

Article

Design and Implementation of an IoT-Oriented Energy Management System Based on Non-Intrusive and Self-Organizing Neuro-Fuzzy Classification as an Electrical Energy Audit in Smart Homes

Yu-Hsiu Lin 

Department of Electrical Engineering, Southern Taiwan University of Science and Technology, 71005 Tainan City, Taiwan; yhlin1108@stust.edu.tw; Tel.: +886-6-253-3131 (ext. 3365)

Received: 12 October 2018; Accepted: 20 November 2018; Published: 22 November 2018



Featured Application: An innovative non-intrusive and self-organizing neuro-fuzzy classification in an Internet of Things-oriented energy management system for smart homes was developed.

Abstract: Smart cities are built to help people address issues like air pollution, traffic optimization, and energy efficiency. Electrical energy efficiency has become a central research issue in the energy field. Smart houses and buildings, which lower electricity costs, form an integral part of a smart city in a smart grid. This article presents an Internet of Things (IoT)-oriented smart Home Energy Management System (HEMS) that identifies electrical home appliances based on a novel hybrid Unsupervised Automatic Clustering-Integrated Neural-Fuzzy Classification (UAC-NFC) model. The smart HEMS designed and implemented in this article is composed of (1) a set of IoT-empowered smart e-meters, called smart sockets, installed as a benchmark in a realistic domestic environment with uncertainties and deployed against non-intrusive load monitoring; (2) a central Advanced Reduced Instruction Set Computing machine-based home gateway configured with a ZigBee wireless communication network; and (3) a cloud-centered analytical platform constructed to the hybrid UAC-NFC model for Demand-Side Management (DSM)/home energy management as a load classification task. The novel hybrid UAC-NFC model proposed in DSM and presented in this article is used to overcome the difficulties in distinguishing electrical appliances operated under similar electrical features and classified as unsupervised and self-organized. The smart HEMS developed with the proposed novel hybrid UAC-NFC model for DSM was able to identify electrical household appliances with an acceptable average and generalized classification rate of 95.73%.

Keywords: IoT; load disaggregation; neuro-fuzzy classification; non-intrusive load monitoring; unsupervised learning; smart homes

1. Introduction

Owing to global warming and climate change, monitoring and managing residential, commercial, and industrial major electrical appliances is of vital importance. Major appliances are controlled and used to respond to Demand Response (DR) schemes from power utilities, so that electrical energy efficiency related to energy demand from downstream sectors in a smart grid can be improved and greenhouse gases produced from carbon pollution can be reduced. DR schemes offer financial incentives to take actions to reduce or shift loads in correspondence to market price behavior. DR plays a crucial role in efficiently capturing the benefits of Demand-Side Management (DSM) to ensure demand flexibility including peak load reduction [1]. To track electrical energy efficiency of individual electrical appliances that are monitored and managed in fields of interest, one way is to

use Internet-of-Things (IoT)-oriented Energy Management Systems (EMS), where energy Information and Communication Technology (ICT) is applied for DSM. In an IoT-oriented EMS deployed in a field of interest, plug-load smart e-meters, called smart sockets, are installed for individual electrical appliances and are wirelessly networked with a centralized gateway. In a smart home connected to a smart grid via Advanced Metering Infrastructure (AMI), the IoT-oriented Home EMS (HEMS), which identifies power consumption on individual major household appliances by many smart e-meters, monitors each individual major household appliance intrusively. However, conducting HEMS burdens consumers with a large construction investment and annual maintenance costs [2].

In contrast with HEMS conducted for DSM/home energy management, Non-Intrusive Load Monitoring (NILM) analyzes composite electrical signals acquired from only one minimal set of plug-panel voltage and current sensors and then provides appliance-level energy usage information and monitors each individual major household appliance non-intrusively. NILM conducted in a smart home with an IoT-oriented HEMS, considered part of DSM in a smart grid, is a cost-effective technique [3] for extracting appliance-level energy consumption information by monitoring and analyzing aggregated signals acquired at the entrance of electric power from a utility. NILM has been examined and applied in many previous studies [3–19]. In Ayub et al. [3], NILM was treated as a linear integer-programming problem, and was solved by an iterative clustering algorithm. Du et al. [4] presented a novel hybrid classification technique that combines the supervised self-organizing feature map with Bayesian classification for NILM. The diversity and similarity of different types of electrical household appliances operated and classified under similar steady-state electrical features were considered in Du et al. [4]. However, the novel hybrid classification technique in Du et al. [4] cannot classify household appliances with multi-state transitions. The classification of electrical household appliances addressed in Du et al. [4] requires an in-depth investigation on operation principles of household appliances [5].

To classify electrical household appliances with multi-state transitions under similar electrical features, Lin et al. [6] proposed an NILM as load classification using fuzzy logic theory considering uncertainties. A mechanism that can automatically and systematically construct fuzzy classifiers in a nearest neighborhood manner was not developed for NILM in Lin et al. [6]. In Azaza et al. [7], the k-nearest neighbors (k-NNR) method, producing an error rate that ranged from 20% to 29% was used to recognize residential appliances. In other prior studies [8–10], a Discrete Wavelet Transform (DWT)-based transient feature extraction method for NILM was proposed. DWT allows simultaneous time and frequency localization, whereas time localization by Fast Fourier Transform (FFT) is not possible. In these three studies [8–10], DWT, instead of FFT, was conducted and used to detect and analyze transient response of electrical appliances as feature extraction for NILM. Chang et al. [11,12] proposed a hybrid classification strategy that combines the conventional Particle Swarm Optimization (PSO) with Back-Propagation-Artificial Neural Networks (BP-ANNs) for NILM. The conventional PSO optimizes the weight coefficients of the BP-ANNs, with the purpose of improving the classification accuracy of load classification. The strategy proposed in Tabatabaei and Chang et al. [10,11] was verified by Electromagnetic Transients Program simulations and field measurements. The results reported indicate the proposed strategy significantly improves the recognition accuracy and computational efficiency of the BP-ANNs under multiple load operation conditions. The k-NN and BP-ANNs were used as load classifiers to classify electrical appliances monitored [7–9,11,12]. However, k-NN and BP-ANNs cannot handle uncertainties in electrical appliances or operational combinations of electrical appliances monitored and classified with similar electrical characteristics, resulting in ambiguities on feature data.

Advanced machine learning has been applied in NILM. In Zeifman et al. [13], a new Markov-style probabilistic framework for NILM was proposed, wherein a modified Viterbi algorithm that uses approximate semi-Markov models to retain a robust computationally-efficient solution to pristinely infer draws of real power (P) of monitored electrical household appliances, was applied and evaluated

in a residence. The main advantage of the modified Viterbi algorithm proposed in Zeifman et al. [13] is that the complexity of the NILM is linearly proportional to the number of household appliances monitored. However, the complexity of the NILM by other Markov-style probabilistic algorithms, which model household appliances by a factorial Hidden Markov Model [14–16], exponentially grows with the number of household appliances monitored [17]. The Markov-style probabilistic algorithms [13–16] experience the same problem in which they are not capable of addressing household appliances with similar P [17].

Ambiguities from similar P exist in feature data. The Graph Shift Quadratic Form constrained Active Power Disaggregation algorithm [18] is also unable to address household appliances that are identical in P. In addition to P, where there may be multiple electrical appliances with a similar power level, power patterns, such as characteristics retrieved from household appliances, were considered for NILM and identified by dynamic time warping in Wang et al. [19]. The NILM techniques developed in the past and surveyed above have improved feature extraction with developed classification algorithms; however, difficulties still remain in distinguishing electrical appliances operated under similar electrical features and classified as unsupervised and self-organized. Electrical appliances with similar electrical features are difficult to discern.

This article focuses on designing and implementing an IoT-oriented smart HEMS based on a novel hybrid Unsupervised Automatic Clustering-integrated Neuro-Fuzzy Classification (UAC-NFC) model in NILM, in order to overcome the difficulties in distinguishing electrical appliances operated under similar electrical features showing ambiguities and classified as unsupervised and self-organized. Fuzziness [6] in fuzzy theory is introduced in the hybrid UAC-NFC model proposed in this article. This work is a revision of the original work by Lin et al. [6]. NILM identifies individual electrical appliances by analyzing composite electrical signals acquired by only one single set of plug-panel voltage and current sensors in a field. The hybrid UAC-NFC model proposed in this article is able to handle uncertainties in which electrical appliances monitored in a realistic experimental household environment are used and classified under similar electrical features. The NFC used is piloted and constructed in an unsupervised and self-organized manner. The diversity and similarity of different types of electrical appliances operated and classified under similar electrical features are also considered. The proposed hybrid UAC-NFC model is implemented and evaluated in a realistic house environment with uncertainties.

The remainder of this article is organized as follows. The IoT-oriented smart HEMS with the proposed hybrid UAC-NFC model is presented in Section 2. Section 3 demonstrates the work completed in this article. The smart IoT-oriented HEMS with the proposed hybrid UAC-NFC model was deployed and evaluated in a realistic house environment with uncertainties, which was used to classify household appliances monitored. Section 4 concludes this article with its future work.

2. Design and Implementation of IoT-Oriented Smart HEMS Having the Proposed Novel Hybrid UAC-NFC Model Applied for NILM

The IoT-oriented smart HEMS utilizing the novel hybrid UAC-NFC model proposed in this article for NILM is presented in this section. Section 2.1. introduces the IoT-oriented smart HEMS conducted for DSM/home energy management and deployed in a house environment for smart homes; Section 2.2 introduces the novel hybrid UAC-NFC model developed for IoT analytics of the HEMS to DSM.

2.1. IoT-Oriented Smart HEMS

Figure 1 shows a block diagram of the centralized IoT-oriented smart HEMS [6] with the proposed novel hybrid UAC-NFC model applied for NILM. The HEMS conducted in a house environment is an ARM® (Advanced RISC Machine) Cortex™-A9-based embedded system (Texas Instruments Inc., Dallas, USA), which is configured with an LAMP (Linux™ Operating Systems (Linus Torvalds, Helsinki, Suomi) + Apache HTTP server (Apache Software Foundation, Forest Hill, MD, USA) +

MySQL™ relational database (Oracle Corporation, Redwood City, CA, USA) + server-side PHP (PHP: Hypertext Preprocessor) scripting language (Rasmus Lerdorf, Qeqertarsuaq/Disko Island, Greenland)) development stack [6]. The HEMS—Home Gateway (HG)—serves as a central home controller connecting the house with a utility for DSM/home energy management via AMI in a smart grid. The centralized HEMS is able to continually determine the power consumption for each major household appliance monitored and networked together through a ZigBee (Zigbee Alliance, Davis, USA)-based wireless communication network. I chose to use the ZigBee-based plug-load smart e-meters in this article to evaluate the recognition rate of the proposed novel hybrid UAC-NFC model applied for NILM.

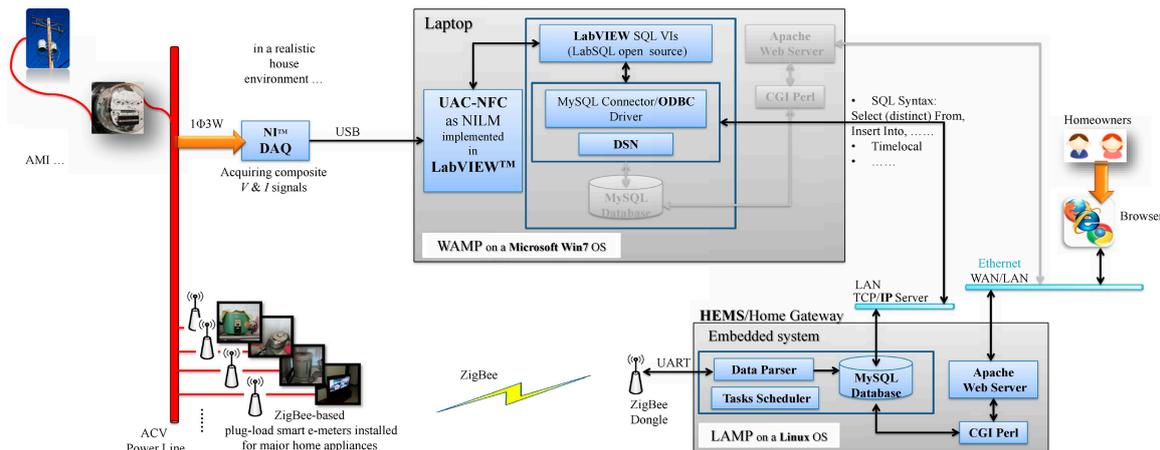


Figure 1. Block diagram of the centralized Internet of Things (IoT)-oriented smart Home Energy Management System (HEMS) with the proposed novel hybrid Unsupervised Automatic Clustering-integrated Neuro-Fuzzy Classification (UAC-NFC) model applied for Non-Intrusive Load Monitoring (NILM).

The model applied for NILM was implemented on a laptop computer in the LabVIEW™ (National Instruments, Austin, TX, USA) environment with MATLAB® (The MathWorks, Inc., Natick, MA, USA). As shown in Figure 1, the ZigBee wireless communication technology, an ICT, was conducted in the HEMS. A standardized MySQL™ (Oracle Corporation, Redwood City, USA) Connector/Open Database Connectivity (ODBC) driver, LabSQL (Jeffrey Travis Studios LLC, Austin, TX, USA) Virtual Instruments using the ActiveX (Microsoft, Redmond, USA) Data Objects (ADO) for object collection, and Structured Query Language (SQL) in LabVIEW™ were installed, conducted, and used. Due to the ZigBee wireless communication network, the HG communicating with the household appliances was able to remotely direct/distribute load control considering DSM/home energy management. An enabled remote access MySQL™ relational database was configured on the HG. Common Gateway Interface (CGI) programs were coded. The HyperText Transfer Protocol (HTTP) server can interact dynamically with homeowners. An HTTP server-based user interface, showing detailed electrical energy information identified by the HEMS utilizing the novel hybrid UAC-NFC model, was designed.

Figure 2 shows the workflow of a typical NILM [6], applied in this article and deployed on the centralized HEMS and studied against the centralized HEMS as a benchmark. In an NILM using the novel hybrid UAC-NFC model proposed in this article, both the raw composite analog current and voltage signals are simultaneously and continuously acquired by a National Instruments (NI)™ Data Acquisition (DAQ) device (National Instruments, Austin, TX, USA) with low-pass filters and Analog-to-Digital Converters (ADC). The DAQ device was installed at the main electrical panel of a realistic house field. The raw composite analog voltage and current signals sensed by one single minimal set of voltage and current sensors are filtered through low-pass filtering. Then, the signals without high-frequency noisy signals removed are digitalized via analog-to-digital conversion. Once the digitized composite signals are analyzable, the NILM executes (1) feature

extraction by steady-state analysis and (2) load classification using the novel hybrid UAC-NFC model applied to extracted and normalized electrical feature data.

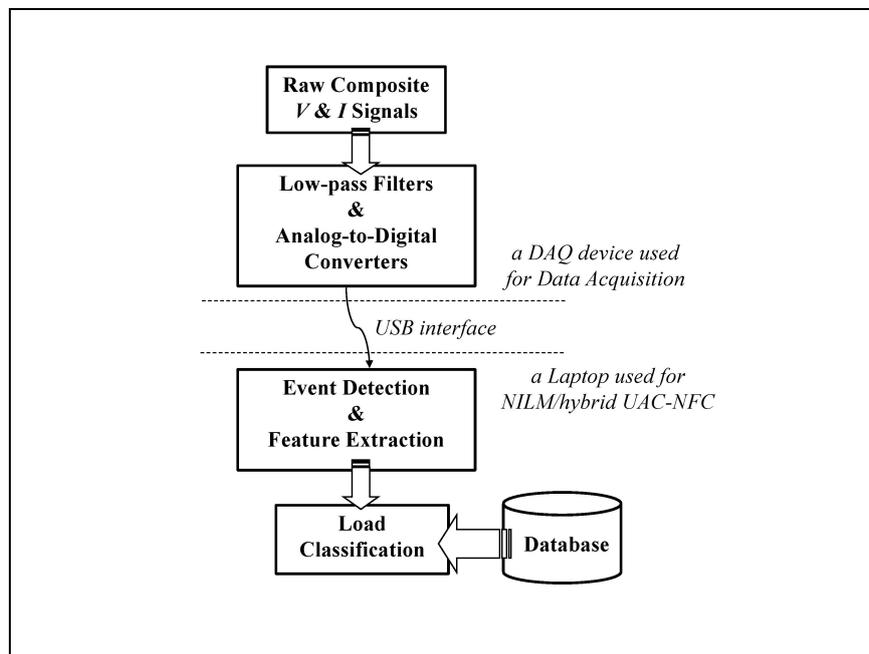


Figure 2. Workflow of a typical NILM.

The NILM in Figure 2 was implemented on a laptop computer wired with the NI™ DAQ device (National Instruments, Austin, TX, USA) via a USB interface. In the NILM, event detection aims to detect abrupt power changes that reflect energizing or de-energizing events of one household appliance operated for use and monitored for DSM. Minor power changes in P are not treated for load classification, as minor power consumption of electrical appliances is viewed as base load. The proposed NILM takes signature readings, analyzes it, and then deduces which electrical household appliance(s) is being energized or de-energized. The proposed novel hybrid UAC-NFC model can be used to classify electrical features extracted with ambiguities.

In the NILM, the proposed novel hybrid UAC-NFC model and developed as a revision of the previously-implemented algorithm in Lin et al. [6] implements load classification, used to classify electrical features representing operations of electrical household appliances monitored and operated under similar electrical features as uncertainties in a realistic house environment.

The proposed novel hybrid UAC-NFC model learns from a training dataset collected on-site and off-line. On-line load monitoring is executed once the training process of the hybrid UAC-NFC has finished. The hybrid UAC-NFC proposed in this article is introduced in Section 2.2. As the main focus of this article is the design and implementation of a novel load classifier that identifies different types of electrical appliances modeled in an unsupervised and self-organized manner and identified with similar electrical features, on-line training is not discussed in this article. In the NILM developed in this article for DSM/home energy management, measured physical meanings—power profiles—from monitored electrical household appliances for long-term load classification vary. Ambiguities exist in feature data extracted from monitored electrical household appliances for load classification. As a result, fuzzy theory is used in this article. This article proposes a novel hybrid UAC-NFC model considering uncertainties to classify electrical household appliances modeled in an unsupervised and self-organized manner and identified with similar electrical features. Compared with the table look-up scheme where membership functions of a fuzzy classifier are fixed, or the method that establishes fuzzy rules based on the basic experience [20], the proposed novel hybrid UAC-NFC model is capable of automatically organizing the structure of its fuzzy membership functions in an

unsupervised manner. Also, structure parameters of the self-organized model are free to be trained according to collected input-output data pairs. Fuzziness [6] in fuzzy theory is introduced in the proposed hybrid UAC-NFC model. In this article, a cross-validation strategy [21] is used to manage sampled data with systematic errors where electrical household appliances monitored operate with similar electrical features resulting in ambiguities on data.

2.2. Novel Hybrid UAC-NFC Model

NFC [6] is presented first. Suppose that a rule base has the form of fuzzy IF-THEN rules as shown in Equation (1) [22]:

$$Ru^{(l)} : IF x_1 \text{ is } A_1^l \text{ and } \dots \text{ and } x_n \text{ is } A_n^l, THEN y \text{ is } B^l, \tag{1}$$

where A_i^l and B^l are fuzzy sets in $U_i \subset R$ and $V \subset R$, respectively; A_i^l is characterized by normalized Gaussian membership functions; B^l is characterized by fuzzy singleton \bar{y}^l ; $x = (x_1, x_2, \dots, x_n)^T \in U \subset R^n$ and $y \in V \subset R$ are input and output linguistic variables, respectively; and M is the total number of fuzzy rules; $l = 1, 2, \dots, M$.

By adopting a singleton fuzzifier, product inference engine, and center average de-fuzzifier, a fuzzy classifier with the form of fuzzy rules in Equation (1) has the form [22]:

$$f(x) = \frac{\sum_{l=1}^M \bar{y}^l [\prod_{i=1}^n \exp(-(\frac{x_i - \bar{x}_i^l}{\sigma_i^l})^2)]}{\sum_{l=1}^M [\prod_{i=1}^n \exp(-(\frac{x_i - \bar{x}_i^l}{\sigma_i^l})^2)]} \tag{2}$$

where $f(x) = y \in V \subset R$ is the computed de-fuzzified output with respect to input x ; the symmetric Gaussian membership functions depend on the two factors: $\sigma_i^l \in (0, \infty)$ and $\bar{x}_i^l \in R$; and $\bar{y}^l \in R$ are the real-valued adjustable parameters of the fuzzy classifier.

The NFC of Equation (2) becomes an optimal NFC, where the one fuzzy rule in Equation (1) is used to match one input-output pair in a collected dataset, if each input-output pair in the dataset is viewed as a fuzzy IF-THEN rule. The zero-order Sugeno model, a crisply defined constant in the following, is used in the NFC of Equations (1) and (2) in this article.

For a classification problem, the decision making of the NFC constructed and trained is based on:

$$Class \ label = \underset{c=1,2,\dots,w}{\operatorname{argmin}} (|f(x) - Class^c|) \tag{3}$$

where $Class^c$, an integer, stands for class label c and w is the total number of load classes.

The fuzzy classifier in Equation (2) can be viewed as a feed-forward ANN-architecture NFC [6,22], as shown in Figure 3. In this article, the NFC of Equation (2) is integrated with the UAC, nearest-neighbor clustering, to construct an NFC in an unsupervised and self-organized manner. The hybrid UAC-NFC model proposed in this article was implemented and used to construct the NFC in Equation (2). Also, The Gradient-Descent (GD) algorithm [22–26], a first-order iterative optimization algorithm for finding the minimum of a given cost function in ANN, is used to train the NFC. In this article, the UAC pilots the NFC to automatically initialize the adjustable network parameters of the constructed NFC. As a result, there is no need to pre-specify the number of clusters to discover data.

The flowchart of the proposed hybrid UAC-NFC model is illustrated in Figure 4. In this novel hybrid UAC-NFC model, two stages are involved.

In stage 1, a UAC process (nearest-neighbor clustering) is used to automatically cluster input-output data pairs from a given dataset collected prior. With the use of UAC instead of the FCM conducted in Lin et al. [6], there is no need to know the number of clusters to be discovered beforehand. The adjustable parameters of Equation (2) are then heuristically allocated. After the UAC

is applied to a collected dataset, discovered data are automatically clustered. Following the UAC process mentioned above, the training process, GD, starts in stage 2. In stage 2, the GD process is used to train the constructed NFC of Equation (2), forming from the adjustable parameters allocated in an unsupervised and self-organized manner and trained from a collected set of data pairs. Finally, the trained UAC-NFC model is applied for load classification in NILM.

The constructed hybrid UAC-NFC model was applied on collected input-output data pairs. The cluster centers found through the UAC process and specified as data points in the same clusters were used to heuristically allocate the adjustable parameters of the Gaussian membership functions of Equation (2):

- (1) The center parameter $\bar{x}_{i,j}$ of Gaussian membership function j on universe of discourse i is initialized by component i of cluster center j , where $i = 1, 2, \dots, n$; n is the total number of universes of discourse (input variables); $j = 1, 2, \dots, N_{MF}$; and N_{MF} , which equals k in the UAC process, is the total number of Gaussian membership functions (cluster centers) on each of universes of discourse. There are k clusters resulting in $k \times k$ fuzzy partitions in a feature space as the partition space in fuzzy logic. The partition space containing $k \times k$ fuzzy partitions is square to the UAC used in this article. The value of k is identified through the UAC process, nearest-neighbor clustering.
- (2) The spread/width parameter $\sigma_{i,j}$ of Gaussian membership function j on universe of discourse i is initialized by:

$$\sigma_{i,j} = \alpha \cdot (x'_i - \bar{x}_{i,j}) \tag{4}$$

where x'_i is component i of a data point that belongs to cluster j with the computed maximum distance between it and one data point in the same cluster and α , a real number, is a non-zero constant.

- (3) Based on the results by the UAC process, heuristically allocate the singleton parameters $\{\bar{y}^l\}_{l=1}^M$ of Equation (3) with the desired output of collected input-output data pairs. The output of the NFC used in this article is defined as the class $\{0, 1, 2, \dots\}$ of load combinations classified. Each single parameter is assigned a unique class label: class label 0, class label 1, class label 2, \dots , or class label w .

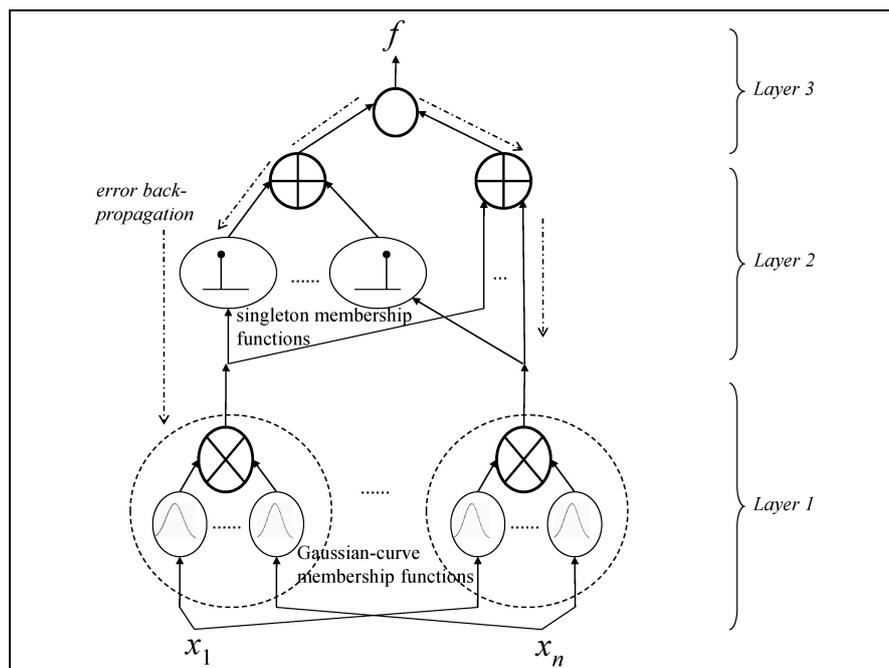


Figure 3. A feed-forward Artificial Neural Network (ANN)-architecture NFC.

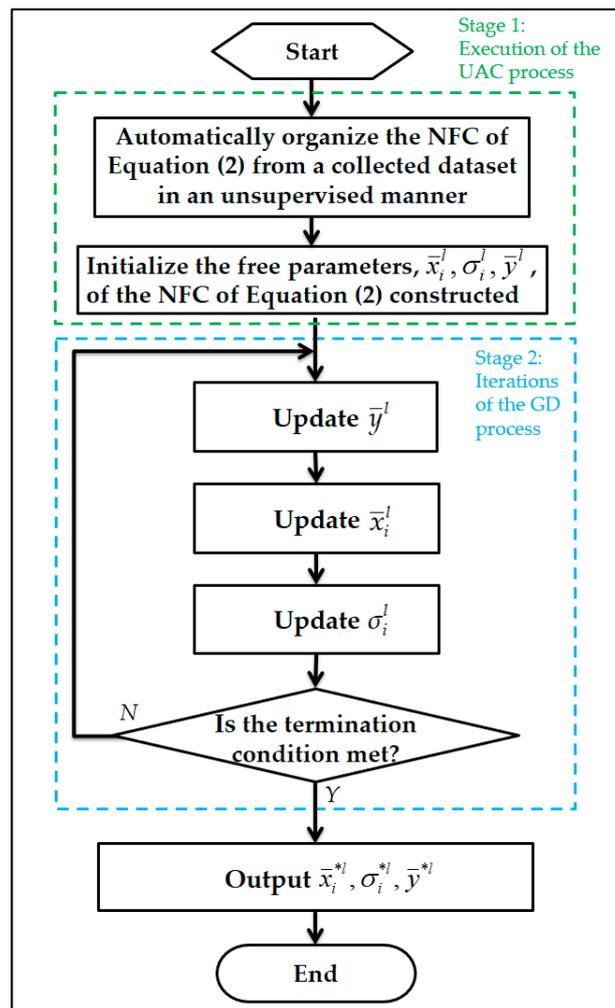


Figure 4. Flowchart of the hybrid UAC-NFC model conducted in the HEMS for NILM and proposed in this article.

After the UAC process shown above is complete, the GD process works as follows. Assume that the following input-output data pairs are collected: $\{(x^p, y^p)\}_{p=1}^N$, where $x^p \in U \subset R^n$ and $y^p \in V \subset R$. The goal of the NFC constructed for load classification in NILM is to fine tune the free parameters of the fuzzy membership functions based on these N input-output data pairs. In Equation (2), σ_i^l , \bar{x}_i^l , and \bar{y}^l are automatically constructed through the UAC process. Once these parameters are pre-specified by the UAC, the quasi-optimal structure of the NFC trained by the GD process can be obtained. The GD process is used to update the adjustable parameters of the initialized NFC, according to Equations (5)–(7) at the q th iteration of the training process with a present input-output data pair (x^p, y^p) . The training process is performed with $q = q + 1$, until the UAC-NFC is trained and terminates when total error $\sum |f(x^p) - y^p|$ with $p = p + 1$ is less than or equal to a pre-specified tolerance is satisfactory. Usually, the training process terminates when the maximum training iteration pre-specified is met.

$$\bar{y}^l(q + 1) = \bar{y}^l(q) - \eta \left[\frac{f(x^p) - y^p}{\sum_{l=1}^M \prod_{i=1}^n \exp(-(\frac{x_i - \bar{x}_i^l}{\sigma_i^l})^2)} \right] \left[\prod_{i=1}^n \exp(-(\frac{x_i - \bar{x}_i^l}{\sigma_i^l})^2) \right] \quad (5)$$

where η is a real number pre-specified within $(0, 1]$, which is the training rate.

$$\bar{x}_i^l(q+1) = \bar{x}_i^l(q) - \eta \left[\frac{f(\mathbf{x}^p) - y^p}{\sum_{i=1}^M \prod_{i=1}^n \exp(-(\frac{x_i - \bar{x}_i^l}{\sigma_i^l})^2)} \right] [\bar{y}^l(q) - f(\mathbf{x}^p)] \left[\prod_{i=1}^n \exp(-(\frac{x_i - \bar{x}_i^l}{\sigma_i^l})^2) \right] \left[\frac{2(x_{0i}^p - \bar{x}_i^l(q))}{\sigma_i^{l2}(q)} \right] \quad (6)$$

$$\sigma_i^l(q+1) = \sigma_i^l(q) - \eta \left[\frac{f(\mathbf{x}^p) - y^p}{\sum_{i=1}^M \prod_{i=1}^n \exp(-(\frac{x_i - \bar{x}_i^l}{\sigma_i^l})^2)} \right] [\bar{y}^l(q) - f(\mathbf{x}^p)] \left[\prod_{i=1}^n \exp(-(\frac{x_i - \bar{x}_i^l}{\sigma_i^l})^2) \right] \left[\frac{2(x_{0i}^p - \bar{x}_i^l(q))^2}{\sigma_i^{l3}(q)} \right] \quad (7)$$

The procedure of the novel hybrid UAC-NFC model proposed in this article is summarized in Table 1.

Table 1. The hybrid Unsupervised Automatic Clustering-integrated Neuro-Fuzzy Classification (UAC-NFC) model proposed in this article.

Stage 1. Automatically construct the UAC-NFC model proposed in this article

Inputs:
 $D = \{\mathbf{x}^1, \mathbf{x}^2, \mathbf{x}^3, \dots, \mathbf{x}^p, \dots, \mathbf{x}^N\}$ // N input-output data pairs to be clustered automatically
 r // radius

Output:
 K // Set of k clusters

Run the UAC process:
 $K_1 = \{\mathbf{x}^1\}$. // the first cluster initialized by \mathbf{x}^1
 Add K_1 to K .

$k = 1$.

for $i = 2$ to N **Do** // for $\mathbf{x}^2, \mathbf{x}^3, \dots, \mathbf{x}^p, \dots, \mathbf{x}^N$
 Find data point \mathbf{x}^m in cluster $K_m \subset K$, where $dist(\mathbf{x}^m, \mathbf{x}^i)$, the Euclidean distance between \mathbf{x}^m and \mathbf{x}^i , is the smallest.
if $dist(\mathbf{x}^m, \mathbf{x}^i) < r$, **then**
 $K_m = K_m \cup \{\mathbf{x}^i\}$. // the same cluster updated
else
 $k = k + 1$.
 $K_k = \{\mathbf{x}^i\}$. // a new cluster created
 Add K_k to K .
End for

Initialize the adjustable parameters, $\bar{y}^l(0)$, $\bar{x}_i^l(0)$, and $\sigma_i^l(0)$, of the NFC of Equation (2) based on the clustering results obtained through the UAC process above and described in Section 2.2.

Stage 2. Execute the GD process [22–26] to train the UAC-NFC model constructed in Stage 1

Do
for $q = 0$ to q_{max} **Do**
for $p = 1$ to N **Do**
 Present the p th input-output data pair (\mathbf{x}^p, y^p) , and compute the output of the NFC associated with the present data pair at the q th iteration of the training process in the forward propagation of the training process.
 Update the adjustable parameters of the NFC according to Equations (5)–(7), in the backward propagation of the training process.
End for
 Obtain total error $\sum |f(\mathbf{x}^p) - y^p|$ with $p = p + 1$.
End for
While The NFC is not satisfactory with a high total error

The intelligent-particle swarm optimization technique in Lin et al. [6] can be conducted in the second stage of the proposed hybrid UAC-NFC model and be used to fine tune the adjustable parameters of the constructed NFC. Sampling is biased if it systematically favors some observations over others. Sampling bias is sometimes called systematic bias. For load classification as predictive

modeling in DSM/home energy management, data being sampled through data acquisition, and then analyzed via feature extraction, evolve over time with a systematic bias between separate training and test datasets. Thus, a cross-validation procedure [21] was conducted to deal with data sampled with systematic errors.

3. Experiment

The IoT-oriented smart HEMS with the developed novel hybrid UAC-NFC model was experimentally validated by being deployed in a realistic residential field with uncertainties. The experimental set-up of the deployed smart HEMS, as a benchmark against the NILM in a realistic house environment with uncertainties in Taiwan, is illustrated in Figure 5 [6,22]. Major electrical household appliances classified by the novel hybrid UAC-NFC model operated with similar electrical features. In this experiment, features extracted, normalized, and classified in the NILM were P and reactive power (Q). As there may be multiple electrical appliances with a similar power level, P does not represent a particular appliance. So, the proposed model identifies electrical appliances based on P and Q as the distinctive characteristics. In the HEMS, ZigBee wireless communication technology was used. A standardized MySQL™ Connector/ODBC driver, LabSQL Virtual Instruments, using the ADO (ActiveX Data Objects) object collection, and SQL in LabVIEW™, were installed and used. For DSM/home energy management addressed, the flow of data stores, signal requests, and remote controls of electrical appliances monitored by the HEMS with the proposed novel hybrid UAC-NFC model are shown in Figure 6. DSM was mainly realized through a heterogeneous network involving ZigBee, Radio Frequency (RF), and Infrared Radiation (IR). Universal Asynchronous Receiver/Transmitter (UART), an RS232 RTU-format protocol, was used in the HEMS.

The deployed smart HEMS with the proposed novel hybrid UAC-NFC model was used to identify major electrical household appliances. In the HEMS, MATLAB® and NI™ LabVIEW software suites installed on an ASUS ZENBOOK™ Prime Core™ i7 UX31A laptop (ASUSTeK Computer Inc., Taipei, Taiwan) were used to implement the novel hybrid UAC-NFC model. Using MATLAB® software script server, MATLAB script in LabVIEW™ calls the MATLAB® software to execute scripts. In this experiment, major household appliances identified in Line Branch 1 (L1) of the residential field included an electric rice cooker (~ 1.10 kW), a multi-mode electric water boiler (~ 0.90 kW), a steamer (~ 0.80 kW), and a television (~ 0.22 kW). The base load in L1 in the household environment was ~ 0.55 kW, which includes permanent loads. The power source of the electrical wiring of the house environment in Taiwan is AC110 V/60 Hz. The composite current and voltage signals acquired from the main electrical panel of the house environment were simultaneously and continuously sampled by an NI™ 9225 DAQ device. The incoming analog signals on each channel of the DAQ device were conditioned, buffered, and then sampled by a 24-bit Delta-Sigma ADC (Texas Instruments Inc., Dallas, USA). With the purpose of providing an accurate representation of in-band signals while rejecting out-of-band signals, the DAQ device uses a combination of analog and digital filtering. An active current transformer that generates output voltage that is proportional to input current was hooked in L1. Its output voltage was wired to one of the channels of the DAQ device. The AC power source of 110 V/60 Hz was directly wired to one of the channels of the DAQ device. The data rate of the DAQ device was set to 2000 samples/s. The DAQ device passed the digitized signals to the laptop via a USB interface every second for the novel hybrid UAC-NFC model in NILM. The laptop ran the NILM to identify if the household appliance(s) was (were) being operated for not. The centralized HEMS, as a benchmark, continually collected data from each of the individual major household appliances every 20 s by talking to the installed ZigBee-based plug-load smart e-meters.

ZigBee is an efficient short-range wireless technology in terms of power consumption and deployment scalability [27]. ZigBee Alliance [28] was formed in 1998 by Honeywell Corporation (Honeywell International Inc., Morris Plains, USA), whose aimed to use IEEE 802.15.4 low-power wireless network protocols as the basis for the development of the specification of IoT applications.

The ZigBee protocol is a low-power wireless transmission protocol, providing a suitable data rate for control and monitoring purposes of smart houses as a use case [27]. So, the ZigBee-based wireless communication network was used in the residential environment for the HEMS presented in this article.

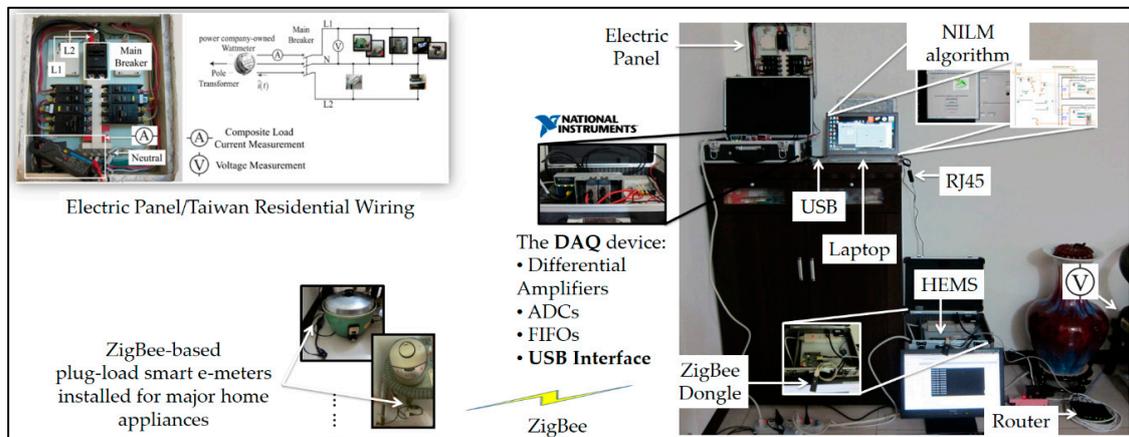


Figure 5. Experimental set-up of the IoT-oriented smart HEMS utilizing the proposed novel hybrid UAC-NFC model in a realistic residential environment.

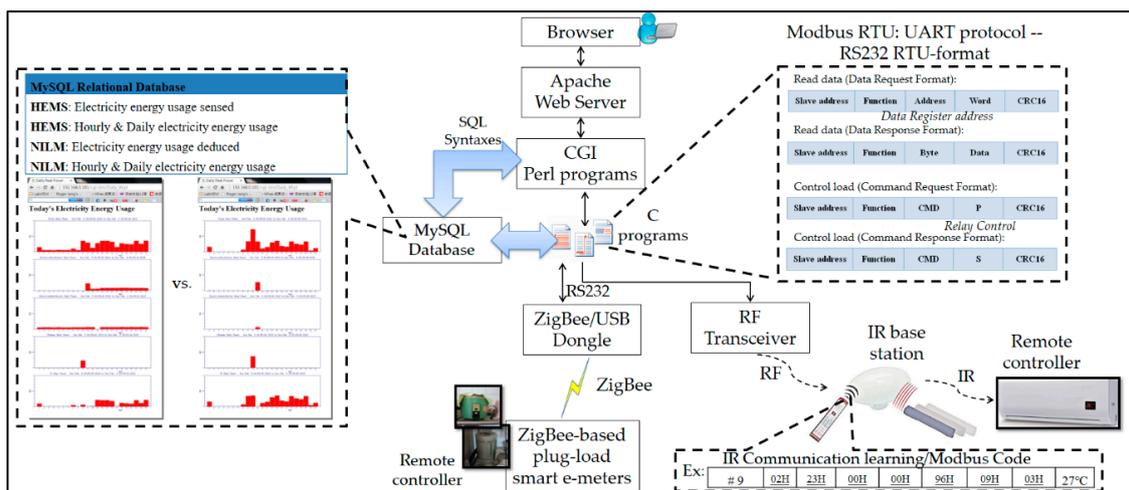


Figure 6. Flow of data stores, signal requests, and controls of electrical appliances monitored in the HEMS.

In this experiment, the total number N_{app} of electrical household appliances powered by L1 of the electrical wiring in the residential environment and monitored by the smart HEMS, having the proposed novel hybrid UAC-NFC model, was four. In total, 16 ($2^{N_{app}}$) operational combinations/classes had to be classified. The household appliances monitored in the residential environment included inductive and resistive loads. The load operation scenarios classified included the scenarios where household appliances are simultaneously energized or de-energized. In this experiment, 4 load operation scenarios were excluded, since, in reality, the power-intensive household appliances should not be used at the same time as the conductor would overload. The centralized HEMS communicating with the plug-load smart e-meters via a ZigBee-based wireless communication network identified the monitored household appliances intrusively. The NILM using the novel hybrid UAC-NFC model to analyze the composite voltage and current signals, acquired at the main electrical panel in the residential environment, classified the household appliances non-intrusively. In Lin et al. [22], only one electrical feature, P, was considered for load classification. In Lin et al. [6],

a mechanism that systematically constructs an NFC by grouping input-output data pairs into clusters to represent fuzzy if-then rules in an unsupervised and self-organized manner was not developed.

In this article, a novel hybrid UAC-NFC model is developed and evaluated using this experiment. In this experiment, on-site 80 voltage and current measurements were recorded off-line for each load operation scenario: 40 randomly-chosen voltage and current measurements were used for training, while the remaining 40 voltage and current measurements were used for tests. A total of 960 data pairs were collected. Figure 7 illustrates the feature space of P (Watts) and Q (Var) in this experiment. P and Q stand for real power and reactive power measured, respectively, which were extracted from the electrical household appliances and used as the electrical features/input feature variables for the NILM as a load classification task for the NFC. There are 12 classes in Figure 7, which are addressed and listed in Table 2. Observation of feature data in Figure 7 shows that high ambiguity existed in the data. The ambiguity was caused by uncertainties where household appliances were identified under similar P and Q. Thus, NFC was conducted. As illustrated in Figure 7, the 12-class load classification problem can be de-composed into 3 classification problems following a divide-and-conquer process.

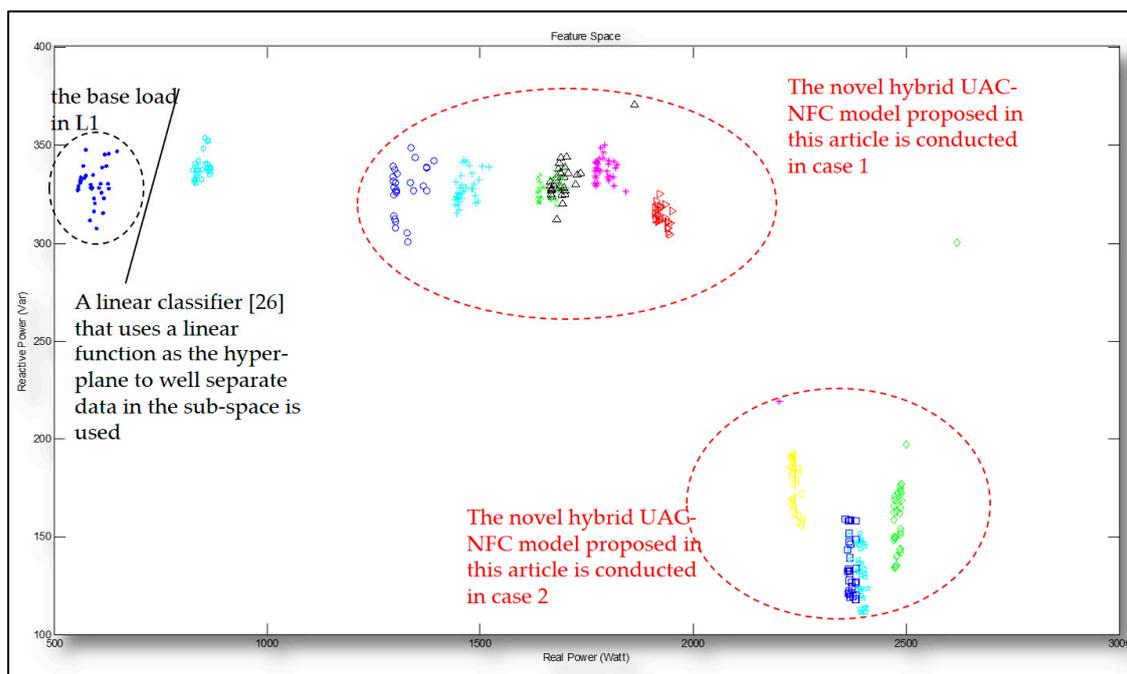


Figure 7. Feature space being of real power (P) and reactive power (Q). There are 12 classes in the feature space, which are marked by different color.

The proposed hybrid UAC-NFC model proposed was applied to cases 1 and 2. In this experiment, the UAC process, the nearest-neighborhood clustering in Section 2.2., was first applied to feature data in Figure 7. Following the UAC process used to automatically construct the NFC of Equation (2) without supervision, the GD process fine tunes the free parameters of the constructed NFC of Equation (2).

The GD process trains the constructed NFC. The NFC, shown in Figure 3 and trained through the GD process, included three network layers, and its training rule was based on Equations (5)–(7). In the NFC, the Gaussian-type membership function, rather than other types of membership function, was chosen for the following three reasons. First, the total number of free parameters to be trained was minimized because the Gaussian-type membership function only requires two factors to be formulated. Second, the Gaussian-type membership function ensures that the firing strength of each fuzzy rule computed is always non-zero. Third, the Gaussian-type membership function is continuously differentiable, and its derivative is always non-zero.

Table 2. Twelve classes addressed in this experiment.

Load Class ^{†,*}	Electric Rice Cooker	Electric Water Boiler	Steamer	Television
0	0	0	0	0
1	0	0	0	1
2	0	0	1	0
3	0	0	1	1
4	0	1	0	0
5	0	1	0	1
6	-	-	-	-
7	-	-	-	-
8	1	0	0	0
9	1	0	0	1
10	1	0	1	0
11	1	0	1	1
12	1	1	0	0
13	1	1	0	1
14	-	-	-	-
15	-	-	-	-

[†] The four load operation scenarios were excluded, since, in reality, the power-intensive household appliances monitored should not be used (0/1: Off/On) at the same time, so the conductor will not be overloaded. ^{*} The NILM performed by the UAC-NFC model for DSM was used to identify which individual major electrical appliance(s) is being turned on or off when each electrical feature reading extracted from aggregated signals is taken apart with chronological time information and is classified, which can be viewed as an energy audit.

The inputs of the NFC in Figure 3 directly convey the extracted and normalized electrical features. During the experiment, feature data were normalized within [0, 1]. The output of the NFC in Figure 3 is an identified class label. Two-fold cross validation was conducted. In the novel hybrid UAC-NFC in case 1, during the UAC process, r , the radius in Table 1, was set to 0.3. α in Equation (4) is 1. During the GD process, the training rate, η , was 0.023; a value for the maximum training iteration of 500 was used. A trained Mean Squared Error (MSE) of 0.004 was achieved, which produced an overall classification rate of 92.92% in training. The overall classification rate in tests was 95.83%, which was obtained with a value of MSE of 0.003 in case 1.

In the novel hybrid UAC-NFC in case 2, during the UAC process, r was set to 0.3. α in Equation (4) was 1. During the GD process, the training rate η was 0.01; the maximum training iteration value of 500 was used. The trained MSE of 0.006 was achieved, which produced an overall classification rate of 95.00% in training. The overall classification rate in tests was 95.63%, which was obtained with a value of MSE of 0.005 in case 2. Table 3 shows the clustering results obtained using the UAC process conducted in cases 1 and 2. Figure 8 shows the training results obtained in cases 1 and 2. Table 4 summarizes the load classification results obtained by the novel hybrid UAC-NFC model proposed in this article and evaluated in this experiment.

A cross-validation procedure [21] was applied to the feature data, where the entire feature dataset was split into a training dataset and a test dataset in this experiment. The proposed and evaluated novel hybrid UAC-NFC model for load classification in DSM produced an average and generalized overall classification rate [29] of 95.73%. Different types of electrical household appliances were identified by the novel hybrid UAC-NFC model for DSM/home energy management. This work is a revision of the original work that was proposed in Lin et al. [6]. A comparison of the optimization methods used to optimize the NFC was presented in the same article [6]. Mainly, this article focused on designing and implementing an IoT-oriented smart HEMS based on a novel hybrid UAC-NFC model in NILM for load classification in order to overcome the difficulties in distinguishing electrical appliances operated under similar electrical features and classified in an unsupervised and self-organized sense.

Table 3. Clustering results by the UAC process conducted in cases 1 and 2.

	NFC Used in Case 1	NFC Used in Case 2
Centers	(0.0299, 0.7167)	(0.0256, 0.3450)
	(0.1854, 0.7172)	(0.3653, 0.1191)
	(0.4023, 0.7175)	(0.4237, 0.1122)
	(0.4394, 0.7467)	(0.6574, 0.2661)
	(0.5587, 0.7604)	-
	(0.6956, 0.6266)	-
Spreads	0.3173	0.1973
	0.1804	0.2255
	0.1398	0.2327
	0.4329	0.9554
	0.9756	-
	0.1384	-

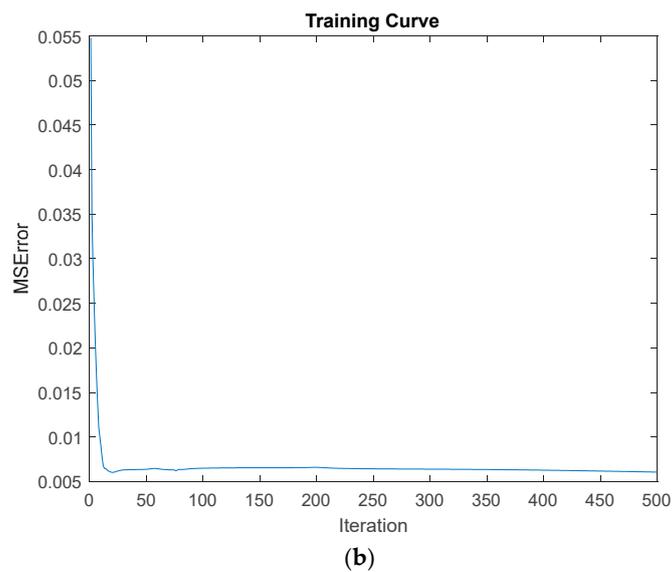
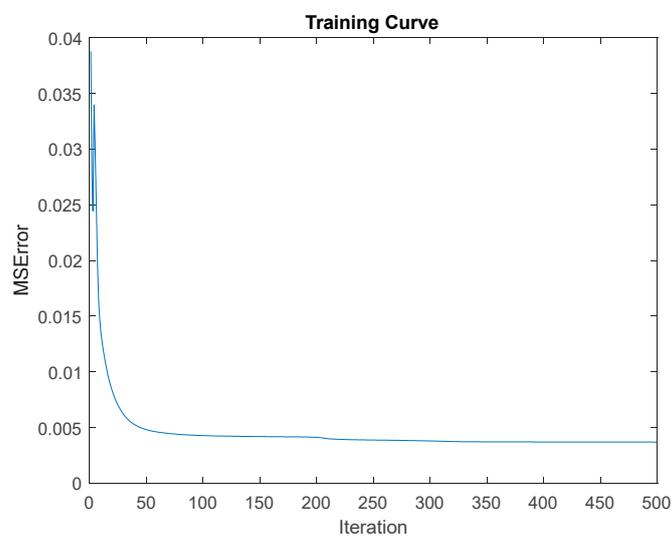


Figure 8. Training results for the (a) NFC used in case 1 and (b) NFC used in case 2.

Table 4. Load classification results obtained by the novel hybrid UAC-NFC model.

Classification Results	Novel Hybrid UAC-NFC Model Used in Case 1	Novel Hybrid UAC-NFC Model Used in Case 2
Overall classification rate [†] in training (%)	92.92	95.00
Overall Classification rate in tests (%)	95.83	95.63
The averaged and generalized overall classification rate obtained in this experiment: 95.73%.		

[†] If the class label of a test/query inputted and identified by the proposed hybrid UAC-NFC model matched the actual class label of the inputted test/query, the test/query was classified correctly; otherwise, it was not classified correctly. The overall classification rate [4] was computed as: $\frac{\text{The total number of tests/queries correctly identified}}{\text{The total number of tests/queries inputted}} \times 100\%$.

4. Conclusions and Future Work

Electricity is one of the most vital and important commodities we use every day. HEMS is used to efficiently capture the benefits of DR for DSM to ensure demand flexibility and peak load reduction while diminishing carbon emissions. Conversely, NILM, which is a low-cost load disaggregation approach [3] that allows the identification of appliance-level energy consumption information through an analysis on acquired aggregated electrical signals, is an economic technique beneficial to power utilities and end-consumers for efficiently improving electrical energy efficiency through load disaggregation.

In this article, an IoT-oriented smart HEMS was created and examined in a real residential house. The smart HEMS employs a novel hybrid UAC-NFC model with NILM to identify individual major electrical appliances for DSM/home energy management in the field of household energy. As the difficulties in distinguishing electrical appliances operated under similar electrical features showing ambiguities and classified in an unsupervised and self-organized manner exist in NILM, the novel hybrid UAC-NFC model was developed to overcome these difficulties. The NFC is integrated with the UAC that eliminates human involvement. As shown by the experiment, the designed and implemented IoT-oriented smart HEMS with novel hybrid UAC-NFC model, deployed and evaluated in a realistic residential house environment, produced an average and generalized overall classification rate of 95.73%, which is workable and feasible. The NILM completed for DSM was used to identify which individual major electrical appliance(s) is being turned on or off when each electrical feature reading extracted from aggregated signals was taken apart with chronological time information and classified, which can be viewed as an energy audit.

On-line training of the UAC-NFC model used in the HEMS was not covered in this article. This will be included with active learning for NILM in DSM in the future. The future goal of the UAC-NFC model that has been introduced in this article is combining its methodology with query-based learning for NILM in DSM.

Author Contributions: Y.-H.L. conceived, designed, and performed the experiments; contributed experimental tools, analyzed the experimental data, and wrote the paper.

Funding: This research received no external funding.

Acknowledgments: This article was supported in part by the Ministry of Science and Technology, TAIWAN, under Grant No. MOST 106-2218-E-218-007-MY2-. The author would also like to thank the reviewers for their valuable comments on this article.

Conflicts of Interest: The author declares no conflict of interest.

References

1. Koolen, D.; Sadat-Razavi, N.; Ketter, W. Machine Learning for Identifying Demand Patterns of Home Energy Management Systems with Dynamic Electricity Pricing. *Appl. Sci.* **2017**, *7*, 1160. [[CrossRef](#)]

2. Tsai, M.S.; Lin, Y.H. Modern development of an adaptive non-intrusive appliance load monitoring system in electricity energy conservation. *Appl. Energy* **2012**, *96*, 55–73. [[CrossRef](#)]
3. Ayub, M.A.; Ul Hassan, N.; Yuen, C. Hybrid iterative algorithm for non-intrusive load disaggregation. In Proceedings of the 2018 IEEE International Conference on Communications (ICC), Kansas City, MO, USA, 20–24 May 2018; pp. 1–6.
4. Du, L.; Restrepo, J.A.; Yang, Y.; Harley, R.G.; Habetler, T.G. Nonintrusive, self-organizing, and probabilistic classification and identification of plugged-in electric loads. *IEEE Trans. Smart Grid* **2013**, *4*, 1371–1380. [[CrossRef](#)]
5. Dong, M.; Meira, P.C.M.; Xu, W.; Chung, C.Y. Non-intrusive signature extraction for major residential loads. *IEEE Trans. Smart Grid* **2013**, *4*, 1421–1430. [[CrossRef](#)]
6. Lin, Y.H.; Tsai, M.S. Non-intrusive load monitoring by novel neuro-fuzzy classification considering uncertainties. *IEEE Trans. Smart Grid* **2014**, *5*, 2376–2384. [[CrossRef](#)]
7. Azaza, M.; Wallin, F. Evaluation of classification methodologies and Features selection from smart meter data. *Energy Procedia* **2017**, *142*, 2250–2256. [[CrossRef](#)]
8. Chang, H.H. Non-intrusive demand monitoring and load identification for energy management systems based on transient feature analyses. *Energies* **2012**, *5*, 4569–4589. [[CrossRef](#)]
9. Chang, H.H.; Chen, K.L.; Tsai, Y.P.; Lee, W.J. A new measurement method for power signatures of non-intrusive demand monitoring and load identification. *IEEE Trans. Ind. Appl.* **2012**, *48*, 764–771. [[CrossRef](#)]
10. Tabatabaei, S.M.; Dick, S.; Xu, W. Toward non-intrusive load monitoring via multi-label classification. *IEEE Trans. Smart Grid* **2017**, *8*, 26–40. [[CrossRef](#)]
11. Chang, H.H.; Lin, L.S.; Chen, N.M.; Lee, W.J. Particle swarm optimization based non-intrusive demand monitoring and load identification in smart meters. In Proceedings of the 2012 IEEE Industry Applications Society Annual Meeting (IAS), Las Vegas, NV, USA, 7–11 October 2012; pp. 1–8.
12. Chang, H.H.; Lin, L.S.; Chen, N.M.; Lee, W.J. Particle swarm optimization based non-intrusive demand monitoring and load identification in smart meters. *IEEE Trans. Ind. Appl.* **2013**, *49*, 2229–2236. [[CrossRef](#)]
13. Zeifman, M. Disaggregation of home energy display data using probabilistic approach. *IEEE Trans. Consum. Electron.* **2012**, *58*, 23–31. [[CrossRef](#)]
14. Kolter, J.Z.; Johnson, M.J. REDD: A public data set for energy disaggregation research. In Proceedings of the SustKDD Workshop on Data Mining Applications in Sustainability (SIGKDD), San Diego, CA, USA, 21 August 2011; pp. 1–6.
15. Kong, W.; Dong, Z.Y.; Ma, J.; Hill, D.J.; Zhao, J.H.; Luo, F.J. A hierarchical hidden markov model framework for home appliance modeling. *IEEE Trans. Smart Grid* **2018**, *9*, 3079–3090. [[CrossRef](#)]
16. Kong, W.; Dong, Z.Y.; Ma, J.; Hill, D.J.; Zhao, J.H.; Luo, F.J. An extensible approach for non-intrusive load disaggregation with smart meter data. *IEEE Trans. Smart Grid* **2018**, *9*, 3362–3372. [[CrossRef](#)]
17. Drenker, S.; Kader, A. Nonintrusive monitoring of electric loads. *IEEE Comput. Appl. Power* **1999**, *12*, 47–51. [[CrossRef](#)]
18. Qi, B.; Liu, L.; Wu, X. Low-rate non-intrusive load disaggregation with graph shift quadratic form constraint. *Appl. Sci.* **2018**, *8*, 554. [[CrossRef](#)]
19. Wang, H.; Yang, W. An iterative load disaggregation approach based on appliance consumption pattern. *Appl. Sci.* **2018**, *8*, 542. [[CrossRef](#)]
20. Hasanien, H.M.; Matar, M. A fuzzy logic controller for autonomous operation of a voltage source converter-based distributed generation system. *IEEE Trans. Smart Grid* **2015**, *6*, 158–165. [[CrossRef](#)]
21. Lin, Y.H.; Hung, S.K.; Tsai, M.S. Study on the influence of voltage variations for non-intrusive load identifications. In Proceedings of the Eighth International Power Electronics Conference (IPEC-Niigata 2018-ECCE Asia), Niigata, Japan, 20–24 May 2018; pp. 1575–1579.
22. Lin, Y.H.; Tsai, M.S.; Chen, C.S. Applications of fuzzy classification with fuzzy C-means clustering and optimization strategies for load identification in NILM systems. In Proceedings of the 2011 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE 2011), Taipei, Taiwan, 27–30 June 2011; pp. 859–866.
23. Lin, C.T.; Lee, G.C.S. *Neural Fuzzy Systems: A Neuro-Fuzzy Synergism to Intelligent Systems*; Prentice Hall/Pearson Education Taiwan Ltd.: Taipei, Taiwan, 2003.

24. Nomura, H.; Hayashi, I.; Wakami, N. A learning method of fuzzy inference rules by descent method. In Proceedings of the 1992 the IEEE International Conference on Fuzzy Systems, San Diego, CA, USA, 8–12 March 1992; pp. 203–210.
25. Hagan, M.T.; Demuth, H.B.; Beale, M. *Neural Network Design*; PWS Pub. Co.: Boston, MA, USA, 1995.
26. Roger, J.S. Data Clustering and Pattern Recognition. Available online: <http://mirllab.org/jang> (accessed on 7 August 2018).
27. Chang, C.Y.; Kuo, C.H.; Chen, J.C.; Wang, T.C. Design and Implementation of an IoT Access Point for Smart Home. *Appl. Sci.* **2015**, *5*, 1882–1903. [[CrossRef](#)]
28. ZigBee Alliance Homepage. Available online: <http://www.zigbee.org/> (accessed on 28 September 2018).
29. Tsai, M.S.; Lin, Y.H.; Chang, S.T. Decomposing power consumption on household appliances using non-intrusive load monitoring integrated with a home energy management system. In Proceedings of the 17th International Conference on Intelligent Systems Application to Power Systems (ISAP 2013), Tokyo, Japan, 1–4 July 2013.



© 2018 by the author. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).