A Different Neural NILM based Energy Disaggregation

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Abstract - Non-Intrusive load provides a low cost monitoring and low cost maintenance method to monitor and detect behavioral patterns of different appliances and disaggregate the load into these patterns to identify application wise energy consumption and anomalies and detect where the energy can be conserved. In this paper we are comparing previous results of energy disaggregation with the results obtained from new and improved machine learning models of DAE, Sequence2Sequence, Sequence2Point and WindowGRU's by deepening the layers, changing width and type of layers and calculate the energy consumption calculated from the predicted and actual reading to have a general understanding of importance of load monitoring.

Key Words: Non Intrusive Load Monitoring, DeepLearning, Machine Learning, Energy Disaggregation, Artificial Intelligence

1. INTRODUCTION

In Today's world energy consumption is one of the most important topics with all the global warming and environmental problems. Which makes it necessary because of the lack of renewable resources. According to a research done by "International Energy Outlook", It was predicted that India's commercial sector accounted for nearly 69% of the country's gross domestic product in 2015, and this share is expected to grow continue, leading to more energy demand in the commercial sector and Electricity's share rises from 46% of the energy delivered to India's residences in2015 to 68% in 2040. Overall a good work in energy consumption can help a country's economy because currently a lot of energy is wasted because of not properly knowing the requirements of energy. Traditionally energy meters can only calculate energy consumption of any house easily but for a better energy consumption insight it is necessary to monitor energy consumption application wise. For Non-Intrusive Load Monitoring energy disaggregation is an important part of it as it can help us to determine energy consumption application wise. From [1] it can be said that energy disaggregation can be done on low frequency energy consumption data. In Load Monitoring there are two methods: intrusive load monitoring and non-intrusive load monitoring. Where intrusive load monitoring no doubt is accurate but in real world situations the costing and management of sensors and equipment is a lot difficult and hard to achieve. Else-where in non-intrusive load monitoring needs only a single energy meter main to easily disaggregate data. So despite of lesser accuracy it is more advantageous to use NILM methods to do load monitoring and monitor energy consumption. In this paper we've tried to present current advances made by us and comparisons of previous models with ours and also a predicted calculation of energy from different meters, on a daily basis which algorithm is more useful in REFIT Dataset, performing energy disaggregation in the simplest way, and achieve a good non-intrusive load monitoring system.

1.1 Dataset Description

There are many open source datasets available for NILM like UK-Dale, REDD, REFIT, etc. Few openly available datasets are as mentioned in table 1. These datasets contain both aggregated and separate metered data to train and test the model on. Most of the dataset is preprocessed, so minimal preprocessing is needed for this project. We have used the REFIT dataset to train our models and test on it. We chose REFIT Dataset because of it's fairly high number of houses and sample frequency is also 8 secs so it is also good. If previous works are considered then this dataset is fairly newer then other datasets so work on this is also lesser in comparison to other big datasets of NILM. In the REFIT Dataset following metadata table.

HouseHold Appliances present in each house of REFit Dataset is as following:

For house 1: Fridge,Freezer,Freezer,Washer Dryer, Washing Machine, Dish Washer, Personal Computer, Television, Electric Heater

For house 2: Fridge freezer, washing machine, dish washer, Television, Microwave, Toaster, Hi-fi, Kettle, Fan

For house 3: Toaster, Fridge Freezer, Freezer, Tumble Dryer, Dish Washer, Washing Machine, Television, Microwave, Kettle

For house 4: Fridge, Freezer, Fridge Freezer, Washing Machine,Washing Machine, Personal Computer, Television, Microwave, Kettle

For house 5: Fridge Freezer, Tumble Dryer, Washing Machine, Dish Washer, Personal Computer, Television, Microwave, Kettle, Toaster etc.

Table -1: Household energy Datasets

Household energy Datasets		
Datasets	Institution	Appliance Sample Frequency
REDD (2011)	MIT	3 sec
BLUED (2012)	CMU	N/A
Smart (2012)	Umass	1 sec
Tracebase (2012)	Darmstadt	1-10 sec
Sample (2013)	Pecan Street	1 min
AMPds (2013)	Simon Fraser U	1 min
IAWE (2013)	IIIT Delhi	1 or 6 sec
UK-DALE (2014)	Imperial College	6 sec
REFIT (2016)	University of Strathclyde	8 sec

In REFIT Dataset both Aggregated and appliance data is sampled at same frequency what else in REDD and UK-DALE dataset both are sampled at different frequency which is why we have used REFIT dataset to reduce the time in preprocessing the data.

1.2 Method

In the scientific literature, several techniques have been proposed to perform NILM.From the research obtained from the findings of [3], [4] an open source NILM library was created to help in NILM preprocessing and disaggregating data. For Intrusive Load Monitoring the accuracy achieved is higher than Non-Intrusive Load Monitoring but if we consider the amount of money invested in maintaining and handling Intrusive loads is quite difficult then Non-Intrusive load monitoring. Monitoring load appliance wise is quite more beneficial then monitoring just a single point load as concluded from the research output of [5]. For NILM there have been few supervised and unsupervised methods like FHMM, HART, DAE, seq2seq, seq2point, CNN's, etc. as mentioned in [6], [7],[4], [1], [8]. Table 3 shows which datasets have been used in which paper for major datasets like REDD, REFIT, UK-Dale, BLUED.

Table -2: HMean Average Error obtained for each method and major appliances are shown in this table.

Mean Average Error obtained for each method and major appliances are shown in this table.	
Dataset	Paper Reference
REDD	[9],[8]
REFIT	[7],[10]
UK-Dale	[11],[4]
BLUED	[6]

In this paper we tried to achieve good results on the previous used models by changing their layers and comparing the results obtained from each model and what can be improved in it to achieve a model with high accuracy. As mentioned in [12] we can achieve higher accuracy appliance wise if Efficient Sequence Length (ESL) is selected for sequence length but in this paper for keepsake purpose we have kept Sequence Length as 60 as we are comparing between not only Sequence2Sequence and Sequence2Point but also DAE and WindowGRU to perform energy disaggregation. All the models have been modified to achieve a better performance than the original proposed model. Figure 1 shows the the modified DAE method that was changed in this paper to perform better than originally proposed method.

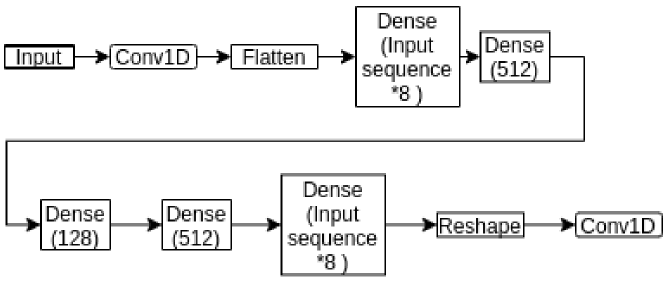


Figure -1: Modified DAE

Second Method that was analysed and changed in this paper is WindowGRU. In the Neural NILM research this is also a presented method to perform energy disaggregation. Figure 2 shows the modified WindowGRU.

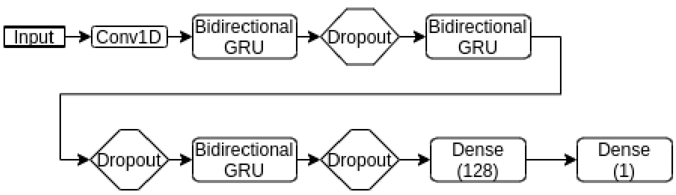


Figure -2: Modified WindowGRU

Third Method that was analysed and changed in this paper is Sequence2Sequence. In the Neural NILM research this is also presented as a method and this is one of the popular methods to perform energy disaggregation. Figure 3 shows modified Sequence2Sequence model.

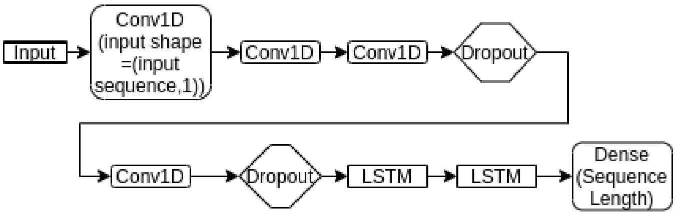


Figure -3: Modified Seq2Seq

Fourth Method that was analysed and changed in this paper is Sequence2Point. In the Neural NILM research this is also presented as a method. Figure 4 shows a modified Sequence2Point model.

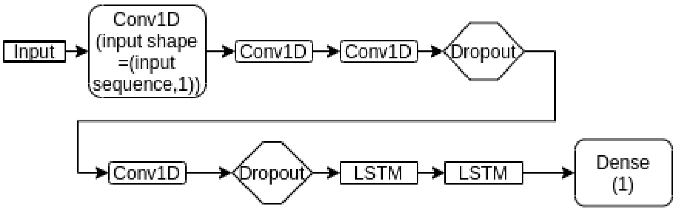


Figure -4: Modified Seq2Point

2. Results

After training all the models following results were obtained. Although accuracy of Seq2Seq and Seq2Point can be increased appliance wise if ESL is selected. Hyper-parameters are few things that have not been changed a lot in this experiment. The data is not down sampled for higher accuracy and also training dataset used is of House 2 of REFIT dataset and it contains 9 appliances. From the 9 appliances in the house following Exploratory data analysis was done. In which energy hungry devices were identified based on the on-time and energy consumption of devices. Figure 5 shows on-time of appliance in house 2 of REFIT dataset and Figure 6 shows the average of daily on-time of an appliance.

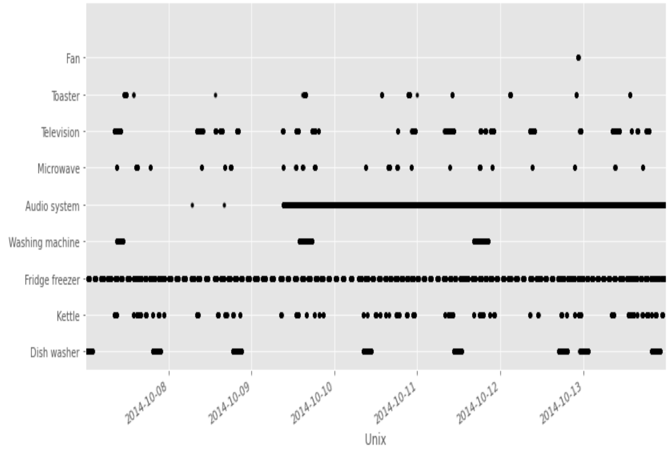


Figure -5: Appliance on-time for house 2

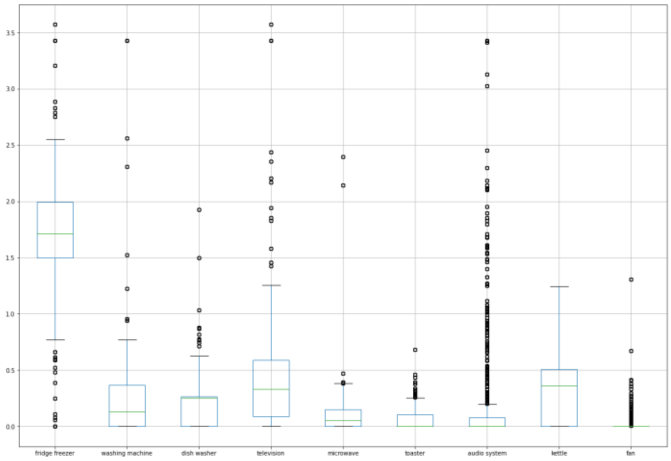


Figure -6: On-time boxplot for house 2

Table -4: Mean Average Error obtained for each method and major appliances

Mean Average Error obtained for each method and major appliances					
MAE	Fridge	Dish Washer	Kettle	Washing Machine	Toaster
DAE	20.33	37.18	19.47	21.50	2.52
WindowGRU	21.09	36.79	20.11	20.23	2.77
Seq2Seq	17.76	33.13	17.94	19.77	2.57
Seq2Point	17.12	33.34	16.09	19.64	2.66

After changing hyperparameters and width and depth of DAE models several times the best output was recorded and considered in this paper For Seq2Seq and Seq2Point models instead of the conventional Dense layers LSTM layers were selected in order for the neural network to learn the order of the values as well from the Conv1D encoded data.

Following are the results of Energy Disaggregation obtained from the following

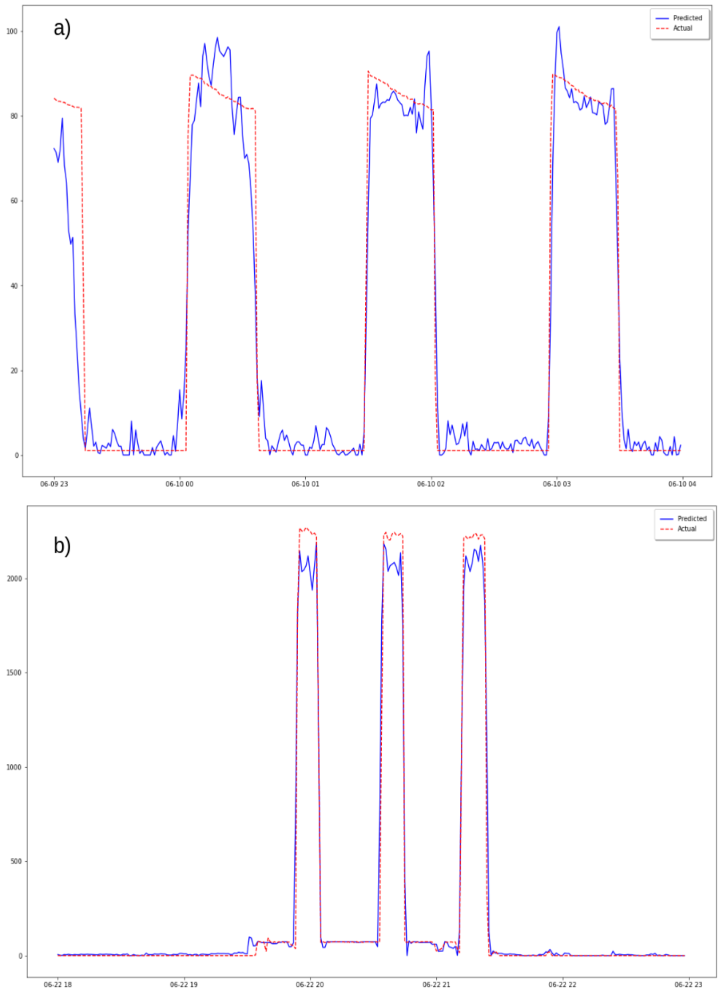


Fig -7: Changed DAE for a: fridge and b: dishwasher

a: shows the trend of predicted data by the DAE model for fridge
b: shows the trend of predicted data by the DAE model for dishwasher

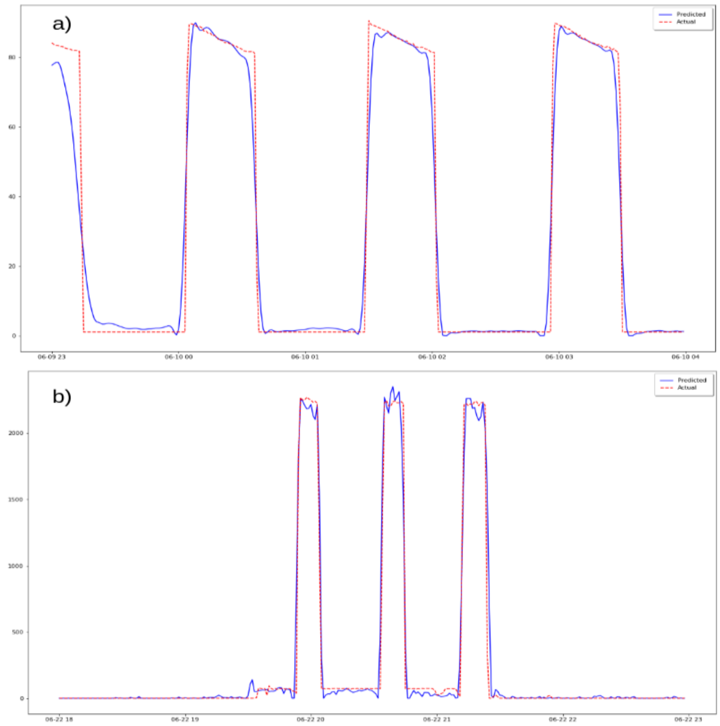
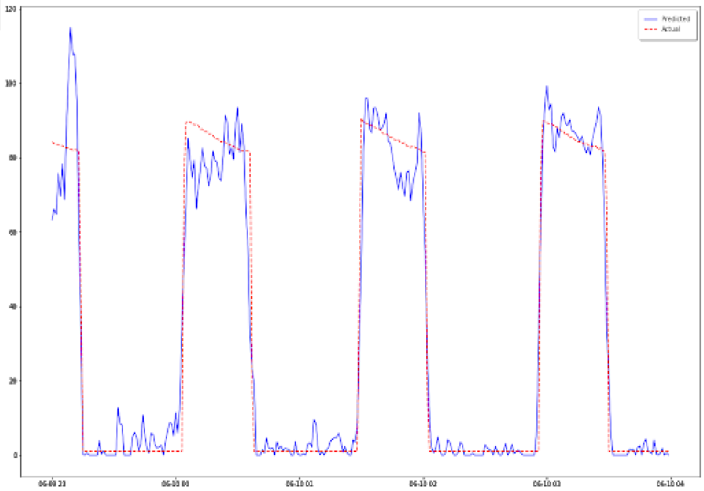


Fig -8: Changed Seq2Seq for a: fridge and b: dishwasher

a: shows the trend of predicted data by the Seq2Seq model for fridge
b: shows the trend of predicted data by the Seq2Seq model for dishwasher
For Seq2Seq and Seq2Point models instead of the conventional Dense layers LSTMlayers were selected in order for the neural network to learn the order of the valuesas well from the Conv1D encoded data.

Fig -9: Changed WindowGRU for Fridge Data



From the figures 7-10, it is clearly visible that Seq2Seq is performing good in energy disaggregation when there and overall and it can also be seen from the table values that Seq2Seq and Seq2Point are having better values and are performing better than DAE and WindowGRU. For Kettle in the House 2 of Refit Dataset Seq2Point was working a little better than Seq2Seq as shown in above figures.

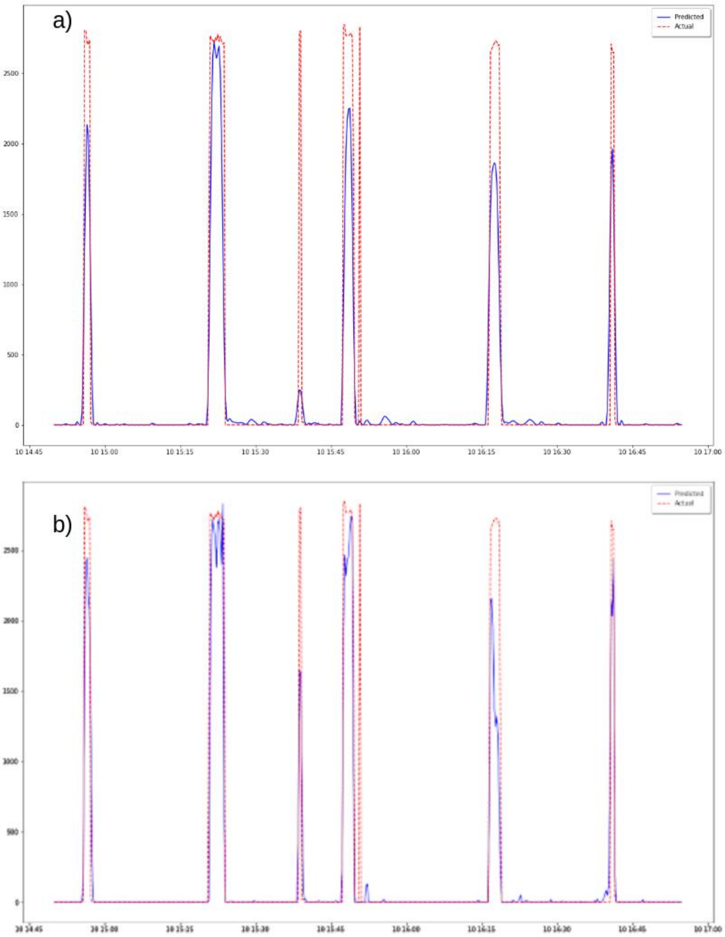


Fig -10: Changed a: Seq2Seq and b: Seq2Point for Kettle data

a: shows the trend of predicted data by the Seq2Seq model for kettle b: shows the trend of predicted data by the Seq2Point model for kettle

From the above figures and data we can say that Seq2Seq and Seq2Point performs better for performing NILM and also when combined with the proceedings of [12] it increases the accuracy of the model for each appliance to perform energy disaggregation and NILM.

3. CONCLUSION

In conclusion from the readings, data and graphs gathered at the time of research of this paper show that the Sequence2Sequence and Sequence2Point Models work better when the Dense layer are replaced with the LSTM layers then the overall accuracy of the model increases and combining current findings with the findings from [12] i.e the Efficient Sequence Length selection increases the accuracy of Se-quence2Sequence and Sequence2Point models more. To identify the patterns of appliance power data LSTM layers are more efficient then Dense layers. Thus resulting in an increased accuracy in performing energy disaggregation then DAE and WindowGRU models.

REFERENCES

[1] Ghahramani, Z., Jordan, M.I.: Factorial hidden markov models. Mach. Learn.29(2–3), 245–273 (1997).doi:10.1023/A:1007425814087

[2] Hart, G.W.: Nonintrusive appliance load monitoring. Proceedings of the IEEE80(12), 1870–1891 (1992).doi:10.1109/5.192069

[3] Batra, N., Kelly, J., Parson, O., Dutta, H., Knottenbelt, W., Rogers, A., Singh, A., Srivastava, M.: Nilmtk: An open source toolkit for non-intrusive load monitoring. In: Proceedings of the 5th International Conference on Future Energy Systems. e-Energy '14, pp. 265–276. Association for Computing Machinery, New York, NY, USA(2014). doi:10.1145/2602044.2602051. https://doi.org/10.1145/2602044.2602051

[4] Kelly, J., Knottenbelt, W.: Neural nilm: Deep neural networks applied to energy disaggregation. In: Proceedings of the 2nd ACM International Conference on Embedded Systems for Energy-Efficient Built Environments. BuildSys '15, pp. 55–64. Association for Computing Machinery, New York, NY, USA (2015). doi:10.1145/2821650.2821672. https://doi.org/10.1145/2821650.2821672

[5] Kelly, J., Knottenbelt, W.: Does disaggregated electricity feedback reduce domestic electricity consumption? A systematic review of the literature (2016). 1605.00962

[6] Zhuang, Z., Hainan, C., Luo, X.: A supervised event-based non-intrusive load monitoring for non-linear appliances. Sustainability10, 1001 (2018). doi:10.3390/su10041001

[7] Jiang, J., Kong, Q., Plumbley, M.D., Gilbert, N.: Deep learning based energy disaggregation and on/off detection of household appliances. CoRRabs/1908.00941(2019). 1908.00941

[8] Bonfigli, R., Felicetti, A., Principi, E., Fagiani, M., Squartini, S., Piazza, F.: Denoising autoencoders for non-intrusive load monitoring: Improvements and comparative evaluation. Energy and Buildings158,1461–1474 (2018). doi:10.1016/j.enbuild.2017.11.054

[9] Kolter, J.Z., Johnson, M.J.: Redd: A public data set for energy disaggregation research. In: IN SUSTKDD(2011)

[10] Zhao, B., Ye, M., Stankovic, L., Stankovic, V.: Non-intrusive load disaggregation solutions for very low-rate smart meter data. Applied Energy268, 114949 (2020). doi:10.1016/j.apenergy.2020.114949

[11] Kelly, J., Knottenbelt, W.J.: 'uk-dale': A dataset recording UK domestic appliance-level electricity demand and whole-house demand. CoRRabs/1404.0284(2014). 1404.0284

[12] Reinhardt, A., Bouchur, M.: On the impact of the sequence length on sequence-to-sequence and sequence-to-point learning for nilm. In: Proceedings of the 5th International Workshop on Non-Intrusive Load Monitoring. NILM'20, pp. 75–78. Association for Computing Machinery, New York, NY, USA (2020).doi:10.1145/3427771.3427857. https://doi.org/10.1145/3427771.3427857

BIOGRAPHIES

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