A Microgrid Energy Management System Based on Non-Intrusive Load Monitoring via Multitask Learning

Çimen, Halil; Çetinkaya, Nurettin; Vasquez, Juan C.; Guerrero, Josep M.

Published in:
IEEE Transactions on Smart Grid

DOI (link to publication from Publisher):
10.1109/TSG.2020.3027491

Publication date:
2021

Document Version
Accepted author manuscript, peer reviewed version

A Microgrid Energy Management System based on Non-Intrusive Load Monitoring via Multitask Learning

Halil Çimen, Nurettin Çetinkaya, Juan C. Vasquez, *Senior Member, IEEE*, and Josep M. Guerrero, *Fellow, IEEE*

***Abstract*-- Non-intrusive load monitoring (NILM) enables to understand the appliance-level behavior of the consumers by using only smart meter data, and it mitigates the requirements such as high-cost sensors, maintenance/update and provides a cost-effective solution. This paper presents an efficient NILM-based energy management system (EMS) for residential microgrids. Firstly, smart meter data are analyzed with a multi-task deep neural network-based approach and the appliance-level information of the consumers is extracted. Both consumption and operating status of the appliances are obtained. Afterward, the energy consumption behaviors of the end-users are analyzed using these data. Accordingly, average power consumption, operation cycles, preferred usage periods, and daily usage frequency of the appliances were obtained with an average accuracy of more than 90%. The obtained results were integrated into an EMS to create an efficient and user-centered microgrid operation. The developed model not only provided the optimum dispatch of distributed generation plants in the microgrid but also scheduled the controllable loads taking into account customers' satisfaction. It was demonstrated with the help of simulation that the proposed NILM-based EMS model improves the operation cost/customer satisfaction ratio between 45% and 65% compared to a traditional EMS.**

***Index Terms*—Non-intrusive load monitoring, microgrid, energy management, recurrent neural network, deep learning**

I. Introduction

In the energy sector, a transition from traditional fossil-based generation to clean and energy-efficient generation has already begun. Undoubtedly, the fundamental basis of this transition is the digitalization of the energy sector, which provides many benefits for both utility and consumers. As a result of digitalization, more active players will be participating in the electricity market and a large amount of data will soon be available in the energy sector [1]. One of the data generators is smart meter, whose deployments represent the first step into digitalization solutions for many utilities. Smart meters may have meaningful information about the consumption behavior of end-users. These data could be a treasure for operation and management of the grid only if they are processed and evaluated carefully using robust techniques.

Non-Intrusive Load Monitoring (NILM) is the process of disaggregating the electricity consumption data of end-users measured by a smart meter into its appliance-level components using various signal processing or pattern recognition methods. NILM makes it possible to monitor each individual load and extract their energy consumption without using any sensor or intervention in the home, only using smart meter data. It has been shown in [2] that providing appliance-level energy consumption feedback to consumers can save up to 20% of energy per dwelling. NILM also contributes to energy suppliers have a deeper insight into their customers' consumption behavior and provides them the opportunity to improve customer satisfaction. As a result, both suppliers and end-users can benefit from the meaningful information provided by NILM. Load monitoring can be also realized using a different approach called Intrusive Load Monitoring (ILM), which monitors each individual load with the help of a separate sensor. This is a costly concept due to the necessity of using many sensors, collecting the data read from sensors in a data center, maintaining and updating all these components. Besides, users can be conservative in sharing their data. NILM is a cost-effective technique proposed as an alternative to ILM since it uses only one sensor, requires fewer updates, and is less intrusive in data privacy.

Although the first study on NILM was conducted in 1992 [3], research has progressed slowly as access to data is difficult. However, with the widespread use of smart meters, acceleration of smart home and energy efficiency studies, NILM is gaining more attention. Although the first study yielded successful results for two-state appliances, which have simple on/off states and are called Type-I (kettle, toaster, etc.), it was insufficient for multi-state appliances, which have multiple states and are called Type-II (dishwasher, washing machine, etc.). Hidden Markov Model (HMM) is a frequently preferred method to improve the results since it enables the modeling of appliance states individually. In [4], 4 different HMM models, which are Factorial HMM (FHMM), Conditional FHMM, Factorial Hidden semi-Markov Model,

This work was supported by The Scientific and Technological Research Council of Turkey (TUBITAK) BIDEB-2214 International Doctoral Research Fellowship Programme, VILLUM FONDEN under the VILLUM Investigator Grant (no. 25920): Center for Research on Microgrids (CROM); www.crom.et.aau.dk and the AAU Talent Project-The Energy Internet-Integrating Internet of Things into the Smart Grid (771116).

H. Çimen and N. Çetinkaya are with the Department of Electrical-Electronics Engineering, Konya Technical University, Konya, Turkey (e-mail: hcimen@ktun.edu.tr, ncetinkaya@ktun.edu.tr).

J. C. Vasquez and J. M. Guerrero are with the Institute of Energy Technology, Aalborg University, Aalborg, Denmark (e-mail: juq@et.aau.dk, joz@et.aau.dk)

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2020.3027491, IEEE Transactions on Smart Grid

and Conditional Factorial Hidden semi-Markov Model, are trained with unsupervised approach. In [5], changes between steady-states are used as the observed sequence, without using a priori knowledge of appliances. These models work well for simple devices but less well for complex appliances. A hierarchical HMM is proposed in [6] using a dynamic bayesian network to model the appliances and it outperforms conventional HMM. Although some robust HMM variants can yield successful results, their biggest disadvantage is their computational complexity, which increases exponentially with the number of appliances [7]. Also, each appliance needs to be modeled in detail for a typical HMM and this is a time-consuming process, which limits its practical use.

In order to overcome these bottlenecks, Deep Neural Network (DNN) has been started to be implemented in the NILM field due to its outstanding achievements in image classification [8]. Since DNN can automatically extract features, it can learn from raw data and minimize the complexity of the problem [9]. In [10], the authors present 3 different DNN models for energy estimation. The study reports that all 3 models outperform HMM-based studies for each analyzed appliance. Afterward, studies focused on improving the results using different kinds of DNN. A sequence-to-point approach based on Convolutional Neural Network (CNN) is presented in [11]. While this model takes a sequence as the input, it estimates one sample at the output. Therefore, its computational burden is high. In [12], the authors proposed a sequence-to-sequence CNN model to reduce the computational burden. It has been reported that the proposed model yield more reliable results even for low power devices. In [13], the authors proposed a two-level neural network based on CNN in order to improve accuracy. The first network filters signatures of the target appliance. The output of the first network is augmented with synthetic data and tested with the second network. A CNN model inspired by Wavenet [14], which is developed for raw audio generation, is adopted for energy disaggregation in [15]. Since Wavenet is designed for long sequences, it can be a suitable model for devices with long operating times. In [16], a sub-network for load identification is combined with the energy estimation network. This sub-network improved NILM performance by reducing the estimation error. Apart from trying to improve disaggregation performance using only different methods, results can be further improved by post-processing, which tries to refine outputs of DNN. In [17] an optimization-based and in [18] CNN-based post-processing approaches are proposed. It has been reported that this process significantly increases NILM performance. When the aforementioned studies are examined, it is seen that they heavily focus on estimating only the energy consumption of appliances. Besides, there is not sufficient analysis on which area and for what purpose the obtained results can be used.

In this paper, a NILM-based EMS integrated into a residential microgrid is proposed. Home EMS is a well-known topic and has already been implemented through smart home architecture, which is generally equipped with smart appliances, smart plugs, a home gateway, a communication infrastructure, sensors to follow temperature and weather information, and a control center. However, the cost of these types of equipment limits the applicability of this system. Besides, the use of many components increases system complexity and requires maintenance/update at certain intervals. In order to decrease complexity, maintenance, and update requirements, NILM can be integrated into EMS for residential consumers. The main advantage to combine NILM with EMS is to take action following DR signals, real-time electricity prices and take advantage of incentives. It is almost impossible for residential consumers to manually control their home appliances and respond to DR signals by monitoring variable electricity prices. Consumers who are willing to change their energy consumption behavior are either elderly or energy-efficient people [2]. Other consumers are either not available or do not know how to appropriately react to DR signals. Therefore, the success of DR can only be achieved with full automation. For the design and implementation of an automated DR strategy for different households, the lifestyles of each consumer should be taken into accounts since the lifestyles of an artist and a student are completely different. Besides, energy management should be provided either with minimum user intervention or without. Using NILM, the life habits and consumption behaviors of each customer can be monitored and learned precisely and cost-effectively. Therefore, by making "consumer-specific" optimization, the energy cost can be reduced more as well as consumer comfort can be maximized. The automated and consumer-specific EMS makes it easier for end-users to participate in DR and get more incentives based on their consumption behaviors with less user intervention. However, there are only a few studies in the literature addressing this issue. The software and hardware infrastructure required to integrate the NILM technique into the Demand Response (DR) is summarized in [19]. If NILM is desired to be used for the DR or EMS, the appliances must be controlled using remotely controllable switches, which can lead to thinking that these switches can also record the status and energy consumption of appliances. Advanced smart switches can achieve this, but their costs are relatively high. Instead, cost-effective simple switches that provide only control (on/off) can be used. In [20], the authors proposed a NILM-based home EMS using the k-nearest neighbor method and genetic algorithm. The proposed NILM requires hand-engineering such as feature extraction and data reduction, which is a time-consuming process. However, it has been proven that DNN can achieve more successful results than machine learning approaches as it can automatically extract hierarchical features [8]. In this paper, a DNN-based approach is proposed to design an effective EMS. The main contributions of this paper are:

- A multi-task DNN-based NILM model capable of analyzing both energy estimation and load status detection is proposed.
- A detailed framework of how to use the NILM results within EMS for residential customers is proposed.
- Developed NILM-based EMS is integrated into a residential microgrid and its effectiveness has been

tested.

II. Deep Neural Network-Based NILM Analysis

NILM is the process of analyzing aggregated data, which is the energy consumed by the whole dwelling, by various optimization, signal processing or learning methods, and obtaining appliance-level information. A vector shown the aggregated power consumption read from the smart meter for T samples can be expressed $P_{agg} = \{p_{agg}(1), p_{agg}(2), ..., p_{agg}(T)\}$. The instantaneous power consumption vector of appliance n can be expressed $P_n = \{p_n(1), p_n(2), ..., p_n(T)\}$. For each sample, aggregated power consumption is assumed to be equal to the sum of the power consumed by all active devices and measurement error as follows:

$$p_{agg}(t) = \sum_{n \in N} s_n(t) \cdot p_n(t) + e(t) \tag{1}$$

where N is the number of appliances and e is the measurement error. s_n is the status (on-off) of appliance n and it is determined according to a threshold. If the energy consumption is bigger than the threshold, it's assumed that the appliance is on. Following a successful NILM analysis, actively operating appliances can be identified, their status changes (on-off), and energy consumption values can be estimated. Using these data, many different benefits such as DR, short-term load forecasting, safety, and Home EMS can be achieved. An illustration of NILM is shown in Fig. 1.

DNN has begun to gain great interest in the academic community following outstanding achievements in areas such as image classification and speech recognition [8, 21]. Due to its robust learning capacity, it can provide great convenience in the field of NILM. Because it allows computers to automatically learn from smart meter data and understand appliance-specific energy consumption in terms of a hierarchy of features. Considering that the number and variety of appliances used in dwellings are very high, automatic feature extraction can both eliminate the time-consuming hand-designed feature extraction process and obtain high-level features that will increase NILM performance.

There are different types of neural network models designed for different purposes. Since NILM is basically based on a time series analysis, the most suitable model is the Recurrent Neural Network (RNN) model, which has the ability to analyze time-series thanks to its memory-based architecture. Considering time-series, current and future data are directly linked to past data. The reason why RNN architecture is called recurrent is that it analyzes each item based on previous outputs. This feature of RNN is very important for NILM because the energy consumption of the appliances is dynamic and can change constantly. These changes are the signature of the appliance. By following these changes, RNN layers can understand which signal belongs to which appliance. The biggest problem of RNN is that as the sequence data gets longer, the learning capacity is weakened [22]. More robust RNN methods such as Long-Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) have been proposed to mitigate this problem.

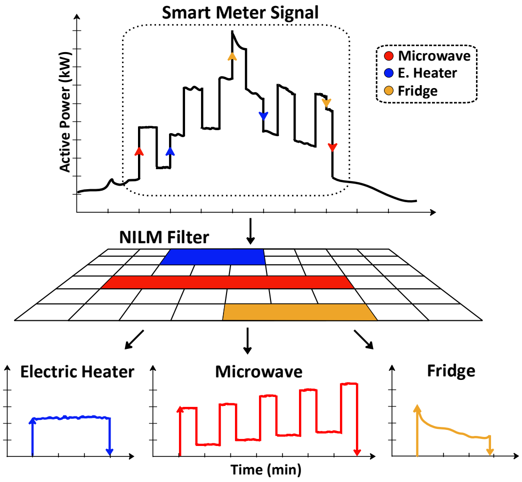

Fig. 1. An illustration of NILM

Comparing LSTM, the input and forget gates are combined to form a single gate called "update gate" in GRU. In addition to that, instead of a cell state, only the hidden state is used. As a result of reducing gates and states, the number of system parameters decreases and the model can give faster results [23]. The calculation of gate outputs and parameters is shown below:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{2}$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{3}$$

$$\tilde{h}_t = \tanh(W \cdot [r_t \cdot h_{t-1}, x_t]) \tag{4}$$

$$h_t = (1 - z_t) \cdot h_{t-1} + z_t \cdot \tilde{h}_t \tag{5}$$

where x_t is the input, z_t is the update gate determining how much of the past data will be remembered, r_t is the reset gate determining the data to be forgotten, $\tilde{h}_t$ is the candidate memory cell storing the candidate past data and h_t is the main memory cell storing the past data to be passed along to the future. W and σ are weights and sigmoid activation function, respectively. In order to improve GRU performance, it can be used with bidirectional layers, which make it possible to analyze the time-series forwards and backward. Before the GRU layer, a 1D convolutional layer can be used to extract the temporal information from raw data, which can increase the model performance.

In this paper, a multi-task GRU (M-GRU) model is proposed. Unlike the studies in the literature which are generally focused on only energy disaggregation or load status detection, this network performs both tasks at the same time. The general architecture of the proposed model is shown in Fig. 2.

Machine learning algorithms are generally optimized for one task by evaluating a single loss function. However, if there are multiple tasks related to each other, we can train the model by optimizing multiple loss functions, which is called

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2020.3027491, IEEE Transactions on Smart Grid

Multi-task learning (MTL) [24]. These tasks can be different tasks such as regression, classification, or reinforcement learning tasks. When there are multiple related tasks, learning together these tasks can lead to performance improvement compared to single-task learning [25]. MTL aims to learn common features between different tasks by sharing knowledge. Energy disaggregation and load status detection are two strongly related tasks. Therefore, sharing the training parameters between them can help increase the NILM performance.

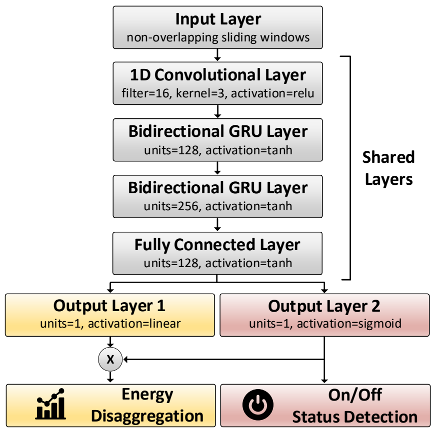

Fig. 2. The multi-task GRU model

Both network architectures are trained with the same inputs using supervised learning. Since we have long-term (over the months) data for training, the inputs should be split using the sliding windows. The splitting process is made as non-overlapping windows since using overlapping windows does not affect the results much [10]. Assuming that the selected window size is w, input data is split as $P_{agg}(t:t+w-1)$. After the input layer, the network is trained using the shared layers until the output layers, which technique is called hard parameter sharing. It's the most commonly used technique for multi-task learning to reduce overfitting risk with fewer parameters [24]. Hyperparameters used in shared layers are taken from [10] due to the promising results obtained. After shared layers, there are two outputs for two different tasks. The output windows corresponding to the input window should be $P_n(t:t+w-1)$ for energy disaggregation, and $s_n(t:t+w-1)$ for status detection output, which are obtained with sub-metering of target appliances. The purpose of the first output is to estimate the energy consumption of the appliances. In this way, it is possible to determine the load patterns and average energy consumption of them. However, in order to design an effective EMS, only energy consumption profile is not enough. Operational information of appliances such as operation time interval during the day, operation duration, and frequency of use should also be known. Although energy disaggregation may give information about them, it might be insufficient due to the highly noisy estimation results, which leads to an incorrect analysis of consumers' behavior. To achieve more accurate results, a second output is used for load status detection. Its main purpose is to detect periods when the target appliance is on. As status detection is an easier task than energy disaggregation, this network tends to yield more successful results, which helps to obtain average operational information of the appliances. Besides, this network has another noteworthy benefit. The energy disaggregation output tends to make noisy estimations for the periods during which the appliance is not active. However, the status detection output gives "0" when the device is off. Therefore, as a result of the product of these two outputs, noisy predictions can be eliminated. In this way, energy disaggregation results can be improved. The linear and sigmoid activation functions are used at the output of energy disaggregation and status detection networks, respectively. The mean squared error loss is selected for energy disaggregation, while binary cross-entropy loss is selected at the output of status detection. The loss values are calculated as follows:

$$L_{ED} = \frac{1}{T}\sum_{t\in T}\left(p_n(t) - \hat{p}_n(t)\right)^2 \tag{6}$$

$$L_{SD} = \sum_{t\in T} -[s_n(t)\cdot \log \hat{s}_n(t) + (1-s_n(t)\log(1-\hat{s}_n(t)))] \tag{7}$$

where $\hat{p}_n$ and $\hat{s}_n$ are outputs of the energy disaggregation, which is estimated power in watts, and the output of status detection, which is a probability that the appliance is "on", respectively. In the proposed network, we assume that the appliance is on for probabilities above 0.5.

For the MTL approach, task-specific loss functions are summed by multiplying them with a weighting factor, and models were trained with a single total loss function [26,27]. In our study, the M-GRU model was trained using a total loss as formulated below:

$$L_{total} = \alpha L_{ED} + (1-\alpha) L_{SD} \tag{8}$$

where α is the weighting factor using for regularizing the scale of the losses.

III. Energy Management In Residential Microgrids

A residential microgrid is a small scale grid including some distributed generation units, energy storage system (ESS) systems, and one or more dwellings. Thanks to its flexible structure, it can be operated both in grid-connected or islanding mode to provide reliable energy to homeowners. A block diagram of the proposed residential microgrid is shown in Fig. 3. On the generation side, the energy sources include the utility grid, a small Photovoltaic (PV) power plant, a Wind Turbine (WT), and an ESS unit, while schedulable and controllable appliances serve as active participants on the demand side.

In order to operate the proposed microgrid optimally, an efficient EMS is required. It manages the operation of domestic appliances in coordination with the renewables, batteries, operational constraints, and microgrid central

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2020.3027491, IEEE Transactions on Smart Grid

controller. Besides, EMS must be capable of transmitting the necessary reference signals to distributed power plants and dwellings to achieve optimal operation. In the proposed microgrid, the utility grid is modeled as an infinite power source that supports the voltage regulation and system frequency of the ac bus, PV/WT are exploited as non-dispatchable renewable energy sources operating with maximum power point tracking, while the ESS unit is modeled as a dispatchable source, which adjusts its output according to reference signals received from EMS.

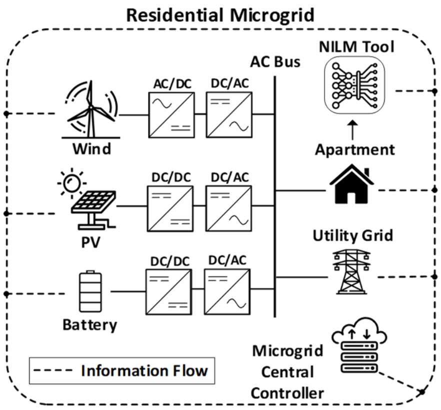

Fig. 3. Residential microgrid structure

Optimum energy management and power control problem in residential microgrid systems can be formulated as mixed-integer programming, taking into account the various objectives and technical constraints described below.

A. Mathematical Model of the Proposed System

Two different objective functions are taken into account for the comfort level of the customers and minimum operation cost. The first objective function, Operation Cost (OC) is minimized in order to reduce the operating cost of the microgrid, and the second one, Comfort Level (CL) deals with the user's comfort level maximization, which are expressed as follows:

$$Min\left\{OC = \sum_{h\in H} RTP(h)\cdot P_{grid}(h)\right\} \tag{9}$$

$$Max\left\{CL = \sum_{h\in H}\sum_{n\in N} \xi\cdot SD_n(h)\right\} \tag{10}$$

where *RTP* is the real-time pricing for electricity consumption, P_{grid} is the power exchanged with the utility grid at a given time *h*, ξ is a penalty factor to adjust consumers' satisfaction degree and *SD* is the satisfaction degree of the consumers, which are determined according to Fig. 4.

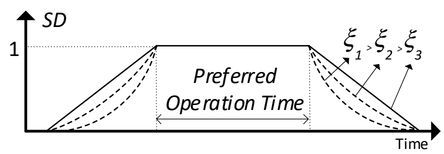

Fig. 4. Satisfaction degree of consumers

SD is directly dependent on the operation time of appliances. If it operates within the preferred period, 1 is assigned as the maximum level, otherwise, *SD* will decrease as it moves away from the preferred period. The distribution pattern of SD can be adjusted by the penalty factor ξ. Depending on the design purpose, one of the penalty factors seen in Fig. 4 can be selected. In our study, the linear curve (ξ_3) is used for the optimization process. Following the aforementioned descriptions, a hybrid objective function (*HOF*) similar to the price-performance ratio can be formulated as follows:

$$Min\left\{HOF = {}^{OC}\!/_{CL}\right\} \tag{11}$$

which is optimized subjected to some constraints. First of all, the energy balance inside microgrid must be fulfilled:

$$P_{grid}(h) + \sum_{i\in NG} P_{G,i}(h) = P_{load}(h) \tag{12}$$

where, P_{load} and *NG* are the power demand and the number of generators, respectively. $P_{G,i}$ is the output power of generator *i* and should be arranged between upper and lower limits as follows:

$$P_{G,i}^{\min} \le P_{G,i} \le P_{G,i}^{\max} \tag{13}$$

In a competitive energy market, power outages and uncertain generation of renewable energy sources are two major disadvantages. For residential applications, ESS can provide reliable energy during a blackout or store excessive energy generated by renewables. An ESS is operated according to certain constraints, and the first one is the State-of-Charge (SoC), which is formulated as (14). ESS should be operated within certain upper and lower SoC limits in order to have a longer lifetime as shown in (15). Similarly, there are certain limits for charging and discharging power for each ESS unit, which are shown in (16-17).

$$SoC(h+1) = SoC(h) + \left\{((P_{bat}^{ch}(h) - P_{bat}^{dch}(h))\cdot \Delta h_{step}) / E_{bat}\right\} \tag{14}$$

$$SoC_{\min} \le SoC(h) \le SoC_{\max} \tag{15}$$

$$P_{bat}^{ch}(h) \le P_{ch,\max}\cdot \eta_{ch}\cdot u_{bat}(h) \tag{16}$$

$$P_{bat}^{dch}(h)\cdot \eta_{dch} \le P_{dch,\max}\cdot (1-u_{bat}(h)) \tag{17}$$

where, E_{bat}, $P_{bat}^{ch(dch)}$, $P_{ch(dch),\max}$ and $\eta_{ch(dch)}$ are energy capacity, charging (discharging) power, maximum charging (discharging) power and efficiency of the ESS unit, respectively. u_{bat} is a binary variable determining that the ESS is charging or discharging. Δh_{step} is the examined time step.

B. Scheduling of Domestic Appliances

Usually, residential appliances are classified as non-schedulable and schedulable. Non-schedulable appliances must operate immediately at the request of the user, while the operation time of the schedulable appliances can be shifted. Temperature-dependent appliances such as air conditioners and refrigerators can be controlled within certain temperature limits [28]. The operation of appliances such as washing machines and dishwashers can be shifted according to *RTP* and user preferences. Schedulable tasks can be planned according to several operating parameters such as power consumption (*PC*), operation time (*OT*), mostly preferred operation interval (*POI*), and the number of uses (*NoU*) of the appliances. The required constraints can be defined as follows [29]:

$$\sum_{h\in H} s_n(h) = OT_n \tag{18}$$

$$\sum_{h\in H} \left| s_n(h) - s_n(h-1) \right| \le 2 \tag{19}$$

$$\sum_{h\in H} s_m(h)\cdot \theta(\lambda - OT_n + \sum_{\bar{h}\in H} s_n(\bar{h})) = OT_m \tag{20}$$

$$P_{load}(h) = \sum_{k\in NN} P_{nsc,k}(h) + \sum_{l\in NS} P_{sc,l}(h)\cdot s_l(h) \le P_{load}^{\max} \tag{21}$$

Equation (18) ensures that appliance n will complete its task within the given *OT*, while (19) enables some appliances such as dishwashers to operate once and without interruption. The operation of some appliances, such as a tumble dryer, depends on the operation of the washing machine. Such consecutive tasks are guaranteed by (20), in which θ is unit step function and λ is a positive value smaller than 1. Due to protection requirements, the instant energy consumption is limited using (21), in which P_{nsc}, P_{sc} and $P_{load}^{\max}$ are power consumption of non-schedulable, schedulable appliances and instant consumption limit of dwelling, respectively. *NN* and *NS* are the number of non-schedulable and schedulable appliances, respectively.

The parameters required for the scheduling of domestic appliances are obtained with the help of the proposed M-GRU model. There are 4 important operating parameters, which are *NoU, OT, POI*, and *PC*, that provide distinctive information about appliances. These parameters are extracted using the output of status detection and energy disaggregation networks as follows:

$$NoU_n = f(\Delta t_{n,\min\_on}) \tag{22}$$

$$OT_n = \sum_{h\in H_{n[\alpha,\beta]}} \hat{s}_n(h) \tag{23}$$

$$PC_n = \frac{\sum_{h\in H_{n[\alpha,\beta]}} \hat{p}_n(h)}{H_{n[\alpha,\beta]}} \tag{24}$$

where $\Delta t_{n,\min\_on}$ denotes the minimum operation time of appliance n. By using (22), the periods longer than the minimum operation time are detected and *NoU* is calculated. This parameter can vary according to the seasons, days (weekday, weekend), and environmental conditions and it is directly related to the number of occupants living at the household. For example, the *NoU* of dishwashers for a household with 4 occupants cannot be the same as a house with a single-occupant. Therefore, analyzing the *NoU* can be useful for designing a more precise EMS. The *OT* is extracted using (23), in which $H_{n[\alpha,\beta]}$ denotes a period $[\alpha,\beta]$ during which appliance n is active. The average *PC* is calculated using the ratio of total energy consumption to operation time. The last parameter, *POI* is a probabilistic value since appliances are used in different periods. To understand the behavior of consumers, a probability density function (PDF) is defined for each appliance.

IV. Simulation Results and Discussions

The performance of the designed NILM-based EMS strategy is evaluated using the microgrid architecture shown in Fig. 3. Simulation results will be shown in two stages. First, the performance of DNN-based NILM analysis will be evaluated, and then its integration into the EMS for residential microgrid will be analyzed.

The developed NILM method has been trained and tested using the REFIT dataset [30], which contains electrical consumption data for 20 dwellings at appliance-level and aggregate, sampled at 8-second intervals. House 2 is chosen, taking into account the appliances, numbers of occupancy, and quality of the recorded data. One model is trained for each target appliance. 5 different appliances, which are washing machine (WM), dishwasher (DW), microwave (MW), kettle (KT), and toaster (TO) are selected as targets since they are only controllable appliances recorded. For appliances with long operating times such as WM and DW, the window size w is selected as 512, and for appliances with short operating time such as MW, KT, and TO, it's 128 samples. The networks are trained with 6 months of data and tested with 3 months of data by using Adam optimizer. Training data is augmented by randomly and systematically adding load patterns of target appliances to aggregated data in parallel with [18]. Before training, data is standardized by subtracting the mean and dividing it by the standard deviation. The results are evaluated using the following two metrics commonly using in the literature, which are mean absolute error (MAE) for energy disaggregation, and F1-score for status detection:

$$MAE_n = \frac{1}{T}\sum_{t\in T} \left| \hat{p}_n(t) - p_n(t) \right| \tag{25}$$

$$F1 = 2\cdot \frac{precision\cdot recall}{precision + recall} \tag{26}$$

$$precision = \frac{True\ positives}{True\ positives + False\ positives} \tag{27}$$

$$recall = \frac{True\ positives}{True\ positives + False\ negatives} \tag{28}$$

First of all, tuning of the weighting factor α in (8) will be evaluated. As we discussed in Section II, α is used to adjust the scale of the losses. Since the input data is standardized, the scale of the loss functions is close to each other. In this paper, weights were obtained empirically with a naive approach. The model is tested by using different α values (between 0 and 1)

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2020.3027491, IEEE Transactions on Smart Grid

for each appliance. The average results for 5 appliances are shown in Fig.5. When the weight balance between tasks was adjusted, we observed improved performance, especially for the energy disaggregation. The individual performance of each

TABLE I. PERFORMANCE COMPARISON OF THE PROPOSED METHOD

	F-1 score (status detection)					MAE (energy disaggregation)				
House-2	Seq2Seq	dAE	Seq2Point	AlexNet-1D	M-GRU	Seq2Seq	dAE	Seq2Point	AlexNet-1D	M-GRU
WM	0.880	0.401	0.920	**0.939**	**0.939**	19.92	36.56	12.33	9.40	**8.70**
DW	**0.809**	0.663	0.792	0.787	0.782	39.03	39.95	21.05	14.94	**13.35**
MW	0.606	0.311	0.580	0.590	**0.685**	7.81	7.85	4.12	3.61	**2.16**
KT	0.865	0.801	**0.881**	0.869	0.876	21.32	21.57	11.31	10.09	**8.36**
TO	0.801	0.290	0.805	0.608	**0.818**	2.19	5.57	1.20	0.86	**0.35**

task can be seen at both edges of the figure, where $\alpha=0$ and $\alpha=1$. The model achieves better results between the points where the weights are between 0.4 and 0.6. For this reason, the weighting factor was chosen 0.4.

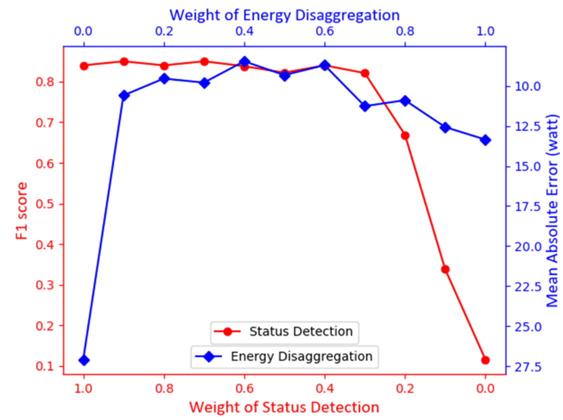

Fig. 5. Comparing the loss weighting factor

The obtained results were compared with sequence-to-sequence (Seq2Seq), sequence-to-point (Seq2Point) [11], denoising auto-encoder (dAE) [10], and AlexNet-1D [13] models. The input window size was selected the same for all models. For M-GRU, Seq2Seq, and dAE models, the size of the output window is the same as the input to make a fair comparison. The output window size of Seq2Point and AlexNet-1D models is equal to one due to their architecture. The results are shown in Table I.

As can be seen from Table I, the M-GRU model achieves better results than the other models. The reason why dAE's accuracy is lower compared to other models is that it has a shallower architecture. Seq2Point and AlexNet-1D models have higher success rates because they have a deeper architecture and they predict only a single point for each input window. For energy disaggregation, the M-GRU model gives better results for each appliance. For status detection, the results are either better or very close to the best. The secret behind the model's success is its ability to analyze the time series. Fig. 6 shows an example of disaggregated data for the washing machine and dishwasher. In Fig. 6, aggregated data shows the energy consumption value of the whole household, while ground truth shows the actual energy consumption value of the target appliance.

NILM studies in the literature are concerned only with the results mentioned above. However, there is limited work on where and how the results will be used. In this paper, it is aimed to contribute to energy management in microgrids with the results obtained above.

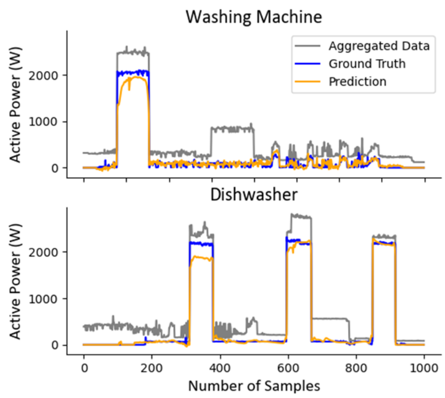

Fig. 6. An output example of energy disaggregation network

To design an efficient EMS, the operating parameters of appliances mentioned in Section III must be obtained. One of the parameters is POI, which shows the time of use of the devices during the day and makes it possible to analyze the consumers' usage habits. To visualize the POI, a PDF is defined for each appliance. The PDFs of the washing machine and dishwasher are shown in Fig. 7.

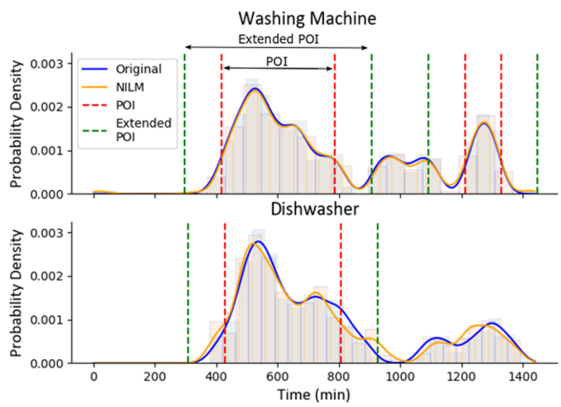

Fig. 7. Probability distributions of washing machine and dishwasher

It can be seen that NILM results perfectly follow the original PDF. The blue line in Fig. 7 was obtained using real sub-metered data, while the orange line was obtained using NILM results. The most preferred time of the appliances obtained from these PDFs is shown in the POI column of

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2020.3027491, IEEE Transactions on Smart Grid

Table III. According to Fig. 7, it is easy to observe the periods during which the consumer prefers to use the appliances. The maximum peak point indicates the period in which the device is frequently used. However, many different peak points can be found in the PDF curve. In this paper, peak points that are smaller than half of the maximum peak point are not taken into account to focus on the frequent use period. The red dashed lines indicate the most frequent usage periods of the appliance according to the area under the curve. Besides, an extra term, Extended POI, is introduced in order to design a more flexible EMS. It defines a wider window than POI. The reason for the extension of the window is the possibility of having more optimal operating points outside the POI. In this way, appliances can be scheduled in periods where RTP is lower. However, if the appliance is scheduled outside the POI, customer satisfaction may reduce due to Fig. 4. For the sake of simplicity, Extended POI limits are set 2 hours before and after the POI limits. Other parameters, PC, OT, and NoU are shown in Fig. 8. It can be easily observed that the NILM results are very close to the original data. The average analysis accuracies for PC, OT, and NoU are 91%, 97%, and 93%, respectively. All these aforementioned results are proof that designing a reliable EMS can benefit from a successful NILM analysis.

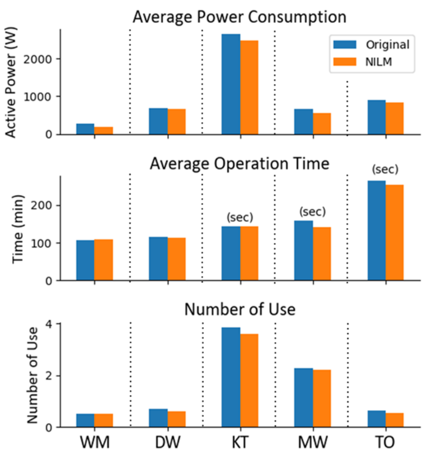

Fig. 8. Comparison of the required operational parameters

TABLE II. OPERATING PARAMETERS FOR MICROGRID

Parameters	Values	Unit	Parameters	Values	Unit
P_{WT}	1.3	kWp	P_{PV}	1.4	kWp
E_{bat}	24	kWh	$P_{ch(dch),\max}$	3.3 (3.3)	kW
$SoC_{\max(\min)}$	80 (20)	%	$\eta_{ch(dch)}$	87 (90)	%

TABLE III. PARAMETERS OF SCHEDULABLE TASKS

Appliance	POI	Extended POI	OT (min)	PC (kW)	NoU
WM	27-53 81-89	19-61 73-96	108	0.26	0.5
DW	29-56	21-64	114	0.68	0.7
KT	22-33 51-67 73-83	14-41 43-75 65-91	2.5	2.65	3.85
TO	42-51	34-59	4.5	0.90	0.64
MW	25-36 61-83	17-44 53-91	3	0.67	2.26

After obtaining the NILM results, their availability for EMS needs to be addressed. In this regard, the performance of the proposed NILM-based EMS model has been tested on the residential microgrid shown in Fig. 3. The parameters of the generation units and ESS are shown in Table II. Besides, the schedulable tasks for the analyzed home using NILM are shown in Table III.

If the parameters in Table III are examined, it is seen that OT is very short for KT, MW, and TO. Therefore, the time interval for optimization should be small in order not to miss the peak consumption of appliances. In this paper, the time interval is determined as 15 minutes, so the total time interval for day ahead optimization is 96. The POI numbers in Table III indicate these intervals. The NoU values are rounded to the nearest integer value if it's higher than 0.5. RTP and meteorological information to estimate PV and WT output power are collected from [31, 32]. The daily estimated power generation profiles of PV and WT are shown in Fig. 9. It is worthy of note that the General Algebraic Modelling System (GAMS) with Cplex/Dicopt solvers is used for the optimization task.

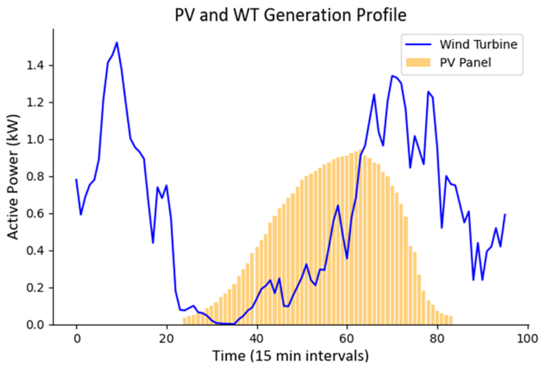

Fig. 9. PV and WT generation profile

Fig. 10 shows the performance comparison of the proposed NILM-based EMS with a traditional EMS. Although both EMS architectures receive RTP signals, traditional one operates only cost-oriented, regardless of customer satisfaction. However, the proposed method takes into consideration not only operation cost but also customer satisfaction thanks to NILM.

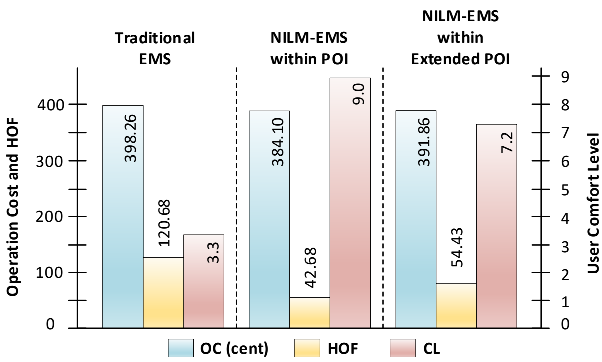

Fig. 10. Comparison of the proposed method with the traditional EMS

The analyzed residential microgrid has the capacity to generate more than consumption because it is supplied by PV,

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2020.3027491, IEEE Transactions on Smart Grid

WT, and ESS. OC indicates the profit since the excess energy is sold back to the grid. Traditional EMS makes the most profit due to cost-oriented scheduling. But it ignores user satisfaction. On the other hand, the proposed method has been evaluated in two different ways. In the first one, scheduling was done only considering the customers' POI. Therefore, the CL value is at the maximum value since the appliances are scheduled within the preferred periods. As expected, the OC value has decreased compared to traditional EMS. In the second, a more flexible EMS structure was desired by expanding the customers' POI values. The CL value has been partially reduced as the appliances can also be scheduled outside the POI. However, an increase is observed in the profit. Considering the HOF value, the proposed method improved it by about 65% with POI and 45% with extended POI compared to traditional EMS. It can also be observed that all three EMSs are quite close to each other in terms of OC.

Given the different periods of the year, PV and WT generation can drastically vary depending on the weather. For this reason, another simulation was carried out by considering that renewable energy production may be low. The low-level generation curves were obtained by reducing the previous renewable energy generation values, which are shown in Fig. 9, by 10 times. The obtained simulation results are shown in Fig. 11.

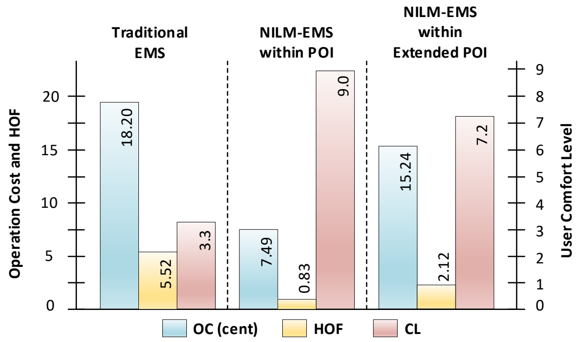

Fig. 11. Comparison of the proposed method with the traditional EMS for the case of low-level renewable generation

It is observed that OC values significantly reduce as renewable energy generation decreases. However, CL values for all EMS are the same as in the previous simulation. Because the operation intervals of the appliances are the same since they are determined by NILM using historical data, and EMS assigns appliances to periods where RTP is cheaper. Since appliances are scheduled considering the customer preferences, the best HOF value was obtained with NILM-EMS within POI. Besides, OC values of NILM-based EMSs are very close to the traditional EMS.

It is also worthy of note that the ESS is charged in periods such as the early hours of the day when the RTP is relatively low. In this period, all the demand is supplied by the utility grid and renewable energy. However, during the periods of high consumption or high electricity price, such as noon and evening hours, the distributed generation units both supply the demand and sell excessive power to the utility. Therefore, OC values for both simulations were obtained as profit. These profits may vary depending on the initial SoC of ESS unit and the price of electricity sold to grid. Considering the demand side, the operations of the controllable appliances are optimally scheduled according to the price signals, the user's preferences, and related constraints as shown in Fig. 12. In terms of visuality, scheduling periods are shown hourly.

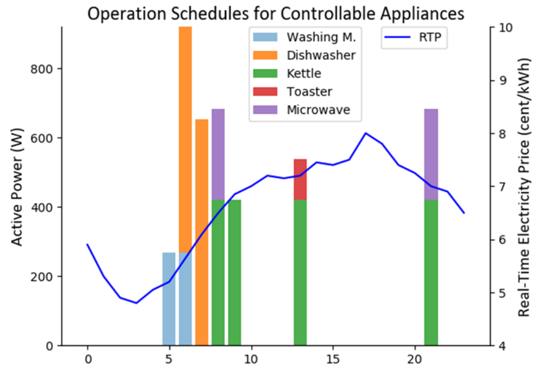

Fig. 12. Optimum scheduling periods of controllable appliances and RTP

In this study, we designed a modest EMS as our main focus is NILM and its EMS integration. However, it is also possible to design an advanced EMS using NILM for different purposes. For example, for some appliances that are not used every day, such as washing machines, the energy management system should know if its operation condition has been satisfied before scheduling. By using NILM, it can be possible to understand whether the operation conditions of appliances have been satisfied before scheduling, by analyzing the last 24 hours of consumption data. If these appliances have been used in the last 24 hours, EMS can update its scheduling and these appliances are not included in the next day's schedule.

V. Conclusion

In this paper, an efficient NILM-based EMS for residential users is defined, mathematically modeled, and verified on a residential microgrid. The proposed study consists of two parts.

In the first part, smart meter data of end-users are analyzed with the DNN-based NILM technique, and the appliance-level information of the consumers is tried to be extracted. Since this technique enables us to analyze the behavior of the consumers with only smart meter data, it mitigates the requirements such as high-cost sensors, maintenance/update and provides a cost-effective solution. Both the consumption and operating status of the appliances were obtained with high accuracy with the proposed DNN-based approach, which is designed as a multi-task network combined with GRU.

In the second part, using the appliance-level data obtained above, the energy consumption behaviors of the end-users are analyzed. Accordingly, the data such as average power consumption, operation cycles, preferred usage periods, and daily usage frequency of the appliances were obtained with an average accuracy of more than 90%. These data were integrated into the microgrid operation to create an efficient and user-centered EMS. The developed model not only provided the optimum dispatch of distributed generation plants in the microgrid but also scheduled the controllable loads taking into account customers' satisfaction. It was demonstrated with the help of simulation that the proposed NILM-based EMS model both reduces operation cost and increases customer satisfaction. Compared to a traditional EMS, the proposed approach improves the operation cost/satisfaction ratio between 45% and 65%.

VI. REFERENCES

[1] C. S. Agut, M. Kottari, "SETIS Magazine: Digitalisation of the Energy sector," European Commission, 2018.

[2] E. Aydin, D. Brounen, and N. Kok, "Information provision and energy consumption: Evidence from a field experiment," *Energy Economics*, vol. 71, pp. 403-410, 2018.

[3] G. W. Hart, "Nonintrusive appliance load monitoring," *Proceedings of the IEEE*, vol. 80, no. 12, pp. 1870-1891, 1992.

[4] H. Kim, M. Marwah, M. Arlitt, G. Lyon, and J. Han, "Unsupervised disaggregation of low frequency power measurements," in *Proceedings of the 2011 SIAM international conference on data mining*, 2011, pp. 747-758: SIAM.

[5] O. Parson, S. Ghosh, M. Weal, and A. Rogers, "Non-intrusive load monitoring using prior models of general appliance types," in *Twenty-Sixth AAAI Conference on Artificial Intelligence*, 2012.

[6] W. Kong, Z. Y. Dong, D. J. Hill, J. Ma, J. Zhao, and F. Luo, "A hierarchical hidden Markov model framework for home appliance modeling," *IEEE Transactions on Smart Grid*, vol. 9, no. 4, pp. 3079-3090, 2016.

[7] M. Zeifman, "Disaggregation of home energy display data using probabilistic approach," *IEEE Transactions on Consumer Electronics*, vol. 58, no. 1, pp. 23-31, 2012.

[8] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Advances in neural information processing systems*, 2012, pp. 1097-1105.

[9] I. Goodfellow, Y. Bengio, and A. Courville, *Deep learning*. MIT press, 2016.

[10] J. Kelly and W. Knottenbelt, "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*, 2015, pp. 55-64.

[11] C. Zhang, M. Zhong, Z. Wang, N. Goddard, and C. Sutton, "Sequence-to-point learning with neural networks for non-intrusive load monitoring," in *Thirty-second AAAI conference on artificial intelligence*, 2018.

[12] K. Chen, Q. Wang, Z. He, K. Chen, J. Hu, and J. He, "Convolutional sequence to sequence non-intrusive load monitoring," *The Journal of Engineering*, vol. 2018, no. 17, pp. 1860-1864, 2018.

[13] G. Cui, B. Liu, W. Luan, and Y. Yu, "Estimation of Target Appliance Electricity Consumption Using Background Filtering," *IEEE Transactions on Smart Grid*, vol. 10, no. 6, pp. 5920-5929, 2019.

[14] A. v. d. Oord et al., "Wavenet: A generative model for raw audio," *arXiv preprint arXiv:1609.03499*, 2016.

[15] J. Jiang, Q. Kong, M. Plumbley, and N. Gilbert, "Deep Learning Based Energy Disaggregation and On/Off Detection of Household Appliances," *arXiv preprint arXiv:1908.00941*, 2019.

[16] C. Shin, S. Joo, J. Yim, H. Lee, T. Moon, and W. Rhee, "Subtask gated networks for non-intrusive load monitoring," in *Proceedings of the AAAI Conference on Artificial Intelligence*, 2019, vol. 33, pp. 1150-1157.

[17] K. He, D. Jakovetic, B. Zhao, V. Stankovic, L. Stankovic, and S. Cheng, "A generic optimisation-based approach for improving non-intrusive load monitoring," *IEEE Transactions on Smart Grid*, vol. 10, no. 6, pp. 6472-6480, 2019.

[18] W. Kong, Z. Y. Dong, B. Wang, J. Zhao, and J. Huang, "A practical solution for non-intrusive type II load monitoring based on deep learning and post-processing," *IEEE Transactions on Smart Grid*, vol. 11, no. 1, pp. 148-160, 2019.

[19] D. He, W. Lin, N. Liu, R. G. Harley, and T. G. Habetler, "Incorporating non-intrusive load monitoring into building level demand response," *IEEE Transactions on Smart Grid*, vol. 4, no. 4, pp. 1870-1877, 2013.

[20] Y.-H. Lin and M.-S. Tsai, "An advanced home energy management system facilitated by nonintrusive load monitoring with automated multiobjective power scheduling," *IEEE Transactions on Smart Grid*, vol. 6, no. 4, pp. 1839-1851, 2015.

[21] A. B. Nassif, I. Shahin, I. Attili, M. Azzeh, and K. Shaalan, "Speech recognition using deep neural networks: A systematic review," *IEEE Access*, vol. 7, pp. 19143-19165, 2019.

[22] R. Pascanu, T. Mikolov, and Y. Bengio, "On the difficulty of training recurrent neural networks," in *International conference on machine learning*, 2013, pp. 1310-1318.

[23] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical evaluation of gated recurrent neural networks on sequence modeling," *arXiv preprint arXiv:1412.3555*, 2014.

[24] S. Ruder, "An overview of multi-task learning in deep neural networks," *arXiv preprint arXiv:1706.05098*, 2017.

[25] Zhang, Y., & Yang, Q., "A survey on multi-task learning," *arXiv preprint arXiv:1707.08114*, 2017.

[26] Ranjan, R., Patel, V. M., & Chellappa, R., "Hyperface: A deep multi-task learning framework for face detection, landmark localization, pose estimation, and gender recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 41(1), 121-135, 2017.

[27] Girshick, R., "Fast r-cnn," *In Proceedings of the IEEE international conference on computer vision* (pp. 1440-1448), 2015.

[28] H. Çimen and N. Çetinkaya, "Voltage sensitivity-based demand-side management to reduce voltage unbalance in islanded microgrids," *IET Renewable Power Generation*, vol. 13, no. 13, pp. 2367-2375, 2019.

[29] A. Anvari-Moghaddam, J. M. Guerrero, J. C. Vasquez, H. Monsef, and A. Rahimi-Kian, "Efficient energy management for a grid-tied residential microgrid," *IET Generation, Transmission & Distribution*, vol. 11, no. 11, pp. 2752-2761, 2017.

[30] D. Murray, L. Stankovic, and V. Stankovic, "An electrical load measurements dataset of United Kingdom households from a two-year longitudinal study," *Scientific data*, vol. 4, no. 1, pp. 1-12, 2017.

[31] A. G. B. o. Meteorology. (2020, 03.05). *Climate Data Online*. Available: http://www.bom.gov.au/climate/data/

[32] A. E. M. Operator. (2020, 03.05). *Electricity Price & Demand*. Available:https://www.aemo.com.au/energy-systems/electricity/national-electricity-market-nem/data-nem/data-dashboard-nem

Halil Çimen received the B.Eng. and M.Sc. degrees in Electrical-Electronics Engineering from Selçuk University, Turkey, in 2011 and 2016, respectively, and he is currently working towards the Ph.D. degree at Konya Technical University, Konya, Turkey. From July-2017 till October 2017 and from April-2019 till July-2020, he was an academic visiting scholar with the Department of Energy Technology at Aalborg University, Aalborg, Denmark. His research interests include distributed generation, non-intrusive load monitoring, and machine learning supported energy management. He also serves as a reviewer in the IEEE Industrial Electronics Magazine, IET Renewable Power Generation, and IET Generation, Transmission & Distribution.

Nurettin Çetinkaya received the B.S., M.Sc., and Ph.D. degrees in Electric and Electronics Engineering from Selçuk University, Konya, Turkey, in 1993, 1998, and 2005, respectively. His research interests include power system planning, smart grid, energy efficiency, renewable energy, power system economics, and management. He is an Associate Professor with the Department of Electrical and Electronics Engineering, Konya Technical University, Turkey. Also, he works as an advisor in Konya organized industrial zone. He received publication awards given by The Scientific and Technological Research Council of Turkey.

Juan C. Vasquez (Senior Member, IEEE) received the B.S. degree in electronics engineering from the Autonomous University of Manizales, Manizales, Colombia in 2004, and the Ph.D. degree in automatic control, robotics, and computer vision from BarcelonaTech-UPC, Barcelona, Spain, in 2009. In 2011, he was an Assistant Professor with the

Department of Energy Technology, Aalborg University, Aalborg, Denmark, where he became an Associate Professor in 2014. In 2019, he became a Professor in Energy Internet and Microgrids and is currently the Co-Director of the Villum Center for Research on Microgrids (CROM). He was a Visiting Scholar with the Center of Power Electronics Systems, Virginia Tech, Blacksburg, VA, USA, and a Visiting Professor with Ritsumeikan University, Kyoto, Japan. He has published more than 450 journal papers in the field of microgrids, which, in total, are cited more than 17,000 times. His current research interests include operation, advanced hierarchical and cooperative control, optimization and energy management applied to distributed generation in ac–dc microgrids, maritime microgrids, advanced metering infrastructures and the integration of Internet of Things and Energy Internet into the smart grid. Prof. Vasquez is an Associate Editor of IET Power Electronics and a Guest Editor of the IEEE Transactions on Industrial Informatics Special Issue on Energy Internet. He received the Highly Cited Researcher Award by Thomson Reuters from 2017 to 2019, and the Young Investigator Award 2019. He is currently a member of the IEC System Evaluation Group SEG4 on LVDC Distribution and Safety for use in Developed and Developing Economies, the Renewable Energy Systems Technical Committee TC-RES in IEEE Industrial Electronics, PELS, IAS, and PES Societies.

Josep M. Guerrero (Fellow, IEEE) received the B.S. degree in telecommunications engineering, the M.S. degree in electronics engineering, and the Ph.D. degree in power electronics from the Technical University of Catalonia, Barcelona, in 1997, 2000 and 2003, respectively. Since 2011, he has been a Full Professor with the Department of Energy Technology, Aalborg University, Denmark, where he is responsible for the Microgrid Research Program (www.microgrids.et.aau.dk). From 2014 he is chair Professor in Shandong University; from 2015 he is a distinguished guest Professor in Hunan University; and from 2016 he is a visiting professor fellow at Aston University, UK, and a guest Professor at the Nanjing University of Posts and Telecommunications. From 2019, he became a Villum Investigator by The Villum Fonden, which supports the Centre for Research on Microgrids (CROM) at Aalborg University, being Prof. Guerrero the founder and Director of the same centre. His research interests is oriented to different microgrid aspects, including power electronics, distributed energy-storage systems, hierarchical and cooperative control, energy management systems, smart metering and the internet of things for AC/DC microgrid clusters and islanded minigrids. Specially focused on maritime microgrids for electrical ships, vessels, ferries and seaports. Prof. Guerrero is an Associate Editor for a number of IEEE TRANSACTIONS. He has published more than 500 journal papers in the fields of microgrids and renewable energy systems, which are cited more than 40,000 times. He received the best paper award of the IEEE Transactions on Energy Conversion for the period 2014-2015, and the best paper prize of IEEE-PES in 2015. As well, he received the best paper award of the Journal of Power Electronics in 2016. During six consecutive years, from 2014 to 2019, he was awarded by Clarivate Analytics (former Thomson Reuters) as Highly Cited Researcher. In 2015 he was elevated as IEEE Fellow for his contributions on "distributed power systems and microgrids".