Deep Learning-Based Energy Disaggregation and Time-Series Analysis for Optimizing Household Appliance Use

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Abstract — ***Energy Management is emerging with the rise of Smart Buildings and Smart Cities. These innovations continue to foster improvement in technology. Thus, effective energy management is necessary to optimize daily consumption. This paper explores the Optimization of Household Appliance Use through Energy Disaggregation and Long Short-Term Memory.***

Energy Disaggregation is essential to breakdown the Main power being consumed into submeters. Different models were used to perform this on the Refit Dataset including: Combinatorial Optimization, Hart85, and Fitting Hidden Markov Models. Out of all the models, Combinatorial showed the best output with 1-3 differences between the predicted and actual value. The Computer Appliance exhibited a 2.16 RMSE using this model as well.

Long Short-Term Memory is used to predict the succeeding values based on the given data. Three different models were also used. These models are Vanilla, Bidirectional, and Stacked LSTM. Out of all the models, Stacked LSTM exhibited the best output with 99.12% accuracy and 21.30 MAE.

Keywords — ***Energy Disaggregation, Non-Intrusive Load Monitoring, Long Short-Term Memory, Refit, hart85, Combinatorial Optimization, Fitting Hidden Markov Models, Optimization***

I. INTRODUCTION

The effects of consumption of energy and carbon emissions on the global climate are frequently estimated in integrated assessments of climate change. A significant amount of the total energy use is susceptible to sudden changes in the weather or environment. However, with the fluctuating weather conditions, people are more inclined to use their appliances and not be able to track their energy usage. This energy demand is dependent on the type of weather the country is experiencing. (1) Due to the increasing demand, The primary cause of the challenges that are expected in the near future may be traced back to the dramatic expansion in global population in recent centuries, especially since the turn of the century, which has been dubbed the "population explosion". (2) This caused unsupervised energy consumption and overuse of resources. Different studies proposed energy conservation strategies to help mitigate the effects of climate change. One of those is the Energy Disaggregation, it can help make energy consumption more efficient and sustainable. This discusses the smart meter capabilities and the effectiveness of measuring, recommending, and giving direct feedback to the users of their consumption. (3). Homeowners frequently don't realize how updates, new appliances, aging appliances, and behavioral shifts in its occupants affect their home's energy efficiency. For instance, if residents cease lowering the thermostat at night, installing a more energy-efficient furnace won't always result in lower energy costs. The only method that can offer the homeowner, the utility company, and the energy auditor meaningful input is the ongoing monitoring of energy consumption. For utility firms to be competitive in the increasingly deregulated energy market, they should provide new services to their customers. (4)

In this paper, Energy Disaggregation and Long Short-Term Memory was performed on the REfit Dataset House 17-18. Three different models were used to compare and analyze the most suitable and efficient among all.

The rest of this paper is organized as follows. Section III describes the Preparation done on the dataset and the environment to make it suitable for the Non-Intrusive Load Monitoring. It also contains the performance of the different models on Long Short-Term Memory as well as its model deployment. The results are analyzed in Section IV. And finally, Section V concludes the paper and outlines the future work of the researchers.

II. METHODOLOGY

A. Preparing the Dataset and Environment

There are different datasets that are available for Energy Consumption including REDD, Refit, UKDALE, etc. REfit Dataset contains the cleaned electricity consumption data, expressed in watts, for a total of 20 households in the English town of Loughborough, designated House 1- House 21 (omitting House 14), from 2013 to early 2015, is included in the REFIT electricity Load Measurements dataset. Each household had a total of 10 power sensors, which included a current clamp for the household aggregate, designated Aggregate in the dataset, and nine individual appliance monitors. designated Appliance

1-Appliance 9 in the dataset. The electrical consumption data were gathered at both the aggregate and appliance levels. (5)

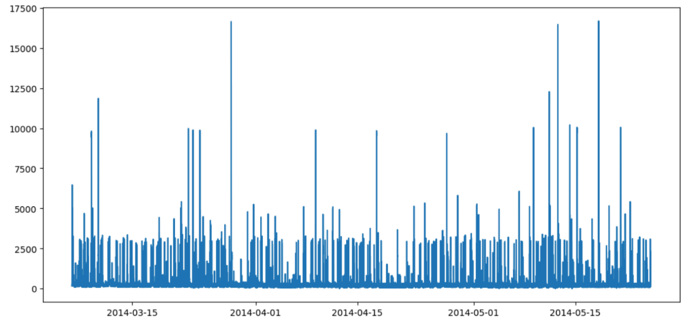

Fig. 1. Aggregated Energy Consumption on Refit Dataset

B. Energy Disaggregation on Refit Dataset

Energy disaggregation uses a single meter to assess the total electricity demand of the home to estimate the electricity consumption of each appliance individually. (6) Researchers utilized Non-Intrusive Load Monitoring Tool Kit (NILMTK) as a diagnostic tool for disaggregating home appliances, utilizing energy efficiency indices from standards and labeling. NILM represents a powerful tool to disaggregate the energy consumption of electrical installations, which can be embedded in modern energy meters. (7)

Three different models in energy disaggregation method were compared and analyzed to achieve optimal results in disaggregating Refit Dataset. Hart85, Combinatorial Optimization, and Fitting Hidden Markov Models. These three disaggregation methods are accessible in the Non-Intrusive Load Monitoring Tool Kit.

Table I. Comparison of Predicted and Ground Truth Values for Freezer using Proposed Models

TIME	Ground Truth	Prediction (CO, Hart85, FHMM)		
2014-03-15 00:00:00+00:00	79.107143	0	0	74
2014-03-15 00:03:20+00:00	77.440000	77.0	0	0
2014-03-15 00:06:40+00:00	76.450000	77.0	159	0
2014-03-15 00:10:00+00:00	75.413793	77.0	159	0
2014-03-15 00:13:20+00:00	74.904762	77.0	0	0

Table II. RMSE Results on Best Model.

Appliances	Combinatorial Optimization
Fridge	54.478097
Freezer	0.000000
Washer dryer	194.975491
Washing machine	49.129420
Dish washer	29.808500
Computer	2.161207
Television	66.294615
Electric space heater	10.254403

Table 2 discusses the Root Mean Squared Error of the Combinatorial Optimization Disaggregation Method, this is the differences between the actual and predicted value of the disaggregated appliances.

C. Long Short-Term Memory

Long Short-Term Memory (LSTM) is a specialized and powerful Recurrent Neural Network (RNN) approach capable of learning long-term dependencies. The LSTM model excels in tasks involving sequential data by effectively remembering information over extended periods.

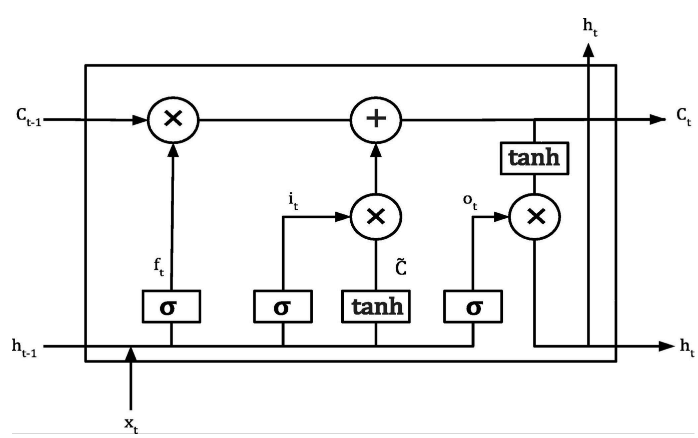

Fig. 2 Structure of Long Short-Term Memory (LSTM)

In figure 2, it describes the structure of LSTM. LSTM consists of memory blocks with three gates: input gate, output gate and forget gate. The gates are important in avoiding the vanishing gradient problem as there will be a significant number of environmental variables. This can analyze a time series with long spans for prediction and effectively solve the vanishing gradient problem. The unit of a hidden layer in LSTM is a linear self-loop memory block that allows gradients to flow through long sequences. The three gates of LSTM can help control the flow of information in and out of the memory block (8).

Table III. Architecture of proposed models

Model	**Hidden Layer**	**Output layer**	**Parameter**
Vanilla	[LSTM(units= 64)]	[Dense(units =3)]	17,603
Stacked	[LSTM(units= 64, activation ='relu', RS = True)]	[Dense(units =3)]	50,627
Bidirectional	[Bidirecional(L STM(units=64))]	[Dense(units =3)]	35,203

The study implemented three types of LSTM models: Vanilla LSTM, Stacked LSTM, and Bidirectional LSTM, each designed to predict energy consumption.The Vanilla LSTM serves as a baseline with a straightforward architecture, the Stacked LSTM introduces deeper layers for capturing intricate patterns, and the Bidirectional LSTM offers an advanced approach by considering information from both directions in the sequence.

D. Model Deployment

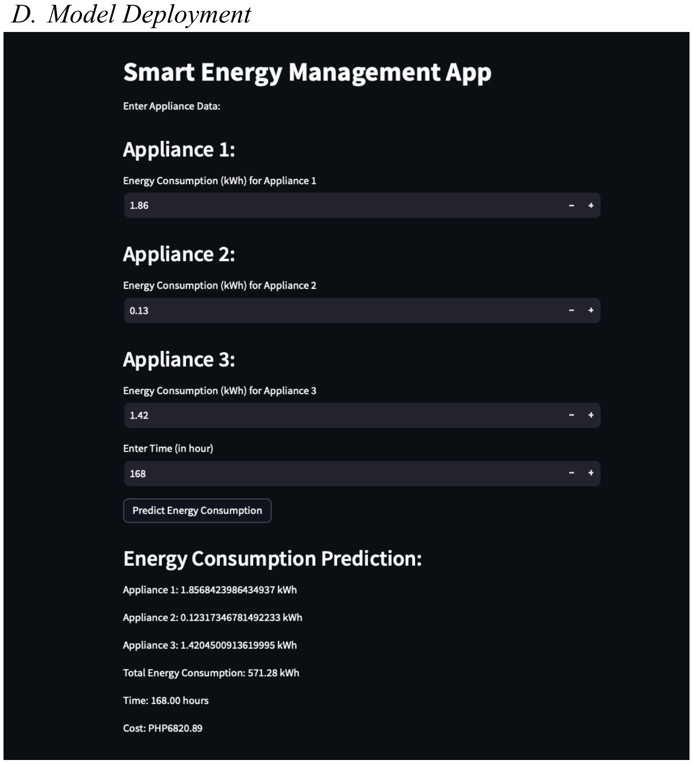

Fig. 3. Smart Energy Management Application

Model demonstration can also be access through this link: Energy Optimization WebApp.mp4

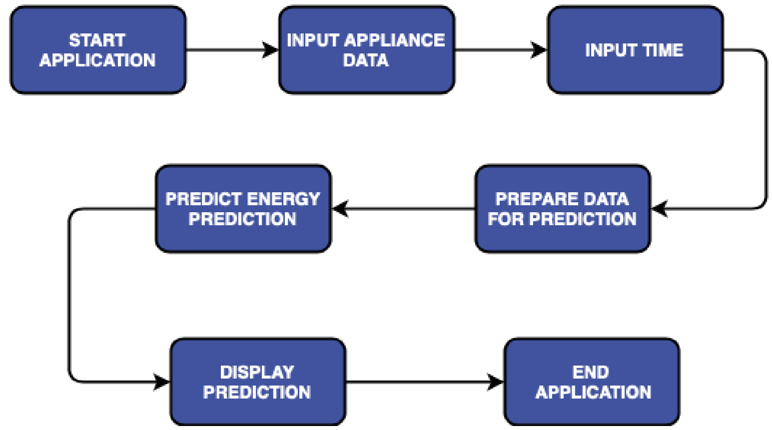

Fig. 4. Process Flow Diagram

Figure 3 shows the User Interface of the Web Application while Figure 4 discusses the process. Users will be inputting the Energy consumed by the appliance that they want to measure then, the application will show the total energy they consumed within the dictated hour and its total cost. This aimed to make customers aware of their energy expenditures and promote optimization in their usage.

III. RESULTS AND DISCUSSION

The disaggregation exhibited an exemplary performance on the Combinatorial Optimization with only 1-3 differences on per given time.

Table IV: Comparison of Root Mean Square Error

Metric	**Hart85**	**Combinatorial Optimization**	**Fitting Hidden Markov Models**
RMSE	2526	54.478097	68.461575

Table 4 exhibits the Root Mean Square Error between the three disaggregation models. Combinatorial Optimization gave an output of 54.48 RMSE which is the lowest among all three. While Hart85 did poorly with 2526, and FHMM did satisfactory with 68.46 Root Mean Square Error. This shows the capability of CO to disaggregate data more efficiently.

Table V. Performance of the three LSTM Models

Metric	**Vanilla LSTM**	**Stacked LSTM**	**Bidirectional LSTM**
Accuracy	98.85	99.12	98.72
MSE	685.69	647.83	679.42
RMSE	26.44	25.45	26.07
MAE	20.88	21.30	19.96

As shown in the table above, three LSTM architectures were used to predict energy consumption in quantum applied systems:

Vanilla LSTM, Stacked LSTM, and Bidirectional LSTM. Each model's performance was evaluated based on key metrics: accuracy, mean squared error, root mean squared error, and mean absolute error. Among the three models, Stacked LSTM achieved the highest accuracy of 99.12%, which just shows its ability to make precise predictions. Additionally, Stacked LSTM has the lowest error metrics.

Table VI. Comparison of Mean Absolute Error

Model	Fridge	Television	Microwave
Vanilla	1.49	0.16	5.69
Stacked	1.27	0.15	4.67
Bidirectional	1.63	0.16	5.79

Table 3 presents a comparison of the Mean Absolute Error (MAE) for the three types of LSTM models: Vanilla, Stacked, and Bidirectional, in predicting energy consumption for a Fridge, Television, and Microwave. Among the evaluated models, the Stacked LSTM exhibited the lowest errors and demonstrated superior accuracy, indicating its effectiveness in predicting energy consumption for these appliances.

IV. CONCLUSION

In this paper, the Refit Dataset was explored using Energy Disaggregation and Long Short-Term Memory for Optimizing Household Appliance Use. The energy disaggregation on the dataset showed its best performance using Combinatorial Optimization which has a 1-3 differences with the Ground Truth value and garnered a value of 2.16 RMSE with the Computer Appliance.

Afterwards, LSTM was applied to the disaggregated data. Among all the proposed models, Stacked LSTM performed the best with 99.12% accuracy and 21.39 Mean of Error. This merely demonstrates its capacity for accurate prediction.

The authors recommended applying additional models for a wide range of comparison between energy optimization techniques.

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