NILM based Energy Disaggregation Algorithm for Dairy Farms

Akhilesh Yadav[†]
Institute of new
Energy Systems
Technische Hochschule Ingolstadt,
Ingolstadt, Bavaria, Germany
Akhilesh.Yadav@thi.de

Anuj Sinha[†]
Institute of new
Energy Systems
Technische Hochschule Ingolstadt,
Ingolstadt, Bavaria, Germany
Anuj.Sinha@thi.de

Abdessamad Saidi
Institute of new
Energy Systems
Technische Hochschule Ingolstadt,
Ingolstadt, Bavaria, Germany
Abdessamad.Saidi@thi.de

Christoph Trinkl
Institute of new
Energy Systems
Technische Hochschule Ingolstadt,
Ingolstadt, Bavaria, Germany
Christoph.Trinkl@thi.de

Wilfried Zörner
Institute of new
Energy Systems
Technische Hochschule Ingolstadt,
Ingolstadt, Bavaria, Germany
Wilfried.Zörner@thi.de

ABSTRACT

Within the present research study, a comparative evaluation of two different approaches for the development of a deep learning-based algorithm for the targeted detection of four selected electricity appliances in dairy farms is presented and discussed. Via a multi-layer deep neural network based on the sequence-to-sequence (S2S) methodology, the algorithm allows to identify the state of the appliances according to the device-specific power signature by reading the daily load profile for the total power consumption. According to preliminary results, the multi-layer One-Directional Convolution Layer-Bidirectional GRU Recurrent Neural Network (1DConv-BRNN) model showed better performance, compared to a Long Short-Term Memory (LSTM)-based deep neural networks.

CCS CONCEPTS

• Computing methodologies ~ Artificial intelligence • Pattern recognition

KEYWORDS

NILM, Energy disaggregation, Smart meter, Dairy farms, Deep neural networks.

ACM Reference format:

Akhilesh Yadav, Anuj Sinha, Abdessamad Saidi, Christoph Trinkl and Wilfried Zörner. 2020. NILM based Energy Disaggregation Algorithm for Dairy Farms. In *The 5th International Workshop on Non-Intrusive Load Monitoring (NILM '20), November 18, 2020, Virtual Event, Japan*. ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3427771.3427846

NILM '20, November 18, 2020, Virtual Event, Japan

ACM ISBN 978-1-4503-8191-8/20/11…$15.00
https://doi.org/10.1145/3427771.3427846

1 INTRODUCTION

The steadily advancing transformation of the German energy system from conventional and centralized power generation to an increased share of decentralized renewable power plants presents considerable challenges in the nationwide electricity grid. To ensure grid stability and security of energy supply despite growing capacities of fluctuating power suppliers such as wind turbines and photovoltaics, smart grid solutions represent a promising approach. For the required intelligent interaction between grid operators, energy suppliers, and consumers, a digital infrastructure and energy

suppliers, and consumers, a digital infrastructure and transparency of the power generation and consumption is necessary. With the introduction of the 'Digitization of the Energy Turnaround Act' in 2016 [1], the research and development activities in Germany in the field of smart meters as the central component for the communication infrastructure have increased significantly [2,3]. The extensive research on Non-Intrusive Load Monitoring (NILM) in Germany is a reflection of the resulting nationwide rollout of smart meters [4]. However, the energy sector is still waiting for rigorous, reliable and robust algorithm for energy disaggregation.

Previous studies have shown that a considerable amount of work has been carried out for residential buildings, while there is a growing appeal for the development of energy disaggregation for industrial buildings [5]. However, the agricultural sector has not yet been given enough consideration. Since, rural areas in Germany, which are characterized by highly heterogeneous renewable power supply structures, are particularly affected by the issue of power grid overload, smart energy management solutions in agriculture can play a major role for a comprehensive promotion of sustainable energy supply.

In this context dairy farms as an energy intensive category of agriculture show a high potential for power grid-oriented demand-side management in addition to benefits such as a comprehensive energy monitoring and the identification of energy savings potentials. The milking system as the major consumer in dairy farming with an average share of 60% in total electricity consumption is focused in the present study (Figure 1).

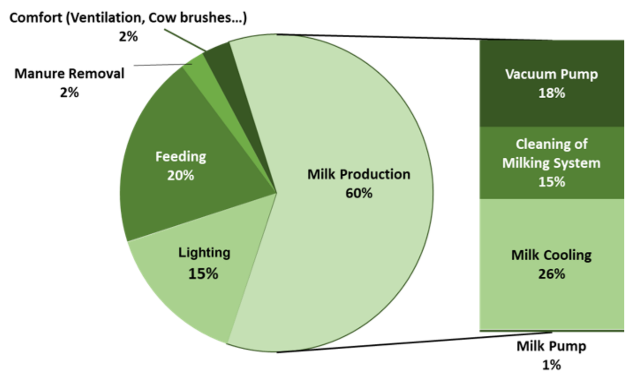

Figure 1: Composition of electricity consumption in dairy farming [6]

Besides monitoring and benchmarking energy disaggregation provides different application fields in the context of demand side management load shifting representing a base for promising technological innovations and business models for the agricultural sector. Based on the algorithm a comprehensive On-farm energy management system considering decentralized renewable energy supplier and the local demand of the power grid can provide significant energy efficiency improvements and additional revenue streams for local farmers. Furthermore, the intelligent system allows a sufficient load management for future developments such an increased demand of electrical capacities for e-mobility.

For the initial development of the NILM-based algorithm, the electricity consumption of the vacuum pump and milk cooling as the main components of the milking system are measured on two dairy farms in Bavaria/Germany is measured for seven fully operational days. Figure 2 clearly shows that milk cooler and vacuum pump have dominant electrical consumption in a dairy farm and therefore these two devices has been considered for disaggregation for initial phase of this project. Furthermore, the monitoring database for the training of the neural network includes the total load profiles for these days, provided by the farmers. The overarching objective of the present algorithm development is to detect the operating times of these individual consumers based on the daily total load profile as input data.

Various machine learning-based approaches have been developed in the recent years and decades, use of Deep Neural Networks (DNN) is reported to be a promising approach [5]. Among the available DNN methods, S2S-based DNN learning has been selected within a pre-study according to the specific requirements and characteristics of the present application field [7-11]. S2S refers to training the model with continuous input sequence of mains reading and getting continuous sequence output of individual appliance reading (which is exactly the case in our work). The presented model in this article, 1DCNN-BRNN and LSTM, are evaluated through the S2S approach.

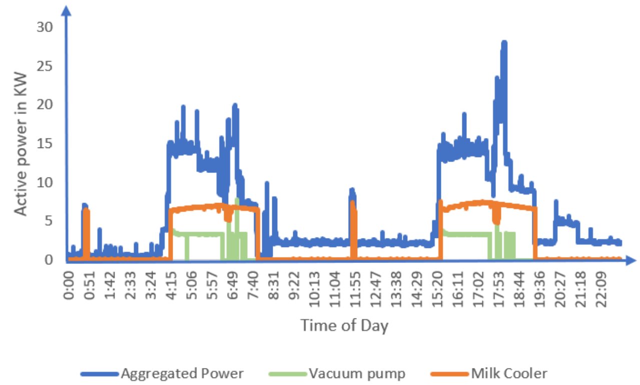

Figure 2: Aggregated active power against power consumption of milk cooler and vacuum pump used in a dairy farm

2 DATA COLLECTION AND PRE-PROCESSING

Deep Learning is a set of techniques, which requires a tremendous amount of historical data to train the model for future prediction. For the current study, two dairy farms are selected for data acquisition. Smart meters were already installed on the premises of both farms to measure and transmit the aggregated power data. To get individual appliance data, four power measuring devices were installed on selected appliances to measure the active power, reactive power, and power factor. However, only the active power was used for training in this work. The acquired data were recorded on 0.5 Hz frequency, i.e. one measurement after two seconds.

Around 85% of the generated dataset are used for training and validation of the algorithm. The validation split is kept at 20%. while the remaining 15%, representing one of the seven testing days, are used for the testing of the model.

Numerous studies revealed that normalizing the data speeds up the learning process by leading to faster convergence of the model [12]. For the present study, the Python solver ‘MinMaxScaler’ from the ‘Sklearn’ library was used to normalize the aggregated and individual appliance power data between 0 and 1.

3 EXPERIMENTAL EVALUATION

For the implementation of the model keras 2.3.1 with backend of tensorflow 2.3.0 is used. A tabular demonstration of the 1DConv-BRNN model and LSTM model is shown in Figure 3. The multi-layer 1DConv-BRNN model consists of the nine following layers:

1. Initial parameter: The size of the input sample is 648, the window size is kept as 512 while the batch size used in the experiment was 128.
2. The input layer is 1D convolution with 8 neurons, 5x5 filter

size, stride as 1. Different experiments have revealed that the convolution layer as input layer improves the results.

3. The first hidden layer is again a 1D convolution layer with 8 neurons and 7x7 filter size. This layer further is for the training of low-level features.
4. The second hidden layer is Maxpooling1D with the pool size 4 and stride as 2. This layer improves the selective sensitivity for important features of the data.
5. The third hidden layer is the Bidirectional GRU with 32 neurons followed by a dropout layer with a dropping rate of 0.5 to restrict the model from overfitting.
6. Another Bidirectional GRU and dropout layer are added, subsequently with 64 neurons and a dropping rate of 0.5, respectively.
7. The eighth layer is a fully connected dense layer with 12 neurons and 'tanh' activation function.
8. The output layer is a dense layer with 1 neuron and linear activation function, as the output of the model can be either 1 or 0.

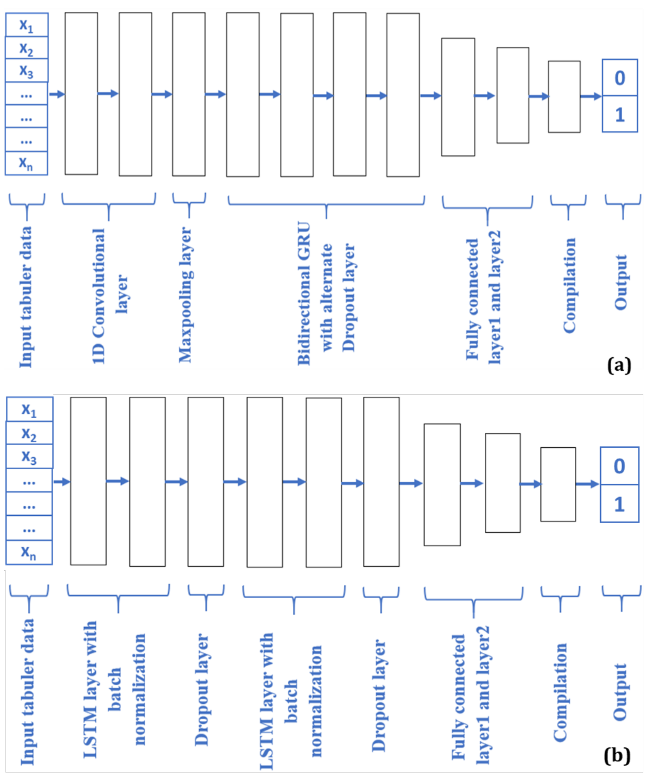

Figure 3: Tabular demonstration of (a) 1DConv-BRNN and (b) LSTM deep neural model

The LSTM-based model consists totally of six layers with the following parameters:

1. Initial parameter: The size of the input sample is again 648, the window size is kept as 512 while the batch size is 128.
2. The input layer is LSTM having 64 neurons with Batch Normalization followed by drop out layer with a dropping rate of 0.5.
3. The next two hidden layers (third and fourth layers) are again the LSTM layer with 32 neurons and dropout layer as stated above.
4. The fifth layer is a fully connected dense layer with 12 neurons and 'tanh' activation function
5. The output layer is a dense layer with 1 neuron and a linear activation function, as the output of the model can be either 1 or 0.

Both models are compiled with an ADAM optimization algorithm and a binary cross entropy loss function.

4 RESULTS AND DISCUSSION

The experiment, as stated above, was carried out on 13 different models out of which the two best performing models are compared in this section. The metrics used for comparison is as follow:

Precision: $$\frac{TP}{TP+FP} \tag{2}$$

Recall: $$\frac{TP}{TP+FN} \tag{3}$$

F1 Score: $$\frac{(2\ X\ Recall\ X\ Precision)}{(Recall+Precision)} \tag{4}$$

with[12],

TP	True Positive	Number of correctly labelled positive samples.
FP	False Positive	Number of negative samples incorrectly labelled as positive.
FN	True Negative	Number of correctly labelled negative samples.
FN	False Negative	Number of positive samples incorrectly labelled as negative.

On comparing the F1 score for both LSTM and 1DConv-BRNN model, it was found that the later performed better for the milk cooling device as well as the vacuum pump, as shown in Figure 4.

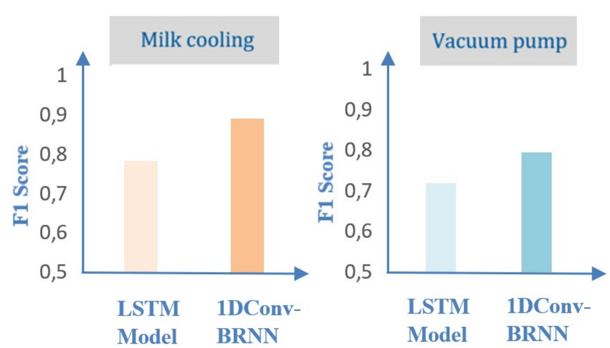

Figure 4: Comparison of F1 Score

The superiority of 1DConv-BRNN was further examined by a precision value of 0.86 & 0.69, for milk cooler and vacuum pump respectively, against 0.81 & 0.56 for the LSTM-based neural network. The graphical representation of predicted output for both models is depicts in Figure 5. The graph clearly depict that 1DConv-BRNN model reponds well to the testing data. However, it should be noted that the model was only tested on a random day of a known farm. Because of unavailability of authentic data, the model could not be tested on unknown farms which makes these promising results permilinary. Furthermore, the model did not learn the features of the milk pump, probably because the pump was only used for few minutes during the day, rest of the time it was off and therefore the active power values available in dataset were too less for pattern recognization. For similar reasons, the automatic cleaning machine was also not properly trained on the models and, hence, not discussed here.

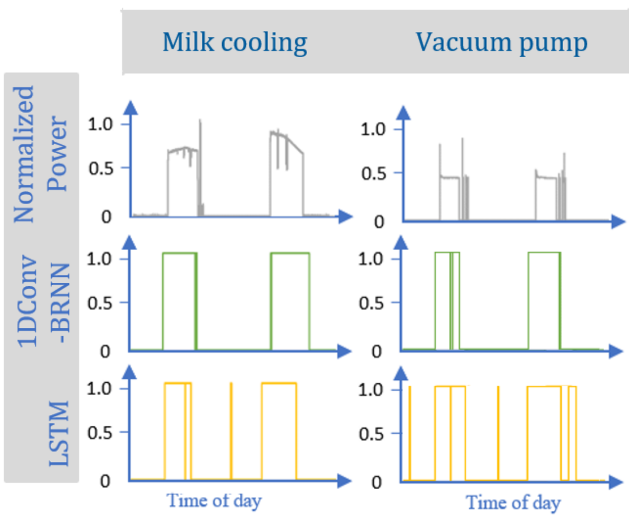

Figure 5: Predicted output for both models

5 CONCLUSIONS AND OUTLOOK

The present research work represents a pre-study to identify promising S2S-based deep neural network modelling approaches in the context of the application for the disaggregation of energy data on dairy farms. The results reveal general tendencies regarding the advantages and disadvantages of the two methods with the highest potential according to the current state of the study. However, these encouraging results must be considered preliminary due to the following limitations:

1. The model is merely trained with consumption data of two farms and was tested on one of those farms.
2. The studies are actually limited to two consumers on a dairy farm.
3. Only the active power is actually considered as a feature for the data disaggregation.

These limitations indicate the upcoming tasks to improve and complement the NILM-based algorithm to ensure a reliable disaggregation of the energy data on dairy farms as a sufficient base for commercial applications. In general, the high accuracy accomplished with the low data set reveal the high potential for future applications.

ACKNOWLEDGEMENTS

This research project is carried out in cooperation with Maschinenringe Deutschland GmbH, intending to develop smart meters particularly dedicated to the application in the agricultural sector. We would like to thank our partner and furthermore are grateful to the farmers for providing the electricity consumption data.

REFERENCES

[1] Michael Kelly. 2018. Germany moving ahead with smart meter rollout plans (2018). Retrieved May 20, 2020 from https://www.smart-energy.com/magazine-article/germany-moving-ahead-smart-meter-rollout-plans/.

[2] Bundesministeriums für Wirtschaft und Energie. 2018. Barometer Digitalisierung der Energiewende (2018). Ein neues Denken und Handeln für die Digitalisierung der Energiewende. Bundesministeriums für Wirtschaft und Energie.

[3] Padraig Scully. 2019. Smart Meter Market Report 2019-2024. IOT Analytics.

[4] Oliver Parson, Grant Fisher, April Hersey, Nipun Batra, Jack Kelly, Amarjeet Singh, William Knottenbelt, and Alex Rogers. 2015. Dataport and NILMTK: A building data set designed for non-intrusive load monitoring. *IEEE Global Conference on Signal and Information Processing (GlobalSIP)*. IEEE, 210–214. DOI: https://doi.org/10.1109/GlobalSIP.2015.7418187.

[5] Jack Daniel Kelly. 2017. *Disaggregation of Domestic Smart Meter Energy Data*. Ph.D. Dissertation. University of London, University of London Imperial College of Science, Technology and Medicine Department of Computing.

[6] Dr. Stefan. Neser, Josef Neiber, Josef Niedermeier, Manfred Götz, Ludwig Kraus, and Prof. K.-H. Pettinger. 2014. Energieverbrauch im Milchviehbetrieb - Effizienz und Einsparpotential. Retrieved August 22, 2020 from https://www.lfl.bayern.de/publikationen/informationen/065687/index.php.

[7] Kunjin Chen, Qin Wang, Ziyu He, Kunlong Chen, Jun Hu, and Jinliang He. 2018. Convolutional sequence to sequence non-intrusive load monitoring. *In the Journal of Engineering*, 17, 1860–1864. DOI: https://doi.org/10.1049/joe.2018.8352.

[8] Maria Kaselimi, Eftychios Protopapadakis, Athanasios Voulodimos, Nikolaos Doulamis, and Anastasios Doulamis. 2019. Multi-Channel Recurrent Convolutional Neural Networks for Energy Disaggregation. *In IEEE Access 7*, 81047–81056. DOI: https://doi.org/10.1109/ACCESS.2019.2923742.

[9] Jack Kelly and William Knottenbelt. 2015. 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)*. Association for Computing Machinery, New York, NY, USA, 55–64. DOI: https://doi.org/10.1145/2821650.2821672

[10] Jack Kelly and William Knottenbelt. 2015. The UK-DALE dataset, domestic appliance-level electricity demand and whole-house demand from five UK homes. *In Scientific data 2*, 150007 (2015). DOI: https://doi.org/10.1038/sdata.2015.7.

[11] Pedro P. M. d. Nascimento, 2016. Applications of deep learning techniques on NILM. M.Sc. UFRJ: Universidade Federal do Rio de Janeiro, Brazil.

[12] Max A. Bramer, 2007. Principles of Data Mining. Springer, London.