Residential Appliance-Level Load Forecasting with Deep Learning

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***Abstract*—Short-term forecasting of the electric load in a household received significant research interest, with applications that include smart grid systems and the possibility to reduce the energy cost to the homeowner. Most previous research focused on forecasting the load at the level of the whole household. In this paper, we propose a novel approach for forecasting the load of *individual* electronic devices. Our approach uses a recurrent deep neural network with Long Short Term Memory (LSTM) cells. We train and validate the system using real-world datasets, and show that the approach outperforms the baseline forecasting approaches.**

***Index Terms*—load forecasting, deep learning, LSTM**

I. Introduction

Understanding and predicting the energy consumption patterns in a household can provide benefits to all stakeholders [1]. For the utility company, which might be using a smart grid, the prediction of the load allows better management of the energy generation and distribution resources, and can inform dynamic pricing to reduce peak demand. For the individual consumers, predicting the load allows the identification of energy loads that can be shifted to off-peak hours, thereby reducing the energy bill. Based on the prediction period, load forecasting is classified as: 1) Very Short-Term Load Forecast (vSTLF): forecasting the load for the next several minutes, 2) Short-Term Load Forecast (STLF): predicting the load from next several hours to a week ahead, 3) Medium-Term Load Forecast (MTLF): predicting the load from a week to a year ahead, 4) Long-Term Load Forecast (LTLF): predicting over the timespan of several years.

Most previous work focused on forecasting the load at the level of the whole household. Our work starts with the insight that while the total load is of interest, individual energy saving or load-shifting actions taken by the users, such as postponing the operation of the dishwasher to the night hours, will usually affect individual appliances. Thus, our work focuses on the appliance-level short-term load forecasting model for residential homes. We take advantage of the recent developments in deep learning techniques to create recurrent neural network, in particular Long Short-Term Memory (LSTM) based predictor. We train the network based on historical data on residential home appliances' energy usage and estimate energy usage for a given appliance in the short term. This problem is more complicated than simply training a number of LSTM-based models for each household appliance, and training a single model for all appliances together is more robust and scalable.

The remainder of this paper is organized as follows. Related work is discussed in Section II. We present our proposed deep learning-based appliance-level load forecasting model in Section III. Section IV describes the experimental setup and we discuss the results in Section V. Finally, Section VI concludes the paper.

II. Related Work

Most literature use one of the following methods of load forecasting: 1) machine learning methods (e.g., Linear Regression, Support Vector Regression, AutoRegressive Integrated Moving Average (ARIMA)); 2) deep learning algorithms (e.g., Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs)); 3) probabilistic forecasting (e.g., Quantile Regression, Density Regression). Probabilistic forecasts may provide more comprehensive information on potential uncertainties rather than predicting the expected load throughout time.

Machine learning-based load forecasting. Wu et al. [2] present a gradient boosting-based multiple-kernel learning framework with the help of transfer learning to forecast electrical load with scarce data. Peng et al. [3] explore load predictability Small-and-Medium Enterprise comparing to residential homes by Approximate Entropy measure (ApEn).

Deep learning-based load forecasting. Tang et al. [4] forecast energy consumption combining two ARIMA and two LSTM models with a fully connected layer as the last layer to estimate energy consumption based on the outcome of these submodels. Kong et al. [5] used VGG-16 CNN network to learn the patterns for different brands and models of appliances and another CNN for post-processing the results of the first network to predict and disaggregate energy consumption for home appliances without sub-meter information.

Probabilistic load forecasting. Wang et al. [6] have combined Quantile Regression Neural Network (QRNN), Quantile Regression Random Forests (QRRF), and Quantile Regression Gradient Boosting (QRGB) methods and choose the process with the most optimized weights. Feng et al. [7] introduced STLF-QMS, a mixture of deterministic and probabilistic load forecasting models with Q-learning dynamic model selection (QMS).

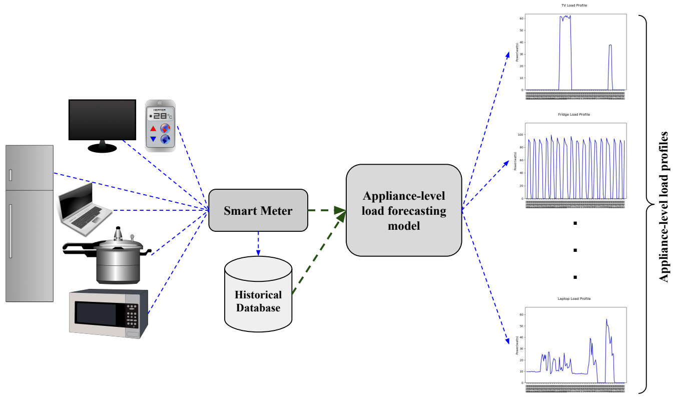

Fig. 1: Framework for the proposed appliance-level load forecasting deep learning-based model.

III. Appliance-Level Load Forecasting with Deep Learning

In this paper, we propose an LSTM recurrent neural network-based model to predict home appliances energy consumption for the upcoming hours. After pre-processing the data collected from the smart meter, we feed it into a deep neural network to produce the predictive load consumption of the appliances. Fig. 1 displays the framework of the proposed model. This section describes the pre-processing steps of the data and the LSTM-based load forecasting model.

A. Data Preprocessing

Different appliances may be in use in any residential household, and the consumer behavior of utilizing home appliances is highly reliant on the consumer lifestyle. Several appliances can be in service multiple times a day, while some may be off for an entire week. Therefore, to forecast the future energy consumption of household appliances, it is necessary to extract certain features indicating the likelihood of using an appliance at a given time.

Several papers use deep learning models or statistical methods to forecast a household's total energy consumption for an entire day; however, more accurate details would provide further insights into the occupants, and they would be more valuable for improved energy-saving plans. We aim to predict appliance-level load consumption at different time intervals throughout the day. This time interval can vary, like every minute, every ten minutes, every fifteen minutes, every half hour. However, as we increase the time between periods, the more difficult it becomes to measure the energy usage for devices with working time duration less than the period.

For this purpose following information would be helpful: (1) *hour* (2) *minute* (3) *day of week* (4) *Last_Seen_On*: the last time step appliance was running (5) *Last_Seen_Off*: the last time step appliance was off. Considering that the data has date and time details, it is simple to split date information into features such as "hour," "minute," and "day of the week." We can save them as categorical vectors for making the training of the model more straightforward.

We normalize the energy utilization data for each home appliance within the spectrum of maximum use to minimum use of the same appliance to prevent large numbers or anomalies impacting the network's learning process. The minimum and maximum energy consumption for each electrical device is unique to its specifications and differs from other appliances. Thus, if we scale it to the same scope for all appliances, the network's output range is identified and would ultimately produce more reliable results.

With pre-processing data, we have introduced two new features: *Last_Seen_On* and *Last_Seen_Off*, to make it simpler for the model to learn consumption pattern for appliances with less repeated energy consumption pattern. We observe that the energy consumption is at the lowest level, and it goes up as the residents of a home decide to use the appliance except for the appliances running continuously, such as the fridge, AC, and heater. These two features are measured according to the historical data at each time step and help the model construct a view of the trend of consumption.

Having energy usage information of each appliance per minute, we can predict the future energy consumption with various time intervals. One solution is to consider the average energy used over the time interval for the input data, but it may shrink the dataset size. On the other hand, we know that the more data we have, the better the model can learn the behavioral patterns of using appliances. Instead of estimating average consumption over time intervals, we generate input sequence, as shown in Fig. 2, having data with $\frac{1}{60}$ Hz frequency for an entire day, but generating input sequence with $\frac{1}{60\times time\_interval}$ Hz frequency ($\frac{1}{600}$ Hz for 10-minute time intervals). Fig. 2 displays each data point in a day by its time and also demonstrates that we can construct different input sequences with data points within two-time intervals, and we can have more input data for the training process that is not augmented or duplicated.

B. LSTM-based Load Forecasting

Recurrent neural networks are a form of feed-forward neural networks that rely on the previous stage output to produce new outputs. In other words, RNNs perform the same input calculation at each stage, taking into account feedback obtained from previous stage results, thereby generate associations with the input feature with its internal memory.

The problem we are investigating here is estimating future load consumption patterns for each home appliance having historical data and using multiple variants that affect output. We assume that the output is a continuous value depending on the previous value and other factors. We believe that LSTM recurrent neural networks are more suitable than standard feed-forward neural networks as LSTM can learn the long-term dependencies in the input features due to the memory cells built into its architecture design.

Table I displays the hyper-parameters used to train the LSTM model for predicting future appliances loads with 10-minutes intervals, with the strongest performance for the ones in bold text. When the LSTM model is trained, it can forecast

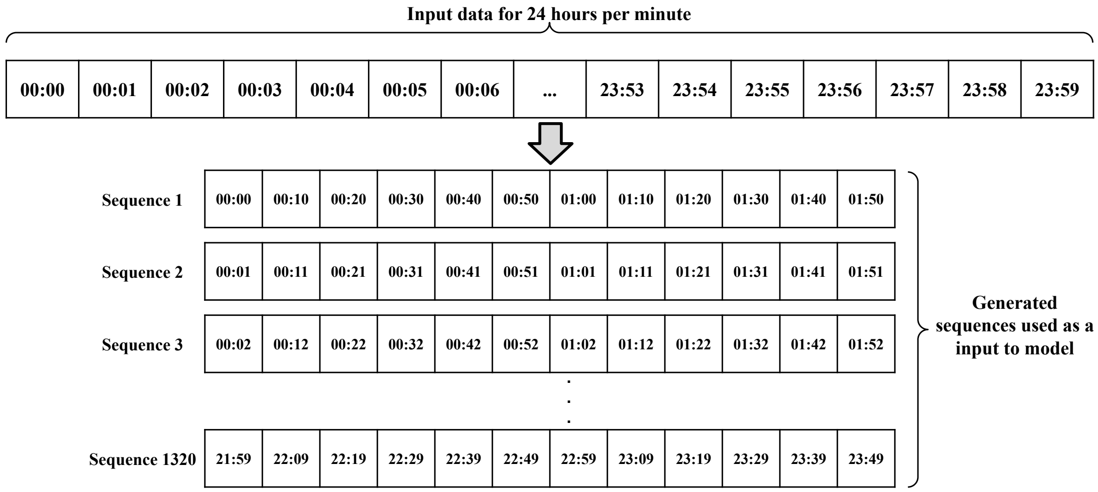

Fig. 2: Generating input sequences for training with time interval = 10 minutes and sequence length = 12.

TABLE I: LSTM model hyper-parameters.

Parameters	Value
Number of layers	**2**, 3, 4
Learning Rate	**0.0001**, 0.001, 0.1
Number of hidden neurons	**128**, 256
Sequence length	**12**, 18, 36, 72, 144
Batch size	128, 512, 1024, 2048, **4096**
Optimizer	GSD, **Adam**
Interval	**10**, **15**

the load consumption for a given appliance, hour, minute, day of the week, and other inputs. In general, the model can predict future energy usage for each home appliance at various time intervals for the following days over a week. The LSTM-based model architecture is displayed in Fig. 3.

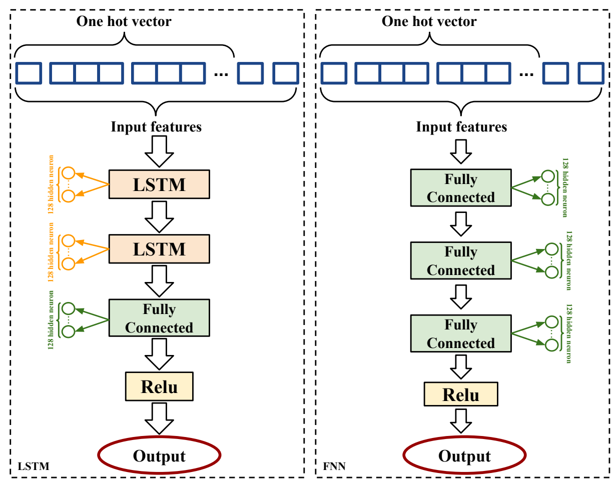

Fig. 3: LSTM-based and FNN-based architectures used to predict appliance-level load.

IV. Experiments

In the experiments, we have used a publicly available dataset, DRED [8], collected in a household from July to December 2015. This dataset has appliance level and aggregated energy consumption, with a sampling frequency of 1Hz of 12 different home appliances. We used the top six most energy-consuming appliances for our experiments: television, fridge, laptop computer, electric heater, microwave, cooker, and the overall house energy consumption. After data pre-processing, there are around 218880 rows of data (152 days) for each appliance. With 60%, 30%, and 10% ratio, we split data into three-part as train, validation, and test sets.

We have implemented our model on a NVIDIA GeForce GTX 1070/PCIe/SSE2 with 15.6 GB memory and 3.6 GHz core clock hardware configuration and used Pytorch library and Python for software implementation.

We used two other load forecasting methods as the baseline for evaluating the performance of the proposed model:

- **Random Forest (RF)**: Most of the previous studies use ARIMA model [4] for load forecasting; however, ARIMA essentially implies a linear relationship between input variables that may be dependent or independent which is not always true for multivariate problems [9]. Random Forest [10] algorithm, on the other hand, has more promising results in a multivariate load forecasting problem.
- **FeedForward Neural Network (FNN)**: We implemented a basic feed-forward network with three fully connected layers to compare its results against the LSTM model (See Fig. 3). The FNN has three fully connected layers with a ReLU activation function [11] as the last layer. The fully connected layers have 128 hidden neurons each, the same as LSTM layers.
- **Long Short-Term Memory Neural Network (LSTM)**: As described in Section III-B.

We used Root Mean Square Error (RMSE) (Equation 1) and Normalized Root Mean Square Error (NRMSE) (Equation 2) to compare the performance of all three models where n is the total number of samples, y_j is the target value and $\hat{y_j}$ is the predicted value, $max(y_j)$ and $min(y_j)$ refer to the maximum and minimum electrical usage recorded for the appliance j.

$$RMSE = \sqrt{(\frac{1}{n})\sum_{i=1}^{n}(y_j - \hat{y_j})^2} \tag{1}$$

$$NRMSE = \frac{\sqrt{(\frac{1}{n})\sum_{i=1}^{n}(y_j - \hat{y_j})^2}}{max(y_j) - min(y_j)} \tag{2}$$

The RMSE is an excellent metric to demonstrate how far the predictions are from the target value. Since we have different appliances and each has its spectrum of energy usage to compare the results against each other, we have computed NRMSE metric which normalizes the RMSE values with the relative load spectrum.

V. Evaluation Results

In the first stage of our experiments, we explored the effect of using two newly introduced features, *Last_Seen_On* and *Last_Seen_Off*. To this end, we have trained our LSTM-based model on time, taking into account these two features and without considering these two features. The NRMSE metric was used to compare the forecasting results of the two models. Fig. 4 demonstrates that the NRMSE score for the LSTM-based model taking into account *Last_Seen_On* and *Last_Seen_Off* is considerably lower compared to the model that does not use these features specifically in appliance-level load forecasting.

Tables II and III present the outcomes of RMSE and NRMSE for the three load forecasting algorithms with ten and 15-minute intervals. The appliances used include TV, fridge, laptop, electric heater, microwave, and cooker. We also show the total load.

The first conclusion we can draw from these numbers is that the LSTM network is a suitable architecture for this multi-variate load forecasting problem. The memory cells in the LSTM architecture help the network properly learn the long-term dependencies between the input variable, which regular feed-forward networks can not.

The other noticeable result is that for some appliances such as the laptop, the results of RMSE and NRMSE for FNN-based and LSTM-based models are quite close. As shown in Fig. 5.c, the LSTM-based model reaches the target value nearest in each step, while FNN and Random Forest models produce an average sequence value during the day to reduce the difference between target and predicted values and RMSE metric However, for particular applications such as energy-saving scheduling, it is essential to know the precise load consumption at each time step nearest to the real value.

The last but not the least conclusion is that all three forecasting models can catch the total load consumption pattern over the day (Fig. 5.g); however, the LSTM-based model is better at learning sudden changes.

Figures 5.a–5.g compare the forecasting performance of the three load forecasting models for TV, fridge, laptop, microwave, cooker and total load consumption of the household.

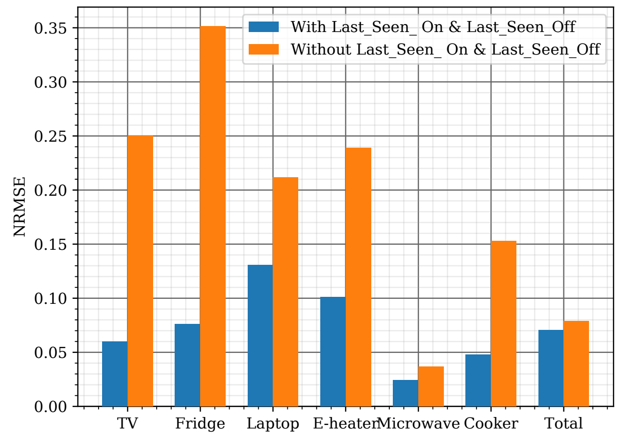

Fig. 4: NRMSE results for LSTM-based model with and without taking into account *Last_Seen_Off* and *Last_Seen_On*.

VI. Conclusion

In this paper, we proposed an appliance-level load forecasting model for residential homes. This model uses LSTM recurrent neural networks to learn energy consumption patterns for individual electrical appliances in a smart home and predict a given appliance's potential load consumption over different time intervals. We evaluated our model on a public dataset comparing with Random Forest and FFN network models. The RMSE and NRMSE results indicate the superior performance and the lowest error rate of the proposed model against the other two models.

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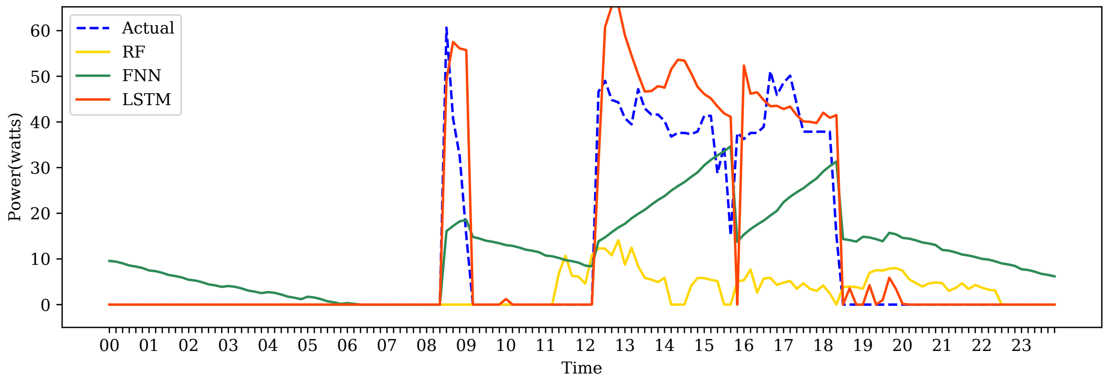
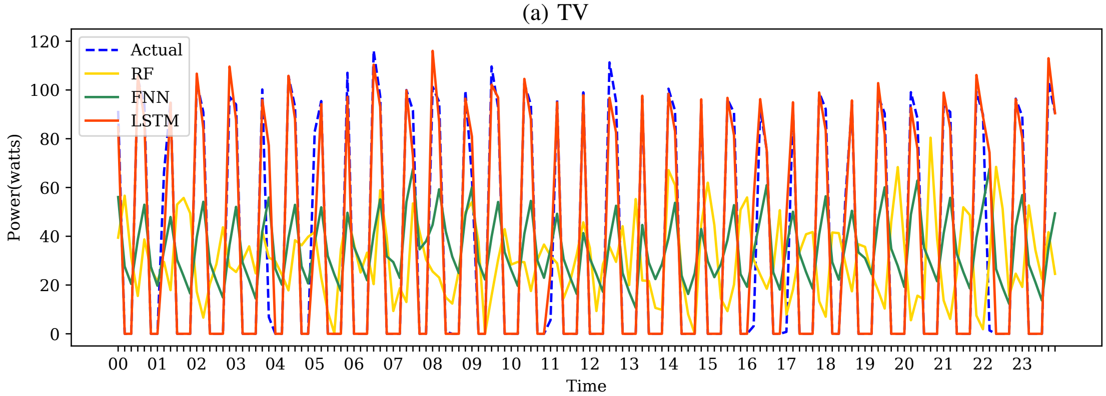
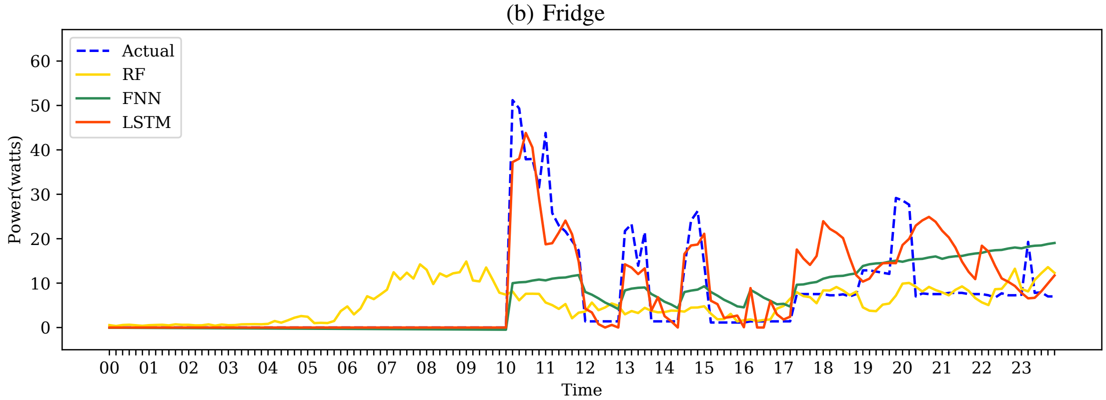


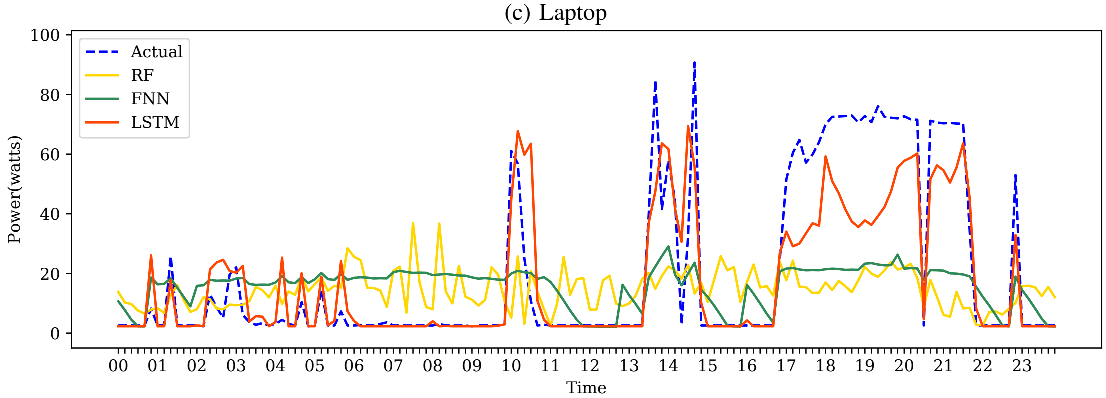
(a) TV



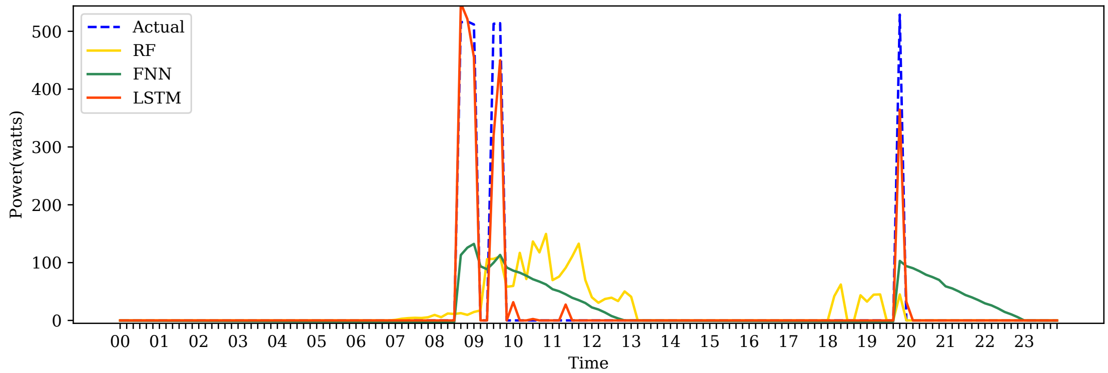
(b) Fridge



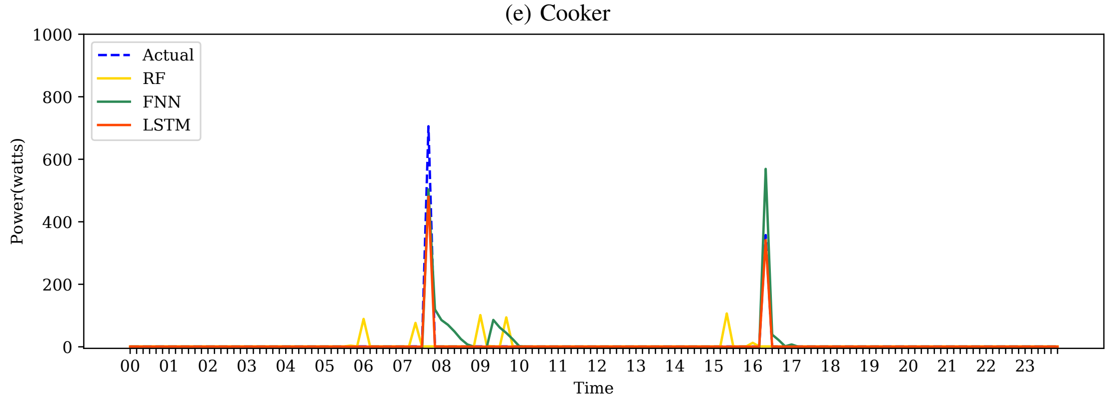
(c) Laptop



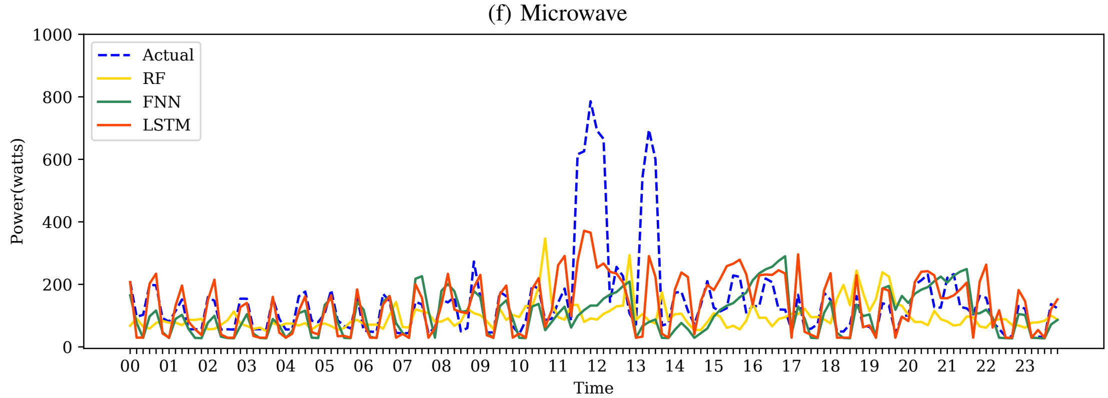
(d) Heater



(e) Cooker



(f) Microwave



(g) Total

Fig. 5: Energy consumption prediction for 24 hours with 10 minutes intervals.

TABLE II: Evaluation Results for 10-minutes intervals.

Model	TV		Fridge		Laptop		Electrical Heater		Microwave		Cooker		Total	
	RMSE	NRMSE	RMSE	NRMSE	RMSE	NRMSE	RMSE	NRMSE	RMSE	NRMSE	RMSE	NRMSE	RMSE	NRMSE
RF	13.947	0.217	47.775	0.319	13.233	0.202	20.084	0.224	57.649	0.042	86.016	0.161	153.439	0.094
FNN	10.042	0.156	33.755	0.226	13.343	0.203	16.268	0.181	64.149	0.046	69.638	0.131	139.349	0.085
LSTM	**3.849**	**0.060**	**11.373**	**0.076**	**8.575**	**0.131**	**9.091**	**0.101**	**33.461**	**0.024**	**25.648**	**0.048**	**128.665**	**0.079**

TABLE III: Evaluation Results for 15-minutes intervals.

Model	TV		Fridge		Laptop		Electrical Heater		Microwave		Cooker		Total	
	RMSE	NRMSE	RMSE	NRMSE	RMSE	NRMSE	RMSE	NRMSE	RMSE	NRMSE	RMSE	NRMSE	RMSE	NRMSE
RF	13.775	0.214	46.275	0.331	12.908	0.205	22.643	0.256	60.748	0.043	78.302	0.148	173.118	0.092
FNN	9.945	0.154	34.094	0.244	10.764	0.171	18.861	0.213	81.402	0.057	60.914	0.115	317.915	0.170
LSTM	**4.214**	**0.065**	**12.008**	**0.086**	**9.627**	**0.153**	**9.786**	**0.111**	**32.516**	**0.023**	**33.036**	**0.062**	**152.543**	**0.081**