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Residential energy management system based on integration of fuzzy logic and simulated annealing

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Abstract: With the increase in prosperity level and industrialization, energy need continues to overgrow in many countries. To meet the rapidly increasing energy needs, countries attach great importance to using limited natural resources rationally, diversifying their energy production using novel technologies, improving the efficiency of existing technologies, and implementing policies and strategies toward alternative energy sources. In particular, individual energy prosumers (someone that both produces and consumes energy) head toward smart home energy management systems (SHEMS) that include renewable energy sources in their homes. By integrating PV solar panels into houses, there is a need to optimize home energy production/consumption scenarios by consumer behavior. In this study, an intelligent residential energy management architecture and algorithm to manage residential energy production/consumption are proposed. The algorithm controls the energy flow in the home according to real-time potential solar power estimation, demanded energy estimation, electricity consumption price, and battery state-of-charge (SoC). The fuzzy logic algorithm has been developed to determine the estimated comfort and cost-effectiveness ratios in the near future. The simulated annealing algorithm, a meta-heuristic algorithm, is performed to obtain the best operating point decision of the battery using the comfort and cost-effectiveness ratios. Energy flow direction and battery SoC are optimized using simulated annealing based on the comfort and cost-effectiveness ratio (comparison of alternatives with respect to multiple criteria of different levels of importance for energy usage). The focus is to generate maximum profit from energy sales for monthly profit to be achieved. Prototyped hardware and software are implemented and tested in real-time. The test results show that the 20% reduces energy consumption, and a monthly gain of $89.2 is obtained from energy sales using the proposed method. Therefore, the test results reveal the effectiveness of the proposed architecture and algorithm.

Key words: Smart grid, renewable energy, fuzzy logic controller, simulated annealing, weather forecast, intelligent residential energy management

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1. Introduction

As a result of the integration of renewable energy sources into homes, the increase in the number of smart devices in daily life, and the strengthening of smart grid infrastructure, the use of smart home energy management systems (SHEMS) has become widespread [1], [2]. In particular, reducing the cost of energy consumption and the demand for the grid during peak hours is one of the most essential benefits of SHEMSs [3]. Moreover, providing personal energy management and determination of energy consumption/production scenario by the consumer make SHEMSs attractive [4], [5]. On the other hand, the proliferation of electric vehicles (EVs) requires intense demand for charging. In a time when household energy consumption for 2020 accounts for 38% of total consumption in the United States [6], it is estimated that with the integration of EVs into household charging stations, grids will suffer high demand [7]. SHEMSs regulate the entire energy flow of a home together with photovoltaic (PV) panels in a scenario where the demand for peak time is reduced [8]. Published studies have shown that 23.1% may reduce the cost of energy and the demand for peak load by 29.6% [9]. In other respects, the progress of communication technologies allows the consumer to access all devices [10]. The consumers are enabled to plan the working schedules of indoor devices with these systems [11]. However, because the resident uses a significant part of the house devices in an uncontrolled and arbitrary manner, sudden energy demand appears, and energy management systems cannot control it [12]. For this reason, academic studies generally focus on energy flow modeling, weather forecast, consumer behavior estimation, power price change estimation, and device consumption trend estimation [13]–[16].

A software to simulate the load demand of devices has been reported in [17]. Authors of [17] aim to create priority load demand and to increase comfort in an apartment. In [18], a "Global model-based Anticipate – Building Energy Management System" software is developed to reduce cost by optimizing people's daily energy needs based on their habits without compromising their comfort. By the "Markov Decision Process" in [19], consumption cost is reduced by using real-time price information and consumption curve. The system includes a central energy management system and a SHEMS. In [20], power consumption and demands of household appliances and heating systems are monitored in the 22-household model. The authors in [20] aim to provide an economically optimal solution to the consumer with an algorithm called "Power Matcher" which has a management system, server, and environmental sensors communicated by IEEE 802.15.4 communication protocol. In [21], the central server tracks weather information, energy cost, and total usage. The interfaces included in the system consist of monitoring, prediction information, statistics, and a control menu. In [22], a system that automatically manages based on grid constraints and consumer priorities is proposed for SHEMS. The proposed system in [22] is based on an intuitive technique that considers the consumer priority, the power delivered from the grid, and energy sources distributed for programming the devices. Solutions are presented by dividing the planning problem of indoor devices into subproblems for different time zones, and an intuitive solution is presented for each subproblem. In [23], considering the maximum consumption amount in a month, a home energy management system planning the optimal use of home energy resources to minimize the daily energy cost of a home with real-time pricing is developed. Authors of [23] develop a NAA (Natural Aggregation Algorithm) as the solving approach method in the proposed system. In [24], a cost-sharing algorithm is developed based on the consumption rates of all consumers by taking the highest energy consumption cost ranking of all consumers in a residential area as a reference. Authors of [24] propose an important solution for the mass housing sector as a scalable energy/cost-sharing algorithm. In [25], a control strategy based on a genetic algorithm can propose an optimal balance between increasing consumer comfort and ensuring the maximum provision of consumed power by renewable energy sources. In the system, real-time electricity price is achieved by optimizing a comprehensive cost function taking into account the most important factors such as energy produced/consumed by each device, consumer preferences, and battery SoC. In [26], an incentive and its structure for consumption preferences are developed by taking into account the preferences of residential consumers. In a simulation performed with a testing system including 1200 residential consumers, 16% demand reduction in peak hours is performed, and financial benefits to the electricity distribution company and consumers are explained. The results show that $28.217 is saved in public resources, and a residential consumer saved $9,37 on average for an hour of demand reduction activity. In the proposed system, achievement has been realized in terms of more efficient use of public energy resources and reducing the cost of consumers. In [27], a scalable methodology that focuses on reducing unnecessary domestic energy consumption and replacing low-efficiency refrigerators and freezers using smart-meter and daily temperature data. An increase in energy efficiency is achieved through determining baseload points of daily energy consumption by the Sliding Window Linear Regression method in which smart-meter and temperature data are used. In [28], an optimal estimation algorithm for energy consumption is developed using K-tool clustering and the Receiver Operating Characteristic Curve. More than 89% F-Score and accuracy have been achieved for high-power loads by the proposed Multitarget Classification Algorithm. In the study, a comprehensive analysis is used on energy consumption, sensor networks, network traffic management, and communication protocols for Internet-of-Things (IoT) modules and SHEMS. In [29], an effective energy management system is proposed for home demand response using Reinforcement Learning (RL) and Fuzzy Logic (FL) methods. In the proposed method, a decision-making algorithm is developed for creating the operating program of devices according to the consumer's energy consumption, electricity price, and peak hours. An energy management method that reduces cost without compromising consumer comfort by learning dynamic electricity price and consumption patterns using the Q-learning method is developed. In the proposed method, electricity cost is reduced by 15%–18.5%. Moreover, optimization of three factors is achieved by a heuristic algorithm in the "Service-Oriented Architecture" study [30]. A smart home management system is designed considering comfort, economic, and environmental factors. In [31], 24-h energy usage estimation is performed using linear and nonlinear learning algorithms. The proposed method stores records of 100 homes for a year with the iRise data collection software. In [32], an autonomous load balancing system is enhanced. By the sensors connected to the ZigBee network in the system, energy data are collected at certain periods, and information is presented to the consumer for changing consumer consumption habits. In [33], an algorithm based on home energy demand response, peak demand, maximum load estimation, user sampling, budget, and social-environmental effects is proposed using "Master Energy Controller". The communication network is in IEEE 802.15.4 standards, and Bluetooth communication is available. The proposed TinyOS software architecture works with low-cost crossbow TelosB hardware. In the present study, a SHEMS architecture and algorithm that orchestrate the energy buying/selling of a home are proposed. An algorithm encouraging energy sales, and maximizing profit from energy sales by an individual consumer is proposed. Studies in the literature are mostly aimed at optimizing the energy consumption of residents. Studies in the literature are mainly aimed at optimizing the energy consumption of residents. On the other hand, it is aimed to transfer the energy produced to the grid or the residents according to the weights of calculated cost and comfort effectiveness parameters in this study. The main contributions of this paper are "making a maximum profit from energy sales", "providing maximum comfort from energy use", "optimal storage of energy produced by the solar system", and "developing suitable hardware and software for smart grid."

In the proposed algorithm, battery SoC, estimated home load demand, actual consumption data from smart plugs, energy amount demanded from the grid, and weather forecast data are used as input of the fuzzy logic algorithm. The purpose of the inputs is to optimize the energy flow for two outputs which are comfort-effectiveness and cost-effectiveness ratios and to generate the decision-making controller reference resulting from the optimization. This optimization is performed by simulated annealing because it guarantees finding an optimal solution and is easy to code, even for complex problems. To what degree the battery be charged and at what rate the grid be supported are decided based on the findings of iterations of the simulated annealing method. As a result of the simulated annealing algorithm, the optimal SoC point of use of the battery is determined. According to the determined critical battery SoC, the direction of energy flow and the energy distribution scenario are determined.

The remainder of this paper is organized as follows: The principles of the proposed fuzzy and simulated annealing integration algorithm are presented in Section 2. The design phase includes the development of constraints of energy flow and management, fuzzy rules, and simulated annealing parameters. In Section 3, software and hardware design steps, the control approach, and experimental results of the proposed method are presented. Additionally, the findings and comparative results are provided in Section 3. Finally, the conclusion is presented in Section 4. The results indicate the practicability and effectiveness of the proposed method for home energy management.

2. Proposed fuzzy logic and simulated annealing integration algorithm

The energy production/consumption scenario is determined by solar energy potential, battery SoC, and the energy amount demanded from the grid. An optimal production/consumption algorithm which is created by the fuzzy logic and simulated annealing algorithms are shown in Figure 1. The fuzzy logic algorithm has been developed to determine the estimated comfort and cost effectiveness ratios in the near future. Fuzzy reasoning is a decision-making model that deals with approximate rather than exact values [35]. A fuzzy inference system (FIS) provides a mapping from the inputs to the outputs based on a set of fuzzy rules and associated fuzzy membership functions (MFs) [36]. Mamdani method is used in this paper because it offers a smoother output [37]. Moreover, the Mamdani method is used in MISO (Multiple Input and Single Output), and MIMO (Multiple Input and Multiple Output) systems [37].

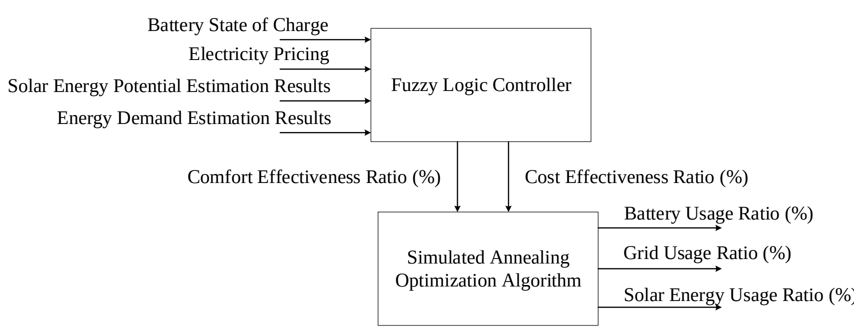
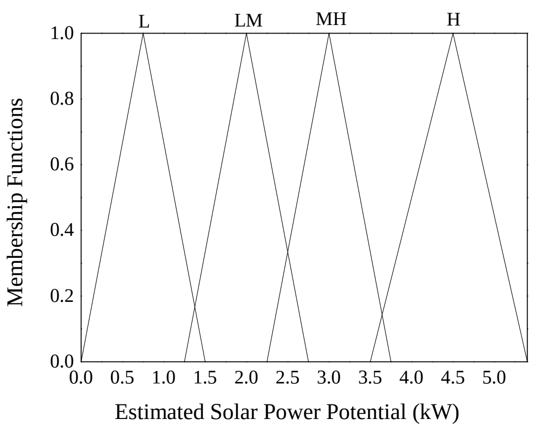


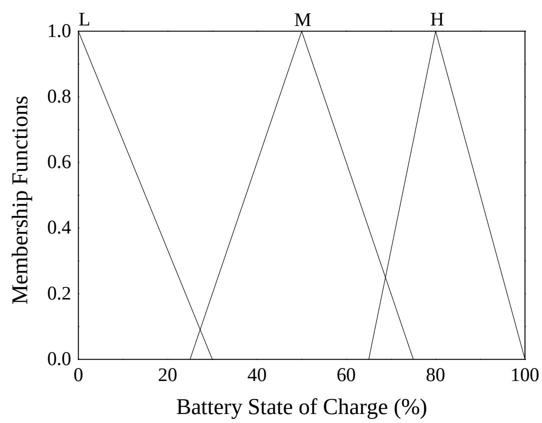
Figure 1. Block diagram of the proposed control and optimization algorithm.

The estimated solar power potential (ESPP), estimated energy demand (EED), electricity price (EP), and battery SoC (BSC) are performed in the fuzzy logic algorithm as inputs and comfort/cost-effectiveness ratios are determined. The MFs for the input variable "Solar Energy Potential Estimation" shown in Figure 2a are triangular and labelled as No [0 0.75 1.5] [kW], Low [1.25 2 2.75] [kW], Medium [2.25 3 3.75] [kW], High [3.5

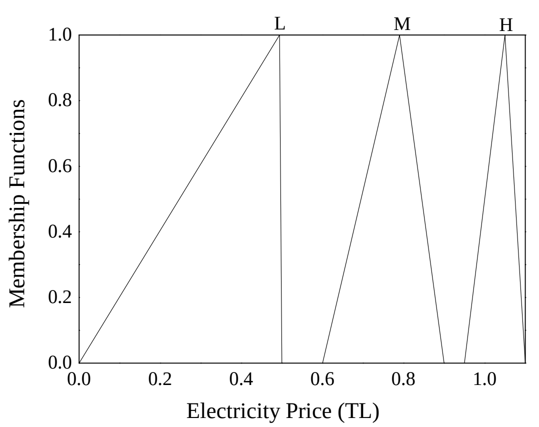
4.5 5.4] [kW]. The MFs for the input variable "Battery State of Charge" shown in Figure 2b are triangular and labelled as Low [0% 0% 30%], Medium [25% 50% 75%], High [65% 80% 100%]. The MF's for the input variable "Electricity Price" shown in Figure 2c are triangular and labelled as daytime (06:00-17:00) (0.11 $/kWh), peak demand (17:00-22:00) (0.162 $/kWh), night time (22:00-06:00) (0.069 $/kWh). The MFs for the input variable "Energy Demand Estimation" shown in Figure 2d are triangular and labelled as Low [0 0.35 0.4] [kWh], Medium-Low [0.35 0.45 0.5] [kWh], Medium [0.47 0.57 0.65] [kWh], Medium-High [0.6 0.7 0.75] [kWh], High [0.7 0.75 0.8] [kWh]. The MFs for the output variable "Comfort Effectiveness Ratio (CME)" shown in Figure 3a are triangular and labelled as Very Low [0% 10% 20%], Low [15% 28% 38%], Low-Medium [35% 45% 55%], Medium [50% 58% 66%], Medium-High [62% 70% 78%], High [75% 83% 90%], Very High [88% 96% 100%]. The MFs for the output variable "Cost Effectiveness Ratio (CSE)" shown in Figure 3b are triangular and labelled as Very Low [0% 10% 20%], Low [15% 28% 38%], Low-Medium [35% 45% 55%], Medium [50% 58% 66%], Medium-High [62% 70% 78%], High [75% 83% 90%], Very High [88% 96% 100%]. Moreover, rules table including 180 rules are presented in Appendix 1.



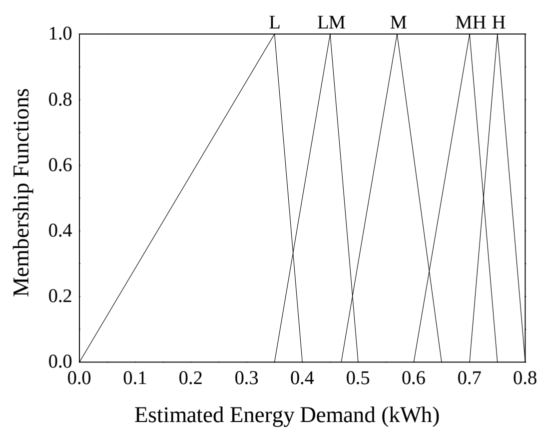
(a) Membership functions of the estimated solar power potential



(b) Membership functions of the battery state of charge

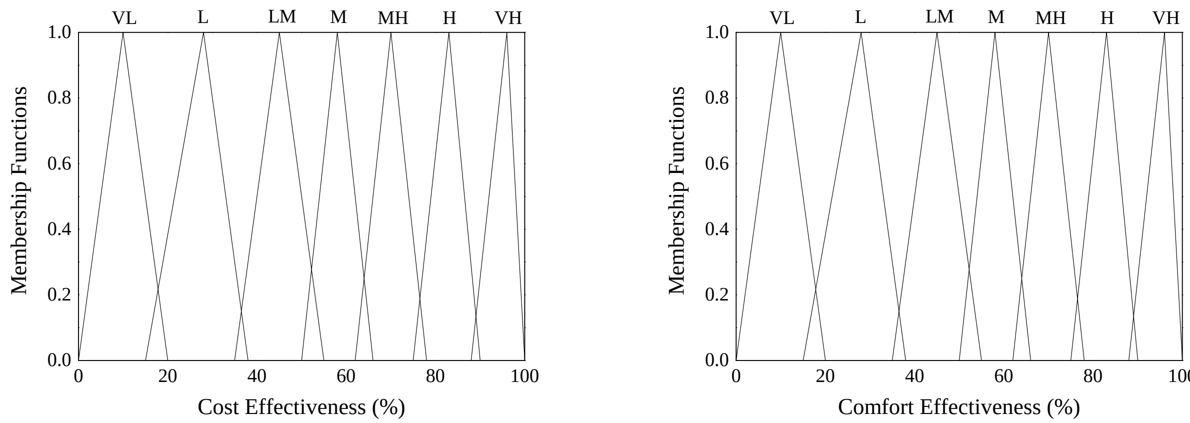


(c) Membership functions of the electricity price



(d) Membership functions of the estimated energy demand

Figure 2. Membership functions of the fuzzy controller.



(a) Membership functions of the comfort effectiveness ratio

(b) Membership functions of the cost effectiveness ratio

Figure 3. Membership functions of the effectiveness ratios

The use of a simulated annealing algorithm in optimization problem solving has been developed as a result of the similarity between finding an optimal solution and low energy level in the annealing procedure of solids [38]. The fundamental principle of the annealing simulation algorithm is to accept solutions worse than the current solution to evade local points in the search space with a certain probability. This is calculated by the difference between the probability values and the temperature value, and the possibility to accept the worst solutions is reduced during the search [39]. The most visible advantage of annealing simulation compared to other methods is its ability to evade the local minimum. The objective function of the simulated annealing algorithm is to search for the optimum battery charge point. Since there are many objective functions in the algorithm, the problem is reduced to a single objective function (battery optimum charge point). Comfort and cost are defined as limiting factors so that the variables used in the optimization problem can take specific values. The algorithm, which is shown in Figure 4 starts with the selection of the initial solution and the calculation of the objective function. A new or neighboring solution is randomly generated, and the objective function is recalculated. The change in the objective function is constantly followed, and the algorithm is run until the best solution is found. When the stopping criterion (the algorithm runs until the average change in the value of the objective function) is met, the best battery SoC point is determined according to the solution value obtained. By obtaining one of the variables, the amount of energy supplied from the grid and provided to the grid is determined using estimated consumption and estimated solar potential.

The charging points of the battery determined by the central controller are considered. A random initial solution is generated in the simulated annealing algorithm for the most optimal status, and it is assigned as the best solution. It is assigned as the specified current temperature value and the initial temperature value. Based on the best solution, a random neighboring solution is created. Considering the difference between the initial solution and the neighboring solution produced, the neighboring solution is assigned instead of the old solution if this value is less than zero. Although the optimization stopping criteria are met, the new solution is assigned instead of the old solution. Taking the charging points determined based on the comfort and cost-effectiveness ratios as a reference, the best solution is sought by creating a random initial solution in the simulated annealing algorithm for optimal battery use, the amount of energy demanded from the grid, and the solar energy use. Using the comfort-effectiveness, cost-effectiveness ratios, and initial battery status ratio obtained by the fuzzy logic algorithm, the targeted optimal battery SoC rate is determined. Moreover,

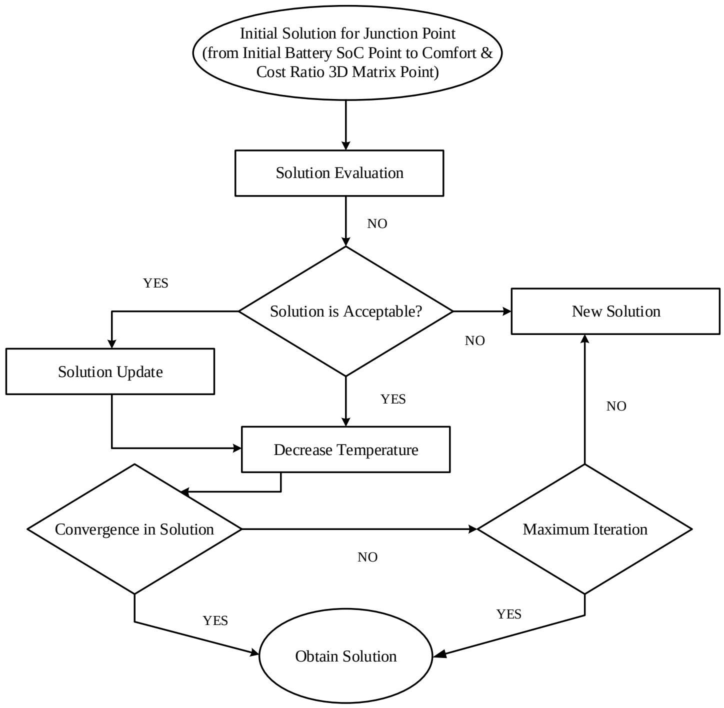


Figure 4. Simulated annealing algorithm flow chart.

the simulated annealing algorithm is performed to obtain the best operating point decision using the comfort and cost-effectiveness ratios. Random initial values form the cost-effectiveness ratio, battery SoC, and comfort-effectiveness ratio matrix. The simulated annealing algorithm is run until the best solution point (junction point of comfort effectiveness ratio, cost-effectiveness ratio, and battery SoC) of the [100x100x100] three-dimensional matrix shown in Figure 5 is obtained. The initial temperature, cooling factor, and iteration number for the process are given as 500 °C, 0.98, 400, respectively.

3. Experimental study

The experimental test laboratory is shown in Figure 6. Twenty pieces of 275 W PV panels in the laboratory have an installed power of 5.4 kW in a 54 m^2 area on the southern facade. Considering the Akfirat region (40.951576 °N, 29.392204 °E) catches the sun for approximately 7 h, 37.8 kWh total production capacity is determined. The main controller, shown in Figure 7a consists of a power electronics unit, display, ESP-WROOM-32, BROADCOM BCM2837, STM32F407, External Input/Outputs, keypad, and antenna modules. ESP-WROOM-32 and BROADCOM2837 communicate with each other via SPI. The STM32F407 processor is performed for backup solution purposes. The central controller communicates with the solar hybrid inverter via the ethernet port and manages to/from the battery and to/from grid options. Smart plugs have unique media access control addresses and can measure current, voltage, and temperature. Prototyped smart plugs, shown in Figure 7b, communicate with the central control unit via wireless communication. Moreover, the overall experimental working principle scheme is presented in Figure 8.

Data collected by smart plugs are presented in Figure 9 for various devices. In Figure 9a, Figure 9b, Figure 9c, and Figure 9d, power consumption of refrigerator, power consumption of television and modem, power

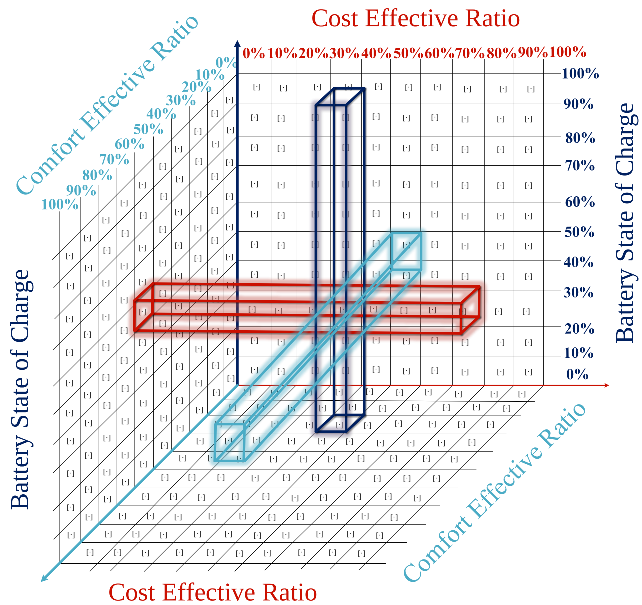
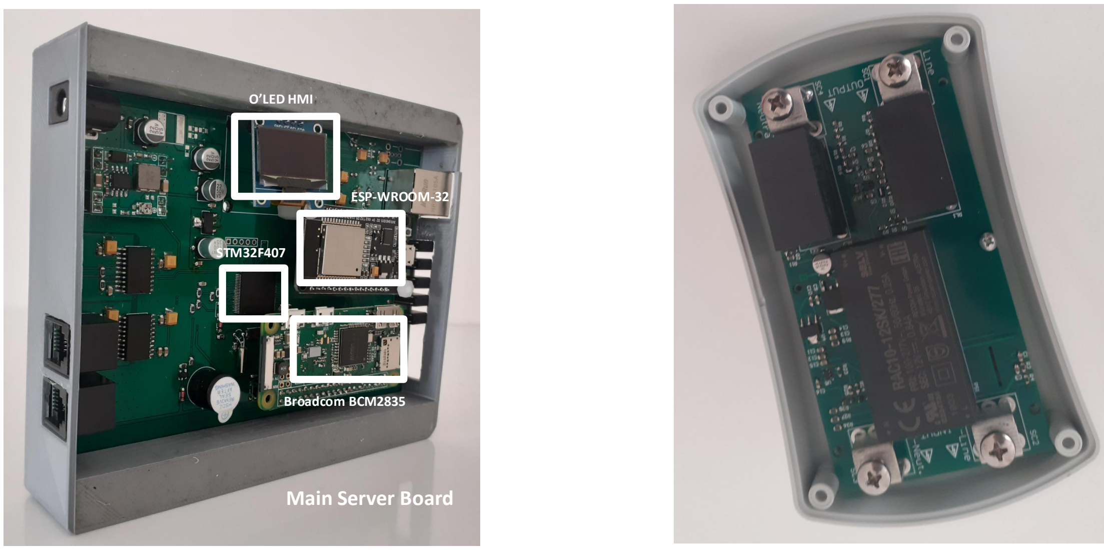


Figure 5. Proposed simulated annealing algorithm principle.

consumption of washing machine, power consumption of dishwasher are presented, respectively. The study was continued for six months (21 December 2019–27 December 2019), and for the sake of brevity, one-week data is presented in this study. Figure 10a shows the power produced from solar panels, Figure 10b represents the change in electricity price according to time, Figure 10c shows the measured and estimated air temperature value, and Figure 10d shows the measured and estimated load demand. As an output of the proposed fuzzy logic algorithm, comfort and cost-effectiveness ratios are shown in Figure 11. In the simulated annealing approach shown in Figure 5, the optimal battery SoC is determined using comfort-effectiveness and cost-effectiveness ratios. The amount of battery usage, battery charging, power supplied from the grid, and electricity sold to the grid are determined by a simulated annealing algorithm. Solar panel energy production is estimated as 1.298 kWh (assumed to be correlated with temperature variation), consumption is estimated as 0.45 kWh, and temperature value is estimated as 18.89 °C on 21 December 2019, from 08.00–09.00. Electricity consumption price measured as \$0.7195 and battery SoC as 72.8%. The optimization algorithm according to the estimation for the next hour and the comfort and cost-effectiveness ratios for the 1380^{th} min are determined as 45% and 70% in Figure 11, respectively. A simulated annealing algorithm is performed, and the optimal consumption-iteration graph is shown in Figure 12. It is determined that 0.32 kWh of energy is supplied from the battery and the energy amount to be transferred to the battery is 0.92 kWh. The energy amount demanded from the grid is determined as 0.13 kWh. Solar panel energy production is estimated as 2.944 kWh, consumption is estimated as 0.52 kWh, and temperature value is estimated as 19.05 °C on 22 December 2019 at 16.00–17.00. Electricity consumption price measured as \$0.11 and battery SoC as 85%. The optimization algorithm according to the estimation for the next hour and the comfort and cost-effectiveness ratios for the 2460^{th} min are determined as 45% and 70% in Figure 11, respectively. A simulated annealing algorithm is performed, and the optimal consumption-iteration graph is shown in Figure 13. It is determined that 0.36 kWh of energy is supplied from the battery and the energy amount to be transferred to the battery is 2.5 kWh. The energy amount demanded from the grid is determined as 0.16 kWh.

Figure 6. Experimental test environment.

Solar panel energy production is estimated as 1.794 kWh, consumption is estimated as 0.51 kWh, and temperature value is estimated as 20.98 °C on 23 December 2019, at 17.00–18.00. Electricity consumption price measured as \$0.162 and battery SoC as 78%. The optimization algorithm according to the estimation for the next hour and the comfort and cost-effectiveness ratios for the 4000^{th} min are determined as 26.7% and 82.5% in Figure 11, respectively. A simulated annealing algorithm is performed, and the optimal consumption-iteration graph is shown in Figure 14. It is determined that 0.47 kWh of energy is supplied from the battery. Also, the energy amount demanded from the grid is determined as 0.04 kWh. Solar panel energy production is estimated as 2.882 kWh, consumption is estimated as 0.48 kWh, and temperature value is estimated as 22.76 °C on 24 December 2019, at 16.00–17.00. Electricity consumption price measured as \$0.11 and battery SoC as 63%. The optimization algorithm according to the estimation for the next hour and the comfort and cost-effectiveness ratios for the 5340^{th} min are determined as 60% and 55% in Figure 11, respectively. A simulated annealing algorithm is performed, and the optimal consumption-iteration graph is shown in Figure 15. It is determined that 0.4 kWh of energy is supplied from the battery. The energy amount to the grid is determined as 0.5 kWh. Also, the energy amount demanded from the grid is determined as 0.08 kWh. Solar panel production is



(a) Main controller (b) Smart plug

Figure 7. Prototyped hardwares.

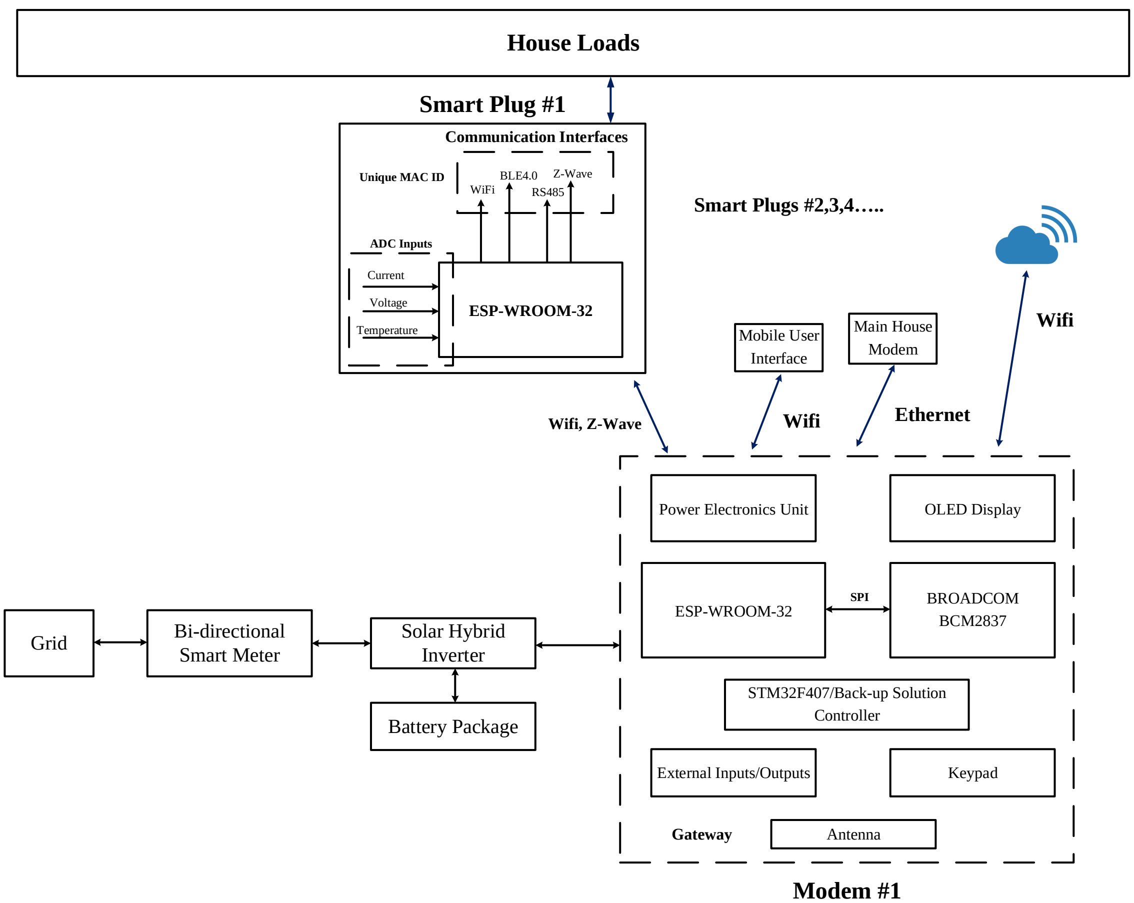
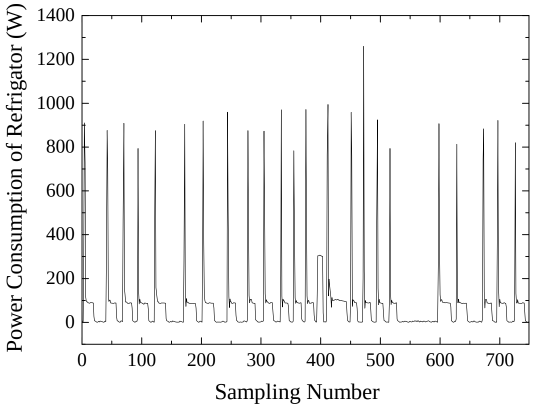
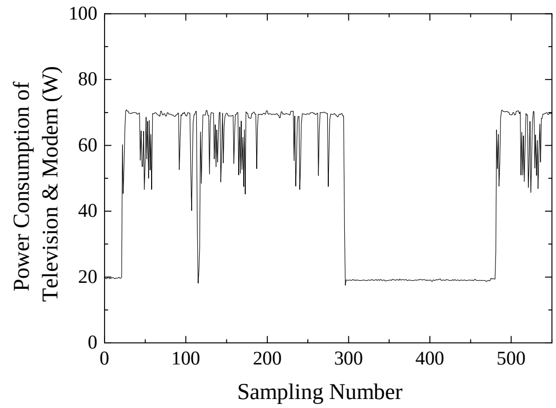


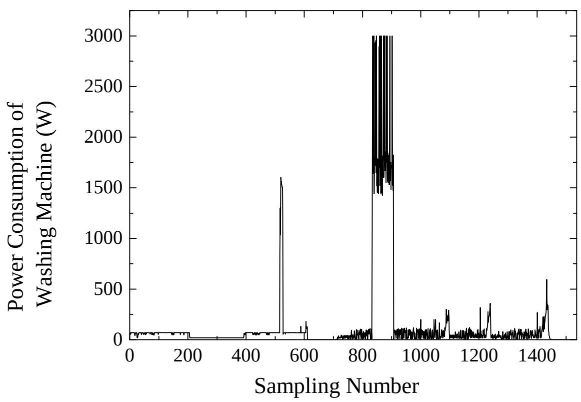
Figure 8. Overall experimental working principle scheme.



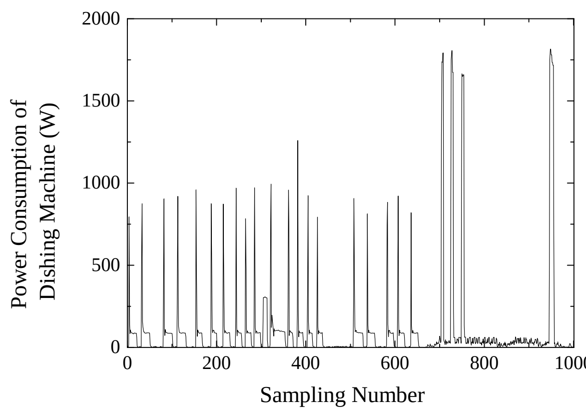
(a) Power consumption of refrigerator.



(b) Power consumption of television and modem.



(c) Power consumption of washing machine.



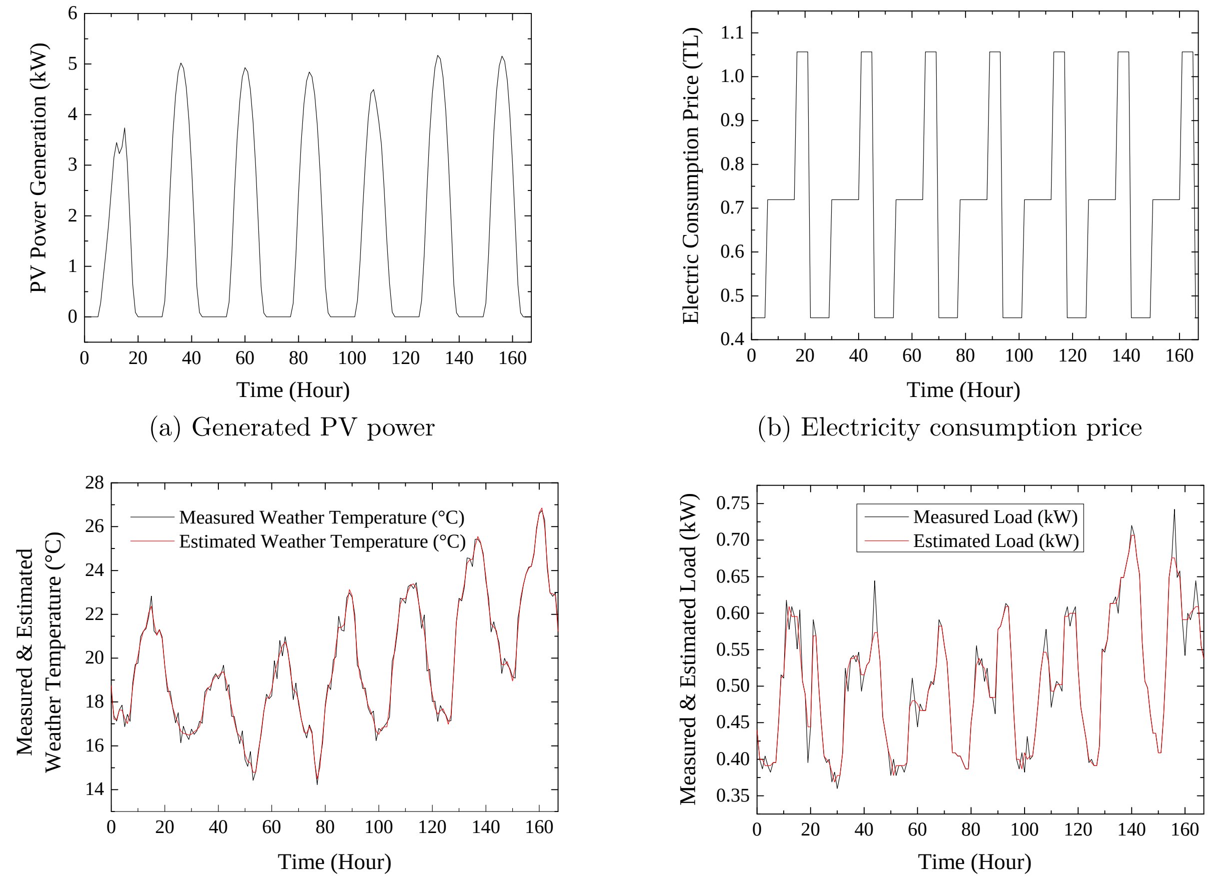
(d) Power consumption of dish washer.

Figure 9. Smart plug data from home appliances.

estimated as 1.24 kWh, consumption is estimated as 0.39 kWh, and temperature value is estimated as 17.14 °C on 26 December 2019 at 07.00–07.00. Electricity consumption price measured as \$0.11 and battery SoC as 86%. The optimization algorithm according to the estimation for the next hour and the comfort and cost-effectiveness ratios for the 7680^{th} min are determined respectively as 64% and 50.5% in Figure 11. A simulated annealing algorithm is performed, and the optimal consumption-iteration graph is shown in Figure 16. It is determined that 0.39 kWh of energy is supplied from the battery. The energy amount to the grid is determined as 0.85 kWh.

4. Conclusion

By including estimation of near-future PV potential and consumer load demand in-home energy management systems, we aim to achieve maximum profit from energy sales without compromising consumer comfort. The proposed intelligent home energy management architecture and control algorithm optimize the energy produced/consumed. The estimated solar energy potential, energy demand, electricity price, and battery SoC are performed in the fuzzy logic algorithm as inputs and comfort/cost-effectiveness ratios are determined. To achieve optimal battery SoC, the outputs of the fuzzy logic algorithm are optimized in the simulated annealing algorithm. Energy consumption reduction of 20%, and a monthly gain of \$89.2 are obtained from energy sales



(a) Generated PV power

(b) Electricity consumption price

(c) Measured and estimated weather temperature

(d) Measured and estimated load demand

Figure 10. Fuzzy logic controller input variables results.

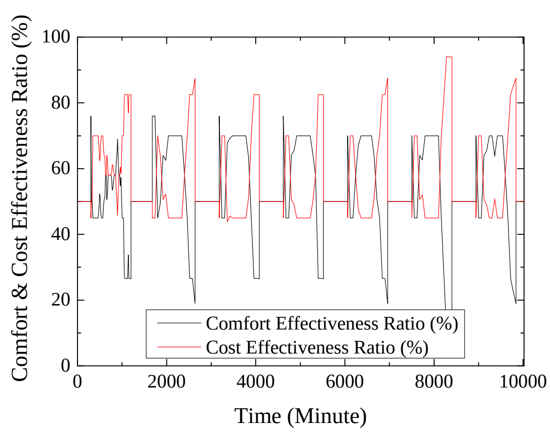


Figure 11. Comfort and cost effectiveness ratio variation using fuzzy logic algorithm.

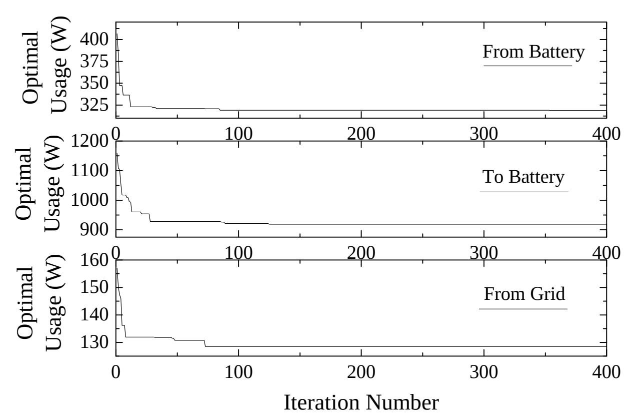


Figure 12. Optimal energy usage for 1380^{th} min.

using the proposed method. Experimental data has been collected over six months. A cost calculation based on one week of data is presented in this paper. Considering one week (21 December 2019–27 December 2019) of values, 268.726 kWh of solar energy is produced, 84.84 kWh of energy is consumed, and an average temperature

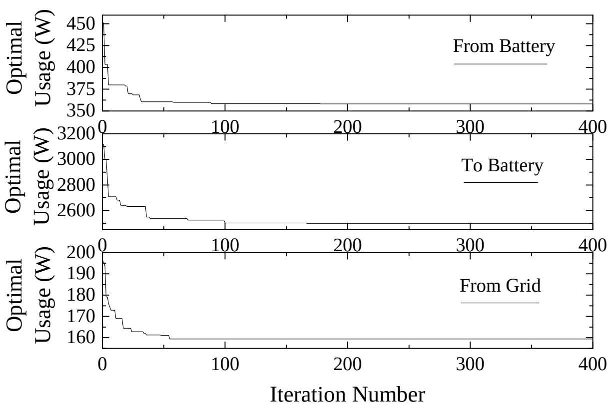


Figure 13. Optimal energy usage for 2460^{th} min.

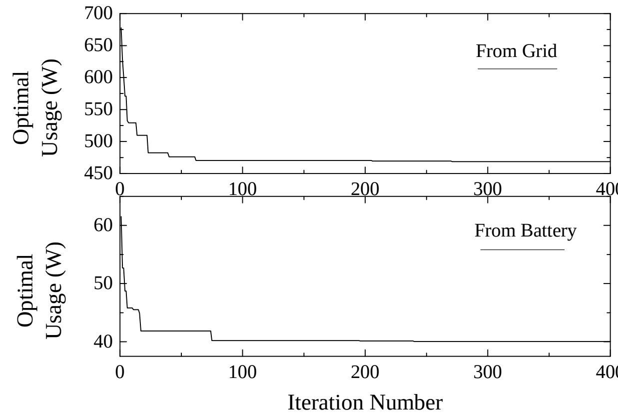


Figure 14. Optimal energy usage for 4000^{th} min.

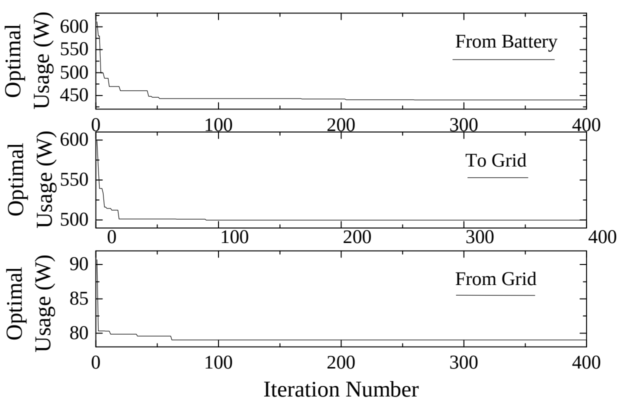


Figure 15. Optimal energy usage for 5340^{th} min.

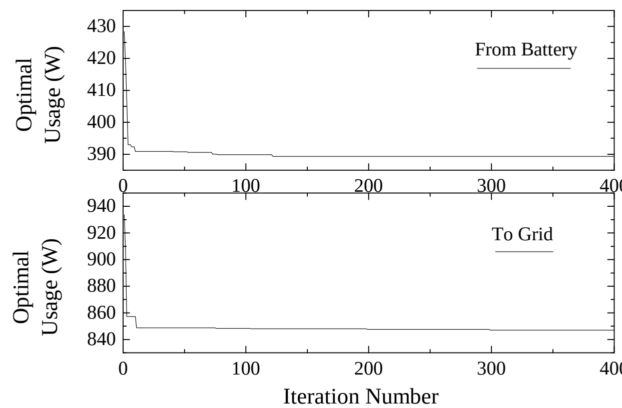


Figure 16. Optimal energy usage for 7680^{th} min.

of 19.68 °C is estimated. If the proposed architecture and algorithm are not performed, the energy cost for one week is calculated as $9.367, excluding taxes and deductions. As a result of the comparisons, which is presented in Table 1, performed with the fuzzy logic-based method [12], it is seen that the proposed approach gives 11% better results. The feasibility and effectiveness of the proposed algorithm are verified by experimental studies.

Table . Comparison of proposed method and fuzzy controller based SHEMs.

Description	**Monthly gain**	**Consumption reduction ratio**
SHEMS based proposed algorithm	$89.2	20%
SHEMS based fuzzy controller	$24	9%

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Appendix

Appendix 1. Fuzzy rules for the residential energy management system.

No	ESPP	EP	EED	BSC	CSE	CME	No	ESPP	EP	EED	BSC	CSE	CME
1	L	H	H	L	VL	VH	**46**	LM	H	H	L	VL	VH
2	L	H	H	M	L	H	**47**	LM	H	H	M	L	H
3	L	H	H	H	L	H	**48**	LM	H	H	H	L	H
4	L	H	MH	L	VL	VH	**49**	LM	H	MH	L	L	H
5	L	H	MH	M	L	H	**50**	LM	H	MH	M	LM	MH
6	L	H	MH	H	LM	MH	**51**	LM	H	MH	H	LM	MH
7	L	H	MH	L	L	H	**52**	LM	H	M	L	LM	MH
8	L	H	MH	M	LM	MH	**53**	LM	H	M	M	M	M
9	L	H	MH	H	M	M	**54**	LM	H	M	H	MH	M
10	L	H	LM	L	L	H	**55**	LM	H	LM	L	M	M
11	L	H	LM	M	M	M	**56**	LM	H	LM	M	MH	LM
12	L	H	LM	H	MH	LM	**57**	LM	H	LM	H	H	LM
13	L	H	L	L	LM	MH	**58**	LM	H	L	L	MH	LM
14	L	H	L	M	MH	LM	**59**	LM	H	L	M	H	L
15	L	H	L	H	H	L	**60**	LM	H	L	H	H	L
16	L	M	H	L	VL	VH	**61**	LM	M	H	L	L	H
17	L	M	H	M	LM	MH	**62**	LM	M	H	M	LM	MH
18	L	M	H	H	M	M	**63**	LM	M	H	H	MH	LM
19	L	M	MH	L	L	H	**64**	LM	M	MH	L	LM	MH
20	L	M	MH	M	M	M	**65**	LM	M	MH	M	M	M
21	L	M	MH	H	MH	LM	**66**	LM	M	MH	H	MH	LM
22	L	M	M	L	L	H	**67**	LM	M	M	L	LM	MH
23	L	M	M	M	M	M	**68**	LM	M	M	M	MH	LM
24	L	M	M	H	MH	LM	**69**	LM	M	M	H	H	L
25	L	M	LM	L	LM	MH	**70**	LM	M	LM	L	M	M
26	L	M	LM	M	M	M	**71**	LM	M	LM	M	MH	LM
27	L	M	LM	H	MH	LM	**72**	LM	M	LM	H	VH	L
28	L	M	L	L	LM	MH	**73**	LM	M	L	L	MH	LM
29	L	M	L	M	MH	LM	**74**	LM	M	L	M	H	LM
30	L	M	L	H	H	L	**75**	LM	M	L	H	VH	L
31	L	L	H	L	LM	MH	**76**	LM	L	H	L	LM	MH
32	L	L	H	M	M	M	**77**	LM	L	H	M	M	M
33	L	L	H	H	MH	LM	**78**	LM	L	H	H	MH	LM
34	L	L	MH	L	LM	MH	**79**	LM	L	MH	L	LM	MH
35	L	L	MH	M	MH	LM	**80**	LM	L	MH	M	M	LM
36	L	L	MH	H	H	L	**81**	LM	L	MH	H	MH	L
37	L	L	M	L	M	M	**82**	LM	L	M	L	M	M
38	L	L	M	M	MH	LM	**83**	LM	L	M	M	MH	LM
39	L	L	M	H	H	L	**84**	LM	L	M	H	H	L
40	L	L	LM	L	MH	LM	**85**	LM	L	LM	L	MH	LM
41	L	L	LM	M	H	LM	**86**	LM	L	LM	M	H	M
42	L	L	LM	H	VH	L	**87**	LM	L	LM	H	VH	L
43	L	L	L	L	H	LM	**88**	LM	L	L	L	H	LM
44	L	L	L	M	H	L	**89**	LM	L	L	M	H	LM
45	L	L	L	H	VH	L	**90**	LM	L	L	H	VH	L

No	ESPP	EP	EED	BSC	CSE	CME	No	ESPP	EP	EED	BSC	CSE	CME
91	MH	H	H	L	LM	MH	**136**	H	H	H	L	M	M
92	MH	H	H	M	LM	MH	**137**	H	H	H	M	MH	M
93	MH	H	H	H	M	M	**138**	H	H	H	H	H	LM
94	MH	H	MH	L	LM	MH	**139**	H	H	MH	L	MH	M
95	MH	H	MH	M	MH	M	**140**	H	H	MH	M	MH	LM
96	MH	H	MH	H	MH	LM	**141**	H	H	MH	H	H	L
97	MH	H	M	L	M	M	**142**	H	H	M	L	H	M
98	MH	H	M	M	MH	LM	**143**	H	H	M	M	H	LM
99	MH	H	M	H	H	L	**144**	H	H	M	H	H	L
100	MH	H	LM	L	MH	LM	**145**	H	H	LM	L	H	LM
101	MH	H	LM	M	H	L	**146**	H	H	LM	M	H	LM
102	MH	H	LM	H	VH	VL	**147**	H	H	LM	H	VH	L
103	MH	H	L	L	H	LM	**148**	H	H	L	L	VH	LM
104	MH	H	L	M	H	L	**149**	H	H	L	M	VH	L
105	VH	H	L	H	VH	L	**150**	H	H	L	H	VH	VL
106	MH	M	H	L	LM	MH	**151**	H	M	H	L	M	M
107	MH	M	H	M	M	M	**152**	H	M	H	M	MH	L
108	MH	M	H	H	MH	LM	**153**	H	M	H	H	H	L
109	MH	M	MH	L	LM	MH	**154**	H	M	MH	L	MH	LM
110	MH	M	MH	M	MH	M	**155**	H	M	MH	M	MH	LM
111	MH	M	MH	H	H	L	**156**	H	M	MH	H	H	L
112	MH	M	M	L	M	M	**157**	H	M	M	L	MH	LM
113	MH	M	M	M	MH	LM	**158**	H	M	M	M	H	L
114	MH	M	M	H	H	L	**159**	H	M	M	H	H	L
115	MH	M	LM	L	MH	LM	**160**	H	M	LM	L	MH	LM
116	MH	M	LM	M	H	LM	**161**	H	M	LM	M	H	L
117	MH	M	LM	H	VH	VL	**162**	H	M	LM	H	H	L
118	MH	M	L	L	H	L	**163**	H	M	L	L	H	L
119	MH	M	L	M	VH	L	**164**	H	M	L	M	VH	VL
120	MH	M	L	H	VH	VL	**165**	H	M	L	H	VH	VL
121	MH	L	H	L	MH	M	**166**	H	L	H	L	M	M
122	MH	L	H	M	H	LM	**167**	H	L	H	M	M	LM
123	MH	L	H	H	VH	L	**168**	H	L	H	H	MH	L
124	MH	L	MH	L	H	M	**169**	H	L	MH	L	MH	M
125	MH	L	MH	M	H	L	**170**	H	L	MH	M	H	LM
126	MH	L	MH	H	VH	VL	**171**	H	L	MH	H	H	LM
127	MH	L	M	L	H	LM	**172**	H	L	M	L	MH	LM
128	MH	L	M	M	H	L	**173**	H	L	M	M	H	L
129	MH	L	M	H	VH	L	**174**	H	L	M	H	H	L
130	MH	L	LM	L	H	LM	**175**	H	L	H	L	H	L
131	MH	L	LM	M	H	L	**176**	H	L	H	M	H	VL
132	MH	L	LM	H	VH	VL	**177**	H	L	H	H	VH	VL
133	MH	L	L	L	VH	L	**178**	H	L	MH	L	H	L
134	MH	L	L	M	VH	VL	**179**	H	L	MH	M	VH	VL
135	MH	L	L	H	VH	VL	**180**	H	L	MH	H	VH	VL