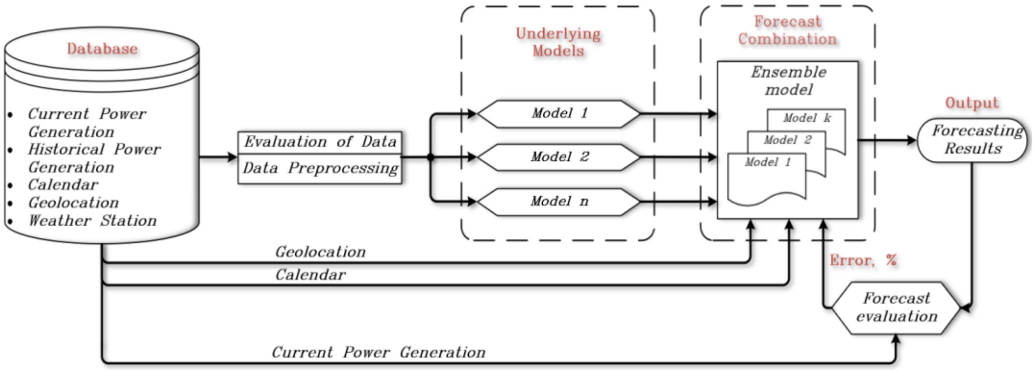

Fig. 2. Ensemble architecture based on the voting of basic models [9]

Historical and current data on photovoltaic (PV) panels, weather data along with calendar variables, and geographical location serve as input data for this forecasting system architecture. These data are used by the base probabilistic models to create individual probabilistic forecasts. In the end, the forecast quantiles returned from the base models are used as input data for the ensemble for their proper combination. During the forecast combination stage, calendar variables and geographical location may or may not be used, differentiating the estimation parameters. The output of the combination procedure is the probabilistic forecast of PV panel power.

3.2. Architecture with aggregation based on averaging of base model forecasts

In the ensemble architecture with averaging, the Second-Level model (Forecast Combination in Fig. 2) is replaced by Equation (1).

$$\left[\hat{y}_f\right] = \frac{\left(a_1\hat{y}_{\alpha 1} + a_2\hat{y}_{\alpha 2} + \ldots + a_N\hat{y}_{\alpha N}\right)}{\left(a_1 + a_2 + \ldots + a_N\right)}, \quad (1)$$

where $\left[\hat{y}_f\right]$ is overall average forecast of Level 1, $\hat{y}_{\alpha 1},\ldots,\hat{y}_{\alpha N}$ are forecasts, which are given by every single N model of Level 1, $a_1, a_2, \ldots, a_N$ are the weights assigned to the outputs of Level 1.

Such architecture is depicted in Fig. 3.

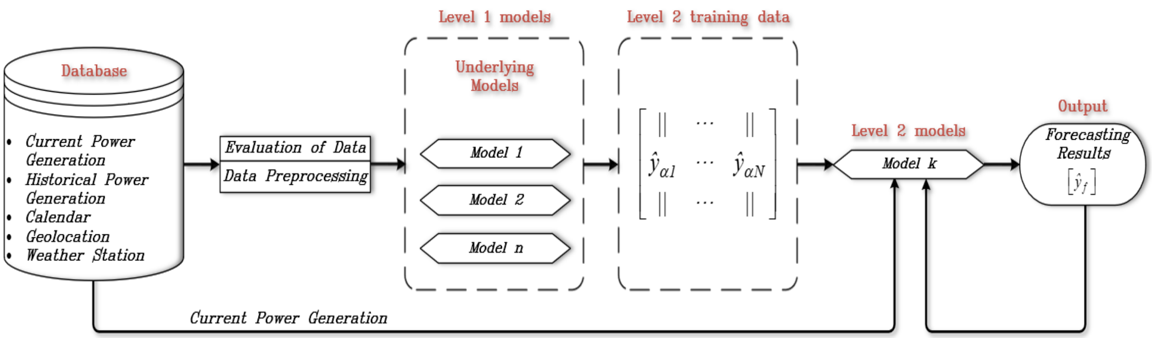

Fig. 3. The ensemble architecture based on averaging the base models

The contribution of each base model located at the first level is considered proportionally to its confidence or performance. In Ensemble Architecture 1, the base models are combined in such a way that the outputs of one level are treated as input data for the next level. Each individual model provides forecasts that are then aggregated into a training dataset for the second level, where the forecast is evaluated.

In Ensemble Architecture 2, after averaging the results of the first-level base models, a second regression model “Model k” is added, which learns the errors made by the previous models. Thus, the primary contribution of the second-level model is to minimize the errors of the previous models.

3.3. Architecture with combined aggregation

Fig. 4 displays simplified ensemble models.

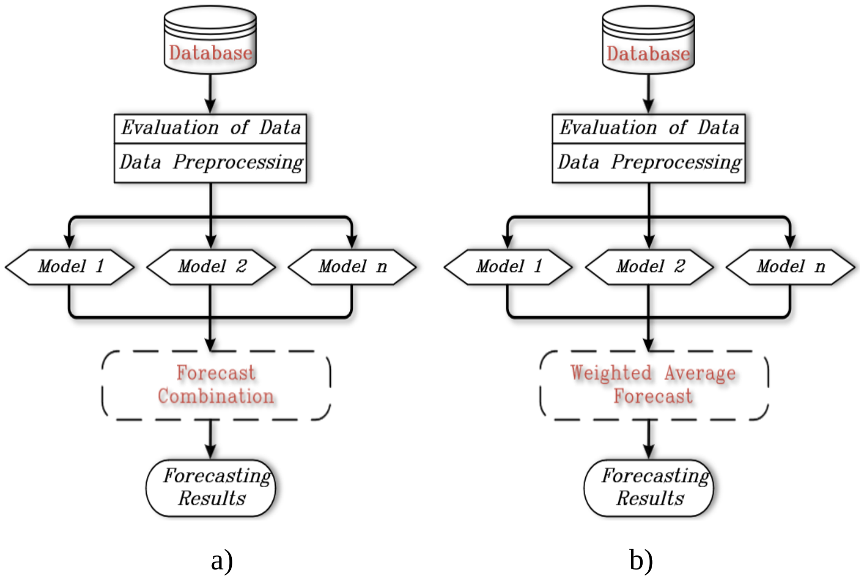

Fig. 4. Ensemble architecture with combined aggregation:
a) simplified competition, b) simplified averaging

In Ensemble 1 (Fig. 4, a), pre-filtered data is provided as input data to the basic models.

Ensemble 2 (Fig. 4, b) provides a weighted average of basic model forecasts as PV generation. The most suitable weights for each model are determined through trial and error. Weights that yield the lowest forecasting error are selected.

When considering a generalized ensemble model that can be applied to any PV station, the ensemble model with the minimum training error should be assigned to the corresponding PVs. Figure 5 depicts the generalized ensemble model.

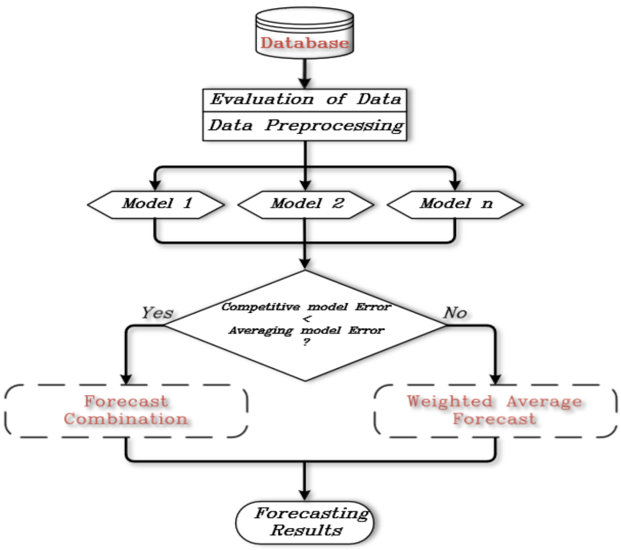

Fig. 5. Combined ensemble architecture with combined aggregation

The output power of a solar energy system primarily depends on direct and diffuse solar irradiation, i.e., the total solar irradiation received on the tilted PV panel. If the irradiation equals zero (e.g., at night), PV plant generation will be zero. Therefore, when the total irradiation equals zero, the generation is set to zero without using a forecasting model. This filter for nighttime can help reduce forecasting errors and computational time during testing. Thus, the accuracy and computational efficiency of the ensemble model can be improved.

Composite, cascade, and hybrid ensembles deserve special attention.

Composite Ensemble (Fig. 6): A composite ensemble is a type of stacking where base models are organized into several layers, each serving a specific purpose.

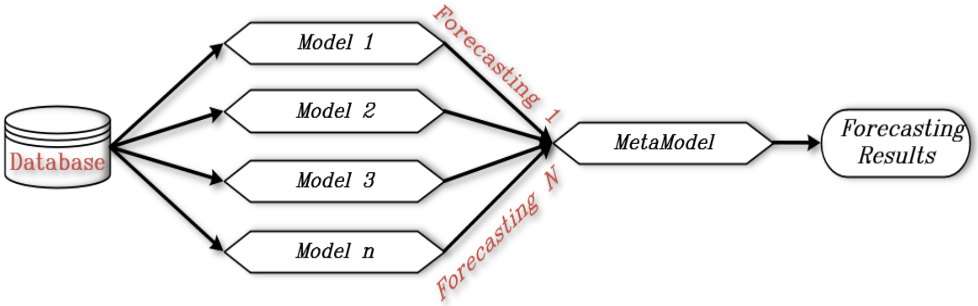

Fig. 6. Composite ensemble architecture

The first level includes base models that make individual forecasts. Subsequent levels may include models that combine the forecasts from the first level and make further predictions (MetaModel). Complex ensembles can be quite powerful but also more challenging to develop and train.

Cascade: Cascade ensembles are designed to filter cases that are easy to classify at the beginning of the forecasting process, so that subsequent models can focus on more challenging cases. Each model in the cascade is trained to be more selective than the previous one, aiming to improve overall efficiency.

Hybrid Ensembles: Hybrid ensembles combine various ensemble techniques or architectures to leverage their strengths. For example, a hybrid ensemble may use bagging to diversify base models and then use boosting to enhance prediction accuracy.

4. Conclusions

This study discusses various strategies for combining individual probabilistic forecasts of PV generation to create more accurate aggregated forecasts than individual predictions.

The article analyzes conceptual approaches to understanding the concepts of an “ensemble” and “ensemble forecasting”. It is noted that there is no consensus among researchers regarding a specific approach to forming an ensemble model. The choice of architecture depends on the specific task, data characteristics, and trade-offs between model complexity and effectiveness. Ensemble methods are a powerful tool in the field of machine learning and can significantly improve forecasting accuracy compared to individual models.

The synthesis of various approaches to ensemble models has led to the development of conceptual architectures that utilize well-known aggregation methods and their combinations, which can be complemented by a weather parameter classification block. The application of these architectures can contribute to solving current challenges in integrating PV energy into the energy system with high efficiency.

Author Contributions.

The author contributed to the conceptualization, methodology, formal analysis, writing, and final approval of the manuscript.

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МОДЕЛІ ПРОГНОЗУВАННЯ ФОТОЕЛЕКТРИЧНОЇ ГЕНЕРАЦІЇ: КОНЦЕПТУАЛЬНІ АНСАМБЛЕВІ АРХІТЕКТУРИ

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Анотація. *Рішення щодо регулювання потужності, планування енергетичних ресурсів та інтеграції «зеленої» енергії в електричну мережу залежать від точних імовірнісних прогнозів. Однією з потенційних стратегій підвищення точності прогнозів є використання методів ансамблевого прогнозування. Це підхід, при якому кілька моделей працюють спільно, досягаючи кращих результатів порівняно з тим, що може забезпечити окрема модель. Ці методи поділяються на дві основні категорії: конкурентні та співпрацюючі ансамблі. Конкурентні ансамблі використовують різноманітність параметрів і даних для створення багатої групи базових моделей. Такий підхід може включати статистичний аналіз, фільтрацію шумів та усунення аномалій. З іншого боку, співпрацюючі ансамблі базуються на взаємодії між моделями для досягнення кращих результатів. До цих методів належать стратегії, такі як зважені прогнози, голосування, агрегування та комбінування результатів моделей. Дослідження методів ансамблевого прогнозування у контексті фотоелектричної генерації є надзвичайно актуальним, оскільки сонячна енергія представляє важливе джерело відновлюваної енергії. Точні прогнози* *виробництва сонячної енергії вирішують проблеми, пов'язані з ефективним використанням фотоелектричних панелей та їх інтеграцією в загальну енергетичну систему. У даній статті досліджуються концептуальні архітектури ансамблів для прогнозування фотоелектричної енергії. Ці архітектури охоплюють різні методи агрегування базових моделей у межах ансамблю, що дозволяє враховувати різні аспекти та особливості сонячних даних, такі як інтенсивність сонячного випромінювання, метеорологічні умови, географічні фактори тощо. Ці концептуальні моделі розроблені на основі перевірених методів статистики, машинного навчання та штучного інтелекту. Таким чином, дана робота надає огляд методів ансамблевого прогнозування для відновлюваної енергії, охоплюючи конкурентні та співпрацюючі ансамблі, а також розробку концептуальних моделей для прогнозування сонячної енергії. Це дослідження має на меті підвищити точність і ефективність прогнозів у сфері відновлюваної енергетики, представляє важливий крок у розвитку стійкого та екологічно чистого виробництва енергії.*

Ключові слова: ймовірнісний сонячний прогноз, ансамблева модель, комбінація прогнозів, конкурентні ансамблі, співпрацюючі ансамблі, концептуальні моделі.

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