

Article

Virtual Energy Replication Framework for Predicting Residential PV Power, Heat Pump Load, and Thermal Comfort Using Weather Forecast Data

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Abstract

It is essential to balance energy supply and demand in residential buildings through accurate forecasting of energy use due to varying daily and seasonal residential building loads. This study demonstrates a data-driven Virtual Energy Replication Framework (VERF) to predict the behavior of residential buildings using weather forecast data. The framework integrates supervised machine learning models and time-ahead weather parameters to estimate photovoltaic (PV) power production, heat pump energy consumption, and indoor thermal comfort. The accuracy of prediction models is validated using TRNSYS simulations of a typical household in Saarbrücken, Germany, a temperate oceanic climate region. The XGBoost model exhibits the highest reliability, achieving a root mean square error (RMSE) of 0.003 kW for PV power generation and 0.025 kW for heat pump energy use, with R^2 scores of 0.94 and 0.87, respectively. XGBoost and random forest regression models perform well in predicting PV generation and HP electricity load, with mean prediction errors of 5.27–6% and 0–7.7%, respectively. In addition, the thermal comfort index (PPD) is predicted with an RMSE of 1.84 kW and an R^2 score of 0.80 using the XGBoost model. The mean prediction error remains between 2.4% (XGBoost regression) and −11.5% (lasso regression) throughout the forecasted data. Because the framework requires no real-time instrumentation or detailed energy modelling, it is scalable and adaptable for smart building energy systems, and has particular value for Building-Integrated Photovoltaics (BIPV) demonstration projects on account of its predictive load-matching capabilities. The research findings justify the applicability of VERF for efficient and sustainable energy management using weather-informed prediction models in residential buildings.

Keywords: time-ahead weather input; supervised learning; ensemble prediction models; energy behavior modeling



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1. Introduction

The increasing use of renewable energy systems (RESs) worldwide can be attributed both to technological advances and to supportive policy frameworks [1]. The large-scale production of solar- and wind-energy components has resulted in reduced unit costs, while

governmental initiatives continue to promote integration of renewables into national grids. Germany's "Energiewende 2030" strategy, for example, targets a renewable electricity capacity of 320 TWh by 2030 [2]. Among various RES technologies, solar power is particularly prominent due to its availability, affordability, ease of installation, low operational requirements, and accessibility.

As integration of photovoltaic (PV) systems has increased in residential energy systems, issues related to demand–supply imbalance have emerged, often resulting in financial or regulatory penalties. These mismatches are especially critical in grid-connected systems with intermittent sources like solar and wind energy [3]. In residential buildings, accurate prediction of electricity consumption, particularly by heat pumps (HPs), is essential to ensure grid stability and cost-effective operation. Accurate forecasting of PV generation and HP electricity use, therefore, can play a key role in scheduling, optimization, and energy management [4].

The transition towards energy-efficient, low-carbon homes has justified the need for reliable short-term energy forecasting under variable conditions. Residential demand is mainly influenced by external climatic factors. Detailed energy modelling tools provide extensive simulation results but often require system-level parameters that are difficult to obtain or to generalize across building types. In contrast, data-driven approaches that use historical data and/or weather forecasts offer greater scalability and flexibility [5,6].

To overcome the limitations of conventional methods, this study proposes a Virtual Energy Replication Framework (VERF): a flexible, modular, and data-driven approach for predicting energy system behavior of residential buildings. VERF integrates supervised machine learning (ML) algorithms with time-ahead weather forecast data to simultaneously estimate photovoltaic electricity generation, heat pump energy consumption, and indoor thermal comfort levels. This integration enables unified, short-term predictions without the need for detailed physical models or extensive instrumentation. Whereas traditional approaches depend on full-scale digital twins or sensor networks, VERF utilizes readily available weather forecast data as inputs, thereby simplifying implementation and reducing deployment costs [7–9]. This architecture makes the framework highly adaptable for a variety of residential scenarios.

To validate the framework's effectiveness, simulation data was generated using TRNSYS for a two-story reference building aligned with the specifications of IEA SHC Task 44/Annex 38 [10]. This enabled a standardized test case for evaluation of forecasting models under realistic boundary conditions. A diverse set of various machine learning algorithms, including ensemble models and neural networks, were trained and tested on this dataset [11,12]. The results demonstrated that short-term accurate predictions of energy use and thermal comfort can be achieved without detailed modelling of building energy systems.

2. Literature Review

Accurate forecasting of energy use and renewable energy supply is crucial for effective demand-side management and stable power-system operation due to continuous variability in both demand and supply. Recent developments in the application of machine learning to building energy systems have enhanced precision in predicting nonlinear relationships between environmental variables and building energy performance.

Different machine learning techniques like lasso regression, decision trees, random forest, XGBoost, and neural networks have been used to model these relationships without requiring detailed system-specific data [6,11,12]. Amasyali and El-Gohary [12] provided a comprehensive comparison of different data-driven building energy models and commonly used input features, including weather parameters, occupancy patterns, and operational

schedules. Sharma et al. [13] compared various regression methods for commercial-building energy forecasting and deduced that regularized regression models performed well, with low complexity. In a residential context, an XGBoost-based approach outperformed conventional regressions for HVAC energy prediction [14]. In addition, a study in *Scientific Reports* (2025) demonstrated the superior accuracy of ensemble models like XGBoost and gradient boosting in forecasting electric vehicle energy use [15]. Some studies have also explored the integration of ML techniques with optimization algorithms and retrofit strategies to enhance predictive accuracy and implementation potential [16,17]. These approaches are especially useful where detailed system specifications are not available, making them well suited for scalable applications.

Some studies have also explored hybrid frameworks, combining physical simulation data with ML models to improve applicability and reduce dependence on real-time instrumentation. For instance, Wei et al. [18] and Yan et al. [19] analyzed the effectiveness of simulation-based surrogate models for realizing dynamic energy behaviors in buildings with limited instrumentation. These hybrid frameworks bridge the gap between detailed physical modeling and scalable AI applications.

Weather forecast integration has been shown to further improve the performance of ML-based predictors. Zhang et al. [5] demonstrated that incorporating time-ahead weather inputs into artificial neural networks (ANNs) significantly enhanced prediction of district cooling energy. Similarly, Ahmad and Chen [20] found that long-term weather-informed forecasting improved prediction robustness under uncertain climate conditions.

Beyond energy consumption, recent studies have expanded predictive modeling to include indoor thermal comfort metrics, such as temperature and humidity profiles. Models predicting occupant satisfaction indicators like the Predicted Percentage of Dissatisfied (PPD) index have been developed to enable proactive control of HVAC systems [21,22]. Additionally, physics-informed neural networks (PINNs) have been employed for heat pump load prediction, effectively embedding thermodynamic constraints into the training process to enhance generalization [23]. Recent trends indicate a shift toward using ML-based surrogate models trained on simulation outputs for cost-effective and scalable forecasting. For example, Deb et al. [24] reviewed time-series forecasting techniques suitable for building energy modeling, advocating for hybrid models that blend simulation and data-driven learning for improved applicability in residential environments.

Despite significant advancements in machine learning applications for building energy forecasting, a notable research gap exists in the development of lightweight, scalable frameworks which are tailored specifically for residential settings and rely solely on time-ahead weather forecasts without requiring real-time instrumentation or detailed physical models. While studies such as Amasyali and El-Gohary [12] provide comprehensive comparisons of data-driven models and input features for energy prediction, and the work of Sharma et al. [13] demonstrates the efficacy of regularized regression methods for commercial buildings, these approaches predominantly focus on institutional or commercial structures equipped with dense sensor networks, limiting their applicability to cost-sensitive residential environments [6,12]. Hybrid frameworks combining simulation data with ML, as explored by Wei et al. [18] and Yan et al. [19], effectively bridge physical modeling and data-driven methods for dynamic behaviors in buildings with limited instrumentation, yet they often demand system-specific parameters or extensive real-time data, hindering scalability across diverse household types. Furthermore, weather-informed models like those reported by Zhang et al. [5] and Ahmad and Chen [20] enhance prediction robustness in district-level or long-term scenarios, but they overlook unified, short-term forecasting for residential PV power, heat pump loads, and thermal comfort metrics such as PPD [21,22]. Even physics-informed neural networks for heat pump loads [23] and time-

series techniques like those reviewed by Deb et al. [24] advocate for hybrid models, but the absence of standardized residential datasets and lightweight implementations leaves a void in accessible, simulation-validated solutions for sustainable energy management in homes.

In summary, the literature supports the growing utility of ML techniques combined with weather forecasts for predicting energy use and comfort in buildings. This study addresses the above gap by implementing a VERF that predicts PV generation, heat pump energy consumption, and indoor thermal comfort using only time-ahead weather forecast data, validated via TRNSYS simulations for a standardized IEA reference building.

3. Main Contributions

This study introduces VERF, a modular, simulation-informed forecasting approach for residential buildings that predicts key performance indicators using only weather forecast data. The framework reduces dependency on real-time measurements and detailed physical models, offering a scalable and accessible alternative to conventional digital twins.

The main contributions of this work are as follows:

- First, it introduces a novel integrated Prediction of Three Key Metrics approach. A unified machine learning framework is developed to forecast heat pump electricity consumption, PV power generation, and indoor thermal comfort, supporting comprehensive residential energy management. By enabling short-term forecasting of energy demand and thermal comfort, VERF supports intelligent HVAC scheduling and energy efficiency strategies under dynamic weather conditions.
- Second, VERF's Input-Efficient and Scalable Design relies solely on multi-step-ahead weather forecast data and ML trained on TRNSYS simulations, eliminating the need for detailed system-level information including real-time sensors. This enables application across a diversity of designs for residential energy planning and autonomous systems, for example, predictive load-matching.
- Third, its performance is rigorously evaluated through comparisons with multiple supervised learning models, including lasso regression, decision tree, random forest, XGBoost, and neural networks.
- Finally, it is validated against benchmarked TRNSYS-generated simulation data, demonstrating robustness. The framework is evaluated using the IEA SHC Task 44/Annex 38 reference building, providing a consistent and replicable basis for assessing performance in a typical residential setting.

4. Methods and System Architecture

The methodology is structured into three distinct phases (e.g., Phase 1, Phase 2 and Phase 3) comprising a five-module architecture. Each phase represents a key component of the proposed VERF, progressing from weather and energy simulation data generation to supervised machine learning model development, and, finally, to prediction execution and performance assessment. Phase 1 and 2 are illustrated in Figure 1.

4.1. Phase 1: Weather Forecast and Energy System Data Generation

This phase generates the input and output datasets for training and validating the machine learning models. Phase 1 is composed of two different data sets. One is for the time-ahead weather data forecasting, while the other one is for the combined prediction model of PV power, Hp energy consumption, and indoor thermal comfort.

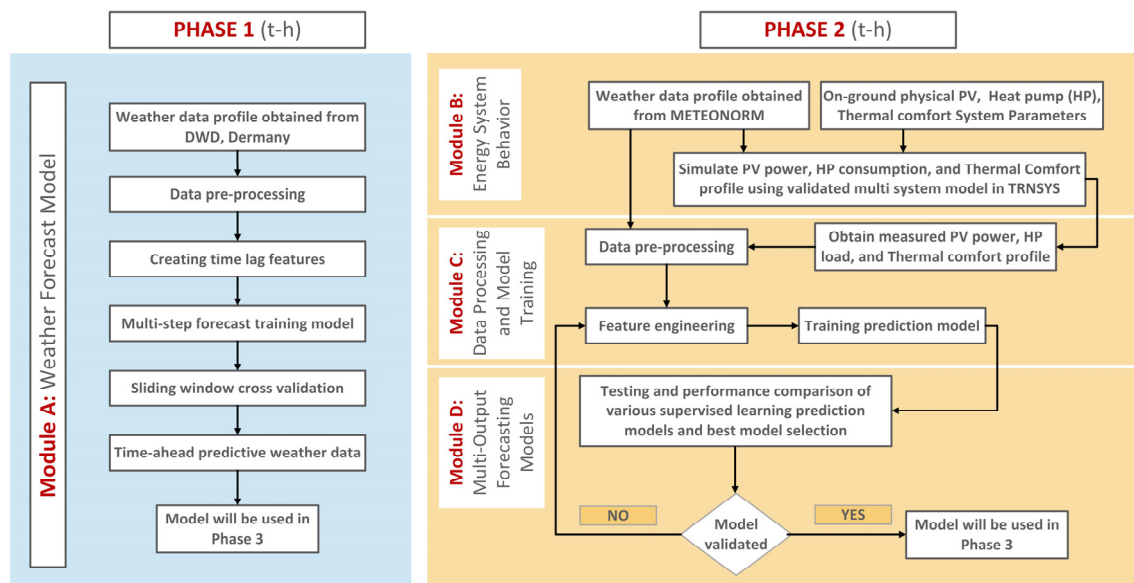


Figure 1. System architecture of the VERF, illustrating the modeling phases for weather forecasting and for energy system behavior.

4.1.1. Module A: Time-Ahead Weather Prediction Module

The weather forecasting model is implemented using a data-driven approach based on historical weather datasets. The module processes historical weather data obtained from the German Weather Service (DWD) [25] to generate multi-step-ahead forecasts for critical parameters including solar irradiance, wind speed, relative humidity, and ambient temperature. The forecasting process employs a multi-variate time-series approach that creates lag features to capture temporal dependencies in weather patterns. For a given time step t , the forecasting model generates predictions for future observations using the following relationship:

$$\hat{y}_{t+h} = \text{predict}(y_t, y_{t-1}, \dots, y_{t-\text{maxlag}}, X_t) \quad (1)$$

where $\hat{y}_{t+h}$ represents the predicted value at time step $t + h$, h denotes the forecast horizon, maxLag specifies the number of historical observations incorporated, and X_t encompasses additional explanatory variables at time t .

The model architecture implements a rolling window cross-validation approach to ensure temporal consistency and prevent data leakage. This predictive data is then used. A 5-fold rolling window cross-validation was employed, with each fold shifting by 1 month to preserve temporal order and handle dependencies, preventing data leakage. To address time-series autocorrelations, lag features (up to $\text{maxLag} = 24$ h) were included in Equation (1), capturing diurnal patterns in weather data. Train/test splits ensured chronological separation (e.g., training on 2013–2014 data, testing on 2014 data, and predicting 2015 values).

4.1.2. Module B: Energy System Behavior

This module utilizes TRNSYS 18 [26] to simulate the energy system behavior of a two-story residential building defined by the IEA SHC Task 44/Annex 38, representing a typical low-energy family home with space heating demand (U-values of $0.20 \text{ W/m}^2\text{K}$ and $0.15 \text{ W/m}^2\text{K}$ for walls and roof, respectively). Figure 2 illustrates the different component types used and the interconnections of those components. The building model incorporates thermal zones, a rooftop PV system, and a heat pump for space heating. The building architecture of a 140 m^2 household along with boundary conditions are modeled using

TRNSYS type 56. This module utilizes online available numerical weather data from METEONORM [27] as input features. Type 15 is used to input the weather data (e.g., solar irradiance, ambient temperature). Type 835 [28] simulates a rooftop PV system with battery, which converts irradiance to DC power. TRNSYS type 927 models the ground source HP (GHP) and separately requires the HP performance data in text files for both heating and cooling. Performance is characterized by the normalized capacity and power of the HP (with respect to the design capacities and power) at entering temperatures, along with the normalized flow rates of the liquids. GHP supplies hot water to the heat exchanger of a thermal storage tank (type 340). Emission heating is provided to the building by utilizing hot water from the storage tank using type 362, a radiator. Additionally, differential controllers (type 2b) were applied to modulate the flow of water streams. Annual TRNSYS simulations generate data sets of PV power generation, heat pump electricity consumption, and indoor air temperature. These outputs are the target variables for supervised learning in the subsequent phases.

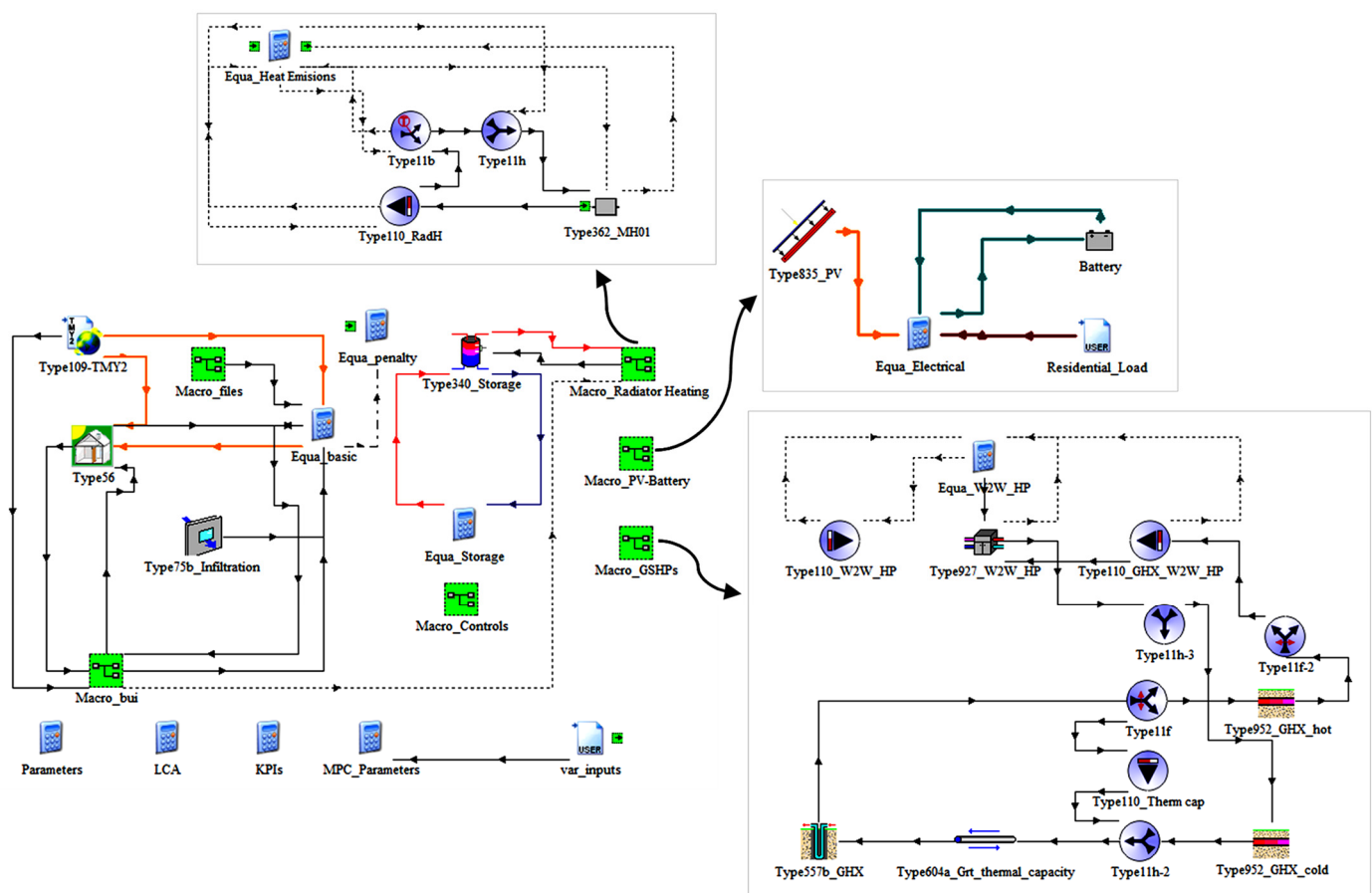


Figure 2. TRNSYS model components for building energy system.

4.2. Phase 2: Data Processing and Machine Learning Model Development

This phase transforms the raw simulation data into a suitable form for training machine learning models, and builds multiple models for three target variables.

4.2.1. Module C: Data Processing and Model Training

The simulation outputs are merged with their corresponding weather data inputs. Data cleaning and feature selection (via correlation analysis) are applied. The data is split into 80% training and 20% testing sets.

The photovoltaic power prediction model integrates solar irradiance, ambient temperature, and wind speed parameters to forecast electrical generation. ML models of PV generation are trained on validated PV system data from TRNSYS simulations. This ensures prediction accuracy under varying weather conditions.

Similarly, the data sets of heat pump consumption and thermal comfort models are TRNSYS-simulated profiles and outdoor climate conditions. Thus, these models capture the complex relationship between weather conditions and heat pump energy use, resulting in indoor thermal comfort under different operating conditions.

4.2.2. Module D: Multi-Output Forecasting Models

The energy system forecasting module develops distinct models for PV generation, heat pump energy consumption, and indoor thermal comfort. Multiple supervised learning algorithms are developed and compared to ensure optimal prediction performance across different system parameters for the city of Saarbrücken in Germany. The model selection process evaluates five primary algorithms: lasso regression, decision tree, random forest, boosting ensembles, and neural networks. These models can be used independently for buildings to establish the long or short-term futuristic power flow and thermal comfort profile. Each forecasting model was trained independently for each of the three outputs.

Lasso Regression: The lasso regression implementation applies regularization to prevent overfitting while maintaining model interpretability. The objective function incorporates both prediction accuracy and feature selection through the following formulation:

$$J(\beta) = \left(\frac{1}{m} \right) \sum_{i=1}^m (\hat{y}_i - y_i)^2 + \lambda \sum_{j=1}^p |\beta_j|, \quad (2)$$

where β_j represents the coefficient for the j -th feature, m denotes the number of training samples, λ controls the regularization strength, and p indicates the total number of features [29].

Decision Tree Implementation: The decision tree algorithm creates hierarchical splitting rules based on feature values to minimize prediction error. The splitting criteria utilize impurity measures such as mean squared error for regression tasks, with the recursive partitioning process continuing until predefined stopping criteria are satisfied [30].

Random Forest Ensemble: The random forest implementation combines multiple decision trees through bootstrap aggregating and random feature selection. Each tree trains on a bootstrap sample of the original dataset while considering only a random subset of features at each split [31]. The final prediction aggregates individual tree outputs through averaging, as follows:

$$\hat{y} = 1/B \sum_{b=1}^B T_b(x), \quad (3)$$

where B represents the number of trees and $T_b(x)$ denotes the prediction from the B -th tree.

Boosting Ensemble Models: The boosting ensemble approach sequentially trains weak learners while adaptively adjusting sample weights based on prediction errors. The final prediction combines all weak learners through weighted voting, as follows:

$$f(x) = \sum_{i=1}^N w_i h_i(x), \quad (4)$$

where N represents the number of weak learners, w_i denotes the weight assigned to the i -th learner, and $h_i(x)$ represents the prediction from the i -th weak learner [32].

Normalized Boosting Ensemble: The normalized boosting variant applies weight normalization to ensure balanced contributions from all weak learners, as follows:

$$f(x) = \sum_{i=1}^N (w_i / \sum_{j=1}^N w_j) h_i(x). \quad (5)$$

This normalization prevents individual learners from dominating the ensemble prediction while encouraging diversity in the learning process [32].

4.3. Phase 3: Forecasting and Model Validation

In the final module of the framework, the performance of the forecasting models is evaluated by comparing their predicted outputs with the corresponding reference values generated through TRNSYS simulation, as shown in Figure 3.

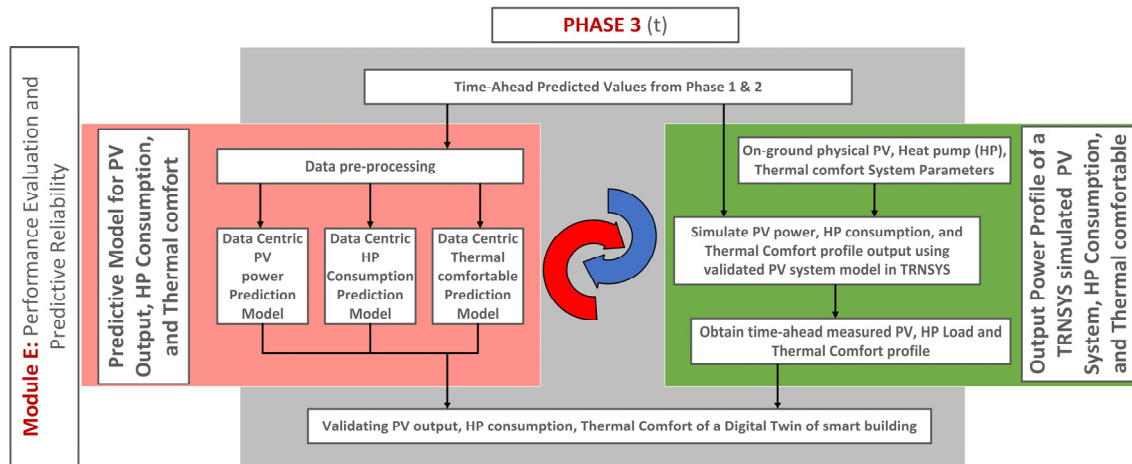


Figure 3. System architecture of the VEF, illustrating validation of the modeling phase 3 prediction using TRNSYS-generated data.

Module E: Performance Evaluation and Predictive Reliability

In this final phase, trained models from Phase 2 are deployed to generate time-ahead predictions of PV output, heat pump electricity use, and indoor thermal comfort based on the forecasted weather inputs from Phase 1. These predicted profiles simulate the behavior of the energy system of the residential building.

This validation step encompasses all three target variables: photovoltaic (PV) power generation, heat pump electricity consumption, and indoor air temperature. The framework employs comprehensive statistical metrics to assess prediction accuracy and model reliability.

The VEF uses root mean squared error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2) as accuracy indicators.

The RMSE quantifies the average prediction error value of a prediction model using the following relation:

$$\text{RMSE} = \sqrt{(1/N \sum_{i=1}^N (\hat{y}_i - y_i)^2)}, \quad (6)$$

where N is the number of predictions, $\hat{y}_i$ stands for the predicted value, and y_i represents the reference value.

The MAE is the average absolute difference between the predicted and actual values, calculated as follows:

$$\text{MAE} = 1/N \sum_{i=1}^N |\hat{y}_i - y_i|. \quad (7)$$

The coefficient of determination quantifies the proportion of variance and is calculated as follows:

$$R^2 = 1 - (\sum_{i=1}^N (\hat{y}_i - y_i)^2) / (\sum_{i=1}^N (\hat{y}_i - \bar{y})^2), \quad (8)$$

where $\bar{y}$ represents the average of measured values.

Overall, this module establishes the reliability of the proposed forecasting framework, confirming its suitability for deployment in residential energy systems.

5. VRF Evaluation and Validation

5.1. Phase 1: Look-Ahead Weather Prediction (Modules A and B)

Historical weather data sourced from DWD is used to develop look-ahead weather forecasting models, while simulation-driven datasets from METEONORM [32] are used directly within the TRNSYS environment for building energy simulations. The DWD dataset spans three years, has an hourly temporal resolution, and includes key meteorological parameters necessary for short-term predictions. Validation procedures prioritized temporal integrity. For the weather forecasting model, a rolling window cross-validation with five folds was implemented, each window advancing by 8760 h (1 year) to simulate real-time deployment and mitigate lookahead bias. This handled dependencies in time-series data, such as seasonal solar irradiance cycles.

Figure 4a–d presents time-series distributions of solar irradiance, wind speed, relative humidity, and ambient temperature. To identify the most relevant features for predictive modeling, correlation analysis is performed between weather parameters and the system's dependent variables. These variables are PV power output (PVelec_kW), heat pump electricity consumption (PelHP_kW), thermal comfort (PPDBui), and the heat pump binary control signal. The resulting correlation matrix is illustrated in Figure 5. Solar irradiance shows strong positive correlation with PV electricity generation, while ambient temperature and relative humidity exhibit significant relationships with both heat pump electricity consumption and thermal comfort (PPD).

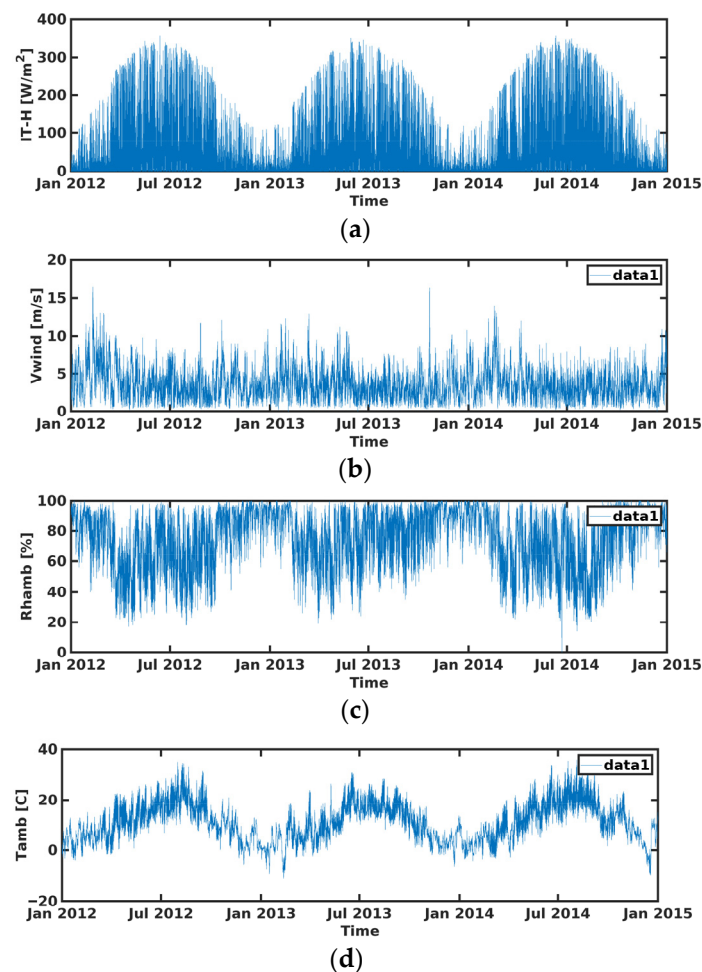


Figure 4. (a) Solar irradiance (IT_H (W/m²)), (b) wind speed (Vwind (m/s)), (c) relative humidity (Rhamb (%)), (d) ambient temperature (Tamb (C)).

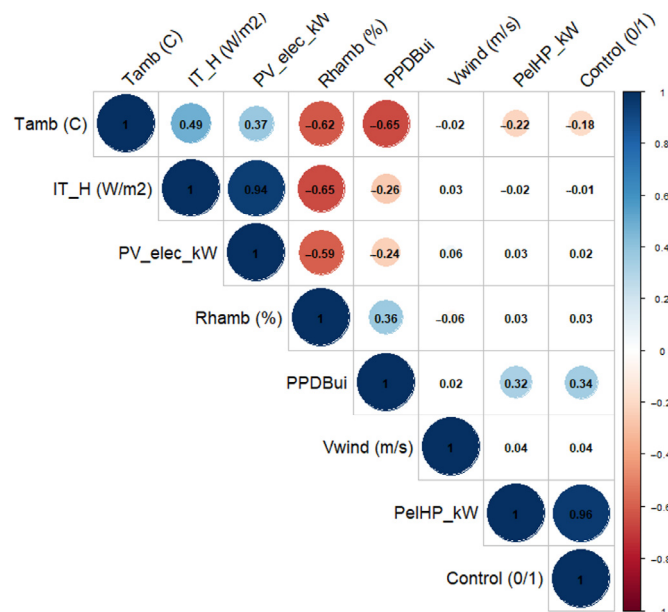


Figure 5. Correlation analysis of system's parameters.

Following the data collection, missing values and outliers are handled through preprocessing steps, and dimensionality reduction techniques are applied to retain only the most significant input features for model training. For each of the four key weather parameters (IT_H , $Vwind$, $Rhamb$, $Tamb$), look-ahead features and response variables for 24 future time steps are generated using lag features and normalized time-series data. For the next 24 h, 23 lag variables indicate how many steps the weather data is shifted backward in time, and 24 response variables correspond to the 24 look-ahead horizons, where each horizon step number represents the number of steps the weather data is shifted forward.

The model development process splits the dataset into an 80% training set and a 20% test set using a hold-out validation approach, with least-squares boosting employed for model training using 150 regression trees and a shrinkage rate of 0.2. The model performance is demonstrated in Figures 6–9, where the measured and predicted values for the first 200 observations in May are compared. These figures also visualize the model's ability to capture diurnal patterns in solar irradiance and temperature while reflecting more irregular behavior for wind speed and relative humidity.

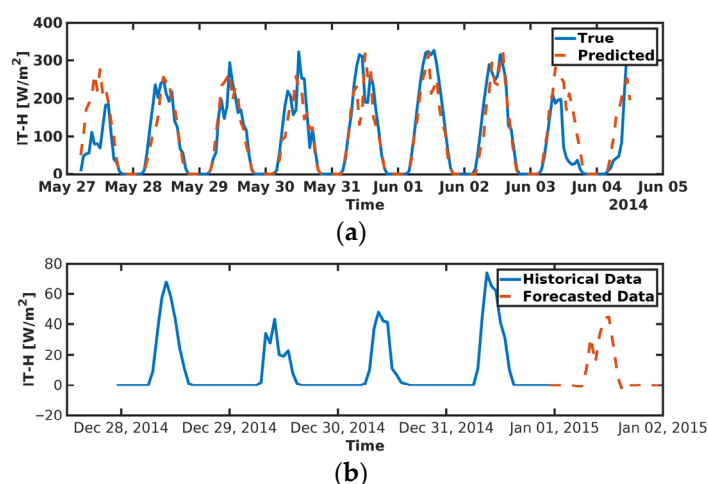


Figure 6. (a) Comparison of measured and predicted solar irradiance for test data with $RMSE = 39.22$ [W/m²], (b) Historical and look-ahead 24-h forecasted solar irradiance.

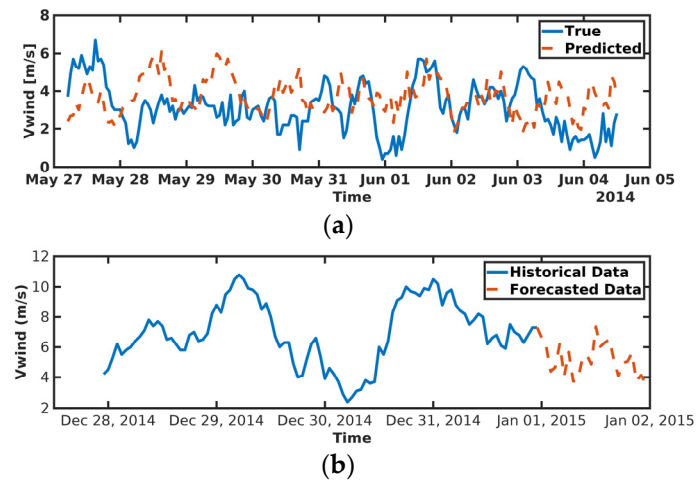


Figure 7. (a) Comparison of measured and predicted wind speed for test data with $RMSE = 1.82$ [m/s], (b) historical and look-ahead 24-h forecasted wind speed.

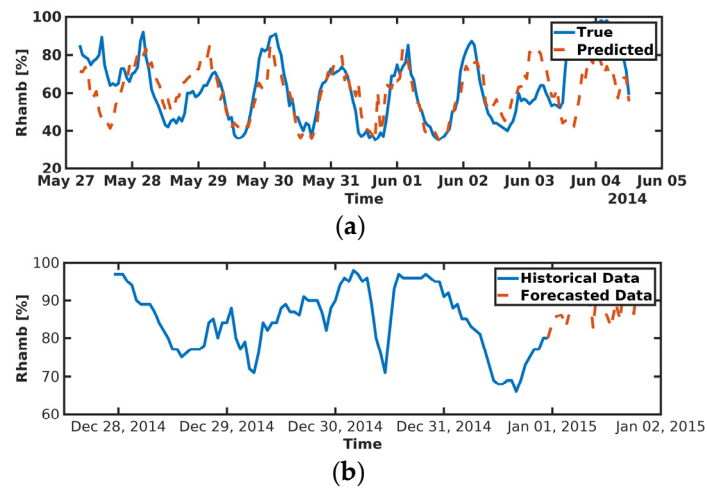


Figure 8. (a) Comparison of measured and predicted relative humidity for test data with $RMSE = 13.4$ [%], (b) historical and look-ahead 24-h forecasted relative humidity.

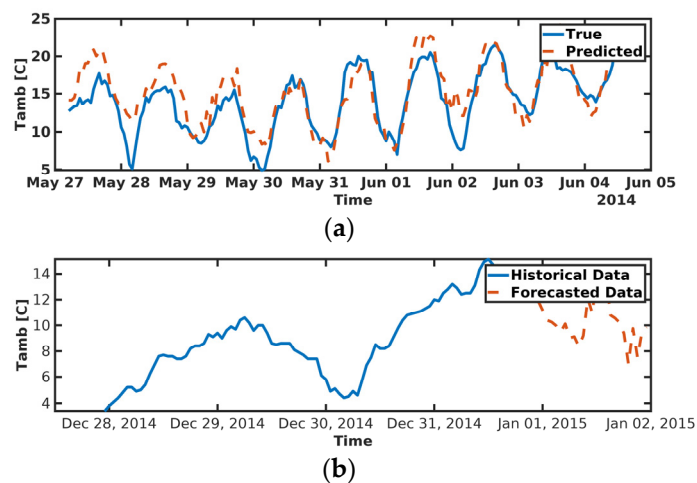


Figure 9. (a) Comparison of measured and predicted ambient temperature for test data with $RMSE = 3.5$ [C], (b) historical and look-ahead 24-h forecasted ambient temperature.

Figure 6a shows true measured global solar irradiance compared to predicted solar irradiance for the first 200 observations in the May test set. Figure 6b presents both the

historical data and look-ahead 24-h forecasted data, illustrating the periodic behavior of solar irradiance over winter days.

Similarly, Figure 7a shows true measured wind speeds compared to the predicted values for the test set, while Figure 7b presents both the historical wind speed data and the look-ahead 24-h forecasted data. Unlike solar irradiance, wind speed exhibits no clear periodic pattern, and appears nonuniform. It is the highly variable and uncertain nature of wind speed which makes it hard to predict, in comparison with other weather parameters.

Figures 8a and 9a depict true measured relative humidity and ambient temperature, respectively, alongside model predictions of these parameters for the test set. Corresponding look-ahead forecast curves in Figures 8b and 9b illustrate 24-h-ahead predictions compared to historical data, both of which display modest periodicity reflecting diurnal variations in humidity and temperature.

5.2. Phase 2: Prediction Models of Energy System Variables (Modules C and D)

This phase integrates weather data and simulation-generated system response variables to train supervised machine learning models for PV power output, heat pump electricity consumption, and thermal comfort. Performance metrics for each model are summarized below.

PV Power Prediction Performance: Table 1 illustrates model performance across five algorithms. XGBoost provides the highest prediction accuracy, achieving an R^2 value of 0.9392 and the lowest RMSE and MAE values.

Table 1. PV generation prediction models' statistics.

Prediction Model	RMSE	MAE	R^2
Lasso Regression	0.0075	0.0483	0.8638
Decision Tree	0.0050	0.0341	0.9087
Random Forest	0.0040	0.0314	0.9262
XGBoost	0.0033	0.0274	0.9392
Neural Network	0.0072	0.0599	0.8691
ARIMA (<i>Benchmark</i>)	0.0087	0.0536	0.8450

Heat Pump Energy Prediction Performance: Table 2 summarizes RMSE, MAE, and R^2 values for HP load forecasting. Both XGBoost and random forest exhibit the lowest RMSE and MAE values and the highest R^2 values, indicating superior predictive performance.

Table 2. HP electricity load prediction models' statistics.

Prediction Model	RMSE	MAE	R^2
Lasso Regression	0.0943	0.2347	0.5027
Decision Tree	0.0536	0.1134	0.7172
Random Forest	0.0286	0.0712	0.8489
XGBoost	0.0252	0.0699	0.8667
Neural Network	0.0469	0.1662	0.7526
ARIMA (<i>Benchmark</i>)	1.0625	0.4248	0.4103

Thermal Comfort Prediction Performance: Table 3 presents the same metrics for indoor thermal comfort using PPD predictions. XGBoost again performs better than other algorithms, achieving the lowest RMSE and MAE values alongside the highest R^2 value, indicating its robustness in modeling occupant comfort.

Table 3. Thermal comfort prediction models' statistics.

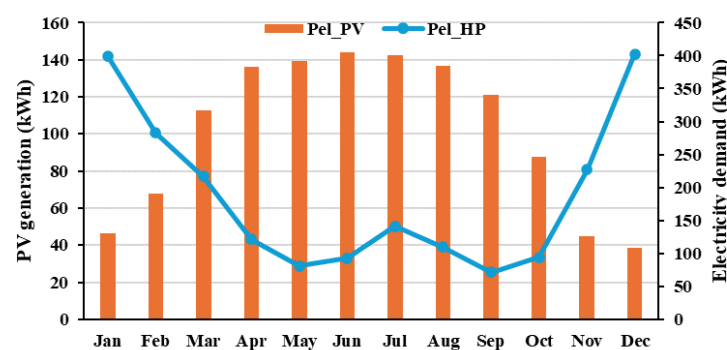
Prediction Model	RMSE	MAE	R ²
Lasso Regression	4.6002	1.7250	0.5042
Decision Tree	3.6804	1.5701	0.6033
Random Forest	2.1109	1.1984	0.7725
XGBoost	1.8431	1.0761	0.8013
Neural Network	2.3465	1.2317	0.7471
ARIMA (<i>Benchmark</i>)	6.7980	2.4302	0.4000

When comparing machine learning models with the benchmark linear statistical ARIMA model, all ML models performed well. This is primarily due to the nonlinear and highly variable nature of the data, which allows ML algorithms to capture complex patterns more effectively than ARIMA. In contrast, ARIMA is best suited for stationary, low-variability time-series data. This further reinforces ARIMA's role as a traditional baseline model which is once again outperformed by advanced machine learning methods in both accuracy and reliability for HP electricity load prediction tasks.

5.3. Phase 3: Prediction and Validation of Look-Ahead Energy System Variables (Module E)

In the final phase, the forecasting models trained on historical and simulation data are tested using look-ahead weather data. The results are compared against the TRNSYS simulation outputs to assess prediction accuracy under future weather conditions, thereby validating the proposed VERF framework.

TRNSYS 18 is used to simulate the IEA SHC Task 44/Annex 38 residential building. Performance data of YAWS series YORKR residential geothermal HPs is used to characterize HP of 4kW rated heating capacity. Electricity production from a 1kW PV array was modelled using Type 835 with performance parameters previously identified experimentally [28]. The annual simulation results for PV generation and HP energy use are shown in Figure 10.

**Figure 10.** Energy consumption vs. PV generation data.

5.3.1. Case Study 1: PV Generation Forecasting

Figure 11a–e compares daily PV predictions by different algorithms with the TRNSYS simulated profile for November, with % error plotted on a secondary axis. While XGBoost, decision tree, and random forest regressions closely match the simulated results, lasso and neural network yield significant deviations. The monthly predicted values range from 18.38 kWh (neural network) to 46.66 kWh (lasso), compared to the simulated 37.7 kWh. XGBoost shows the best match (39.17 kWh) and the lowest daily mean prediction error (5%). The % error in predicted PV generation per day reaches 64% in the case of the lasso prediction model, while a figure of −91% is reached in the case of neural network regression.

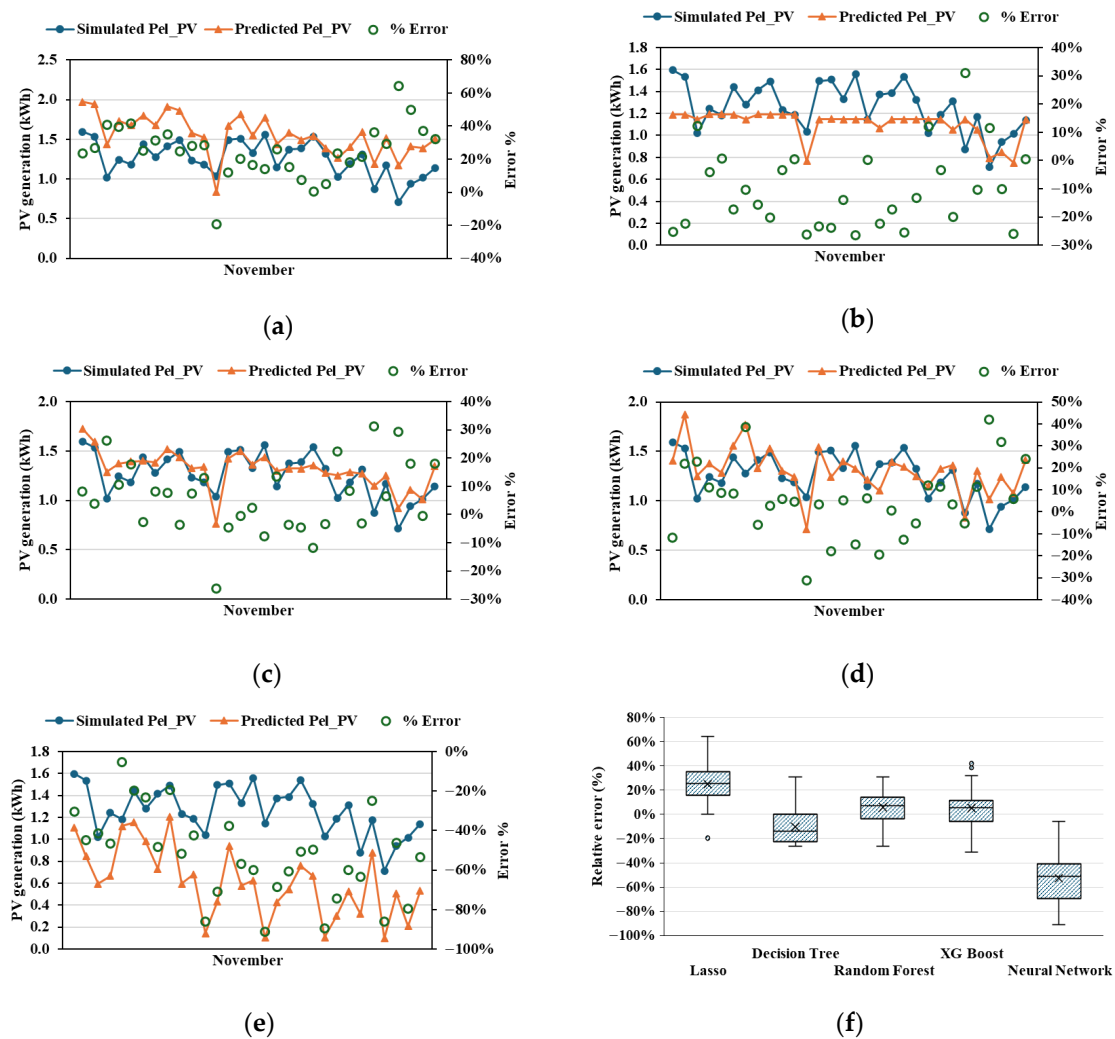


Figure 11. Comparison of monthly predicted PV electricity generation profile with simulated profile. (a) Lasso model vs. TRNSYS model; (b) decision tree model vs. TRNSYS model; (c) random forest model vs. TRNSYS model; (d) XGBoost model vs. TRNSYS model; (e) neural network model vs. TRNSYS model; (f) relative errors of forecasted models.

Relative errors of algorithms: In Figure 11f, the box plots describe the relative errors of the regression models employed in this work. It is evident that the XGBoost model has the minimum mean error (5.27%), while the maximum mean error (−52.77%) was produced by the neural network model. Overall, error rates vary between −31% and 42% for decision tree, random forest, and XGBoost regression, while neural network regression shows an error spread from −5% to −91%.

5.3.2. Case Study 2: Heat Pump Load Forecasting

Figure 12a–e shows November HP electricity consumption forecasts. In addition, error in predicted electricity demand is also shown as a dot plot on the secondary vertical axis. Lasso and neural network models underpredict consumption, while XGBoost, random forest, and decision tree models perform well. The TRNSYS model calculates the electricity demand of HP to be 285.4 kWh in November. Predictions vary from 192.3 kWh (lasso) to 309.5 kWh (random forest). The XGBoost model gives the most accurate prediction of 288.3 kWh PV generation in November. Decision tree regression also shows good alignment with simulated results, and predicts a 306.2 kWh electricity demand. Lasso regression

produces the maximum prediction error, with a rate of -42% being obtained, while error values do not exceed -28% in other prediction models.

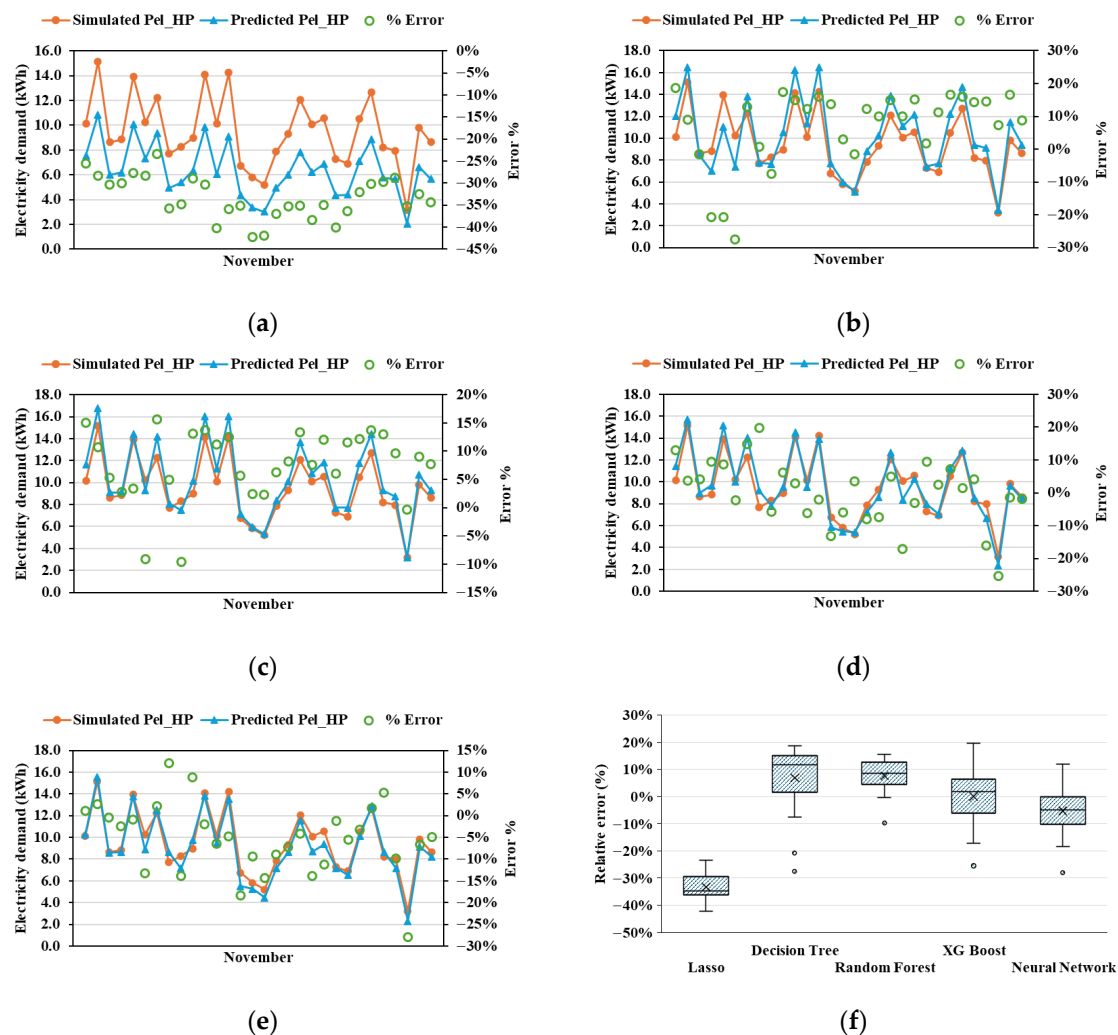


Figure 12. Comparison of monthly predicted HP electricity consumption profile with simulated profile. (a) Lasso model vs. TRNSYS model; (b) decision tree model vs. TRNSYS model; (c) random forest model vs. TRNSYS model; (d) XGBoost model vs. TRNSYS model; (e) neural network model vs. TRNSYS model; (f) relative errors of forecasted models.

Relative errors of algorithms: In Figure 12f, regarding errors in prediction, XGBoost, decision tree, random forest, and neural network demonstrate minimal error in HP electricity consumption prediction. Lasso regression has the highest mean error of -33.3% , followed by decision tree regression with a mean error of -7% . XGBoost has the lowest (approximately zero) mean error, with error in daily demand varying between -25% and 20% . Random forest has the minimum error spread of between -10% and 16% , with an average of 7.7% . Error values range from -27% to 17% in the case of decision tree and from -28% to 12% in the case of neural network.

5.3.3. Case Study 3: Thermal Comfort Forecasting

Table 4 presents the predicted monthly PPD values for each model. The TRNSYS reference PPD is 12.7. XGBoost again delivers the best accuracy, with a minimal average prediction error of -2.4% and a range of approximately $\pm 4\%$, while lasso performs worst, with an error of -11.5% .

Table 4. PPD predictions and errors of different regression models.

Prediction Model	PPD	Mean % Error
Lasso Regression	11.2	−11.5%
Decision Tree	13.1	3.7%
Random Forest	12.2	−3.9%
XGBoost	12.4	−2.4%
Neural Network	13.2	4.0%

5.4. VERF-Based Scalability and Load-Matching Potential

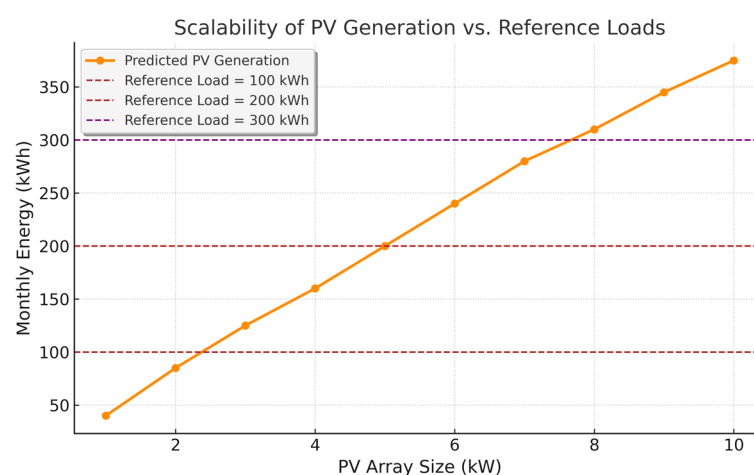
A key strength of the proposed VERF lies in its potential for scalability and application to residential energy planning and autonomous system design [33]. This capability is demonstrated through the integration of results from Case Study 1 (PV generation) and Case Study 2 (heat pump electricity consumption), thereby enabling predictive load-matching assessment under varying system capacities.

In Case Study 1, the monthly photovoltaic (PV) generation forecast for a 1 kW PV system, using the most accurate regression models (e.g., XGBoost and random forest), was observed to be in a range of 39.17–39.44 kWh for the month of November. In parallel, in Case Study 2, the November space heating electricity demand of the heat pump (HP) was predicted as 288.3 kWh using XGBoost regression, an accurate estimation of the TRNSYS simulation benchmark value of 285.4 kWh.

To evaluate the framework’s scalability, the PV system size required to fully offset the HP energy demand can be estimated as follows:

$$\text{Required PV Size} = (285.4 \text{ kWh}) / (37.7 \text{ kWh}) \approx 7.57 \text{ kW} \quad (9)$$

This calculation implies that a scaled-up PV system of approximately 7.57 kW would be sufficient to fulfill the entire monthly heating electricity requirement of the HP, under similar meteorological conditions. Figure 13 illustrates the predicted PV output for different array sizes (1–10 kW), overlaid with horizontal reference lines representing typical electricity demand levels (100 kWh, 200 kWh, and 300 kWh), thus highlighting the framework’s ability to support capacity matching for varying residential demand scenarios.

**Figure 13.** Scaled-up PV generation predictions versus monthly electricity demand thresholds.

Furthermore, the robustness of the predictive models under short-term temporal variability reinforces the practical applicability of the framework. As illustrated in Figure 12f, the XGBoost regression model for HP load prediction maintains a mean daily error of approximately zero, with an error distribution between −25% and +20%. In the case

of PV prediction, the XGBoost and decision tree regression demonstrate a wider error band (−31% to +42%) but maintain a relatively low mean error of 5.27%, as presented in Figure 11f.

These quantifiable accuracy margins validate the reliability of the VERN approach for informed decision-making in system sizing, energy autonomy planning, and performance evaluation without reliance on real-time sensor infrastructure.

Although the VERN framework is validated using simulation data for a representative building located in Saarbrücken, its modular design and input-efficient nature enhance its potential for broader applicability. Because the framework relies solely on weather forecast data and does not require detailed system-level or sensor-specific inputs, it can be easily adapted to other climates by retraining the machine learning models using simulation or historical data relevant to the new context. Additionally, because the IEA SHC Task 44/Annex 38 building is a widely used reference model, it provides a consistent baseline from which VERN can be scaled or refined for different building configurations.

6. Discussion

6.1. Applications in Control & Operation

VERN models offer significant potential in the control and operation phases of residential energy systems. By providing accurate short-term forecasts of PV generation, heat pump electricity consumption, and indoor thermal comfort, VERN enables model predictive control (MPC) strategies that optimize heat pump operation based on anticipated weather and loads, achieving 10–20% energy savings. For instance, during periods of high forecasted solar irradiance, the system can preemptively schedule heat pump heating to maximize PV self-consumption, reducing grid penalties and operational costs. This aligns with demonstrations of hybrid ML-MPC frameworks in experimental residential heat pump systems, where predictive models improved efficiency by up to 15%. In operation, VERN integrates with HEMS to achieve demand responses such as shifting loads to align with PV peaks or maintaining PPD below 10% through proactive ventilation adjustments. VERN supports grid stability by forecasting imbalances, enabling predictive curtailment or storage dispatch. Future implementations could extend to battery coordination or to EV charging, enhancing energy autonomy in temperate climates like Germany.

VERN's scalability and predictive load-matching capabilities hold particular promise for Building-Integrated Photovoltaics (BIPV) demonstration projects. By assessing PV generation and heat pump load compatibility under varying system capacities, validated with RMSE values below 0.05 kW, VERN enables precise energy planning for BIPV installations such as facade-integrated panels in residential buildings. This supports practical demonstrations by optimizing self-consumption and grid interaction, reducing installation risks in temperate climates like Germany. Future pilots could leverage VERN to simulate BIPV retrofits, enhancing energy autonomy and aligning with sustainable building standards.

6.2. Limitations and Challenges

Despite its contributions, this work has several limitations. Methodologically, the framework relies on simulation data from TRNSYS, which may not capture real-world variabilities such as equipment degradation or occupant interactions, potentially overestimating prediction accuracy (e.g., RMSE < 0.03 for PV). Data constraints limit validation to a temperate oceanic climate (Saarbrücken, Germany), restricting generalizability to diverse regions. Broader datasets are needed for comprehensive assessment. In terms of applicability, while VERN is input-efficient, its dependence on accurate weather forecasts could result in its faltering under uncertain conditions. In addition, the black-box nature of ensemble models like XGBoost hinders physical interpretability. Operationally, the framework has

not been tested in real-time control scenarios, where latency or integration challenges might arise. Addressing these through field trials and hybrid physics–ML approaches would enhance robustness.

6.3. Mitigation Approaches

To address identified limitations, targeted strategies can strengthen VERF's reliability. Sensitivity to weather forecast errors, as observed with DWD data, could be mitigated by integrating multiple forecast sources or employing Bayesian ML for uncertainty quantification, potentially reducing PV power RMSE inflation (10–20%) under variable conditions [34]. Generalizability beyond temperate climates (e.g., Saarbrücken) could be improved by validating against diverse METEONORM datasets, accounting for extreme environments like arid regions where dust affects PV performance [35]. The unexplored impact of extreme weather events (e.g., storms causing irradiance drops) warrants sensitivity analyses with perturbed inputs to assess error propagation. Lastly, TRNSYS biases from idealized assumptions (e.g., Type 56) neglecting occupant variability or degradation could be addressed through hybrid physics–ML refinements or incorporation of real-field data, enhancing predictive fidelity [36].

7. Conclusions

This study introduced and validated VERF, a modular, data-driven approach for forecasting energy generation, electricity consumption, and indoor thermal comfort in residential buildings. Unlike conventional sensor-based or physics-heavy approaches, VERF uses only time-ahead weather forecast data as input, offering a generalized and scalable methodology for energy prediction and planning. The framework was validated using simulation data from TRNSYS for a representative two-story residential building modeled according to IEA SHC Task 44/Annex 38.

The framework consisted of three integrated phases: (i) generation of TRNSYS-based simulation data and weather forecasts, (ii) machine learning model development using data-centric strategies, and (iii) predictive validation under forecasted conditions. Supervised learning algorithms including lasso regression, decision tree, random forest, XGBoost, and neural network were trained to predict three target variables: photovoltaic (PV) electricity generation, heat pump (HP) energy demand, and indoor thermal comfort (expressed as PPD).

Across all prediction tasks, ensemble models (XGBoost and random forest) consistently delivered superior accuracy, with RMSE values as low as 0.0033 kW for PV generation and 1.84 for thermal comfort index prediction. Furthermore, predictive reliability was confirmed by daily error spreads which showed stable performance across varying weather conditions, specifically when using XGBoost and random forest regression models.

The scalability of VERF was validated in a dedicated case study, where predictions for a 1 kW PV array were extrapolated to estimate the array size required to match a monthly heating load of 285.4 kWh. Results indicated that scaling to 7.57 kW would suffice to meet this demand entirely. Additional case studies highlighted the framework's ability to generalize across different energy targets without reconfiguring physical system models.

In summary, VERF's scalable framework and predictive load-matching offer a robust tool for residential energy planning, with significant potential for BIPV demonstration projects to advance sustainable building integration. The findings presented here demonstrate the feasibility of short-term energy and comfort forecasting without dependency on real-time sensor networks or detailed building configurations. This makes VERF a promising tool for microgrid design, autonomous building operation, and forecast-informed energy management systems, with high transferability to diverse residential contexts.

While VERF demonstrates high accuracy, its acknowledged limitations mean that its full potential in control phases must await future enhancements.

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