COMPARING LOAD-FORECASTS OF RESIDENTIAL HEATPUMPS WITH TRANSFORMER AND XGBOOST ON FIELD DATA

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Introduction

To meet the targets set by the German federal government, greenhouse gas emissions in the building sector must be drastically reduced in the coming years [1]. One way to achieve this goal is the widespread installation of heat pumps (HP) for space heating and domestic hot water supply. During periods of high heat demand, photovoltaic (PV) generation in our geographic latitudes is generally relatively low [2]. Nevertheless, accurate HP load forecasting supports the efficient utilization of PV energy and, importantly, helps to avoid overloading the grid connection point [3]. Effective coordination based on forecasts enables optimized energy management, ensuring both increased self-consumption of PV energy and grid reliability [3, 4].

Methodology

Related Work and Selection of the Forecasting Methods

Demands vary greatly from building to building, which is why not every load forecasting model is suitable for every application [5]. Related work often focuses on forecasting aggregated HP loads [6], e.g. in energy communities [7], in commercial buildings [8–10] or with a detailed measurement concept which is not universally scalable [4]. One reason is the high level of uncertainty, in particular due to the highly individual nature of consumption patterns [5, 11]. Although no direct comparison is possible, Semmelmann [7] shows that the Transformer model outperforms Random-Forecast, Long Short-Term Memory (LSTM) and Extreme Gradient Boosting (XGBoost) forecasting the HP load. In Addition, Wang [12] recommends XGBoost for a day-ahead forecast, comparing LSTM und XGBoost. Consequently, this study comparatively evaluates two state-of-the-art forecasting methodologies: The Transformer, a deep learning model designed to capture long-range temporal dependencies, and XGBoost, a gradient-boosted decision tree algorithm with strong performance on tabular data.

Data Preprocessing, Analysis and Feature Selection

For this work, real-world load data from residential air source heat pumps was used: A dataset from the United Kingdom [13] (306 HP systems) and a dataset from Germany [14] (two HP systems).The data preprocessing involves outlier detection, interpolation, dropping sequences with larger gaps and resampling to a consistent time resolution of 15 minutes. The datasets were thoroughly analysed to gain a better understanding of consumption patterns and, consequently, their influence on feature selection. From this analysis, it can be inferred that the highly individual load patterns can be classified into categories, which is also evident from examining the autocorrelation function: strongly recurring and weakly recurring patterns.

The feature selection is performed using correlation analysis and Random Forest analysis [7]. The result corresponds to comparable literature [7]. Various features are selected, including the outside temperature, past load and temperature values, and cyclical variables. Additionally, models are trained with specific features omitted to investigate their individual impact on forecast accuracy. This approach allows for a systematic evaluation of feature relevance and the identification of the most influential predictors for the forecasting task.

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Model Training and Forecast Assessment

A linear regression model and a daily persistence model serve as benchmarks due to their ease of implementation. To increase the accuracy of the forecasts, the hyperparameters of the Transformer and XGBoost models were optimised, with early stopping also being applied.

Table 1 shows a comparison including benchmark models for different metrics. The coefficient of determination (R^2), the nRMSE normalised to the value range, and a peak error are shown. The peak error is defined as the difference between the actual value and the forecast value for all points in time where the forecast is smaller than the actual value. Since the quality of the forecast depends on the extent to which the pattern is recurrent, the evaluation is based on a time series with a strong pattern (EOH2504) and one with a less strong pattern (EOH1700) from the UK data set.

Further analysis includes applying the models to unknown data, examining models with different features, and further comparisons of the models based on the test data.

Table 1: Comparison of Forecasting Methods via different error metrics

	EOH1700			**EOH2504**		
	R^2	nRMSE	$Peak_{Err}$	R^2	nRMSE	$Peak_{Err}$
Lin. Regr.	0.74	0.075	798.16	0.408	0.078	358.10
Transformer	0.80	0.066	<u>713.90</u>	0.775	0.048	293.25
XGBoost	<u>0.81</u>	<u>0.064</u>	777.52	<u>0.838</u>	<u>0.041</u>	<u>246.08</u>
Persistence	0.55	0.099	917.87	0.587	0.078	358.10

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