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Forecasting Hot Water Consumption Demand for Residential Dwellings Using Hybrid Regression Technique

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Abstract—Residential buildings contribute approximately 30% of global greenhouse gas emissions, with electric water boilers accounting for around 20% of total energy consumption. The development of a smart renewable energy system and control requires adequate and accurate forecasting models to mitigate both short-term and long-term energy demand. Accurate forecasting of hot water consumption is crucial for optimizing load demand scheduling and grid energy management in residential dwellings. This study develops hybrid forecasting models by combining a seasonal auto-regressive model (SARIMA) with machine learning models, specifically Support Vector Regression (SVR) and Artificial Neural Network (ANN). The study uses six months of hot water consumption data from residential electric boilers, categorized into hourly and daily scenarios. The models are evaluated based on performance metrics, including Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). Results obtain, indicate that the SARIMA-ANN model outperforms the SARIMA-SVR model in terms of both predictive accuracy and computational efficiency. The SARIMA-ANN model’s superior feature mapping, in both long- and short-time frames, makes it optimal and robust for Model Predictive Control (MPC) applications and real-time use, especially in renewable energy grid integration. It offers a more scalable solution compared to the hyperplane-dependent SARIMA-SVR model.

Index Terms—Energy consumption, Electric water boilers, Hybrid machine learning model, Hot water consumption, Residential buildings.

I. INTRODUCTION

With the rise in global warming, transitioning to green energy sources like PV systems has become essential. This shift is crucial, especially given the projected 50% increase in energy demand due to industrial and residential activities, with the residential sector accounting for 20% of this increase. A significant portion of residential energy consumption comes from hot water use, including showering, kitchen activities, and bathing, which contributes to energy demand fluctuations. Electric water boilers alone account for 45.8% of home energy consumption [1]. Implementing energy-saving measures in this sector can significantly reduce overall energy usage, lower greenhouse gas emissions, and

support a more sustainable energy system. The development of robust forecasting models that can accurately predict hot water usage based on hourly and daily consumption can help mitigate this challenge [2], [3]. These hot water consumption patterns span across the year and include various end-use activities such as showering, kitchen use, bathtub reheating, and bathtub filling.

Accurate models are crucial for enhancing Model Predictive Control (MPC) strategies for demand side response management. However, developing these models presents challenges, particularly in handling the complexities of time series data, regression analysis, and the non-linearity of user pattern and behavior. This non-linearity is especially evident in the hourly, daily, and seasonal variations in hot water usage. Load demand models have evolved from traditional statistical methods to advanced machine learning and hybrid techniques [4]–[7]. Time series models like ARIMA are widely used for capturing seasonal trends, stochastic behaviours, and temporal dynamics in hot water consumption data [6], [8]–[12].

Aurore Lomet et al. [13] developed an ARIMA model to forecast daily domestic hot water (DHW) consumption, accounting for weekly periodicity, prior-day consumption, and random fluctuations, demonstrating its potential. Traditional regression analysis, such as linear regression, remains important for modeling the relationship between hot water and energy consumption, considering factors like ambient temperature and usage behaviour over time [14], [15]. Techniques like Support Vector Regression (SVR) are also effective for handling non-linearity and are recognized as powerful tools in machine learning, complementing classical methods like ARIMA, exponential smoothing, and ARMAX [16]–[18].

In recent years, machine learning technologies such as Artificial Neural Networks (ANNs) have become popular for modeling hot water consumption due to their ability to manage the complexities of non-linear end-user consumption [19]–[21]. Sheng Cao et al., [22] proposed using a

support vector machine (SVM) to predict occupants' showering behaviors, achieving a 33% reduction in hot water demand compared to traditional control methods. Similarly, techniques like SVR and ensemble methods have shown exceptional performance in managing high-dimensional and non-linear data [4], [6], [23]. Christopher Bennett et al., [19], developed an ANN-based model for residential water end-use demand forecasting. Combining classical regression methods with machine learning has paved the way for more accurate and hybrid load demand models, particularly in scenarios involving complex stochastic user behaviour in residential building applications for grid demand response management [24]. These hybrid models leverage the strengths and compensate for the weaknesses of each approach to obtain a more accurate hot water consumption profile [25].

Our study highlights the need for a comparative analysis of hybrid models (SARIMA-ANN and SARIMA-SVR) specifically for hot water consumption in residential building applications, an area that has received limited attention. Such a study could help identify the most suitable modeling technique based on forecasting accuracy and computational efficiency. Table I summarizes related literature on hot water consumption in residential dwellings, focusing on research methods, forecast horizons, data scenarios, and gaps in hybrid model comparisons. This study combines classical regression (SARIMA) with two machine learning techniques (SVR and ANN) to develop SARIMA-ANN and SARIMA-SVR models. The focus is on forecasting hot water consumption in residential buildings and comparing the accuracy of these models in both short-term and long-term forecasting horizons using various performance metrics. The article is structured as follows: first, the methodology for developing the forecasting models; followed by results and discussion; a comparative analysis of the models; and concluding with recommendations for future research.

II. METHODOLOGY

The research methodology employed in this study aims to compare two hybrid forecasting models that integrate time series and regression techniques (SARIMA) with machine learning methods (SVR and ANN). These integrations yield two hybrid models: SARIMA-SVR and SARIMA-ANN, which are developed through empirical evaluation and a structured methodology. The primary objectives are to compare the prediction and forecast accuracy of these models across two different scenarios for domestic hot water boiler consumption, as detailed in Table II. The models' performance is evaluated using RMSE and MAE performance metrics. This section outlines the detailed model development and research methodology framework, as illustrated in Figure 1.

A. Data description and processing

The hot water consumption data for this case study was obtained from 67 apartments. Data were collected from

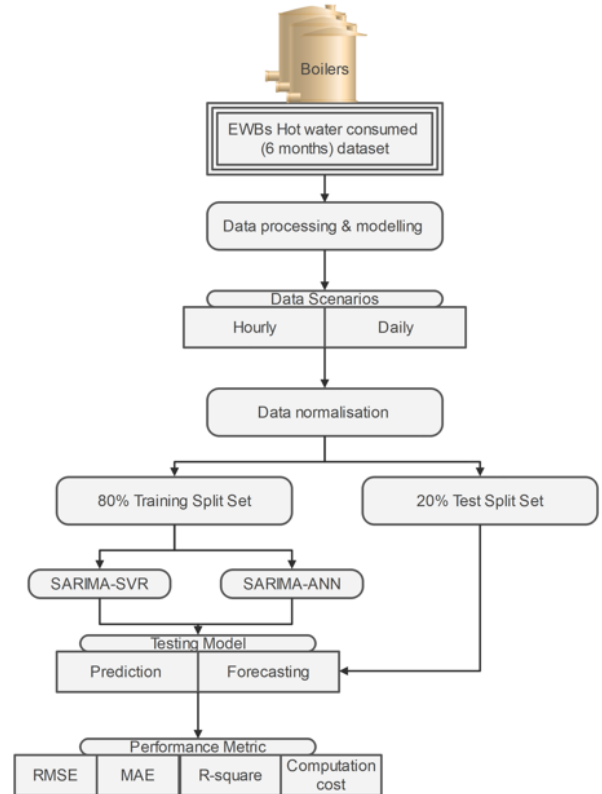


Fig. 1. Research methodology framework

December 1, 2020, to June 11, 2021. The data were used to evaluate forecasts, categorizing the consumption into two distinct scenarios, as detailed in Table II. The statistical description of the training period data-set is presented in Figure 2 and Figure 3.

The daily consumption scenario (Fig. 3) shows more significant variability and higher average usage compared to the hourly scenario (Fig. 2), indicating more consistent daily consumption patterns with distinct peaks, especially in apartments 4, 5, and 10. Furthermore, the models were trained using 80% of the data, with the remaining 20% serving as the test set. Furthermore, Table II, outlines the different scenarios used for evaluating the forecasting models, detailing the time-step, training period, and forecast length for each scenario.

B. Hybrid model development

In this study, the hybridization of seasonal learning regression (SARIMA) with machine learning techniques (ANN and SVR) is modeled using a two-stage prediction and forecasting approach. In the first stage, the SARIMA model is employed to capture the seasonal linear components within a 24hour seasonality. The residuals obtained from the SARIMA model, along with the hourly and daily data, are then used as features in the second stage prediction using the machine learning models.

TABLE I
COMPARISON OF VARIOUS RESEARCH METHODS AND DATA SCENARIOS

Authors	Research Methods			Forecast horizon	Data Scenarios	Research disparity
	Regression	Machine Learning	Hybrid			
Fargallo et al. [26]	✓ ^a			– ^b	98 apartments, 2015 to 2021	failed to compare hybrid techniques
Louis-Gabriel et al. [27]		✓		–	40-unit residential building located in Quebec City (Canada)	failed to compare Hybrid techniques
Ferrantelli et al. [28]	✓			–	Finland dwellings, November & August	failed to compare Hybrid techniques
Juan de Santiago et al. [29]	✓			–	401 per person in swiss dwelling	failed to compare Hybrid techniques
Azar Nilsson et al. [20]		✓		monthly	Yazd, Iran, from 2011 to 2020	Did not consider Hybrid techniques
Xin Zhou et al. [25]		✓	✓	–	Female hostel university in Xi'an, China, 1 March to 30 Nov. 2022	Did not consider various periods or scenarios
Gelazan et al. [30]	✓			hourly	1hour, 2hours, 3hours for 2006 EWB	failed to compare hybrid models
Lomet et al. [31]	✓			daily	8 residents EWBs in France, 2009 to 2011, 10 Liters timesteps	failed to compare hybrid models
Barteczko et al. [32]	✓			–	130L EWB 47 data	failed to compare hybrid models
Denis et al. [14]	✓			yearly	USA dwelling hot water consumption	failed to compare hybrid models
Xu et al. [7]		✓		daily	150 EWB hot water consumption	failed to compare hybrid models
Bennett et al. [19]	✓			liter/person	Southeast queen land residential end-user study (SEWREUS)	failed to compare hybrid models
S. Cao et al. [22]	✓			–	7 occupants, 8.33L/min daily and hour consumption	failed to compare hybrid models
Aki et al. [4]	✓			–	Osaka Japan, April 2007 to March 2010	failed to compare hybrid models
D. Kim et al. [33]	✓			–	2017 to 2022, data of apartment complex in Seongnam-si, Korea	failed to compare hybrid models
Rzeknik et al. [34]	✓			daily	2021 Grudziadz, in Central Poland	Neglected to consider hybrid models

^a Method considered by author

^b Demand not considered by author

TABLE II
SCENARIOS (TIME-STEP) DATA FOR FORECASTING MODEL EVALUATION

Scenarios	Time-step	Training period	Forecast length
Hourly	hourly	7 days	24 hours
Daily	24 hours	6 months	30 days

The SARIMA residuals, representing the significant non-linear relationships between the actual time series data and the SARIMA-predicted values, are input into the machine learning models (ANN and SVR) to address the non-linear complexities that the SARIMA model could not capture. The final prediction is obtained by combining the weighted outputs from both the SARIMA model and the machine learning models. The novel hybrid models developed in

this research, SARIMA-ANN and SARIMA-SVR, aim to enhance prediction accuracy by leveraging the strengths of both regression and machine learning techniques.

C. SARIMA-ANN Model Development

The Auto ARIMA algorithm searches for the optimal combination of p , d , q , P , D , Q , and s parameters to find the best-fitting SARIMA model based on the Akaike Information Criterion (AIC). The best-fit SARIMA configuration, $((1, 0, 1), (1, 0, 1, 24))$, was selected for hybridization with machine learning models (ANN and SVR) from empirical analysis. By analyzing 24-hourly hot water consumption data with $s = 24$ representing the daily cycle, the model captures both regular daily consumption patterns and non-linear variations. This configuration enables accurate predictions for both short-term (hourly) and long-term (daily) forecasts. The

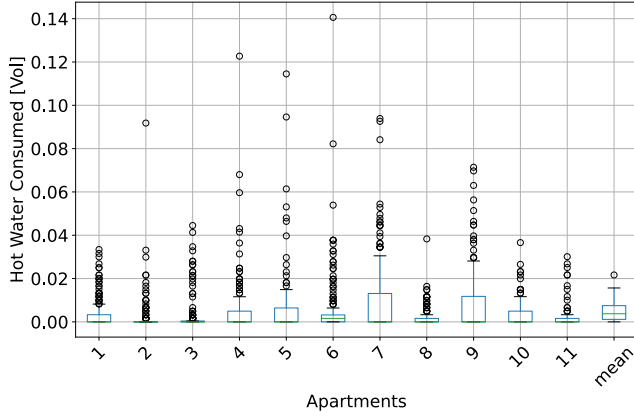


Fig. 2. Hot water hourly consumption scenario

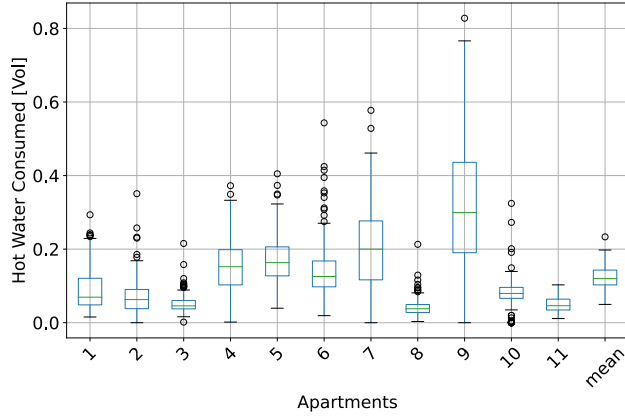


Fig. 3. Hot water daily consumption scenario

hot water forecasting model uses the entire dataset to predict future consumption levels:

$$\hat{x}_{t+1} = \zeta + \phi_1 \Delta x_t + \phi_2 \Delta x_{t-1} + \phi_3 \Delta x_{t-2} + \theta_1 \epsilon_t \quad (1)$$

where \hat{x}_{t+1} is the forecast at time $t + 1$, ζ is a constant, and θ_1 models the error as a linear combination of past errors up to the q -th lag. The residual error of the SARIMA forecast is used as input to the machine learning models to capture the non-linear components that the SARIMA model cannot address. Forecast errors are computed as the difference between the actual observed values in the test set and the forecasted values produced by the SARIMA model:

$$f_t = y_t - \hat{y}_t \quad (2)$$

where y_t is the actual observed value at time t and \hat{y}_t is the forecasted value at time t . The forecast error f_t reflects the discrepancies between the actual outcomes and the model's

forecasts. Both e_t (residuals) and f_t (forecast errors) are used as inputs to the ANN, which aims to learn from these errors to correct similar mistakes in future predictions and capture the non-linear patterns that the linear model (SARIMA) might miss. The hybrid forecasts subsequently combine the SARIMA forecasts $\hat{y}_{f,t}$ with the ANN-forecasted $\hat{z}_{fore,t}$ using a weighted sum, yielding the final forecasts of the hybridized model:

$$\hat{y}_{f,adj,t} = w_1 \cdot \hat{y}_{f,t} + w_2 \cdot \hat{z}_{fore,t} \quad (3)$$

where $\hat{y}_{f,adj,t}$ is the final hybrid forecast at time t , and w_1 and w_2 are the respective weights for the SARIMA and ANN forecast contributions.

D. SARIMA-SVR Model Development

Similar to the SARIMA-ANN implementation, the SARIMA model in the SARIMA-SVR design calculates residuals e_t as follows:

$$e_t = X_t - \hat{y}_t \quad (4)$$

where e_t represents the residual at time t , X_t is the actual observed value at time t , and \hat{y}_t is the value predicted by the SARIMA model at time t .

The forecast \hat{y}_{t+k} for a future time $t + k$ is given as:

$$\hat{y}_{t+k} = \text{SAR}(X_t) \quad (5)$$

where \hat{y}_{t+k} is the forecasted value k periods ahead of the last observed time t . The forecast from the SARIMA model for future time $t + k$ is denoted as $\hat{f}_{t+k}^{\text{SAR}}$, while $\hat{f}_{t+k}^{\text{SVR}}$ is the corresponding forecast from the SVR model for the same future time $t + k$.

The hybrid forecasts $\hat{f}_{t+k}^{\text{hyb}}$ for future time $t + k$ are computed as:

$$\hat{f}_{t+k}^{\text{hyb}} = w_1 \cdot \hat{f}_{t+k}^{\text{SAR}} + w_2 \cdot \hat{f}_{t+k}^{\text{SVR}} \quad (6)$$

where w_1 and w_2 are the weights assigned to the SARIMA and SVR predictions, respectively, and $\hat{f}_{t+k}^{\text{SAR}}$ and $\hat{f}_{t+k}^{\text{SVR}}$ represent the individual model forecasts at time $t + k$.

III. RESULTS AND DISCUSSION

The SARIMA-ANN shows superior accuracy, particularly in short-term forecasting (1-hour), where it achieves an R^2 of 0.9766 and an RMSE of 0.0223. However, SARIMA-SVR is significantly computationally expensive, making SARIMA-ANN a more efficient model for real-time forecasting in both short and long-term scenarios.

The computational efficiency was evaluated by comparing computation times under identical simulation parameters across different scenarios. The models were developed using the Python programming language and tested on a system equipped with an 8th Gen Intel Core i5-8265U CPU @ 1.60GHz, 1.80GHz, and 16.0 GB RAM. Comparative results

TABLE III
SUMMARY OF FORECAST PERFORMANCE METRICS FOR SARIMA-SVR AND SARIMA-ANN MODELS

Scenario (Timestep)	Algorithms Model	Computation Time	R^2	RMSE	MAE	MSE
1 hour	SARIMA-SVR	3 mins 44.2 s	0.5080	0.0862	0.0692	0.0074
	SARIMA-ANN	0.7802 s	0.9766	0.0223	0.0074	0.0005
24 hours	SARIMA-SVR	3 mins 13.0 s	0.2678	0.0616	0.0466	0.0038
	SARIMA-ANN	0.6949 s	0.4051	0.1229	0.1032	0.0152

for the prediction and forecasting capabilities are presented in Table III. The SARIMA-ANN model demonstrated low computation times in both scenarios, while the SARIMA-SVR model was the most computationally expensive, taking 3 minutes and 44 seconds in scenario one (hourly).

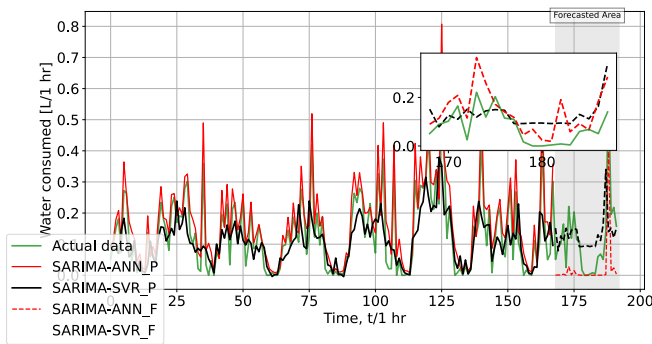


Fig. 4. Prediction & forecasting for hourly Scenario

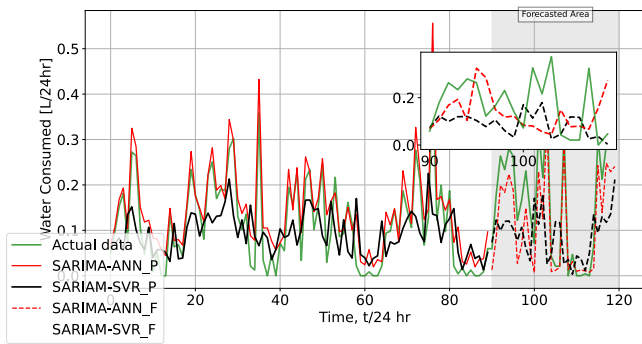


Fig. 5. Prediction & forecasting daily Scenario

The results in these figures 4 and 5, show a clear pattern in how the SARIMA-ANN and SARIMA-SVR models fit to time series hot water boiler consumption data. In both hourly and daily scenarios, the SARIMA-ANN model (black line) aligns more closely with the actual data (green line), capturing both short-term fluctuations and long-term trends more accurately than the SARIMA-SVR model (red line), which exhibits greater deviations. The forecasted areas further emphasize SARIMA-ANN’s superior ability to model hot water boiler consumption patterns, maintaining better consistency in both trends and forecasted values, whereas

SARIMA-SVR struggles, especially during peak consumption periods, making SARIMA-ANN a better choice for hot water boiler consumption forecasting.

IV. CONCLUSION

To accurately address demand response with the integration of green energy systems in residential dwellings, it is crucial to develop accurate and robust models for hot water consumption, which this research aims to achieve. The novelty lies in incorporating daily and time-of-day features into the ANN model, along with the non-linear residuals that SARIMA could not capture in the second-stage prediction. These feature inputs enhance the hybrid model’s accuracy and robustness in capturing stochastic user behavior. SARIMA-ANN has demonstrated optimal performance in both short-term and long-term predictions, which is significant for real-time kWh deployment, smart meter management, and mini-grid integration for demand response applications.

The SARIMA-ANN model proved more effective in mapping features than the SARIMA-SVR model, which relies on hyperplanes and incurs higher computational costs as the feature space and scalability increase. The hidden layers of the ANN effectively learned and captured the high dimensional feature space. Future work should explore the use of 1D Convolutional Neural Networks (CNN) or transformer models to better forecast intrinsic variations, further improving forecasting accuracy and computational efficiency.

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