Consumer Appliance-level Load Shedding Optimization for Real-time Application

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Abstract: Load Shedding (LS) is implemented by Distribution Utilities (DUs) in addressing power supply insufficiency problems to avoid DU system damages. This is commonly implemented by the installation of LS relays in every DU feeder. However in either scheduled or unscheduled supply disruptions, huge amount of unnecessary de-loading is taking place in a feeder level LS implementation. In addition, the consumers connected to a de-loaded feeder are in total blackout, that is, consumers have no choice over which appliances to spare from being de-loaded. This paper proposes an LS implementation that replaces feeder-level de-loading by a finer consumer-appliance-level de-loading and allows consumers to have some control over their de-loading. In this method, consumers can set an appliance priority level to their selected connected loads at a given time, to avoid total blackout. Furthermore, to deal with the enormous data involved in this proposed method, both centralized and distributed optimization approaches are employed to expedite the system processing response. Simulations are conducted to verify the proposed method's functionality. Lastly, an economic analysis is done to assess the proposed method's viability.

1. Introduction

The electrical power supply and demand balance is essential in power systems. Power Plant Operators (PPOs), Transmission System Operators (TSOs), and Distribution Utilities (DUs) are in close coordination to maintain this balance. When the supply shortage is not large, moderate load shedding measures such as conservative voltage reduction are enough [1]. However, when the supply shortage is large, hard load shedding measures are necessary that cut off power supply by LS relays in every DU feeder. Such is the case in Mindanao, the southern island of the Philippines. The recurring drought in the region impacts hydro power plants which cover 30% of the power supply [2]. DUs in this case, has to resort to the hard load shedding, which is simply referred to as load shedding (LS) hereafter, to avoid system damages.

LS is a more economical and realistic solution to the supply demand imbalance than installing more generating capacities, which involves huge monetary investments and tedious negotiation processes between stakeholders. However, LS can be an expensive strategy [3][4]. Excessive de-loading often takes place in feeder-level load shedding. For example, even when the necessary de-loading is only half of the load connected to the feeder, the whole connected load is de-loaded in the current LS implementation.

To address the mentioned issues, immediate solutions were presented by several published papers that focused on the development of fast LS [5], operation optimization of under-frequency load shedding (UFLS) [6], and under-voltage load shedding (UVLS) relays to reduce and optimize load shedding occurrences [7][8]. Shekari *et al.* [9] proposed an adaptive wide-area centralized load shedding by determining the amount of necessary demand reductions, locations of load drops, and the load shedding event types are optimally simulated. Potel *et al.* [10] proposed a clustering-based method to improve the selection of feeders in a UFLS implementation. Abdelwahid *et al.* [11] verified the effectiveness of UFLS scheme implemented in real-time through hardware implementation and simulations. Babaei *et al.* [12] developed an algorithm to handle load shedding implementations especially during natural disasters taking the uncertainty of contingencies into consideration. Also, Yaun *et al.* [13] proposed a method for preventive-coordinated load shedding considering power supply uncertainties. Cavalcante *et al.* [14] and Shen *et al.* [15] introduced a self-healing scheme that minimizes the unsupplied demand while maintaining the faulted network isolated. Furthermore, the study of Hoseinzadeh *et al.* [16] addresses the decentralized load shedding by using the instantaneous voltage deviation of load buses as a parameter in determining the frequency thresholds of UFLS relays. These papers are feeder-level load shedding optimization which can be made finer into a consumer appliance-level load shedding to maximize the available power utilization and avoid too much LS. The study of Bhattacherjee *et al.* [17] explores the possibility of residential-based load shedding with the use of smart-meters, single-board computers, and a monitoring server to implement an efficient load shedding. Sigrist [18] and Yao *et al.* [19] proposed a residential-level load shedding to minimize the load losses by detecting frequency mismatch which also considers the rate of change of frequency. Moreover, appliance-level LS provides an opportunity for each consumer to experience partial blackout, wherein not all of their electrical devices are turned-off unlike the current LS implementation. Xiang *et al* [20] developed an appliance level load shedding with the use of Internet of Things (IoT) technology to control individual devices through cloud servers. Azasoo *et al.* [21] and Jabian *et al.* [22] proposed an appliance-level LS that aims to minimize excessive and unnecessary de-loading that considers consumer's comfort. Azasoo *et al.* [21] developed a heuristic approach in an appliance-level LS but the power demand is pre-determined in the simulation, thus, variations of power demand and power supply in real-time and fairness of implementation among consumers are not evaluated. On the other hand, Jabian *et al.* [22] provide consumers a way to participate in every de-loading implementation by considering their respective appliance priority levels. Also, they introduced a fairness function to make the load shedding fair among consumers. However, power allocation was determined based on the forecasted load without paying attention to risks possibly incurred by the unavoidable existence of forecasting errors due to uncertainties in power systems [23]. Also, the optimization results showed that Genetic Algorithm (GA) is effective in this kind of problem but they did not investigate another optimization techniques to further elaborate its superiority. Moreover, performance evaluations regarding the employed optimization technique and the introduced fairness function were limited only to specific sets of appliances. Furthermore, economic analysis to assess the economic impact of the proposed method was not part of the study.

In this paper, the researchers propose a method that improves the appliance-level LS implementation of Jabian *et al.* [22] by incorporating a measure to cope with forecasting errors based on error analysis that improves system stability. Also, the researchers have selected Binary Particle Swarm Optimization (BPSO), a widely used optimization technique in power system, as a comparison to GA in order to confirm the technical viability of the latter by providing an extensive assessment in terms of optimization quality and execution time in dealing with this kind of optimization problem. Furthermore, a comprehensive evaluation of effectiveness in the introduced fairness function among consumer on different sets of appliances' power ratings is demonstrated. Lastly, economic analysis is performed to ascertain its economic impact from the viewpoints of both DU side and consumer side.

The rest of this paper is organized as follows. In Section 2, the proposed load shedding system is described including the overall two-level system architecture, determination of load capacity to be shed, efficient and fair supply capacity allocations with consumers' priority levels considered, and economic analysis,. Results on fairness function evaluation, optimization method comparison, economic analysis, and case studies are presented in Section 3. Finally, conclusions are given in Section 4.

2. Proposed System Design

In this section, the system topology of communication and decision making system is first described followed by the consumer participation scheme. Then the improved load shedding procedure is described. Finally, criteria used in the economic analysis will be discussed.

2.1. System Network Topology

Appliance-level LS optimization has to deal with a large number of appliances (i.e., more than 65,000 variables). This causes large burdens on a centralized communication and decision making system, which is not practical for low-cost implementation and real-time application. Thus, the authors decide to utilize the combined centralized and distributed topology as depicted in Fig.1. Appliances owned by consumers are monitored and controlled by control nodes X_{jk}, which are under control of an aggregated appliances controller. The central station (CS) is in DU's server and in charge of power management, monitoring, data logging, and instructing appliances controllers K_j [22]. Communication between these components is assumed to have a bi-directional protocol.

2.2. Consumer Appliance Priority Level Setting

In the existing LS implementation, consumers have no part in the decision making of which areas to be de-loaded, more so, of which appliance to be de-loaded. In the proposed scheme, consumers assign priority levels p to their appliances based on their comfort and prerogative. The LS scheme decides which appliances should be off so that excessive load shedding is minimized while respecting the priority levels, avoiding the total blackout and reducing consumers' inconvenience. Appliances of the same priority

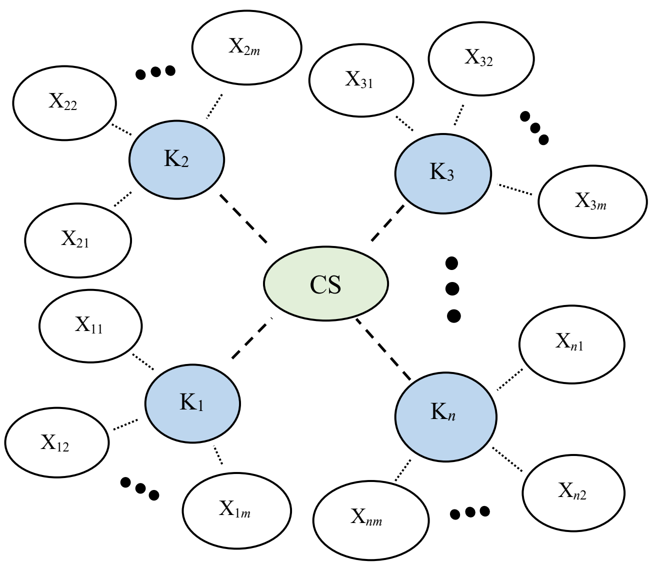

Fig.1. *Proposed Overall System Topology*

level are collectively controlled by a node X_{jk} and therefore they are treated as if a single controllable appliance. The appliance rated power is denoted as $L_{jk}^1, \ldots, L_{jk}^5$, with L_{jk}^5 as the appliance rating with the lowest priority level [22].

1.1. Procedure

The ultimate goal of the proposed procedure is to determine in a best manner whether each of the appliances nominated by consumers is to be switched on or off. From the DU's point of view, the best way is to utilize the supply capacity maximally, or equivalently to minimize loss of revenue chances. As shown in the following subsections, this is addressed by minimization of unallocated supply capacity. From the consumers' viewpoints, the best way is to respect their own appliances' priorities, to avoid repeated on and off over a short period of time, and to be fair among consumers. To avoid repeated on and off caused by short-sighted prospect into the future, appropriate load forecast is performed and analyzed. Consumers-specified priority levels are taken into consideration when the minimization of unallocated supply capacity is done. Among obtained solutions, the fairest one is chosen.

1.1.1. Step 1: System Voltage and Frequency Monitoring

DUs CS monitors the overall system voltage and frequency to ensure that these parameters are always in their respective allowable ranges. For example, according to the Philippine Distribution Code (PDC), the system is under-voltage if the system voltage is less than or equal to 90 percent of the nominal voltage, and it is over-voltage if it is greater than or equal to 110 percent. Also, the DUs' system frequency should be between 59.7 Hz and 60.3 Hz [24]. Hence, when CS detects that the system voltage or frequency is below its allowable lower limit for more than one minute, then LS implementation is necessary.

1.1.2. Step 2: Short-term Load Forecasting

An LS implementation is necessary when under voltage or frequency is detected. If the power reduction percentage P_R, i.e., the percentage of load to be shed, is determined based on the current supply shortage, it could be too small and could cause another LS implementation within a short period because the demand may continue to grow. Thus, a 15-minute ahead load forecast is done to determine P_R that accommodates the demand variations within that period. This reduces the possibility of repeating an LS implementation and avoids possible flickering effect of appliances' switching. The following equation is used to forecast the load [22]:

$$L_{forecast} = L_{actual} + \left(L_{actual} \times G_{t_{avg}}\right), \tag{1}$$

$$G_{t_{avg}} = \frac{\sum_{l=1}^{D} \frac{L_t^{d-l} - L_{t-1}^{d-l}}{L_{t-1}^{d-l}}}{D}, \tag{2}$$

where, $L_{forecast}$ is the forecasted demand after 15 minutes in MegaWatts (MW), L_{actual} is the actual total connected load power in MW, $G_{t_{avg}}$ is the average load power increase, t denotes the data logging time interval, L_t^{d-l} is the demand power at time t on day $d-l$ in MW, d is the current day, and D is the number of available historical data.

Also, forecasting error $E_{forecast}$ is defined as shown in the following equation:

$$E_{forecast} = \left|\frac{L_{forecast} - L_{actual}}{L_{actual}}\right|. \tag{3}$$

1.1.3. Step 3: Power Allocation for each Load Controllers

The CS instructs each controller K_j to reduce their load L_j by the ratio of P_R so that the sum of load in the forecasting horizon will be equal to the total available but presumably insufficient power supply S_G provided by the TSOs. In other words, the power reduction ratio P_R is defined as the ratio of S_G to the total forecasted load $L_{forecast}$.

In any forecasting method, forecasting error is always present due to uncertainties in power systems caused by the unpredictable variations of power output from renewable sources (e.g. photovoltaic sources, wind power supply) and abrupt changes in power demand. The LS implemented based on P_R defined above could be insufficient due to under-forecast of the load. To deal with this risk, the power supply capacity S_j^{new} allocated to controller K_j is determined taking a margin M into consideration:

$$S_j^{new} = (P_R - M) \times L_j. \tag{4}$$

Here, M indicates the maximum forecasting error $E_{forecast}$ that is likely to happen, i.e., 95% of errors are below this value. This is to ensure that no repeated LS implementation happens over a short period of time due to insufficient load shedding.

1.1.4. Step 4: Load Controllers' Optimization

Upon receiving the new allocated power S_j^{new}, each load controller K_j distributes power allocation starting with the top priority level, level 1. The proposed method verifies if the power supply capacity is large enough to energize the appliances at that priority level. If that is the case, all the appliances in that level are allocated with power and the remaining supply capacity is handed over to the next priority level as the following equations indicate:

$$S_j^1 = S_j^{new}, \tag{5}$$

$$S_j^p = S_j^{p-1} - \sum_{k=1}^{m} L_{jk}^{p-1}, \tag{6}$$

where, S_j^p is the power supply capacity available for the appliances at priority level p under the controller K_j and L_{jk}^p indicates the total load of appliances of priority level p owned by user k under control of K_j. If the power supply becomes, at a certain priority level p_c, insufficient, i.e., $S_j^{p_c} < \sum_{k=1}^{m} L_{jk}^{p_c}$, then optimization is executed to determine which set of enrolled appliances of priority level pc is a candidate to be turned-off or deloaded.

2.3.4.1 Objective Function

The optimal switching status $x_{jk}^{p_c}$ defined by (8) of each appliance is determined so that as much of the supply capacity $S_j^{p_c}$ as possible is allocated to appliances by minimizing (7) under the condition (9).

$$S_j^{p_c} - \sum_{k=1}^{m} x_{jk}^{p_c} L_{jk}^{p_c}, \tag{7}$$

$$x_{jk}^{p_c} = \begin{cases} 1, on \\ 0, off \end{cases}, \tag{8}$$

subject to,

$$S_j^{p_c} \geq \sum_{k=1}^{m} x_{jk}^{p_c} L_{jk}^{p_c}. \tag{9}$$

This binary combinatorial problem is to be implemented in each distributed load controller K_j where its designed processor has limited computing capability to perform complex calculations due to cost considerations. Also, multiple sets of equally good solutions are expected to be derived from this optimization process for fairness evaluation as explained further in the following subsections. Thus, the authors opted to utilize a meta-heuristic optimization method due to its low computing capability requirement, considerable convergence performance, and a possibility of getting multiple sets of equally good solutions. However, meta-heuristic methods do not necessarily give the optimal solution. So, the condition (10) is used to judge whether the derived solution is good enough,

$$S_j^{unallocated} = S_j^{p_c} - \sum_{k=1}^{m} x_{jk}^{p_c} L_{jk}^{p_c} < L_{jk_{min}}^{p_c}, \tag{10}$$

where, $L_{jk_{min}}^{p_c}$ is the lowest power rating among the turned-off appliances at priority level p_c nominated by K_j for possible power reallocation.

2.3.4.2 Population Generation

The optimization problem defined previously is solved by a metaheuristic technique, typically GA or BPSO. Either algorithm usually generates the initial population of solution candidates randomly, which are called individuals in GA and particles in BPSO and are vectors of switching variables x. However, it has been observed that those initializations often lead to unacceptable computation time. In this paper, the researchers modify the initial population generation to speed up the running time.

Initial population depends on the relationships between the available power supply $S_j^{p_c}$ and the total target load $L_j^{p_c}$ as follows:

$$\left(0.9 \times L_j^{p_c}\right) \leq S_j^{p_c} < L_j^{p_c}, \tag{11}$$

$$\left(0.1 \times L_j^{p_c}\right) < S_j^{p_c} < \left(0.9 \times L_j^{p_c}\right), \tag{12}$$

$$L_{jk_{min}}^{p_c} < S_j^{p_c} \leq \left(0.1 \times L_j^{p_c}\right). \tag{13}$$

When the condition (11) holds, there is nearly sufficient power that can be distributed among the connected appliances. Then, the solution is expected to contain many switching-ON actions. Therefore, each individual in the initial population is generated so that 90% of the variables x have value 1. When condition (12) is satisfied, the population is randomly initialized with equal chances for variable values of 0s and 1s. Furthermore, in the case where condition (13) holds, the initial population should have approximately 10% chance of producing switching variable value of 1s or 90% chance of producing variable value of 0s.

2.3.4.3 Optimization Method

The problem formulated in the above subsection is an optimization problem that involves a large number of binary variables. There can be a number of equally good solutions that satisfy the condition (10). Among them the 'fairest' solution will be selected as described in the next subsection. So, we need to apply an optimization technique that can deal with this type of optimization problem and produces a set of solutions, not a single solution. Here the authors have chosen GA which is widely applied in the field of function optimization, combinatorial optimization, and automatic control [25] known for its strong robustness and general optimization ability [26].

GA showed satisfactory performance in both quality of solutions and computation time [22]. In this paper, the binary particle swarm optimization (BPSO), which is used by many researchers especially in power systems application due to its known promising performance [27], is also employed to confirm and analyze the satisfactory performance of GA.

2.3.5 Step 5: Fairness Function Evaluation

It is not fair that a specific appliance of a certain consumer is repeatedly turned off while other appliances are kept on. To exclude these unfair solutions, Jabian *et al.* [22] introduced a fairness measure as shown in following the equations:

$$F_{fairness}\left(x_{j1}^{p_c}, \dots, x_{jm}^{p_c}\right) = \sum_{k=1}^{m} x_{jk}^{p_c} R_{jk,p_c}^{ON}, \tag{14}$$

$$R_{jk,p_c}^{ON} = \frac{n_{jk,p_c}^{ON}}{n_{jk,p_c}^{ON} + n_{jk,p_c}^{OFF}}, \tag{15}$$

$$f\left(F_{fairness}\left(x_{j1}^{p_c}, \dots, x_{jm}^{p_c}\right), S_j^{unallocated}\right) = a \cdot F_{fairness}\left(x_{j1}^{p_c}, \dots, x_{jm}^{p_c}\right) + b \cdot S_j^{unallocated}, \tag{16}$$

where, n_{jk,p_c}^{ON} is the number of turning-on switching operations of the consumer k's appliance of priority level p_c over a certain past period, n_{jk,p_c}^{OFF} is the number for turning-off switching operations, and thus R^{ON}_{jk,p_c} is the ratio of the number of turning-on operations to the total number of switching operations. Equation (14) becomes large when appliances which have been frequently switched on are switched on again, which is an unfair situation. Therefore (16) is a good measure to evaluate quality of solution in both terms of efficiency (small unallocated supply capacity) and fairness when the weights a and b are properly determined by the DU.

Evaluation of the fairness function is always performed after every optimization process at CS and K_j to ensure that no consumer experiences repeated appliance de-loading.

2.3.6 Step 6: Central Station's Optimization

The central station collects remaining unallocated power capacity after optimization at each K_j and redistributes them to appliances nominated by load controllers, where equation (17) is the objective function:

$$S_T^{unallocated} - \sum_{j=1}^{n} x_j^{cs}\, L_{jk_{nom}}, \tag{17}$$

$$x_j^{cs} = \begin{cases} 1, on \\ 0, off \end{cases}, \tag{18}$$

and the constraint is,

$$S_T^{unallocated} \geq \sum_{j=1}^{n} x_j^{cs}\, L_{jk_{nom}}, \tag{19}$$

where, $S_T^{unallocated}$ is the accumulated $S_j^{unallocated}$ reported by each K_j. After the execution of this final optimization, CS communicates the switching status of the nominated appliances to each K_j which in turn transmit the allocation to those nominated appliances. This optimization is accomplished to maximize the power utilization of the unallocated power $S_j^{unallocated}$ from each K_j.

The final LS implementation commences as soon as the load controllers K_j receive the switching combination from CS for the nominated appliances.

2.4 Economic Analysis

To validate the feasibility of this research, economic analysis is conducted. Estimated DU loss, device cost, installation and maintenance cost, and consumer investment are considered. Although consumer comfort and satisfaction is one of the important values that the proposed LS scheme provides, its monetary evaluation is not given because of its difficulties.

2.4.1 Estimated DUs Loss

In the existing feeder-level LS implementation, every LS execution costs at least one or more feeder capacity to be de-loaded even if the necessary power reduction is only half of the feeder's capacity. This excessive LS can be avoided and become an additional DUs revenue when power utilization is maximized.

2.4.2 Consumers' Investment

DU facility enhancements that directly benefit the consumers can be fully recovered from the consumers upon approval by the ERC [28]. So, the total cost in implementing the proposed method can be divided among the consumers, depending on their subscription and assumed as their corresponding investment. In the Philippines, specifically in Iligan City, residential consumers are categorized into two, namely, the regular residential consumers and the lifeline residential consumers. Lifeline residential consumers are those who have minimal power consumption (i.e. lighting fixtures only) due to their social economic status and are approximately 40% of the total registered residential consumers. Hence, it is important to identify the consumer's subscription category because the device cost also varies depending on their subscriptions. Consumers under the lifeline category are assumed to have a single relay located before their main circuit breaker as the control point to minimize the investment cost. Consumer investment formulas are given below for regular residential consumers and lifeline residential consumers, respectively:

$$I_{reg} = \frac{C_{dev}^{T_{reg}}}{n_{regular}} + \frac{C_{fhs}^{T} + C_m^{T}}{n_{regular} + n_{lifeline}}, \tag{20}$$

$$I_{lifeline} = \frac{C_{dev}^{T_{lifeline}}}{n_{lifeline}} + \frac{C_{fhs}^{T} + C_m^{T}}{n_{regular} + n_{lifeline}}, \tag{21}$$

where, $C_{dev}^{T_{reg}}$ is the total device cost for all $n_{regular}$ regular consumers, C_{fhs}^{T} is the total cost for firmware, hardware, and software, C_m^{T} is the total maintenance cost, and $C_{dev}^{T_{lifeline}}$ is the total device cost for all $n_{lifeline}$ lifeline consumers. In line with ERC, that mandate to fairly recover costs from the consumers, they are only charged those devices and accessories that they benefit from. Since all consumers equally benefit from the DUs overall software, firmware, server and maintenance costs, the total cost of C_{fhs}^{T} and C_m^{T} is divided to all consumers to recover its costs. On the other hand, devices' cost for a certain consumer group is also divided among themselves.

Consumer investment is evaluated using the future value formula (22) and annuity payment formula (23) given respectively below,

$$FV = PV\left(1 + \frac{r}{\tau}\right)^{\tau T}, \tag{22}$$

$$C_p = \frac{\frac{r}{\tau}(FV)}{1 - \left(1 + \frac{r}{\tau}\right)^{-\varphi}}, \tag{23}$$

where, FV is the future worth value, PV is the present value, C_p is the monthly payment for every consumer, r is the rate of interest, τ is the compounding period in one year, and φ is the number of months payable.

3. Performance Evaluation

In this section, several simulations are conducted to show effectiveness of the proposed LS implementation in efficiently utilizing the available power supply.

3.1 Simulation Model

The simulation model is based on a local DU in Iligan City, Philippines. The local DU has the average demand of approximately 20MW with more than 10 installed feeders for residential and commercial consumers. Out of 65,000 total registered consumers, approximately 60,000 of them have residential classification. Currently, the local DU employed supervisory control and data acquisition (SCADA) in its distribution network for transformer and feeder control and monitoring only. However, in this research, it is assumed that CS is integrated in the local DUs' SCADA for continuous overall system voltage and frequency monitoring, data logging and overall power management.

In these simulations, the connected loads of the regular and lifeline residential consumers are assigned to a distributed load controller K_j. Each K_j is assumed to have a maximum connected load of 150kW, where all K_j's are to perform load optimization simultaneously. The appliance power ratings owned by the regular consumers are randomly selected based on the actual appliance power rating provided by the local DU. Also, priority levels are assigned depending on the type of appliances (i.e., lightings, kitchen appliances, ventilation, entertainment, etc.) and ranked based on typical consumer must-haves during low power supply situations. On the other hand, lifeline residential consumers are assumed to have only one type of appliances (i.e., lightings) and assigned to have the top priority level.

3.2 Short-term Load Forecasting

Figure 2 shows a histogram of a typical 1-week forecasting error percentage calculated by equation (3). The results indicate that the errors are below 6% with only two outliers which are caused by unexpected power curtailments.

To get the margin M, a cumulative error density analysis is performed as shown in Figure 3. This indicates that errors smaller than 2% happen at a probability of 95%, and therefore we set 2% as the margin to be used in equation (4).

3.3 Fairness and Optimization Method Evaluation

GA showed satisfactory performance in both quality of solutions and computation time [22]. To further verify its superiority in this specific optimization problem, we employed BPSO for comparison. As mentioned, these techniques are widely used in power systems applications. The two methods are evaluated in terms of the achieved unallocated power and corresponding CPU time after 1000 iterations. In this comparison, a single iteration in GA comprises an evaluation of 50 individuals in a population, individual ranking and selection, and reproduction using crossover and mutation strategy. On the other hand, a single iteration in BPSO consists of evaluating 50 particles in a swarm, evaluation of local best and global best to update the velocity function in order to produce new particles. Each of the particles in BPSO and individuals in GA is composed of 50 binary numbers that represent consumer appliance switching conditions.

After the selection between the mentioned optimization techniques and a reasonable good solutions have been derived, they are checked for fairness using equation (16). The "fairness" of derived solutions is evaluated by means of their corresponding Coefficient of Variation (CV) as shown in the following equation:

$$CV = \frac{\sigma}{\mu} \times 100\%, \tag{24}$$

where, μ is the mean of turning-ON frequencies R^{ON}_{jk,p_c} of appliances and σ is the standard deviation. A lower CV value signifies that the derived set of switching operation is fairer.

Based on several simulations, it is observed that the fairness function and optimization methods vary their performance depending on how the appliance power rating distributions are diversified. Hence, case studies are conducted for the appliances combinations with low and high diversities of appliance power ratings.

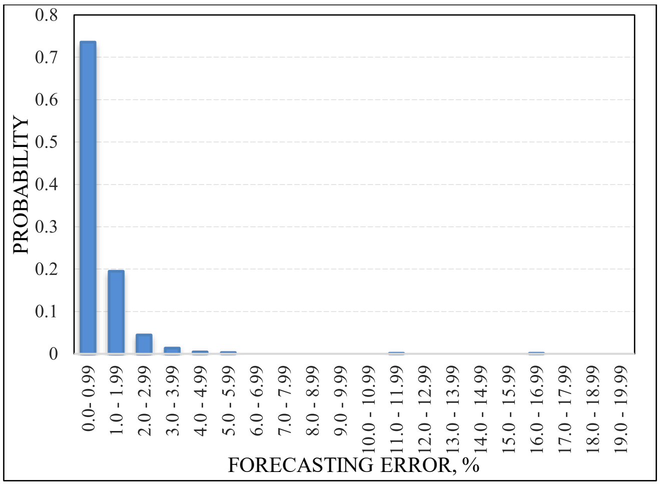

Fig. 2. *Typical 1-Week Forecast Error Percentage*

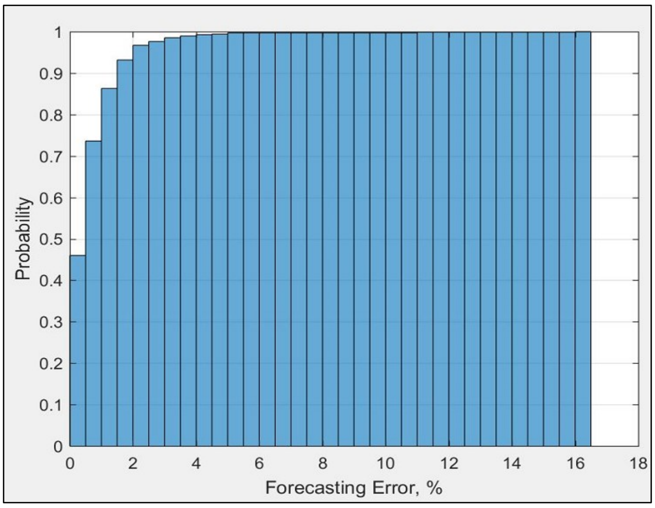

Fig. 3. *Forecasting Error Cumulative Density Analysis*

3.3.1 Case 1: Appliances with Low Diversity of Power Ratings

Low diversity of appliances possessed by consumers means that they have appliances with similar power ratings. This is usually the case for appliances with relatively high priority levels because consumers have similar needs for those appliances.

Here, we assume that there are only two kinds of appliances at priority level 3 owned by 50 consumers under a certain K_j. Actual power ratings are assigned to appliances randomly as shown in figure 4.

3.3.1.1 Optimization Method Comparison

Figure 5 shows the convergence process of GA and BPSO where 1336W of supply capacity is distributed to 50 appliances. After 1000 iteration, GA derived an unallocated power of approximately 20W and BPSO achieved approximately 100W, which indicates that GA has the advantage over BPSO in terms of effective allocation of the supply capacity.

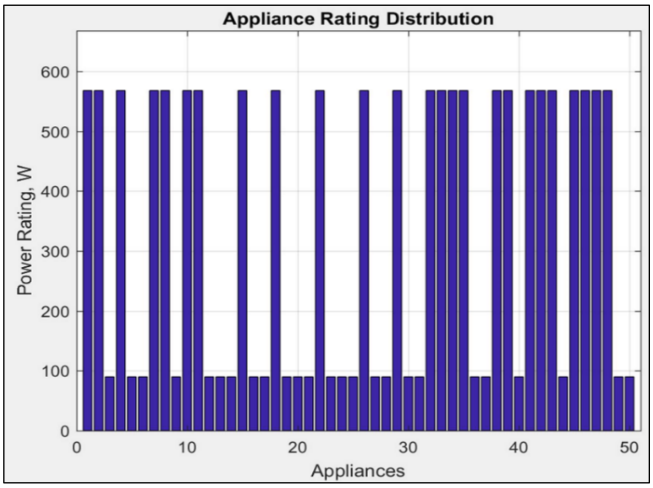

Fig. 4. *Appliance Power Ratings at Priority Level 3*

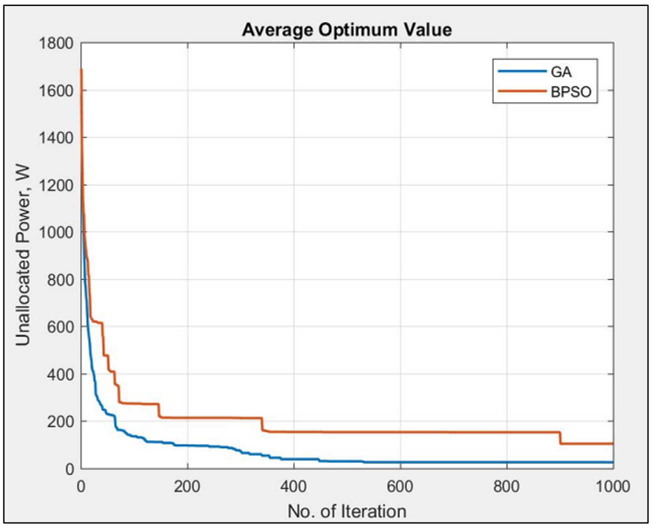

Fig. 5. *GA and BPSO Convergence Process for Appliances with Low Diversity of Power Ratings*

Figure 6 shows processing time of both GA and BPSO. GA implementation converges faster than BPSO; its CPU execution time is approximately less than 30% of the BPSO's.

3.3.1.2 Fairness Evaluation

Based on the previous subsection, GA shows superiority in terms of processing time and the achieved good solutions. Hence, we used GA's achieved solutions and evaluate their corresponding fairness values. Figure 7 shows the CV of the switching combinations derived with and without the fairness function. From the figure, it can be deduced that the CV is lower when the fairness function is considered and that the fairness function is effective to produce fairer solutions.

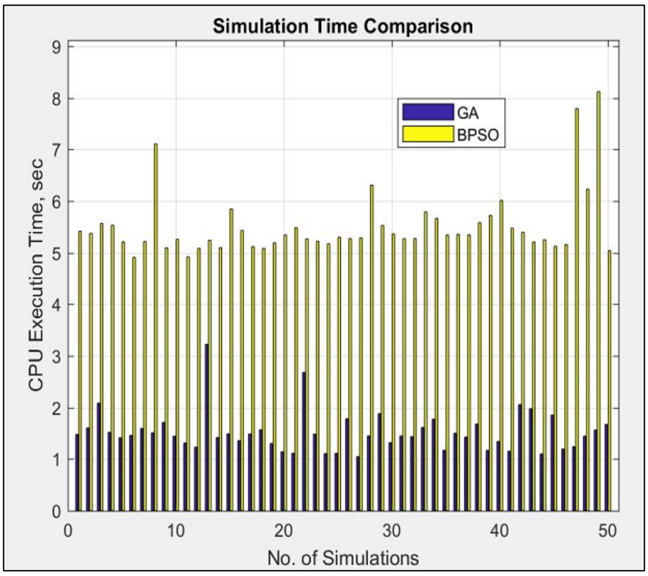

Fig. 6. *GA and BPSO Processing Time for Appliance with Low Diversity of Power Ratings*

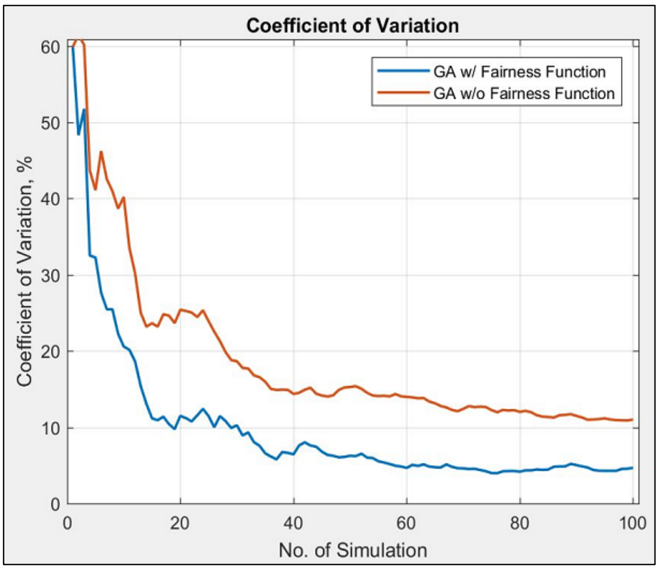

Fig. 7. *Coefficients of Variation Appliances with Low Diversity of Power Ratings*

3.3.2 Case 2: Appliances with High Diversity of Power Ratings

Appliances with high diversity of power ratings appear at lower priority levels. Figure 8 shows the appliances combination with highly diversified power ratings. This time, consumers are expected to have different choices and different sets of appliances to consider based on their own comfort level especially during low power supply.

3.3.2.1 Optimization Method Comparison

Figure 9 shows the convergence performance of GA and BPSO for the appliances with high diversity of power ratings. Here, BPSO leads slightly compared to GA based on their individual achieved value

Figure 10 shows both GA and BPSO processing time after 1000 iterations. GA has shorter CPU execution time compared to BPSO which is approximately less than 30% of BPSO's.

3.3.2.2 Fairness Evaluation

As shown in the previous subsection, BPSO performs slightly better than GA in terms of their achieved unallocated power. However, GA is found to be superior over BPSO in terms of CPU processing time. Thus, GA's achieved solution is used to determine the CV of switching combinations obtained with and without the fairness function as shown in Figure 11. By inspection, the switching combination with the fairness function have lower CV values and thus are fairer.

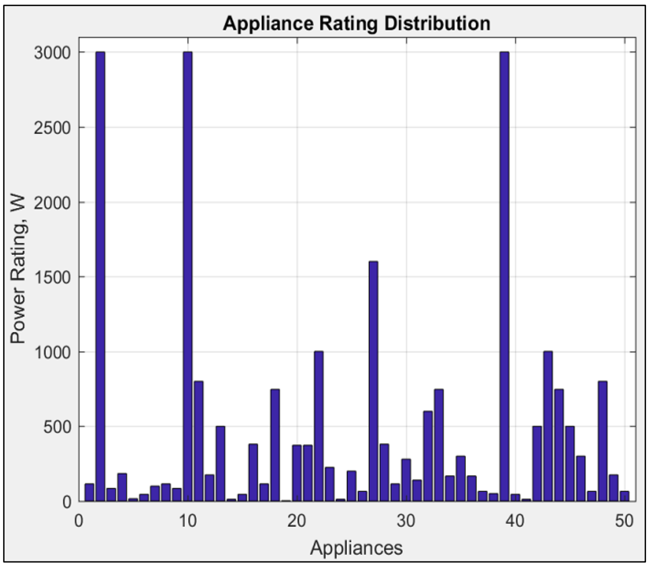

Fig. 8. *Appliance Power Ratings at Priority Level 4*

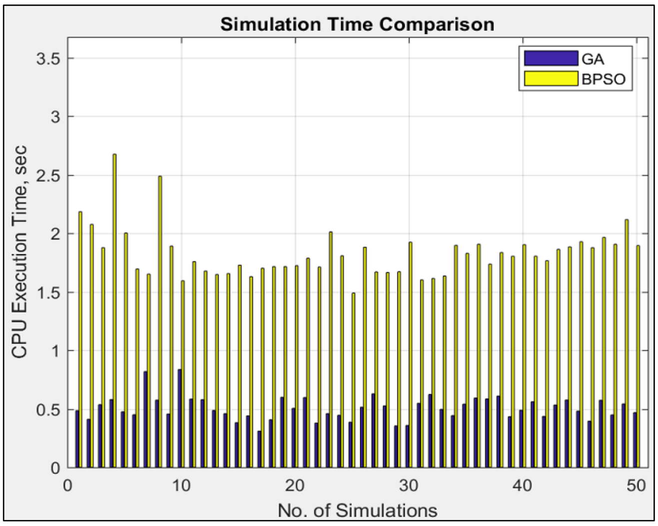

Fig. 10. *GA and BPSO Processing Time for Appliances with High Diversity of Power Ratings*

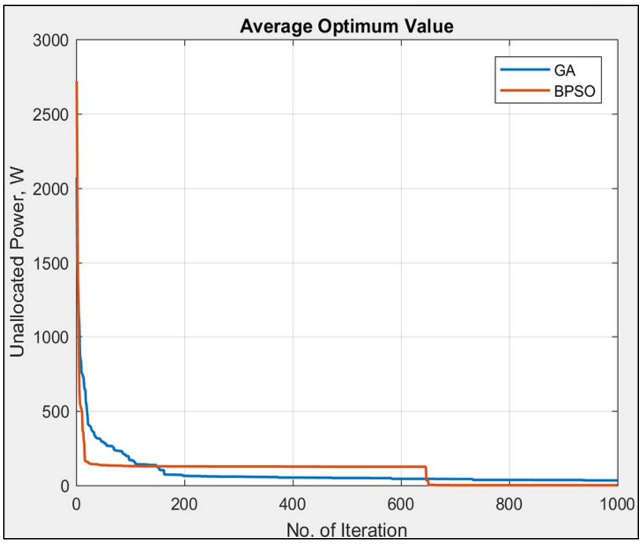

Fig. 9. *GA and BPSO Convergence Process of Appliances with High Diversity of Power Ratings*

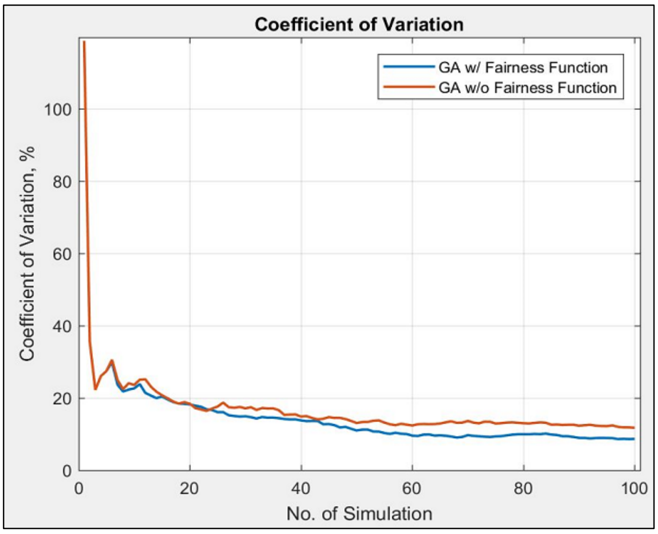

Fig. 11. *Coefficient of Variation for Appliances with High Diversity of Power Ratings*

3.3.3 *Conclusions on Fairness and Optimization Method Evaluation*

Both GA and BPSO showed exemplary results in minimizing unallocated supply capacity. GA is more time efficient and more suitable for real time applications. These support our previous finding that GA is appropriate for this type of problem. The superiority of GA in computation time can be explained as follows: in GA, there is a possibility that the new solution directly inherits an excellent parent trait by skipping the mutation and crossover process because the process is applied probabilistically, whereas, in BPSO, every time a new particle is generated it is different from its parent and loses the excellent trait.

The CV values confirms the effectiveness of the proposed fairness function.

3.4 *LS Optimization Performance Evaluation*

Now that we have confirmed that GA is an appropriate optimization method for this problem and that the fairness function is useful, we closely investigate optimization performance at both CS and K_j levels by GA with fairness function.

3.4.1 *Distributed Load Controllers' Optimization*

The actual appliance power ratings for residential consumers posted in the DU's website are considered in this research. Figure 12 shows a sample of randomly selected appliance power ratings for the optimization process in K_j at priority level 4.

Figure 13 shows the fairness values of the possible switching combinations derived after employing GA. As shown, the 7th switching combination provides the least fairness value or the fairest among the switching combinations, hence, the 7th switching combination is selected as the initial switching combination for an LS implementation.

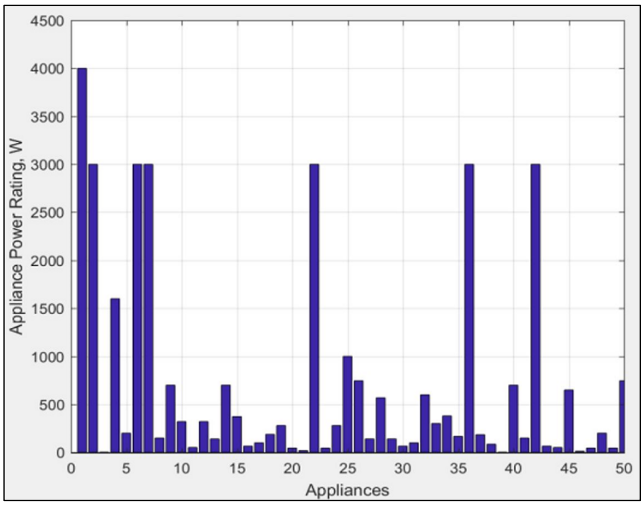

Fig. 12. *Randomly Selected Appliance Power Ratings*

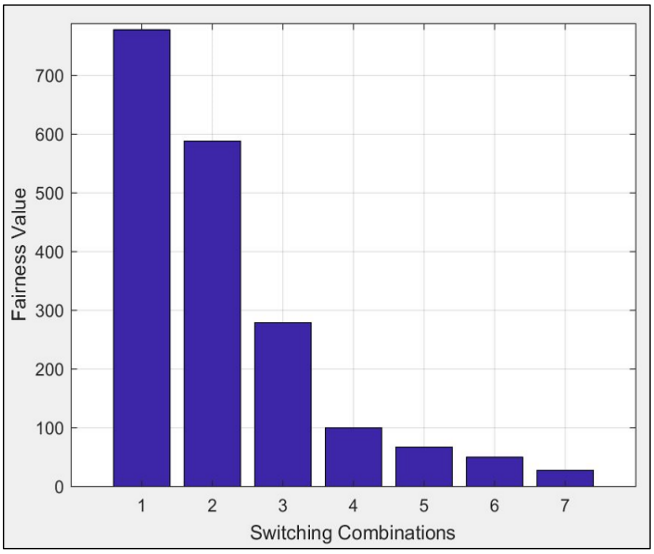

Fig. 13. *Fairness Values of the Switching Combinations using GA*

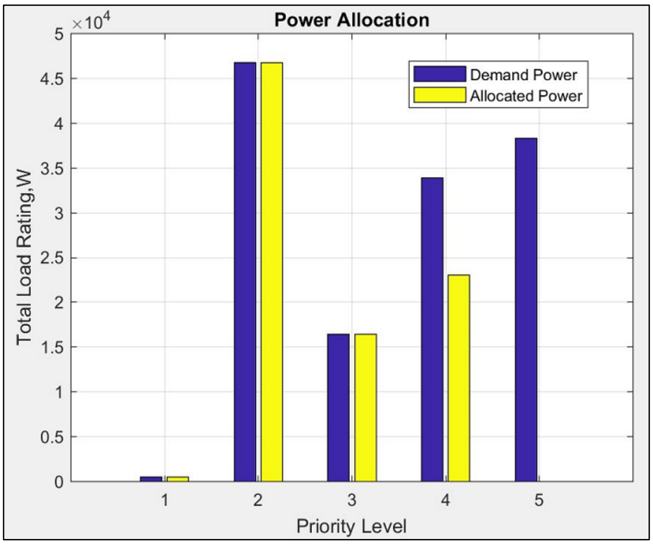

Fig. 14. *Power Allocation per Priority Level*

Figure 14 shows the power allocation for every priority levels in K_j. In priority level 1 to 3, demand power was matched with allocated power. This means that appliances in these priority levels will be energized. On the contrary, in priority level 5, demand power has no or zero allocated power. This means that all appliances will be de-loaded.

The optimization begins in the case of priority level 4 wherein the demand power is greater than the allocated power S_j^4.

Optimization process using GA is employed at priority level 4 wherein out of 23,100W power to be allocated, S_j^4, the final unallocated $S_j^{unallocated}$ is 21W. The resulting unallocated power $S_j^{unallocated}$ is already negligible since it is lower than the lowest power rating of the appliance connected at this priority level. However, to further optimize the system, this unallocated power $S_j^{unallocated}$ is reported to CS for the 2nd optimization process done at CS for final power reallocation.

3.4.2 *Central Station's Optimization*

Figure 15 shows the power reallocation for the nominated appliance $L_{jk_{nom}}$ by each load controller K_j.

In this simulation, the DUs CS receives 2618W total unallocated power $S_j^{unallocated}$ reported by each load controller K_j. After GA implementation, a total of 2617W of the appliance power rating were supplied and only 1W is the remaining overall unallocated power. The corresponding CPU processing time was 103ms.

3.5 *Economic Analysis*

3.5.1 *Estimated DUs Loss*

Currently, 14 feeders are installed with the maximum feeder capacity of 6.7MW and a minimum feeder capacity of 1.81MW. Even when one of the feeders is switched-off, it is already a huge amount of loss for the DU and discomfort on the part of the affected consumers for the duration of approximately 2 to 4 hours.

Based on the optimization results of the proposed LS implementation, the unnecessary de-loading or unutilized energy can be reduced to a negligible level, thus, can maximize the DU's revenue.

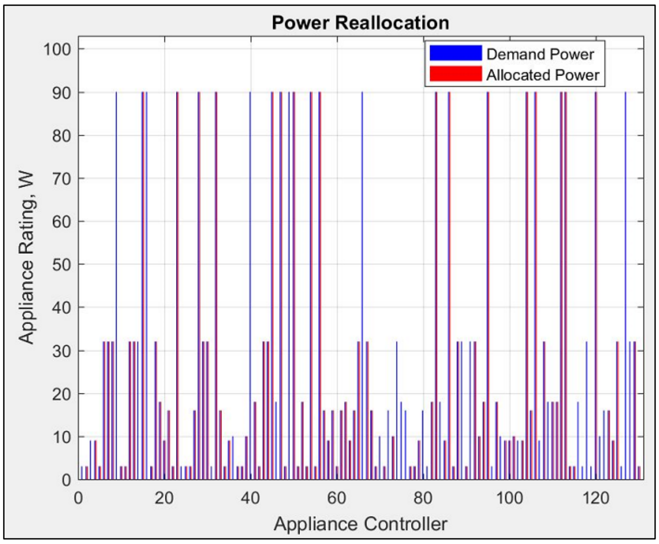

Fig. 15. *Nominated Appliances' Power Reallocation*

3.5.2 *Consumer's Investment*

Initial costing for the lifeline consumers is approximately Php3,916 which composed of a wireless module, a digitally controlled relay, power supply, and a device casing. On the other hand, the regular consumer's initial device cost is approximately Php13,327 which composed of a wifi and a radio-frequency (RF) module for wireless communication, 5 smart outlets, and a house appliance controller board. The estimated costs for device components are based on the off-the-shelf devices that can be purchased online.

The total systems cost is based on the actual connected consumers of the local DU. The estimated systems cost is approximately Php46.69M for 3635 distributed load controllers K_j and the DUs CS server. The estimated maintenance cost is approximately 10% of the total systems cost [29].

The consumers' investment were calculated based on equation (20) and equation (21) for lifeline and regular residential consumers, respectively.

For lifeline residential consumers, the total initial cost is approximately Php3967 while regular residential consumers has the initial cost of approximately Php13,822. Assuming that the DU shoulders the overall initial investment and obliges the consumers to partially pay the invested amount in a monthly basis for about 5 years with 12% interest rate, by using the future worth formula (22) and annuity equation (23), the monthly payable for lifeline subscription is approximately Php155 and approximately Php540 for regular consumers. Note that the average residential consumer in the Philippines consumes approximately 400kWhr every month which is about Php4800 [30]. This cost will result to an increase of approximately 11% of the average monthly bill of a regular consumer.

4. Conclusion

In this paper, we proposed a load shedding implementation that aims to maximize power utilization by replacing the feeder-level load shedding with appliance-level load shedding. Also, the proposed method provides an opportunity to consumers to take part in the decision making in every load shedding implementation by means of assigning a priority level to their chosen connected loads.

The appliances' historical switching activities were evaluated using the developed fairness function, as introduced in the previous paper, to avoid repetitive de-loading. This is further verified with the resulting coefficient of variations. Moreover, power allocation during load shedding implementation is improved by incorporating short-term load forecasting errors to avoid insufficient de-loading and repeated load shedding in a short period due to underestimate of power supply shortage. The comparison of Genetic Algorithm with Binary Particle Swarm Optimization confirms that Genetic Algorithm is an appropriate optimization technique when dealing with this kind of problem because Genetic Algorithm has a chance to preserve excellent parent resulting in fast convergence. Furthermore, performance evaluations of the introduced fairness function and the optimization techniques were completed using different appliance power ratings distribution diversity.

Based on the above results, closer evaluation and improvements on the proposed method confirms the promising outcomes with significant accuracy. Also, the proposed method is a sound investment since the un-utilized energy could be an additional revenue for the distribution utility. On the other hand, consumer satisfaction will be enhanced since they can take part in deciding which appliances to turn off first during load shedding implementation. In effect, distribution utilities will have a fair, automated, and efficient load shedding process which improves system stability, reliability and power quality.

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6. References

[1] B. Milosevic, “Capacitor Placement for Conservative Voltage Reduction on Distribution Feeders,” vol. 19, no. 3, pp. 1360–1367, 2004.

[2] DOE Report, “2016 Philippine Power Situation Report | DOE | Department of Energy Portal,” 2016. [Online]. Available: https://www.doe.gov.ph/electric-power/2016-philippine-power-situation-report-0. [Accessed: 17-Feb-2018].

[3] J. Yan, C. Li, and Y. Liu, “Adaptive load shedding method based on power imbalance estimated by ANN,” in *TENCON 2017 - 2017 IEEE Region 10 Conference*, 2017, pp. 2996–2999.

[4] B. Hoseinzadeh, M. H. Amini, and C. L. Bak, “Centralized load shedding based on thermal limit of transmission lines against cascading events,” in *IEEE Power and Energy Society General Meeting*, 2018, vol. 2018-January, pp. 1–5.

[5] C. Wester, T. Smith, J. Theron, and D. McGinn, “Developments in fast load shedding,” in *IEEE Conference Record of Annual Pulp and Paper Industry Technical Conference*, 2014, pp. 28–33.

[6] T. Amraee, M. G. Darebaghi, A. Soroudi, and A. Keane, “Probabilistic under Frequency Load Shedding Considering RoCoF Relays of Distributed Generators,” *IEEE Trans. Power Syst.*, vol. 33, no. 4, pp. 3587–3598, 2018.

[7] X. Xu *et al.*, “Automatic Underfrequency Load Shedding Study of the PJM System,” 2020, pp. 1–5.

[8] C. Kim, K. Kim, P. Balaprakash, and M. Anitescu, “Graph Convolutional Neural Networks for Optimal Load Shedding under Line Contingency,” 2020, pp. 1–5.

[9] T. Shekari, A. Gholami, F. Aminifar, and M. Sanaye-Pasand, “An Adaptive Wide-Area Load Shedding Scheme Incorporating Power System Real-Time Limitations,” *IEEE Syst. J.*, vol. 12, no. 1, pp. 759–767, Mar. 2018.

[10] B. Potel, F. Cadoux, L. De Alvaro Garcia, and V. Debusschere, “Clustering-based method for the feeder selection to improve the characteristics of load shedding,” *IET Smart Grid*, vol. 2, no. 4, pp. 659–668, 2019.

[11] S. Abdelwahid, A. Babiker, A. Eltom, and G. Kobet, “Hardware implementation of an automatic adaptive centralized underfrequency load shedding scheme,” *IEEE Trans. Power Deliv.*, vol. 29, no. 6, pp. 2664–2673, Dec. 2014.

[12] S. Babaei, R. Jiang, and C. Zhao, “Distributionally Robust Distribution Network Configuration Under Random Contingency,” *IEEE Trans. Power Syst.*, pp. 1–1, 2020.

[13] H. Yuan and Y. Xu, “Preventive-Corrective Coordinated Transient Stability Dispatch of Power Systems with Uncertain Wind Power,” *IEEE Trans. Power Syst.*, pp. 1–1, 2020.

[14] P. L. Cavalcante *et al.*, “Centralized self-healing scheme for electrical distribution systems,” *IEEE Trans. Smart Grid*, vol. 7, no. 1, pp. 145–155, Jan. 2016.

[15] F. Shen, J. C. L, Q. Wu, and S. Member, “Transactions on Power Systems Distributed Self-healing Scheme for Unbalanced Electrical Distribution Systems Based on Alternating Direction Method of Multipliers,” vol. 14, no. 8, 2019.

[16] B. Hoseinzadeh, F. M. Faria Da Silva, and C. L. Bak, “Adaptive Tuning of Frequency Thresholds Using Voltage Drop Data in Decentralized Load Shedding,” *IEEE Trans. Power Syst.*, vol. 30, no. 4, pp. 2055–2062, 2015.

[17] T. Bhattacherjee, A. K. Saha, S. P. Ramalingam, P. K. Shanmugam, and S. Padmanaban, “Server Monitoring and Priority based Automatic Load Shedding Algorithm (SEMPALS),” in *IEEE Region 10 Annual International Conference, Proceedings/TENCON*, 2019, vol. 2019-Octob, pp. 1863–1868.

[18] L. Sigrist, “A UFLS Scheme for Small Isolated Power Systems Using Rate-of-Change of Frequency,”

IEEE Trans. Power Syst., vol. 30, no. 4, pp. 2192–2193, Jul. 2015.

[19] W. Yao *et al.*, “A Fast Load Control System Based on Mobile Distribution-Level Phasor Measurement Unit,” *IEEE Trans. Smart Grid*, vol. 11, no. 1, pp. 895–904, Jan. 2020.

[20] Y. Xiang, X. Lu, Z. Yu, D. Shi, H. Li, and Z. Wang, “IoT and Edge Computing Based Direct Load Control for Fast Adaptive Frequency Regulation,” 2020, pp. 1–5.

[21] J. Q. Azasoo, T. Kanakis, A. Al-Sherbaz, and M. O. Agyeman, “Heuristic Optimization for Microload Shedding in Generation Constrained Power Systems,” *IEEE Access*, vol. 8, pp. 13294–13304, 2020.

[22] M. E. Jabian, R. Funaki, and J. Murata, “Load Shedding Optimization Considering Consumer Appliance Prioritization Using Genetic Algorithm for Real-time Application,” vol. 2018, no. Dlc, 2018.

[23] H. M. Merrill and A. J. Wood, “Risk and uncertainty in power system planning,” vol. 1, no. 2, pp. 81–90, 1991.

[24] ERC, “Philippine Grid Code,” no. December, 2001.

[25] D. Shi, X. Xie, and L. Tong, “Studies on parameter identification using genetic algorithm in power system,” *Proc. IEEE Power Eng. Soc. Transm. Distrib. Conf.*, vol. 2005, pp. 1–5, 2005.

[26] L. Liu, Q. Sun, Y. Wang, Y. Liu, and R. Wennersten, “Research on short-term optimization for integrated hydro-PV power system based on genetic algorithm,” *Energy Procedia*, vol. 152, pp. 1097–1102, 2018.

[27] Shih-An Yin and Chan-Nan Lu, “Distribution Feeder Scheduling Considering Variable Load Profile and Outage Costs,” *IEEE Trans. Power Syst.*, vol. 24, no. 2, pp. 652–660, 2009.

[28] F. ERC, “Frequently Asked Questions on Value-Added,” no. March 2005, pp. 1–6, 2003.

[29] T. S. Wong, J. Lopez-Roldan, and T. Saha, “Development of a life cycle cost estimating tool to compare GIS and AIS substation projects,” *IEEE Power Energy Soc. Gen. Meet.*, vol. 2015-Septe, no. 1, pp. 1–5, 2015.

[30] PHILSTAR, “Electricity rates up in August 2018 | Philstar.com,” 2018. [Online]. Available: https://www.philstar.com/headlines/2018/08/08/1840675/electricity-rates-august-2018. [Accessed: 10-Jan-2019].