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An Advanced Home Energy Management System Facilitated by Nonintrusive Load Monitoring With Automated Multiobjective Power Scheduling

Yu-Hsiu Lin and Men-Shen Tsai, *Member, IEEE*

***Abstract*—Nowadays, electricity energy demands requested from down-stream sectors in a smart grid constantly increase. One way to meet those demands is use of home energy management systems (HEMS). By effectively scheduling major household appliances in response to demand response (DR) schemes, residents can save their electricity bills. In this paper, an advanced HEMS facilitated by a nonintrusive load monitoring (NILM) technique with an automated nondominated sorting genetic algorithm-II (NSGA-II)-based multiobjective in-home power scheduling mechanism is proposed. The NILM as an electricity audit is able to nonintrusively estimate power consumed by each of monitored major household appliances at a certain period of time. Data identified by the NILM are very useful for DR implementation. For DR implementation, the NSGA-II-based multiobjective in-home power scheduling mechanism autonomously and meta-heuristically schedules monitored and enrolled major household appliances without user intervention. It is based on an analysis of the NILM with historical data with past trends. The experimental results reported in this paper reveal that the proposed advanced HEMS with the NILM assessed in a real-house environment with uncertainties is workable and feasible.**

***Index Terms*—Data fusion, demand response (DR), energy management system, ensemble learning, nonintrusive load monitoring (NILM), power scheduling, smart grid, smart house.**

Nomenclature

$x^a_{t,d}$	On/off status of household appliance a at time slot t in day d.
UR^a_t	Usage rate (UR) of household appliance a at time slot t.
$[\alpha_a, \beta_a]$	Time interval in which appliance a is expected to be used.
l_a	Length of household appliance a used from start to end.
δ_a	Slack parameter used to margin scheduled household appliance a for use (i.e., to margin the time interval $[\alpha_a, \beta_a]$).
s_a	Time in which household appliance a is started for use.
τ_a	Time shift, $\lvert s_a - \alpha_a \rvert$, of household appliance a.
$\mathrm{Price}_h(\cdot)$	Day-ahead real-time pricing (RTP) combined with five-level inclining block rates (IBR).

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Y.-H. Lin is with the Graduate Institute of Mechanical and Electrical Engineering, National Taipei University of Technology, Taipei 10608, Taiwan (e-mail: yhlin731108@gmail.com).

M.-S. Tsai is with the Graduate Institute of Automation Technology, National Taipei University of Technology, Taipei 106, Taiwan (e-mail: mstsai@ntut.edu.tw).

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I. Introduction

ELECTRICITY is one of the most popular forms of energy used in the modern society. Nowadays, electricity energy demands requested from down-stream sectors of a smart grid constantly increase. One way to meet those electricity energy demands is use of home energy management systems (HEMS) to monitor and effectively manage major household appliances in response to demand response (DR) programs. In a smart house equipped with green energy facilities, the home gateway (HG), the essence of the HEMS communicates with smart appliances and major electric appliances with smart plugs via a wireless communication network, gathers power consumption on each of the monitored household appliances intrusively [1]–[5]. In response to DR programs in exchange for a discount on electricity prices, the HEMS coordinates all the monitored and enrolled household appliances and green energy facilities for a better use of electricity energy. Such a smart house can be realized. However, high market price of smart appliances and noninteroperability among them are now barriers for the widespread adoption of smart appliances [6]. Instead, smart plugs are adopted in the transitional period. However, smart plugs monitoring power consumption on household appliances intrusively are costly power meters [7]–[11]. Also, the house gets over-loaded in complexity with extra investment including annual maintenance costs, as the number of household appliances monitored increases in number [7]–[11]. As a result, it is necessary to monitor household appliances in a cost-effective way for demand-side load disaggregation.

For demand-side load management by residential DR strategies, some load control strategies for shedding household appliances [3], [4] and several power scheduling methods for scheduling in-home power consumption [12]–[16] have been proposed in the past. Also, there have been several well-known techniques used to solve in-home power scheduling problems [12], such as linear programming [14] and particle swarm optimization [16]. In [13], an in-home load scheduling method that reduces the electricity cost was realized. However, the peak power demand leading to a relatively high peak-to-average ratio (PAR) may emerge when the electricity price is low. The IBR should be considered for residential DR implementation. In [14], both the electricity cost and PAR are simultaneously reduced, but the assumptions made seem impractical as pointed in [12]. In order to alleviate the defects that arise in [13] and [14], a genetic algorithm (GA)-based in-home load scheduling approach proposed in [12] schedules smart appliances based on RTP combined with IBR. However, in [12], the inhabitants need to manually indicate the physical characteristics of each of enrolled smart appliances. In [15], a heuristics-based autonomous in-home load scheduling scheme that schedules the household appliances based on their "time of use" (ToU) probabilities is presented. To evaluate the performance of the autonomous in-home load scheduling scheme presented in [15], the authors simulated daily usage of 22 household appliances. As the simulation results reported in [15] showed, the total electricity energy consumption does not exceed a prespecified demand limit so as to reduce the household's electricity bills. In [15], only the RTP is considered; the IBR that diminishes the peak power demands is not taken into account. Residential load management in a house environment is a complex task, the compensation is naturally decentralized, and the housel environment and user demands change with time and season [17]. In [17], a decision-support system is developed. Based on the user's lifestyles and environmental factors—season and room temperature, the decision-support system can forecast power demand of monitored smart appliances and enable the user to improve the household's in-home power consumption by predicting potential schedules for the smart appliances. The decision-support system with an adaptive neural fuzzy inference system forecasts the time in which each monitored smart appliance with their predicted operation duration is turned on. Also, it with a "branch and bound" technique schedules the smart appliances to respond to DR events with TOU pricing. The power profiles of the monitored smart appliances—an air conditioner and a washing machine were gathered by watts-up power meters. The scheduled smart appliances include a dishwasher, washing machine, and a dryer. The simulation results reported in [17] confirm that the decision-support system is an effective solution for residential DR implementation.

As surveyed in this paper, most of the residential DR strategies are heuristics-, rules-, or tasks-scheduling-based residential DR strategies with user intervention in which occupants need to manually set customer-driven load priorities and comfort preferences in advance. Also, with responding to a DR event, the residential DR strategies and the GA-based in-home load scheduling approach [12] with user intervention provide only single optimum solution to occupants for demand-side load management. For a design and implementation of a residential DR strategy for demand-side load management, it is necessary to autonomously and meta-heuristically schedule household appliances without user intervention, while considering occupants' desired comfort preferences and lifestyles. A combination of RTP with IBR is necessary as well for demand-side load management.

Therefore, in this paper, an advanced HEMS facilitated by a nonintrusive load monitoring (NILM) technique with a nondominated sorting genetic algorithm-II (NSGA-II)-based multiobjective in-home load scheduling mechanism is proposed.

The proposed NILM as an energy audit monitors household appliances in a cost-effective way where a data acquisition (DAQ) device with only one single minimal set of voltage and current sensors is installed. Through an analysis on acquired aggregated electricity signals, the NILM is able to identify household appliances. Refer to [8] for more details on existing NILM methods. Existing NILM methods in [6]–[11] and [18]–[21] have explored and made an extensive effort on either feature extraction or load disaggregation, in order to address the difficulties in distinguishing household appliances with similar electrical features. However, it is acknowledged by most of the researchers that the traditional application of NILM has seen no great progress in recent years [21]. Thus, this paper conducts a promising actual application of NILM for residential DR implementation. The proposed NILM automatically and autonomously characterizes physical characteristics of scheduled household appliances without user intervention through an analysis on historical data with past trends. It does not require user intervention. As a result, the proposed NILM, an extension of NILM, is different from the existing NILM methods presented in [6]–[11] and [18]–[21].

The proposed NSGA-II-based in-home load scheduling mechanism with a grey relational analysis (GRA) rather than the existing residential DR strategies proposed in the past and surveyed in this paper is acted as a customized electricity energy consultant that is able to provide a set of feasible nondominated Pareto load schedules to residents. The demand-side load management addressed by the proposed day-ahead NSGA-II-based in-home load scheduling mechanism is viewed as a multiobjective optimization (MOO) problem, in which electricity bills-versus-residents' desired comfort preferences and lifestyles trade-offs are considered. With responding to a DR signal, the existing residential DR strategies provide only single optimum solution instead of a set of trade-off solutions to residents. With use of the proposed advanced HEMS, it is expected that more incentives for customer participation in DR are achieved and obtained. The residents are not similarly naive about electricity energy savings for demand-side load management with the consideration of their desired comfort preferences and lifestyles. Finally, from the viewpoint of utilities, there is one solution to effectively deliver residential energy savings and peak-demand reduction. The utilities can provide sufficient electricity energy during peak-demand durations to down-stream sectors of a smart grid and maintain grid stability and safety at acceptable costs. The proposed advanced HEMS is deployed and assessed in a real-house environment with uncertainties in Taiwan. This paper is organized as follows. The novel framework of the advanced HEMS is given in Section II. Section III presents the proposed methodology. Section IV demonstrates the experimentation. Finally, the conclusion is made in Section V.

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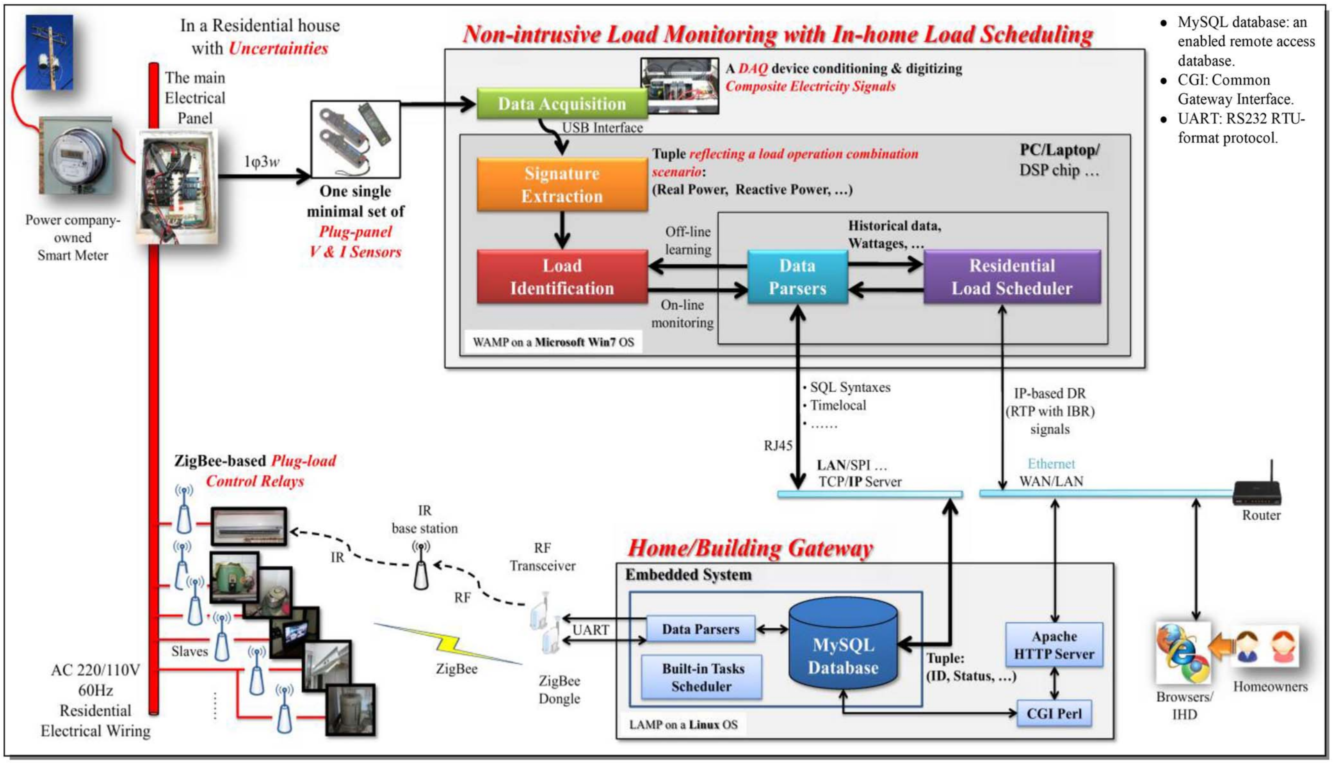


Fig. 1. Framework of the proposed advanced HEMS deploying to a real-house environment.

II. Framework of the Advanced HEMS

Fig. 1 shows the framework of the advanced HEMS proposed in this paper. In this framework, two different types of sensors installed in the house environment co-work in a data-fusion fashion.

A. Low-Cost Plug-Load ZigBee-Based Control Relays

The plug-load ZigBee-based control relays to remotely ON/OFF control major household appliances in response to DR signals with direct or alternation load controls are used to label load combinations of the major household appliances.

B. One Single Minimal Set of Plug-Panel (Nonplug-Load) Current and Voltage Sensors

The plug-panel current and voltage sensors connected to a DAQ device sense aggregated whole-house electricity signals to be further analyzed by the NILM with the in-home load scheduling mechanism. The NILM deduces how many household appliances monitored are being energized or de-energized in a supervised learning manner. It also estimates how much power goes into each of them. On-line load monitoring process starts once the Off-line load learning process has been done. Data acquired and analyzed by the NILM are very valuable for: 1) defect diagnosis on monitored household appliances; 2) healthcare service for inhabitants; and 3) residential DR implementation. In this paper, residential DR implementation is realized. Based on historical data identified and pared by the proposed advanced HEMS with the NILM, the proposed in-home load scheduling mechanism automatously and meta-heuristically schedules enrolled household appliances ahead of the day, while taking the residents' desired comfort preferences and lifestyles into account.

As Fig. 1 shows an USB interface makes a communication between the DAQ device and the PC. The PC is the essence of the NILM with the in-home load scheduling mechanism. An HTTP server-based user interface acted as the in-home display (IHD) in the house environment is designed. To communicate with the HG via LAN TCP/IP, the PC installs a standardized MySQL connector driver (open database connectivity) matching data source name; LabSQL virtual instruments using activeX data objects in LabVIEW are used [22]. The NILM with the in-home load scheduling mechanism in this paper is presented in Section III.

III. NILM With In-Home Power Scheduling

To increase the clarity, feasibility, and practicality of the proposed advanced HEMS with the NILM having the in-home load scheduling mechanism deployed in a real-house environment, Fig. 2 shows the flowchart of the proposed methodology before the experimentation to be followed in Section IV is presented afterwards. As shown in Fig. 2, the flow of the proposed methodology consists of three parts: 1) Off-line load learning and modeling; 2) on-line load monitoring; and 3) day-ahead in-home load scheduling. Off-line load learning and modeling and on-line load monitoring are conducted by the NILM, which is presented in Section III-A. Day-ahead in-home load scheduling is presented in Section III-B.

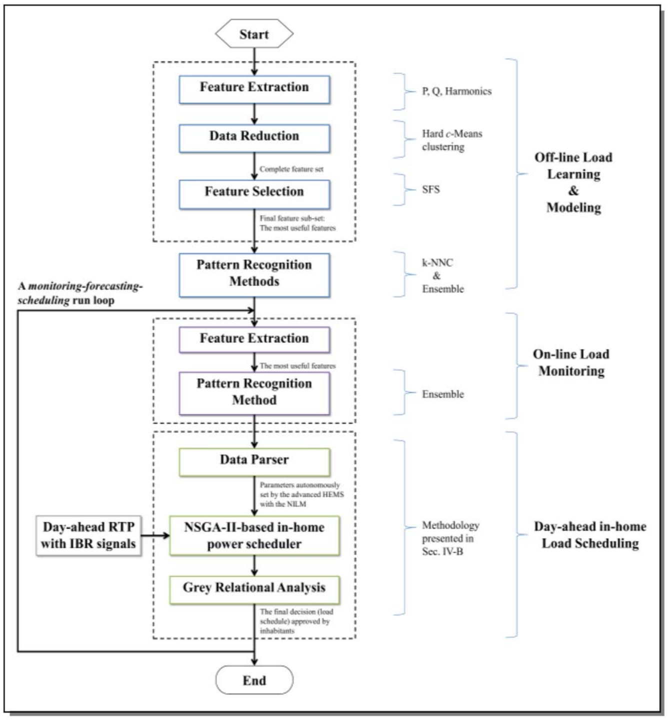


Fig. 2. Flowchart of the proposed methodology—NILM with in-home power scheduling.

A. NILM

As Fig. 2 shows, a feature extraction process that extracts electrical features from acquired aggregated electricity signals is performed first. In this paper, electrical features as feature candidates are composite real power (P), reactive power (Q), and harmonics extracted by the fast fourier transform from the acquired aggregated current signals [18], [19]. A data reduction process is conducted during the Off-line load learning process in this paper, where a hard c-means clustering algorithm finds representative prototypes of data instances with the same class label so as to trim the collected training dataset in size and reduce noise on data [23]. After the data reduction process terminates, a feature selection process by a sequential forward selection (SFS) method [23], [25] is conducted.

The SFS method sequentially judges the feature combination in which the most influential and relevant features that give the highest classification accuracy out of the feature candidates are selected and used by pattern recognition methods. Thereafter, the pattern recognition methods [23]–[25] employed in this paper and compared for a better load disaggregation include a hard c-means-based k-nearest neighbor classifier (k-NNC) [23] and an ensemble [24] that classifies features in a divide-and-conquer manner. The pattern recognition method that can better perform load disaggregation as load classification with the most useful features can be elected in this Off-line load learning process. The uncertainties in which household appliances or load combinations of the household appliances may be identified under similar P [8] can be treated by the proposed NILM, since supplementary features in addition to P are selected and used in this paper. Finally, on-line load monitoring process is executed once the Off-line load learning process has been finished.

In this paper, the proposed PC-based NILM algorithm takes a feature reading every minute, analyzes it, and then identifies how many monitored household appliances are being used in the house field. Hourly power consumption on each of them can be further estimated. Lastly, based on an analysis on historical data identified and parsed by the NILM, the day-ahead in-home load scheduling process that is presented in the following subsection starts.

B. Automated NSGA-II-Based In-Home Power Scheduling Approach

In residential DR implementation, an automatic DR strategy in which residents do not need to manually set physical characteristics of enrolled household appliances via an IHD panel is expected. In this paper, an NSGA-II [26]-based in-home load scheduling mechanism with a GRA [27] is proposed. It is acted as a customized electricity energy consultant that provides a set of feasible nondominated Pareto load schedules to the residents. The GRA quantizes the relationship among the feasible Pareto solutions in the Pareto-optimal front, which is found by the NSGA-II, for the final decision approved by the residents. Fig. 3 illustrates the workflow of the proposed in-home load scheduling mechanism that automatously and meta-heuristically schedules household appliances enrolled for participation in DR programs without user intervention in this paper. According to the final decision approved by resident(s), the HG commands the scheduled household appliances for home automation and demand-side load management.

The proposed automated NSGA-II-based in-home load scheduling mechanism with a GRA involves the following three steps.

Step 1: Uses the proposed advanced HEMS with the NILM to parse gathered historical data with past trends, in order to autonomously generate initial load schedules without user intervention.

This step to automatically characterize physical characteristics of each enrolled household appliance without user intervention for customer participation in DR programs is described in detail later. The physical characteristics, which are set without user intervention by the proposed NILM with gathered historical data, of enrolled household appliances include: 1) the duration of each of the enrolled household appliances from start to end; 2) the hourly power consumption by each of them; and 3) the load priorities with the past trends parsed.

Step 2: Executes the NSGA-II to find the Pareto-optimal front. Details about how the NSGA-II works to identify the Pareto-optimal front for an MOO problem are given in [26].

In this paper, the in-home power scheduling problem is viewed as an MOO problem where electricity bills-versus-residents' desired comfort preferences and lifestyles trade-offs are considered. The Pareto-optimal front found by the NSGA-II in this step contains a set of feasible nondominated

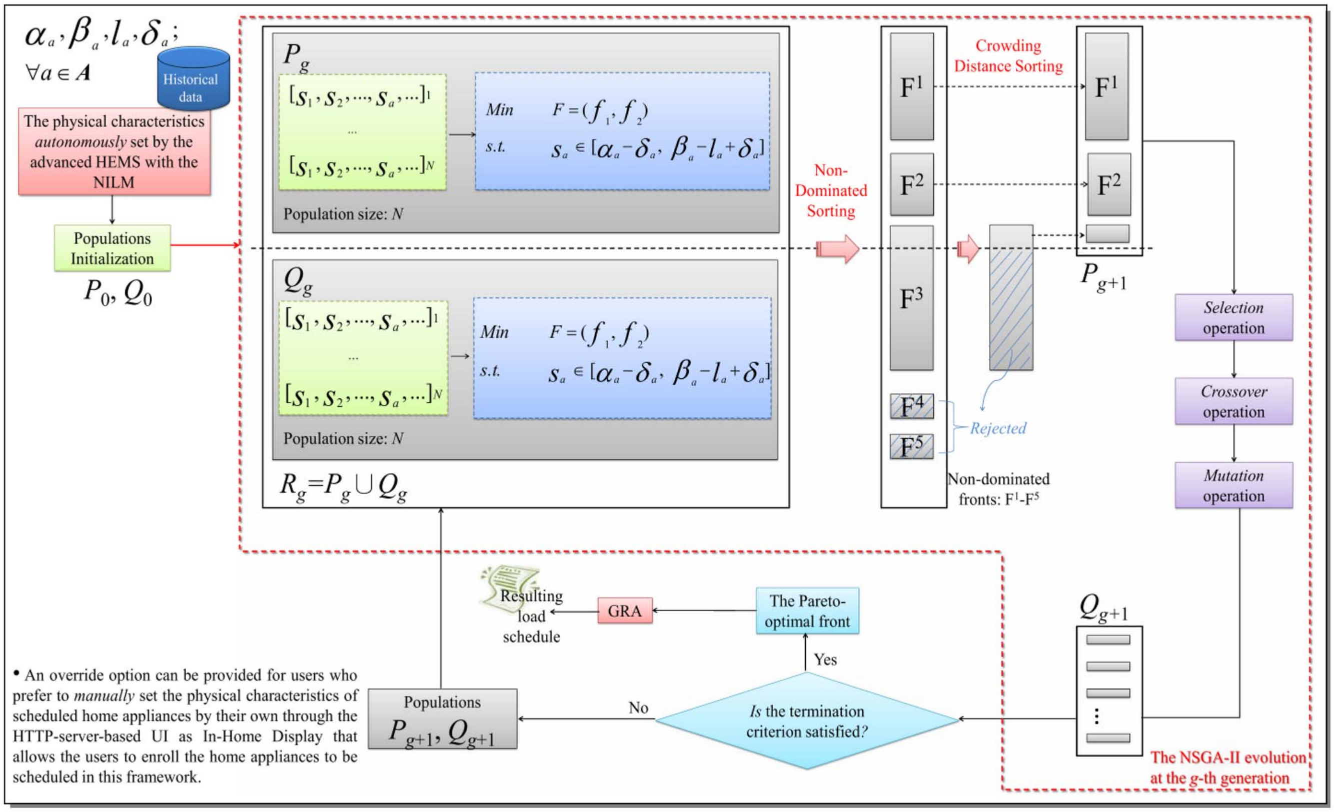


Fig. 3. Workflow of the automated NSGA-II-based in-home power scheduling mechanism with a GRA in this paper.

load schedules. They are further analyzed by a GRA for the final decision with respect to the residents' desired request approved, as involved in Step 3.

Step 3: Performs the GRA to quantize the relationship among the feasible solutions in the Pareto-optimal front found in Step 2. Here, the NSGA-II with the GRA is viewed as a customized "consultant" consulted by the residents. The final decision is implemented through the remote load controls of the advanced HEMS.

This step to identify the appropriate feasible load schedule from the found feasible solutions in the Pareto-optimal front with respect to a desired request approved by the residents through the GRA is described in depth in the end of this section.

Historical data gathered and identified by the proposed advanced HEMS with the NILM are parsed as follows.

Suppose that, there are T time slots in one day, where $\boldsymbol{T} = \{1, 2, \ldots, t, \ldots, T\}$. T for instance is equal to 1440 a day, if 1 h is divided into 60 time slots. That is, the time resolution is 1 min. Also assume that, there are A household appliances enrolled and monitored in the house field, where $\boldsymbol{A} = \{1, 2, \ldots, a, \ldots, A\}$. During the Off-line load learning and modeling (data collection) process, household appliance $a \in \boldsymbol{A}$ is monitored and identified by the advanced HEMS with the NILM for D days where $\boldsymbol{D} = \{1, 2, \ldots, d, \ldots, D\}$.

The TOU-like UR of household appliance a at time slot $t \in \boldsymbol{T}$ in the past D days is computed, as given in (1) to figure out a global or macro behavior profile of household appliance a used in the past D days

$$\mathrm{UR}_t^a = \frac{\sum_{d \in \boldsymbol{D}} x_{t,d}^a}{D}. \tag{1}$$

In (1), $x_{t,d}^a$ represents the On/Off status of household appliance a at time slot t in day $d \in \boldsymbol{D}$; $x_{t,d}^a \in \{0, 1\}$, where 0: "Off," 1: "On".

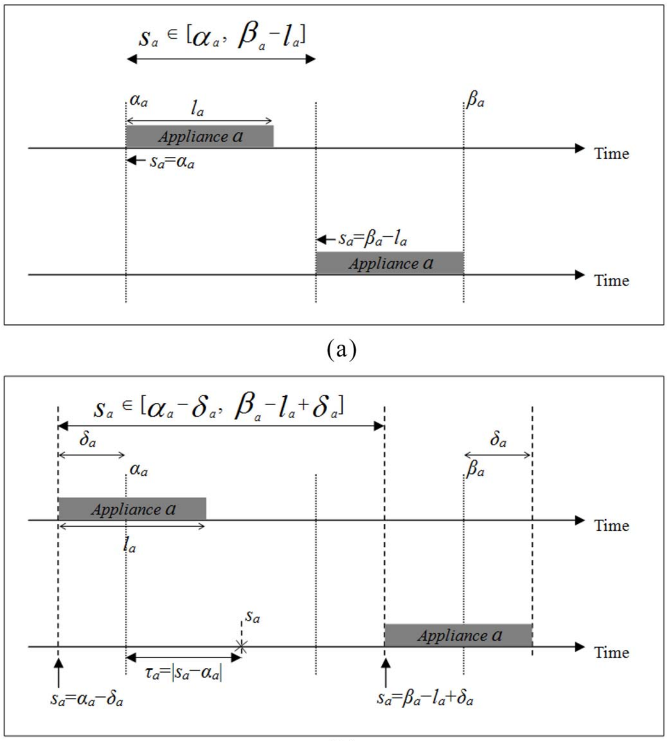
An activation function, $\mathscr{T}r(\cdot)$, that transfers the behavior profile of household appliance a into an activation profile is further designed

$$\mathscr{T}r\left(\mathrm{UR}_t^a\right) = \begin{cases} 0, & \text{if } \mathrm{UR}_t^a < \text{Const} \\ 1, & \text{if } \mathrm{UR}_t^a \geq \text{Const.} \end{cases} \tag{2}$$

If the activation function is assigned a value 1, household appliance a at time slot t is turned On; otherwise, it is turned off.

The in-home power scheduling problem is declared as an MOO problem in this paper, solved by the NSGA-II with the GRA, and described below.

First, 1 day contains 24 h, where $\boldsymbol{H} = \{1, 2, \ldots, h, \ldots, H = 24\}$. There are T time slots in one day, and there are A household appliances enrolled for participation in the in-home power scheduling process. Define that $[\alpha_a, \beta_a] \in \boldsymbol{T}$ is the time interval in which household appliance $a \in \boldsymbol{A}$ is expected to be used. Also define that, l_a being integer multiples of time slot $t \in \boldsymbol{T}$ is the length of household appliance a used from start to end. Where, $\beta_a - \alpha_a$ being integer multiples of time slot t must be greater than or equal to l_a. In the meantime, it must



(a)

(b)

Fig. 4. Illustration of the time interval of household appliance a (a) without the slack parameter or (b) with the slack parameter.

be less than or equal to T. Further define that, s_a stands for the time in which household appliance a is started for use, where s_a ranges from time interval $[\alpha_a, \beta_a - l_a]$. Illustration of the time interval is given in Fig. 4(a). The time interval in which household appliance a is valid to be scheduled is automatically identified in this paper by the proposed NILM with historical data with past trends. In this paper, a slack parameter, δ_a, is defined for household appliance a, as shown in Fig. 4(b). The slack parameter defined for household appliance a that is valid to be scheduled is used to margin household appliance a for use (with respect to the past trends). Illustration of the slack parameter for margining household appliance a for use is shown in Fig. 4(b). As shown in Fig. 4(b), $s_a \in [\alpha_a - \delta_a, \beta_a - l_a + \delta_a]$. This time interval implies that, household appliance a to be scheduled is shifted through a control of time shift τ_a. τ_a of household appliance a in Fig. 4(b) is: $|s_a - \alpha_a|$. It has to be integer multiples of time slot t.

In this paper, two objective functions are defined, considered, and addressed for demand-side load management. The first objective function, f_1, to be minimized is a function of electricity expenses paid by the residents

$$f_1 = \sum_{h \in \boldsymbol{H}} \text{Price}_h\left(p_h^{\text{tot}}\right) \cdot p_h^{\text{tot}}. \tag{3}$$

In (3), p_h^{tot} is the total hourly power consumption in kilowatt-hour (kWh) in the house field. Also, $\text{Price}_h(\cdot)$ denotes the computed and paid hourly electricity expense in NT\$/kWh; it combines day-ahead RTP with five-level IBR by the power utility (Taipower) in Taiwan

$$\text{Price}_h\left(p_h^{\text{tot}}\right) = \begin{cases} \text{RTP}_h, & \text{if } p_h^{\text{tot}} \le 0.1667 \\ 1.276 \cdot \text{RTP}_h, & \text{if } 0.1667 < p_h^{\text{tot}} \le 0.4590 \\ 1.347 \cdot \text{RTP}_h, & \text{if } 0.4590 < p_h^{\text{tot}} \le 0.6950 \\ 1.111 \cdot \text{RTP}_h, & \text{if } 0.6950 < p_h^{\text{tot}} \le 0.9722 \\ 1.122 \cdot \text{RTP}_h, & \text{if } p_h^{\text{tot}} > 0.9722. \end{cases} \tag{4}$$

In (4), RTP_h changing every hour denotes the hth RTP assumed to be predicted ahead of the day [12] and received by the residents for the day-ahead in-home power scheduling process implemented in this paper. The IBR imposes more expense and diminishes the PAR.

p_h^{tot} used in (3) and (4) is estimated by the proposed advanced HEMS with the NILM every hour

$$p_h^{\text{tot}} = \sum_{a \in \boldsymbol{A}} \frac{\text{Wattage}_a \times \sum_{t=1+60(h-1)}^{60+60(h-1)} x_t}{1000 \times 60}. \tag{5}$$

In (5), Wattage_a accounts for the power of household appliance $a \in \boldsymbol{A}$ in Watts; $t \in [1 + 60(h-1), 60 + 60(h-1)]$, where $h \in \boldsymbol{H}$; x_t stands for the On/Off status of household appliance a at time slot t in hour h; $x_t \in \{0, 1\}$, where 0: status Off while 1: status On. The power, Wattage_a used in (5), of each household appliance is statistically computed from the training data collected by the NILM on-site during the Off-line load learning process. In this paper, the power consumption of all monitored and scheduled household appliances every hour is near constant, not time-varying. By summing up all the 24 amounts of the total hourly power consumption on the household appliances, the proposed advanced HEMS obtain the daily power consumption in kWh. Due to the time division with a 12-min solution, the number of h to be a dummy variable can become 120 instead of 24.

Meta-heuristic algorithms, for example GAs can be used to solve f_1 in (3) by scheduling in-home power consumption. However, residents' desired comfort preferences and lifestyles have not been taken into account yet. This paper further defines an objective function that considers residents' comfort preferences and lifestyles during the in-home load scheduling process. The second objective function, f_2, to be minimized is a function of the time shift of scheduled household appliances with the consideration of residents' desired comfort preferences and lifestyles

$$f_2 = \sum_{a \in \boldsymbol{A}} \tau_a. \tag{6}$$

In (6), $\tau_a = |s_a - \alpha_a|$ is the time shift [refer to Fig. 4(b)] of household appliance a.

In this paper, the addressed in-home load scheduling problem is viewed as an MOO problem where electricity bills$^{[f_1\ in(3)]}$-versus-residents' desired comfort preferences and lifestyles$^{[f_2\ in(6)]}$ trade-offs are considered. As a result, the slack parameter illustrated in Fig. 4(b) used to margin the household appliance for use is needed.

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The in-home load scheduling problem considered as the MOO problem and solved by the NSGA-II in this paper is clarified

$$\begin{aligned}&\text{Minimize} \quad F(X) = (f_1(X), f_2(X))\\&\text{s.t.} \quad s_a \in [\alpha_a - \delta_a, \beta_a - l_a + \delta_a].\end{aligned} \tag{7}$$

In (7), $X = (s_a, \tau_a)$ represents a 2-D solution. The constraints of the two variables, s_a and τ_a, are determined without user intervention. It is based on an analysis on historical data with the past trends, in which the proposed advanced HEMS with the NILM uses (1) and (2) to figure out residents' preferences and lifestyles emerging with electricity energy consumption. In this paper, the following constraints are also made. First, the scheduled household appliances are not interruptible. Second, in each time slot, the total load must not exceed the ampere capacity of the circuit breakers in the main electrical panel of the house environment. Exceeding the "ampacity" of the circuit breakers may lead to overheating or fire. During the NSGA-II process, the above-mentioned constraints and $s_a \in [\alpha_a - \delta_a, \beta_a - l_a + \delta_a]$ have to be satisfied. Since (7) is an MOO problem, there is no single best solution that overcomes the dilemma between f_1 and f_2. It is an "electricity bills-versus-residents' desired comfort preferences and lifestyles" trade-offs optimization problem, which is solved by the NSGA-II with the GRA in this paper. The Pareto-optimal front containing all feasible nondominated load schedules is viewed as a customized consultant consulted by the residents approving the desired appropriate load schedule through a GRA. The GRA used is described below.

The grey theory was first initiated by Prof. Deng in 1980s [27]. In this paper, the GRA is used to measure the relationship between a desired/preferred load schedule as a reference sequence and each of the found feasible load schedules as normalized comparative sequences.

Consider that there is a reference sequence $x_0 = (x_0(1), x_0(2), \ldots, x_0(i), \ldots, x_0(n))$ where $i = 1, 2, \ldots, n$. And, there are m comparative sequences $x_j = (x_j(1), x_j(2), \ldots, x_j(i), \ldots, x_j(n))$ where $j = 1, 2, \ldots, m$. The grey relational coefficient (GRC) of x_j with respect to x_0 at the ith item is computed

$$\gamma\left(x_0(i), x_j(i)\right) \equiv \frac{\Delta_{\min} + \zeta\,\Delta_{\max}}{\Delta_{0j}(i) + \zeta\,\Delta_{\max}}. \tag{8}$$

In (8)

$$\Delta_{\max} \equiv \operatorname*{Max}_{\forall j} \operatorname*{Max}_{\forall i} \left|x_0(i) - x_j(i)\right|$$

$$\Delta_{\min} \equiv \operatorname*{Min}_{\forall j} \operatorname*{Min}_{\forall i} \left|x_0(i) - x_j(i)\right|, \; \Delta_{0j}(i) \equiv \left|x_0(i) - x_j(i)\right|$$

and typically ζ is 0.5.

The grey relational grade (GRG) being a scalar falling in interval [0, 1] between any of the m comparative sequences x_j and the reference sequence x_0 can be computed as the mean value of the GRCs

$$\Gamma_{0j} \equiv \frac{1}{n}\sum_{i=1}^{n} \gamma\left(x_0(i), x_j(i)\right). \tag{9}$$

In (9), Γ_{0j} represents the relation degree between the comparative sequence x_j and the reference sequence x_0. One can use (9) to evaluate the similarity between each of the comparative sequence x_j and the reference sequence x_0: the higher GRG is, the more similar comparative sequence x_j to the reference sequence x_0 there would be.

In this paper, Pareto solutions in the Pareto-optimal front found by the NSGA-II are regarded as the m comparative sequences x_j; the n items ($n = 2$ here) are f_1 and f_2; x_0 is regarded as ($\sim$1, $\sim$0) if the final decision approved by the residents is highly f_1-driven. Finally, the final decision can be made and implemented in the house environment. The GRA quantizes the relationship among all feasible load schedules in the Pareto-optimal front, for the (desired) appropriate load schedule (Pareto-optimal solution) with respect to the desired request x_0 approved by the residents. Auto-remote load controls in response to the DR addressed in this paper are realized as home automation service.

IV. Experimentation

Experiments are conducted in this section. The proposed advanced HEMS with the NILM is deployed to and assessed in a real-house environment with uncertainties in Taiwan. The experimental set-up in the house environment is shown in Fig. 5. In the house environment, household appliances whose operation is related and closed to residents' lifestyles consume large power are clarified as the major household appliances. Major household appliances monitored in hot L1 of the residential electrical wiring include: an electric rice cooker ($\sim$1104.381 W), an electric water boiler ($\sim$917.183 W), a steamer ($\sim$801.967 W), a TV ($\sim$221.799 W), a range hood ($\sim$138.243 W), and a PC with peripherals ($\sim$142.271 W/214.302 W). Major household appliances monitored in hot L2 of the residential electrical wiring include: a hair dryer ($\sim$1176.108 W) and a washing machine ($\sim$301.342 W). An air conditioner drawing variable power draws is monitored intrusively. The ZigBee-based plug-load control relays and the one single minimal set of plug-panel current and voltage sensors co-work in a sensor-fusion fashion. The time resolution is 1 min. Daily and hourly power consumption on each of the major household appliances is estimated by the NILM. Lastly, the day-ahead in-home power scheduling process is executed by the proposed NSGA-II-based in-home load scheduling mechanism in response to received IP-based day-ahead RTP with the IBR signals. Demand-side load disaggregation in this paper is demonstrated in Section IV-A; demand-side load management in this paper is demonstrated in Section IV-B.

A. Demand-Side Load Disaggregation by the Advanced HEMS With the NILM

In this experiment, the major household appliances are learned and modeled Off-line for 20 days. The k-NNC and a set of back-propagation artificial neural networks (BP-ANNs) that makes up an ensemble are employed as the load identifiers of the NILM.

During the Off-line load learning process, the NILM takes a feature reading every minute (i.e., 1 h is divided into 60 time slots; 1 day has 1440 time slots), analyzes it, and

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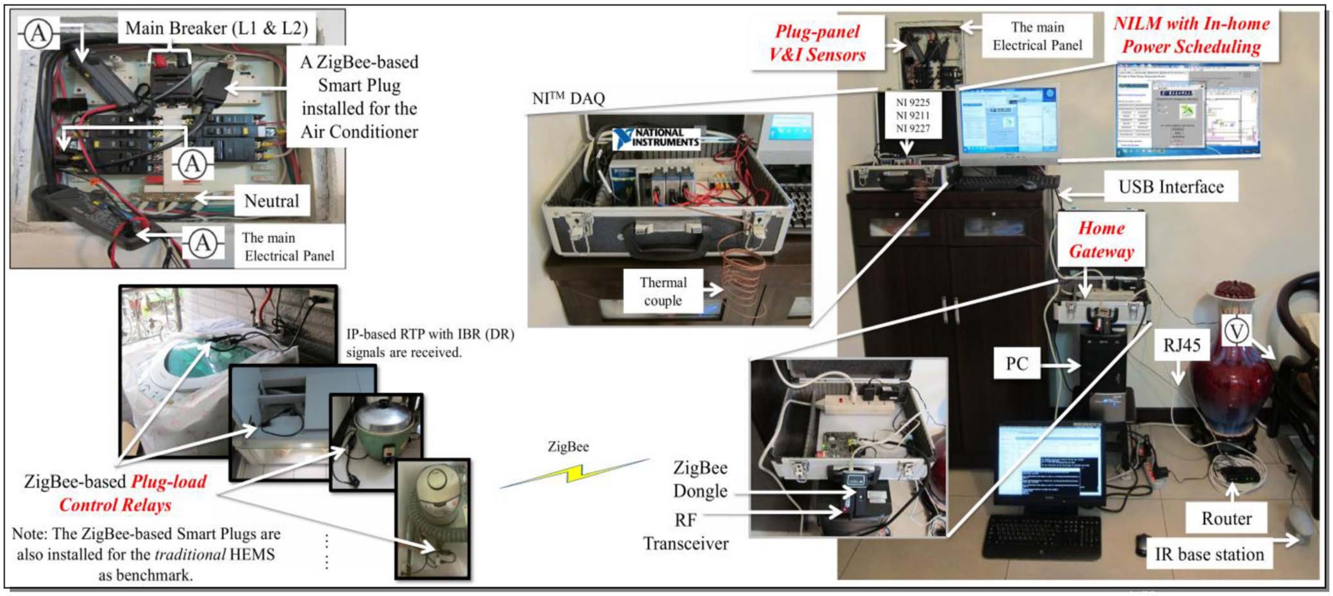

Fig. 5. Experimental set-up in a real-house field. The proposed system was tested in February and March in 2014. The HG is an ARM Cortex-A9 embedded system with an LAMP$^{\text{(LinuxOS+ApacheHTTPserver+MySQL+Perl/PHP)}}$ development environment. It is able to send command signals to and receive gathered data from the monitored household appliances. The NILM with the in-home load scheduling mechanism is implemented on an Intel Core i7 CPU 930 @2.80 GHz PC with a National Instruments DAQ device. The sampling rate of the DAQ device is set to 2kSamples/second.

then deduces how many major household appliances monitored are being used in the house environment. A total of $1440 \times 20 = 28\,800$ data are gathered on-site. Data gathered in the first 15 days of the Off-line load monitoring process are used for training; data gathered in the last five days of the Off-line load learning process are used for test. The hard c-means clustering is conducted for data reduction. It finds $c = 250$ representative prototypes representing the original training data in each class that contains data instances over 500 in number. The size of the trimmed training dataset is 2013 in number. The total number of test data instances is 7200. The entire dataset is 9213 in number. The wattage, which is used in (5), of each monitored household appliance is computed statistically from the training data.

In this experiment, a total of 17 load combination scenarios that need to be learned and identified occur in the house field. Potential electrical features evaluated by the SFS include P, Q, and the magnitude of up to the 11th-order harmonics of the acquired aggregated current signal. The k-NNC is evaluated by a leave-one-out (LOO) cross-validation test. The feature subset found by the SFS is {P, Q, $I_{\text{Mag}}^{2^{nd}}$, $I_{\text{Mag}}^{7^{th}}$} giving the highest LOO classification accuracy of 89.83%. The time consumed by the NILM during the SFS process with the LOO cross-validation test is 11 913.773 s. Besides, the BP-ANNs-based Ensemble evaluated by a three-fold cross-validation test is conducted; each BP-ANN is trained by the Levenberg–Marquardt algorithm [7]. The time consumed by the NILM during the Off-line load learning and modeling process with the three-fold cross-validation test is 3 623.420 s. Table I summarizes the classification results obtained by the two different types of load identifiers to identify the major household appliances in hot L1. As shown in Table I, the BP-ANNs-based ensemble can better deal with demand-side load disaggregation. The NILM executes the on-line load monitoring process, once the BP-ANNs-based ensemble, which has been trained and identified as the one that gives the highest classification accuracy, is suitable for on-line load monitoring.

TABLE I
CLASSIFICATION RESULTS–k-NNC VERSUS BP-ANNS-BASED ENSEMBLE

Load identifiers[a]	**Classification Accuracy/Generalization**[c] **(%)**
k-NNC evaluated by an LOO cross-validation test	89.83
BP-ANNs-based Ensemble evaluated by a 3-fold cross-validation test	90.51[b]

[a] The Hard c-means clustering is conducted in this experiment.
[b] The classification accuracy is averaged by 3.
[c] The major household appliances powered in L2 are quite distinguishable in P. Hence, they are distinguished by *IF-THEN rules*. The classification accuracy is higher than 90%.

For a long-term evaluation, the proposed HEMS with the ensemble-based NILM monitors the household appliances in hot L1 and L2 in the house field for ten days. The averaged classification accuracy is shown in Fig. 6. The averaged daily power consumption on each of the household appliances is estimated by the proposed NILM, as shown in Fig. 7.

Table II shows the computed mean absolute percentage errors (MAPE%) [28]. As shown in Table II, the total MAPE% is ~13.32%. During this experiment presented above, a total of 397 002 data gathered 1 min apart were received and stored in the MySQL database configured on the HG; only 935 data were misgathered.

In the next subsection, day-ahead demand-side load management by the proposed advanced HEMS with

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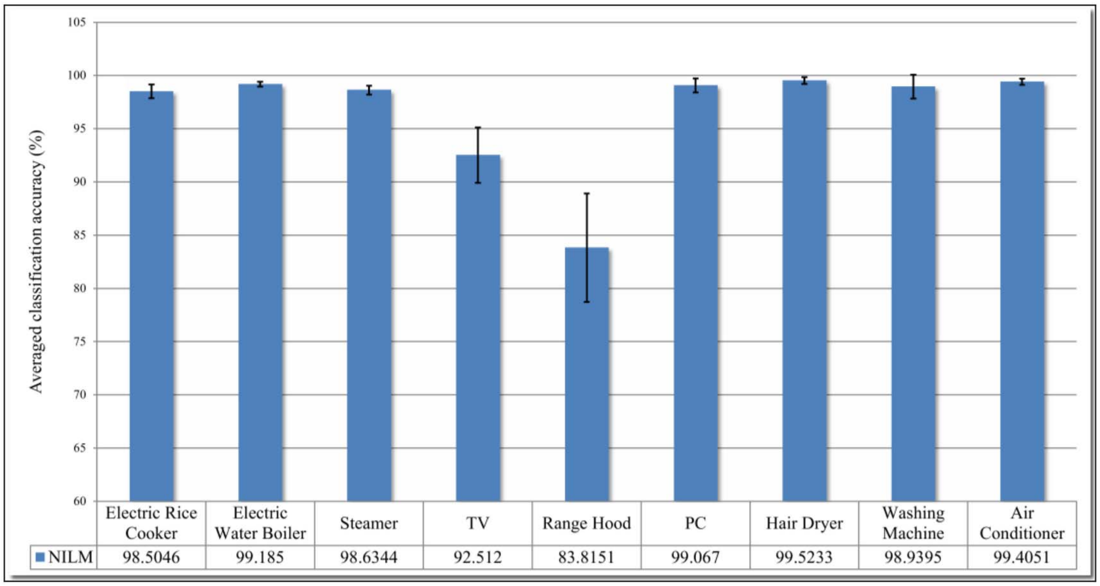
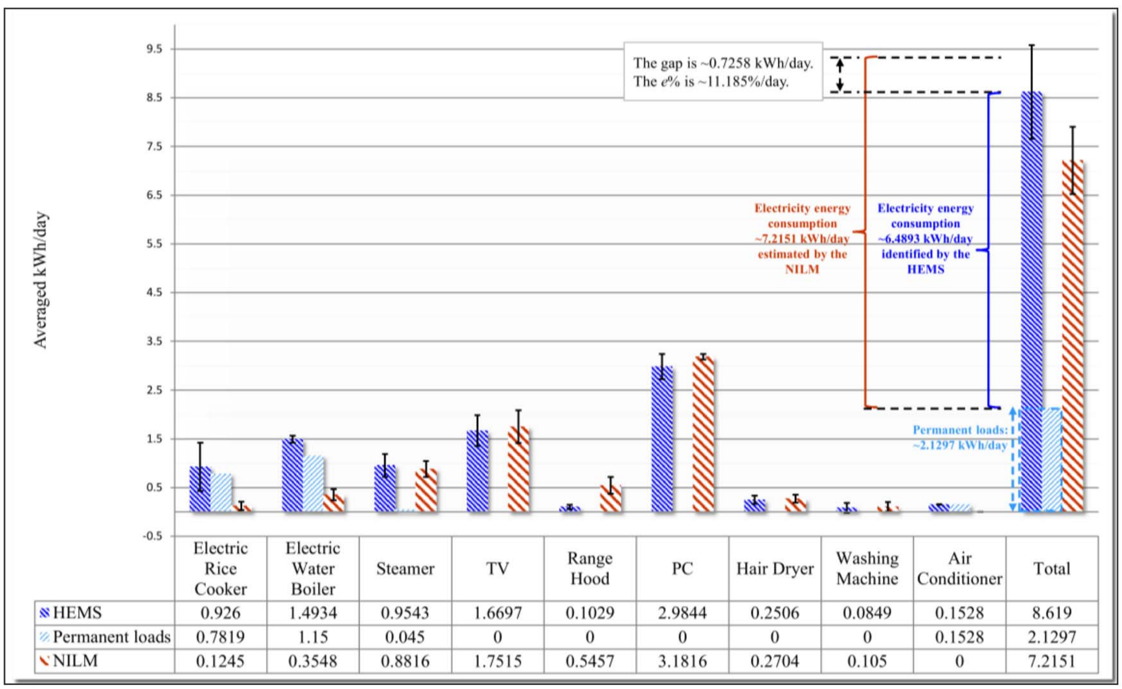


	Electric Rice Cooker	Electric Water Boiler	Steamer	TV	Range Hood	PC	Hair Dryer	Washing Machine	Air Conditioner
NILM	98.5046	99.185	98.6344	92.512	83.8151	99.067	99.5233	98.9395	99.4051

Fig. 6. Averaged classification accuracy. The classification accuracy on classification of the monitored household appliances per day is computed as: $\sum_{t\in\boldsymbol{T}} x_t \big/ T$, where $x_t \in \{0, 1\}$. If the status of one household appliance identified by the proposed NILM matches with the status of the one identified by the "traditional" HEMS as benchmark at time slot $t \in \boldsymbol{T}$, x_t is equal to 1; otherwise, it is equal to 0.



	Electric Rice Cooker	Electric Water Boiler	Steamer	TV	Range Hood	PC	Hair Dryer	Washing Machine	Air Conditioner	Total
HEMS	0.926	1.4934	0.9543	1.6697	0.1029	2.9844	0.2506	0.0849	0.1528	8.619
Permanent loads	0.7819	1.15	0.045	0	0	0	0	0	0.1528	2.1297
NILM	0.1245	0.3548	0.8816	1.7515	0.5457	3.1816	0.2704	0.105	0	7.2151

Fig. 7. Daily averaged power consumption on each of the household appliances in hot L1 and L2 in the house field is estimated by the proposed NILM. The traditional HEMS as benchmark is conducted and compared by the proposed NILM. The $e\% = |((8.619 - 2.1297) - 7.2151)/(8.619 - 2.1297)| \times 100\% = 11.185\%$. The total base load (baseline) including the permanent loads in the house environment monitored by the NILM is $\sim$8.372 kWh/day.

the NSGA-II-based in-home load scheduling mechanism presented in Section III-B is demonstrated.

B. Day-Ahead Demand-Side Load Management by the Advanced HEMS With the NSGA-II-Based In-Home Load Scheduling Mechanism With the GRA

In this experiment, the proposed NSGA-II-based in-home load scheduling mechanism with the GRA is demonstrated. The major household appliances enrolled and scheduled in response to DR signals are the electric water boiler and the steamer in hot L1.

Here, IP-based day-ahead RTP with the IBR signals are assumed and received. Based on an analysis on the historical data identified by the advanced HEMS with the NILM and parsed according to (1) and (2), the proposed NSGA-II-based in-home load scheduling mechanism automatically generates initial load schedules for residential DR implementation without user intervention first. Thereafter,

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TABLE II
MAPEs Obtained in This Experimentation

	Electric Rice Cooker	Electric Water Boiler	Steamer	TV	Range Hood
MAPE%	27.65	19.49	6.15	8.60	490.85
	PC	**Hair Dryer**	**Washing Machine**	**Air Conditioner**	**Total[a]**
MAPE%	9.55	13.19	12.46	N/A (~0)	13.32

[a] The MAPE%: Less than 10%: data are highly accurately estimated; 10%-20%: data are well estimated; 20%-50%: data are reasonably estimated; and greater than 50%: data are inaccurately estimated [28].

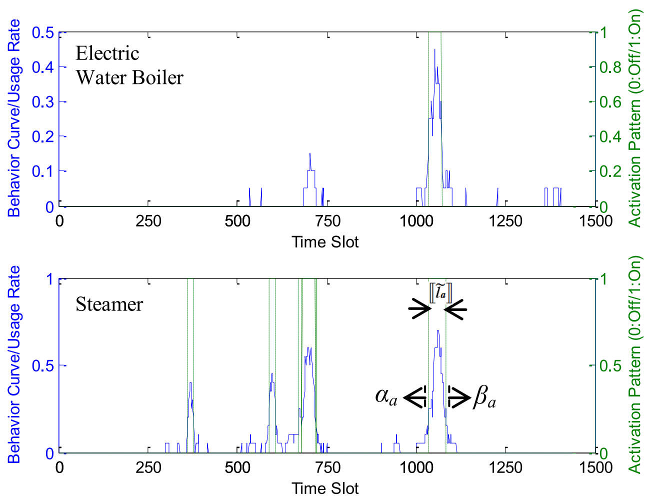


Fig. 8. UR, which is translated by the activation function, of the electric water boiler and the steamer.

TABLE III
Physical Characteristics of the Enrolled Household Appliances

Household appliances	$[\alpha_a, \beta_a]$	$[\![\tilde{l}_a]\!]$	δ_a
Electric Water Boiler	[1035, 1071]	23	180
Steamer[1*]	[361, 379]	15	60
Steamer[2]	[589, 606]	15	90
Steamer[3]	[672, 721]	36	90
Steamer[4]	[1035, 1084]	24	90

[*] Steamer[1-4] denote the steamer is used four times in chronological order in one day. $[\![\cdot]\!]$ rounds the averaged l_a, $\tilde{l}_a$ ($<\delta_a$) from the historical data identified by the proposed advanced HEMS with the NILM, to the nearest integer.

TABLE IV
Parameters Setting of the NSGA-II

NSGA-II	
Population size	200
Max. generation	50
Selection method	Binary tournament selection operator
Crossover method	Intermediate crossover operator
Mutation method	Gaussian mutation operator

the NSGA-II meta-heuristically schedules the household appliances to minimize (7). Fig. 8 shows the UR of the electric water boiler and the steamer. D in (1) is 20. The constant/threshold in (2) is set to 0.155. The physical characteristics, which are statistically obtained by the proposed NILM with (1) and (2) and used by the NSGA-II for automatic DR implementation, of the enrolled household appliances are listed in Table III. Suppose that, in this paper the RTP that is predictable is received ahead of the day. Also, the IBR by Taipower in Taiwan in 2013 is conducted. The parameters used by the NSGA-II are listed in Table IV. The Pareto-optimal front that is meta-heuristically found by the NSGA-II is shown in Fig. 9. The elapsed time is 398.99 s. The NSGA-II is executed for 20 runs. It has a Std. of $(f_1, f_2) = (0.01, 8.54)$, where its mean is $(f_1, f_2) = (26.39, 183.70)$.

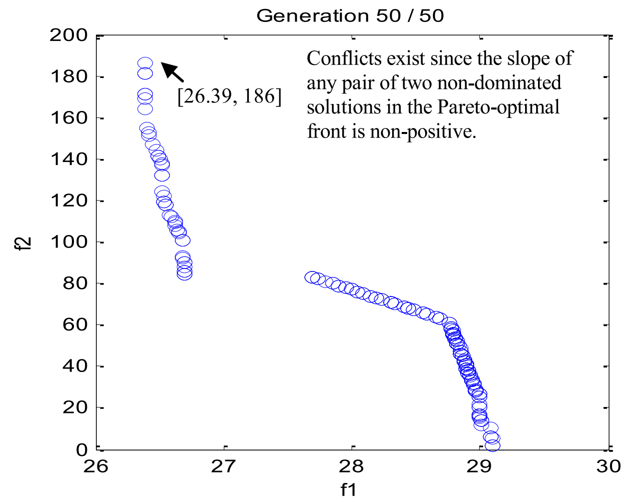
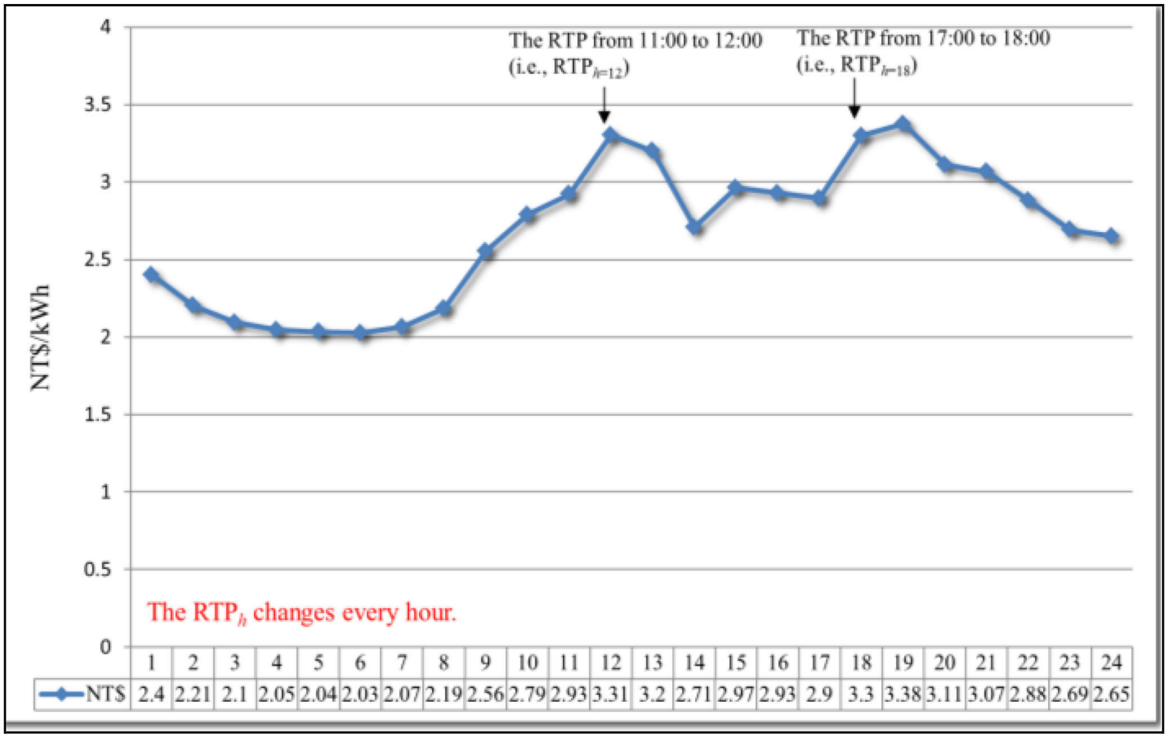


Fig. 9. Pareto-optimal front found by the NSGA-II.

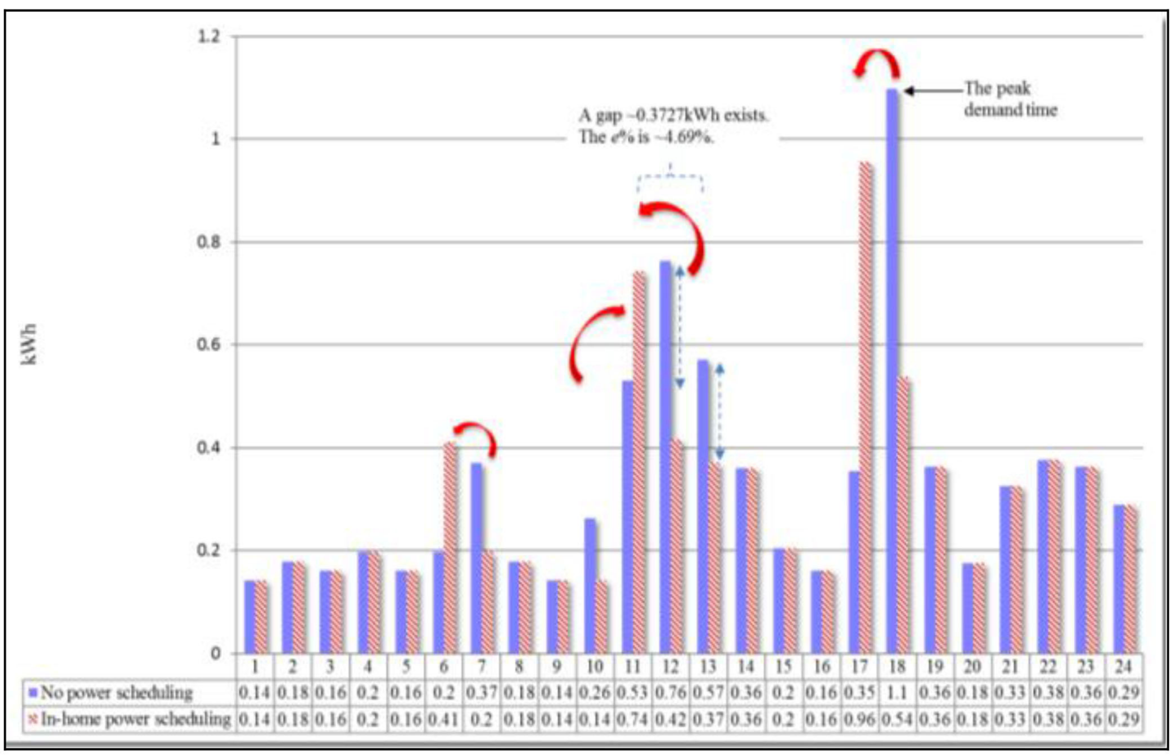
Finally, in order to get the highest profit involving the lowest f_1, the residents set x_0 as (1, 0) for the GRA to identify the final load schedule. According to this request, s_a^* approved by the residents in time slots is

$$\begin{gathered}\left[\text{Electric Water Boiler},\ \text{Steamer}^1,\ \text{Steamer}^2,\ \text{Steamer}^3,\ \text{Steamer}^4\right]\\ \parallel \\ [988, 345, 635, 635, 995].\end{gathered}$$

Fig. 10(a) shows the simulated and received day-ahead RTP profile combined with the IBR on March 6th, 2014. The RTP_h varies every hour according to the total electricity energy distributed through power distribution systems in Taiwan in 2013, where the electricity price is somewhat proportional to the total power generation cost by Taipower. According to the RTP profile shown in Fig. 10(a), the resulting in-home power consumption optimized, approved, and implemented in the house environment is shown in Fig. 10(b). Economic benefits achieved by the proposed automatic DR strategy for the residents to manage the enrolled household appliances are summarized as follows. As seen in Fig. 10(b), the proposed NSGA-II-based in-home power scheduling mechanism is conducted: the daily total electricity payment drops from ~NT\$28.45 to ~NT\$26.39 with a ~7.25% reduction, and the PAR declines from ~3.32 to ~3.03 with an ~8.65% reduction. With the use of the proposed advanced HEMS



(a)



(b)

Fig. 10. In-home power scheduling optimization. (a) Day-ahead RTP profile assumed and received on March 6th, 2014 in Taiwan. (b) In-home power consumption with/without the automatic DR mechanism proposed in this paper.

with the automatic in-home power scheduling mechanism, the electricity expense and the PAR are reduced simultaneously. Finally, it can be expected that the residents could save ~NT$123.60 in two months.

A workflow that shows how the resulting load schedule to auto-command the scheduled household appliances to run at their particular time is performed without user consent is illustrated in Fig. 11.

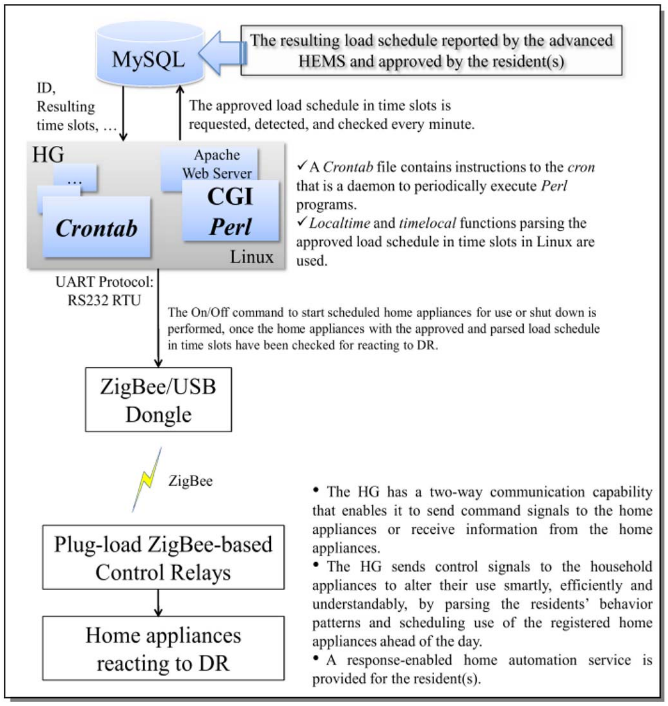


Fig. 11. Auto-remote load controls in response to DR addressed in this paper are realized in the house environment.

V. Conclusion

In this paper, an advanced HEMS with an NILM technique is proposed. Also, an automated NSGA-II-based in-home load scheduling mechanism with a GRA is presented. The proposed methodology is deployed to and assessed in a real-house environment in Taiwan. As demonstrated in this paper, the proposed advanced HEMS with the NILM having the automatic DR mechanism is workable and feasible. Future work is drawn below.

1) The wattage used in (5) of the household appliances will be adaptively updated, so that the daily power consumption estimated for the household appliances can be more accurately estimated. The $e\%$ and MAPE% reported in this paper will be reduced. As a result, an on-line load learning and modeling process with the hard c-means clustering can be conducted in the future. Besides, a considerable number of household appliances to accomplish routine housekeeping tasks in a household have either a daily periodic use or a multiday periodic use. In this paper, the future usage of one household appliance, which is monitored and scheduled by the advanced HEMS, at a particular time slot is forecasted through averaging of the past trends, as given in (1). In a macro view where the past trends are smoothed over multiple days, the advanced HEMS considers the UR of the household appliance at a particular time slot rather than a particular time slot on a particular day. The following guide could be very useful to readers who are interested in demand-side load management as well as human life-pattern identification and who would like to extend the proposed advanced HEMS to work with other types of household appliances for making a further effort and providing more value-added home services to customers in the future. An improved version of the advanced HEMS proposed in this paper can use a set of behavior modules with (1) to capture habits of inhabitants using household appliances in a micro view (i.e., to identify the residents' life patterns in one day of a week in the past several weeks). Also, in order to adaptively and chronologically figure out the past trends, one can formularize (1) in a weighted form. (The monitoring-forecasting-scheduling run loop in Fig. 2 is executed.) With this improved version of the proposed advanced HEMS, the UR of the household appliance at a particular time slot on a particular day can be taken into account. Also, it can be expected that, $\tilde{l}_a$ listed in Table III are set more precisely and the $e\%$ ($\sim$4.69%) shown in Fig. 10(b) is reduced. This is because the URs of each monitored and scheduled household appliance are forecasted more precisely. Based on a set of ANN-based human life-pattern learners and identifiers with a relational (relevance) analysis on the past trends parsed by the improved advanced HEMS, the improved advanced HEMS will be capable of providing more value-added home services (e.g., health-care service from use of home appliances) to inhabitants. Compared with a video-based health-care system which suffers from privacy concerns, the improved advanced HEMS is aware of the context of domestic daily activities from aggregated load profiles of the household. Finally, since habits of inhabitants using household appliances vary depending on weather conditions, the URs in the improved version of the proposed advanced HEMS can be modified with the inclusion of environmental factors [15] in the future.
2) In a smart house equippd with renewable energy, the advanced HEMS should be able to deal with a variety of issues. In the future, the proposed advanced HEMS can be incorporated with a forecasting system that predicts renewables based on past trends. With an integration of such a forecasting system with the advanced HEMS, it is expected that, the advanced HEMS with the NSGA-II based in-home load scheduling mechanism is able to optimize the electricity energy with locally-generated renewables. In addition, conducting a meta-heuristics-based optimization approach, the advanced HEMS is capable of optimally reconfiguring the green energy facilities that clean generate power varying with insolation, wind speed, and power demand. In the future, with construction of the green energy facilities communicated with the advanced HEMS having a "modified" NSGA-II based in-home load scheduling strategy in the house environment, more economic benefits can be achieved and obtained.
3) As indicated in [17], demand-side load management in a house environment is a complex task, the compensation is naturally decentralized, and the house environment and user demands change with time and season. In the future, the advanced HEMS with the NILM for making DR decisions in this paper will take

social and environmental factors [17] in account. In this manner, the proposed advanced HEMS with the NILM moves toward a multimodal sensing framework with social and environmental factors. The social and environmental factors impact the power consumption of the monitored household appliances and provide contextual information for residential demand-side load disaggregation and load management. For instance, users' location acquired and taken can be used to enhance the performance of the load disaggregation algorithm for a better residential demand-side load disaggregation and load management.

4) In the future, the cost-benefit analysis will be conducted for the assessment of the cost-effectiveness of the proposed advanced HEMS, before it is suitable for mass production to customers.

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Yu-Hsiu Lin was born in Taiwan in 1984. He received the Doctoral degree in mechanical and electrical engineering from the Graduate Institute of Mechanical and Electrical Engineering, National Taipei University of Technology, Taipei, Taiwan, in 2014.

His current research interests include applications of artificial intelligence/pattern recognition techniques with soft-computing strategies to solve nonintrusive appliance load monitoring, demand-side load management, and distribution system service restoration problems.

Men-Shen Tsai (M'86) was born in Taiwan in 1961. He received the Doctoral degree in electrical engineering from the Department of Electrical Engineering, University of Washington, Seattle, WA, USA, in 1993.

He is currently a Professor with the Graduate Institute of Automation Technology, Taipei, Taiwan, and an Associate Dean with the College of Mechanical and Electrical Engineering, National Taipei University of Technology, Taipei. His current research interests include applications of intelligent systems to power systems and smart grid, and comprise applications of distributed systems for distribution automation.