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Robust ensemble learning framework for day-ahead forecasting of household based energy consumption

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HIGHLIGHTS

- An ensemble framework is proposed to forecast mean daily household energy usage.
- The methodology shows the use of the ensemble learner in smart energy systems.
- The utilized diversity parameters and robust integration produce a unique learner.
- The proposed ensemble framework is applied to a case study in France.
- Improved day-ahead energy usage forecasts are shown when compared to other models.

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ABSTRACT

Smart energy management mandates a more decentralized energy infrastructure, entailing energy consumption information on a local level. Household-based energy consumption trends are becoming important to achieve reliable energy management for such local power systems. However, predicting energy consumption on a household level poses several challenges on technical and practical levels. The literature lacks studies addressing prediction of energy consumption on an individual household level. In order to provide a feasible solution, this paper presents a framework for predicting the average daily energy consumption of individual households. An ensemble method, utilizing information diversity, is proposed to predict the day-ahead average energy consumption. In order to further improve the generalization ability, a robust regression component is proposed in the ensemble integration. The use of such robust combiner has become possible due to the diversity parameters provided in the ensemble architecture. The proposed approach is applied to a case study in France. The results show significant improvement in the generalization ability as well as alleviation of several unstable-prediction problems, existing in other models. The results also provide insights on the ability of the suggested ensemble model to produce improved prediction performance with limited data, showing the validity of the ensemble learning identity in the proposed model. We demonstrate the conceptual benefit of ensemble learning, emphasizing on the requirement of diversity within datasets, given to sub-ensembles, rather than the common misconception of data availability requirement for improved prediction.

1. Introduction and motivation

The demand for energy is continuously rising and, consequently, leading to unsustainable exhaustion of the nonrenewable energy resources. The increase in urbanization have led to an increase in electricity consumption in the last decades [1–3]. Many countries are continuously moving toward decentralized power systems; therefore, the use of distributed generation of electrical energy instead of the traditional centralized system is becoming popular [4–8]. To face the growing electricity demand and reinforce the stability of this new energy infrastructure, a more decentralized microgrid represents the key tool to improve the energy demand and supply management in the smart grid [9,10]. This is achieved via utilizing information about electricity consumption, transmission configuration and advanced technology for harvesting renewable energy on a finer demand/supply scale. These systems are expected to improve the economy and deliver sustainable solutions for energy production [11,12].

Furthermore, power balance is one of the major research frontiers in decentralized energy systems; the high penetration levels of renewables prompt additional demand–supply variability which may lead to

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Nomenclature

ANFIS	adaptive neuro fuzzy inference system
ANN	artificial neural network
BANN	ANN based bagging ensemble model
DT	decision tree
EANN	proposed ensemble framework
KF	kalman filter
MAD	median absolute deviation
MAPE	mean absolute percentage error
MDEC	mean daily electricity consumption
MLP	multi-layer perceptron
MLR	multiple linear regression
OLS	ordinary least squares
RBF	radial basis functions
rBias	relative bias error
RF-MLR	robust fitting based MLR
RMSE	root mean square error
rRMSE	relative RMSE
SANN	single ANN model
SCG	scaled conjugate gradient
SVM	support vector machines

serious problems in the network [13,14]. Also, the relatively small scale of new decentralized energy systems highlights the importance of predicting the demand projections, which are not similar to the demand projections in the main grid and impose additional variability in the net-load of the system [9,15]. Hence, short-term load forecasting at the microgrid level is one of the critical steps in smart energy management applications to sustain the power balance through proper utilization of energy storage and distributed generation units [3,16,17]. Day-ahead forecasting of aggregated electricity consumption has been widely studied in the literature; however, forecasting energy consumption at the customer level, or smaller aggregation level, is much less studied [13,18]. The recent deployment of smart meters helps in motivating new studies on forecasting energy consumption at the consumer level [11,13,19]. On the other hand, forecasting energy consumption at smaller aggregation level, down to a single-consumer level, poses several challenges. Small aggregated load curves are nonlinear and heteroscedastic time series [13,20,21]. The aggregation or smoothing effect is reduced and uncertainty, as a result, increases as the sample size of aggregated customers gets smaller. This is one of the major issues leading to the different challenges in household-based energy consumption forecasting. The studies in [22–24] discuss the importance and the difficulties in forecasting the energy consumption at the household level.

Further, the behavior of the household energy consumption time series becomes localized by the consumer behavior. Additional information on the household other than energy consumption, such as household size, income, appliance inventory, and usage information can be used to further improve prediction models. Obtaining this information is very difficult and poses several user privacy challenges. For example, Tso and Yau [25] achieve improved household demand forecasts by including information on available appliances and their usage in each household. The authors describe the different challenges in attaining such information via surveying the public. As a result, innovating new models that can overcome prediction issues with the limited-information challenge is indeed one of the current research objectives in this field. In short-term forecasting of individual households' energy consumption, ensemble learning can bring feasible and practical solutions to the challenges discussed earlier. Ensemble learners are expected to nullify bias-in-forecasts, stemming from the limited features available to explain the short-term household electricity usage. However, to the best of our knowledge, there has not been much work done on utilizing ensemble learning frameworks for the problem at-hand.

This work focuses on the specific problem of practical short-term forecasting of energy consumption at the household level. More specifically, we present a proper ensemble-based machine learning framework for day-ahead forecasting of energy consumption at the household level. The study emphasizes on the successful utilization of diversity-in-learning provided by the two-stage resampling technique in the presented ensemble model. This ensemble framework allows for utilizing robust linear combiners, as such combiners are not used before due to the unguided overfitting behavior of the ensemble model in the training stage. The results of the study focus on the ability of the presented ensemble to produce improved estimates while having limited amount of information about the household energy usage history (in terms of variables and observations available for the training).

This paper is organized as follows; Section 2 presents a concise background on common techniques for forecasting of energy

Table 1
General characteristics of classical, single and ensemble machine learning models (not only for energy applications).

Broad Group	Attributes and advantages	Weaknesses and disadvantages
Non-Machine Learning Methods	– Common and well established in the wide literature – Perform well in forecasting aggregated load time series at different temporal resolutions – Provide statistical significance of prediction – Usually quantify uncertainty in obtained predictions – Fast-Implementation to any case study	– Poor performance in forecasting short-term complex time series – Dependence of various assumptions which may be very unreliable – Limited ability to utilize additional variables in the prediction model – Sensitivity to correlations within explanatories – Curse of dimensionality
Single Machine Learning Methods	– Do not require assumptions on the nature of variables – Increasingly accepted methods for various applications in the literature – More flexible methods that can fit better to complex time series – Can accommodate different variables in time series forecasting – Often provide better generalization ability than classical methods	– May be computationally more expensive than classical methods – In time series forecasting, mostly used for curve-fitting objectives rather than statistical interoperability of predictions – Fitting-behavior of many methods are still poorly understood – Curse of dimensionality – Inherent instability in the learning of a case study, even with similar training configurations
Ensemble Machine Learning Methods	– Do not require assumptions on the nature of variables – Very flexible methods that can provide the best fitting approaches – Enjoy far more stable performance than single modeling frameworks – Can provide information on uncertainty – Can significantly reduce the effect of dimensionality; high dimensional systems are handled better without significant impact on performance	– Relatively new learning frameworks – Learning in-series may create computationally expensive methods – Mostly available for classification problems rather than regression – Diversity concept, contribution to its generalization ability, is not usually tackled in an explicit manner in many of the common ensemble models – Generalized learning frameworks require careful consideration when applied to a definite field and a certain case study