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IFAC PapersOnLine 51-28 (2018) 486–491

Load Shedding Optimization Considering Consumer Appliance Prioritization Using Genetic Algorithm for Real-time Application

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Abstract: In the event of energy supply-demand imbalance caused by deficiency in energy generation, Distribution Utilities (DUs) implement load shedding methods to avoid system damages. In the current distribution set-up, consumers experience unscheduled or scheduled total blackouts with no control over which appliances to spare. This paper introduces a novel method to implement automated load shedding, which considers appliance activities and priority levels as predefined by the consumers, in a smart distribution system. The proposed method utilizes the information from the distributed appliance controllers which are assumed to have power monitoring and direct load control capabilities with bidirectional communication. Since consumer appliance switching is binary in nature, Genetic Algorithm (GA) is used to perform the optimization which is to allocate the available power supply to as many appliances as possible considering the consumer-defined appliance priority levels. With the limited power supply, consumer power allocation is determined by executing two GA processes, in each appliance controller and in the central station, respectively. The GA process in each appliance controller allocates the available supply capacity to the enrolled appliances to determine their switching on or off considering their priority levels. In order to avoid repeated switching of particular appliances, 'fairness' of switching implementations is judged by a proposed criterion. The remaining unallocated supply capacity is collected and optimally redistributed by GA in the central station. The case study results showed that the proposed method ensures optimum power utilization to avoid total blackouts with fast convergence signifying a promising capability for real-time applications. Furthermore, the proposed method is able to involve consumers in deciding which appliances to deload through their priority level inputs.

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Keywords: Power Distribution, Frequency Stabilization, Distribution Automation, Distributed Control, Genetic Algorithm, Load Frequency Control, Load Regulation, Optimal Control, Priority

1. INTRODUCTION

A Distribution Utility (DU) in the Philippines, as a franchise holder of a certain area is obliged to source for its consumers' power consumption and maintain the required technical standards as specified in the Distribution Code of the country. In accordance with the existing implementing rules and regulations of the Electric Power Industry Reform Act of 2001 law, the DUs in Mindanao, a southern part/island of the Philippines, have base load power sources consisting of indigenous and renewable energies: hydro, geothermal, biomass and solar power plants (EPIRA, 2001). The country's Department of Energy (DOE) reported that only almost 40% of the total capacity came from renewable energy and 31% of that came from hydro power plants but was unfortunately having reduced generation due to adverse effect made by El Niño that lead to curtailment of power supply during the first half of the year 2016 (DOE Report, 2016). DUs in the region are receiving complaints from their consumers due to poor service quality, unscheduled blackouts, long hours of power interruption and increased electricity rates, among others. The repeated blackouts caused inconvenience to both households and businesses, since consumers in the affected areas have no control over which appliances to spare, not even a single lighting fixture. On the other hand, the country has a traditional grid power system wherein a unidirectional infrastructure flow of electricity is in effect. Power system adjustments are communicated from grid operators to each of the DUs system operators to do the manual switching. In times of massive power supply-demand imbalance, the grid operators have the capacity to do an automatic or manual load dropping to stabilize the grid (ERC, 2001). Typically, load dropping can be resolved by installing more power supply capacities. In fact, privately-owned coal-fired power plants started its testing and commissioning stages early 2017 (DOE Report, 2017). However, this is a costly and not easily accessible solution especially during peak demand.

The utilization of Direct Load Control (DLC) with bidirectional communication is a favourable alternative

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10.1016/j.ifacol.2018.11.750

solution to the power supply-demand imbalance and sudden changes in frequency and voltage levels in the distribution system. The study of Mortaji *et al.* (Mortaji *et al.*, 2016) showed that smart DLC was able to reduce high peak load demand to average demand and minimized the blackouts. Liu, Hill and Zhang (Liu, Hill and Zhang, 2016) designed a switching controller that enables DLC to quickly respond to frequency disturbance and then gradually transfer the frequency restoration to the power generators to achieve a smooth transition from load control to automatic generation control in real time. Moreover in Dandan Zhang *et al.* (Dandan Zhang *et al.*, 2016) study, the strategy was optimized in a load shedding control that considered economic cost of load shedding and multi node frequency balancing. These studies have shown that investments on DLC equipment and infrastructure in a smart distribution system is efficient in optimizing the consumption of the available power supply. However, these studies did not include consumer inputs as part of the load shedding control variable.

A smart distribution system is an improved power distribution network using technologies that enhance communication between DUs and their consumers to effectively respond to changes or disturbances in the network. With this set-up, the information on frequency and voltage levels are easily monitored which is crucial in the management of power supply-demand balance.

In this paper, we propose a method to automate load shedding in a smart distribution system that considers consumers' appliance priority levels and switching activities to avoid repeated deloading. The research assumes that DU's distribution and designated consumer nodes are installed with smart appliance controllers that have power monitoring, data logging, and DLC capabilities with bidirectional communication. The proposed method uses LFC droop relation as in the study of (Elrayyah, Cingoz and Sozer, 2017) to verify that the adjusted load or the new supply allocation keeps the system frequency within the allowable range prior to optimization. Then the method selects suitable appliances to be deloaded considering the consumer-defined priority levels, amount of loads to be shed and the appliances' switching activities. The method further utilizes a two-level hierarchical structure to facilitate the optimization and switching operations that involve a large number of appliances for real time application. In binary combinatorial problems, the use of metaheuristic techniques is highly favorable in dealing with a large number of variables. Among them, Genetic Algorithm (GA) is promising due to its execution speed and considerable accuracy (Uddin, Abido and Rahman, 2003), which is the case in the current problem as will be validated in the case studies. GA is executed in each level, at each appliance controller (K) and at the central station (CS), respectively. In K, GA finds the set of appliances to be switched on. The appliances in the set should have higher priority levels and the sum of their power consumption should be as close as possible to, but not higher than the power supply capacity allocated to K by CS. The resulting appliance combinations, from GA execution, are subjected to the developed fairness function. This is done to eliminate or avoid biased/unfair switching actions. The next GA is in CS. Before its execution, the remaining unallocated power and appliance nominations with the least power consumption and low switching activity from each K are collected. The accumulated power becomes the available power supply for reallocation. In CS, given the appliance nominations from each K to CS, GA finds a set of suitable appliances to be switched on. The sum of the power consumption of the appliances in the set should be as close as possible to, but not higher than the remaining available power supply. The combined results of the GA executions determine the final solution for each K, for the final switching implementation. Case study simulations show that the proposed method enables the consumers to have control over which appliances to switch off and avoid total blackouts. Furthermore, the GA optimization processes in this study converge quickly, which signifies that the proposed method is capable of real time applications.

2. PROPOSED SYSTEM DESIGN

2.1 System Network Topology

Figure 1 illustrates the overall system network topology. The Central Station (CS) is the DU's main server for power management, monitoring, data logging and switching controls, K_1, K_2, … and K_n are the distributed appliance controllers, where n corresponds to the number of installed K, and X_{j1}, X_{j2}, … and X_{jm} are individual consumer appliance control and monitoring nodes under K_j, where m corresponds to the number of enrolled consumer appliances. Each of the X_{jk} consists of 5 appliances, with corresponding consumer priority levels p, set as 1 to 5. 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, indicating that the consumer readily accepts that

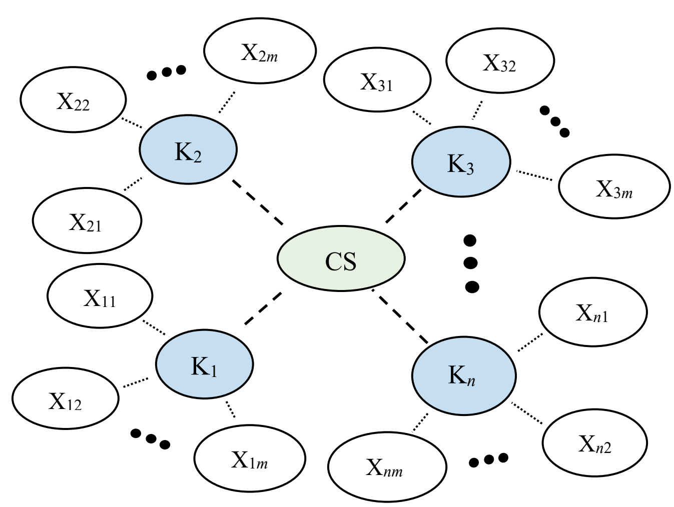

Fig. 1. Proposed Overall System Topology

such appliance is being deloaded at a specified time. The total number of K is DU determined, taking into consideration the strategic locations of the participating consumers while the number of X depends on the capacity of each K. The communication between K_j and CS can either be wired or wireless or even both for a more reliable network.

2.2 System Monitoring

The CS keeps monitoring the DU's system technical data such as system frequency, voltage level, total enrolled/connected loads of each K_j, and the real-time total power delivered by the power generating plants. In the event of system low frequency and voltage level, CS performs a short term demand forecasting for the next 15 minutes of the connected load based on historical data and the current load using the equation below:

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

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

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.

Given the forecasted power demand, the system checks if the frequency will still be within the allowable range using equation (3) (Elrayyah, Cingoz and Sozer, 2017) as follows:

$$\omega_s = \omega_{ref} - ZP_L, \tag{3}$$

where, ω_s is system angular frequency in rad/sec, ω_{ref} the reference angular frequency in rad/sec, P_L is the forecasted demand $L_{forecast}$, and Z is a frequency droop coefficient and is dependent on the actual connected load which varies for every DU. When the frequency is forecasted to be within the range, CS will do nothing. However, when it is not the case, the following process will be activated. The new power allocation for each K_j is determined by:

$$S_j^{new} = P_R \times L_j, \tag{4}$$

where, L_j is the total connected load for K_j in all priority levels, S_j^{new} is the new total power supply to be allocated to K_j, and P_R denotes the ratio of the total available power supply S_G provided by the transmission grid operator to the forecasted total load $L_{forecast}$.

2.3 Optimization in Appliance Controller K

After each K_j has received its individual power allocation, K_j distributes the available power to each of its corresponding X_{jk} based on the consumer-defined appliance priority level p. Starting with the top priority level, level 1, it is checked if the power supply capacity is large enough to energize the appliances at that priority level. If it is, 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 equation indicates:

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

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

where S_j^p is the power supply capacity available for the appliances at priority level p or less important 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 the first optimization using GA is executed to determine which set of enrolled appliances of priority level p_c is a candidate to be turned-off or deloaded. The GA minimizes the objective function (7) below whose decision variables are defined by (8),

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

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

Subject to,

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

until the following stopping condition holds,

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

where $x_{jk}^{p_c}$ represents the switching operation of the appliance at priority level p_c owned by user k under control by K_j, $S_j^{unallocated}$ is the remaining power supply capacity after optimization, and $L_{jk_{min}}^{p_c}$ is the smallest among $L_{j1}^{p_c}, \dots, L_{jm}^{p_c}$.

In actual scenarios, consumers can have identical devices with the same power rating enrolled in the DLC program. Hence, there is a possibility that multiple optimal solutions are found. Also, during the switching implementation there is a possibility that a certain consumer experiences a biased implementation or repeated deloading of the same appliance over a certain time. To avoid the biased and unfair switching operations, a fairness function below is imposed on the solutions to evaluate fairness:

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

$$+ b \cdot S_j^{unallocated}, \tag{11}$$

$$R_{jk,p_c}^{ON} = \frac{n_{jk,p_c}^{ON}}{n_{jk,p_c}^{ON} + n_{jk,p_c}^{OFF}}, \tag{12}$$

where, R_{jk,p_c}^{ON} is the ratio of the number of turning-on operations to the total number of switching operations of the consumer k's appliance of priority level p_c over a certain past period, n_{jk,p_c}^{ON} is the number of turning-on switching operations of the appliance over the period, n_{jk,p_c}^{OFF} is the number of turning-off switching operations, a and b are weight constants to be determined by the DU. The value of the first term in (11) is high when appliances that have been on are again decided to be on leaving those which have been off still kept off. The weights balance between the 'unfairness' and the quality of supply capacity application $S_j^{unallocated}$. The smaller $F_{fairness}$ is, the better the solution is. In case of multiple solutions having the least fairness value, a roulette wheel selection is used to select a single solution. Once the unique solution is obtained, the appliance with the minimum rated power consumption among those which are to be turned off is found and nominated as a candidate for possible turning-on in the next step. Let its rated power consumption be denoted by $L_{jk_{nom}}$. The sum of unallocated supply capacity $S_T^{unalloated} = \sum_{j=1}^{n} S_j^{unallocated}$ is reallocated to the controllers K.

2.4 Optimization in Central Station CS

The second GA maximizes the power utilization by using the following equations, where equation (13) is the objective function:

$$S_T^{unallocated} - \sum_{j=1}^{n} x_j^{cs} L_{jk_{nom}}, \tag{13}$$

$$x_j^{cs} = \begin{cases} 1, on \\ 0, off \end{cases}, \tag{14}$$

and the constraint is,

$$S_T^{unallocated} \geq \sum_{j=1}^{n} x_j^{cs} L_{jk_{nom}}. \tag{15}$$

After the execution of this final GA, CS communicates the optimized power reallocation to each K_j. This is done to make sure that the total unallocated power is close to zero.

3. CASE STUDY

3.1 DU Model

To evaluate the effectiveness of the proposed method, we apply the method to the model of a local DU in Mindanao, Philippines. In this case study, the DU has approximately 20MW total power demand and 130 installed Ks, each with approximately 150kW total connected load. Also, considering a DU-specific system power rated values, we use 2.36×10^{-8} Hz/W as the frequency droop coefficient Z based on a Matlab simulation. The appliances used are the common loads of residential and commercial establishments, and their rated value are listed in a local DU website. Based on this list, the appliance's power rating and its corresponding priority levels p are randomly assigned to each X_{jk}. Figure 2 shows a sample of randomly selected appliance ratings with priority level 4. It is assumed that the power generation is less than the DUs actual connected demand and load shedding needs to be initiated. In the figure, a few appliances have similar power ratings indicating that some consumers use such appliances at the same time, which is a possibility in practical scenarios.

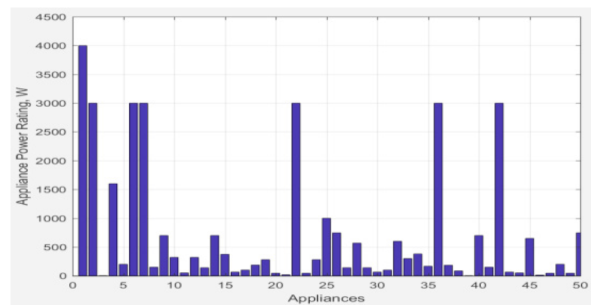

Fig. 2. Appliance power rating at priority level 4

3.2 GA Population Initialization

Following the usual GA population initialization which is random in nature, we encountered convergence issues after several test runs. From these runs, it was observed that if the available power supply $S_j^{p_c}$ is below 10% or above 90 % of the total load power rating ($L_j^{p_c} = \sum_{k=1}^{m} L_{jk}^{p_c}$), GA was unable to come up with a solution in 100 generations. To speed up the convergence and facilitate the real-time applications, we use different population initialization strategies depending on the relationships between the available power supply $S_j^{p_c}$ and the total target load $L_j^{p_c}$ as follows:

$$(0.9 \times L_j^{p_c}) \leq S_j^{p_c} < L_j^{p_c}, \tag{16}$$

$$(0.1 \times L_j^{p_c}) < S_j^{p_c} < (0.9 \times L_j^{p_c}), \tag{17}$$

$$L_{jk_{min}}^{p_c} < S_j^{p_c} \leq (0.1 \times L_j^{p_c}). \tag{18}$$

When the condition expressed by equation (16) holds, it is expected that the solution contains the majority of switching-on actions, which corresponds the majority of gene values equal to 1 since there is nearly sufficient power to distribute among the connected appliances. When this condition holds, each individual in the initial population is generated so that its 90% of genes have the value 1. When equation (17) is satisfied, the GA population is randomly initialized with equal probabilities for 0s and 1s. Furthermore, in the case where equation (18) holds, the initial solutions should have approximately 10% chance to have a value of 1 or mostly have values equal to 0.

3.3 Appliance Controller K

After several simulations, it is found that the following GA parameters produced considerable results: the number of generations = 100, population size = 50, the number of genes or the number of consumer appliances connected = 50, the probability of mutation = 35%, the probability of crossover = 40%, and the weight constants a and b for 'fairness' evaluation are set to 1. Bit inversion and order changing are the two mutation methods used, and for crossover methods, single point crossover, double point crossover and uniform point crossover are utilized. A mutation and a crossover methods are randomly selected and applied in every generation.

Figure 3 shows a sample optimization result in one K. The total enrolled/connected load for this specific K is 145.844kW based on the randomly selected appliance ratings mentioned in the previous section. From the forecasted total power demand, we assumed that only 90kW was allocated for this particular K. All the load with the top priority level, level 1, was allocated with necessary power, and similarly load of levels 2 and 3 was determined to be energized, which left the supply capacity of 2666W for the priority level 4 load that required 34717W in total. Here the GA optimization was executed and the solution was found at the 61st generation or after 51.75ms (milliseconds) of CPU time, which left only 2W of unallocated power supply. The priority level 5 load was totally left off.

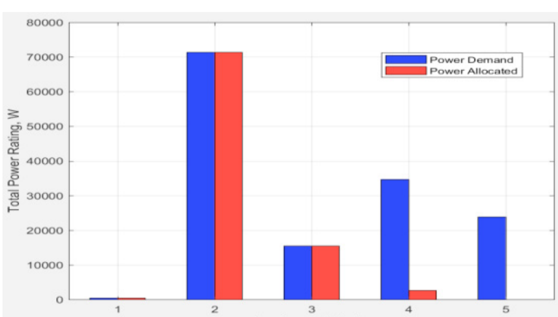

Fig. 3. Power allocation in K

Figure 4 shows the optimization process over 100 generations. In each iteration, a minimum value is saved and is updated until the 100th generation. The solutions that qualifies equation (10) are the candidates for fairness function evaluation.

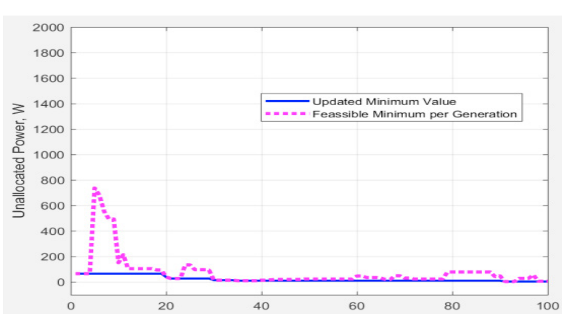

Fig. 4. Optimization process for 100th generation

Figure 5 shows the resulting fairness values for each of the generated solution (combination of switching statuses of 50 appliances). It has been observed that the 8th combination has the least/best fairness value hence it is selected as the final appliance combination for this specific K.

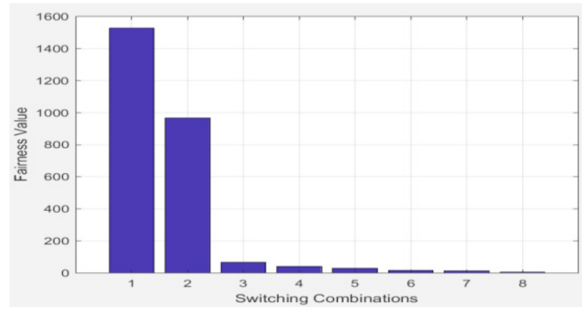

Fig. 5. Fairness values of the switching combinations

3.4 Central Station (CS) Controller

After determining the switching statuses of appliances in each K_j, there is corresponding $S_j^{unallocated}$ or the remaining power allocated to K_j but are not allocated to the appliances under its control since it is not an optimal choice to further allocate. The second stage of GA optimization is based on the sum of $S_j^{unallocated}$ reported by each K_j along with the appliance with the minimum power rating $L_{jk_{nom}}$, and its corresponding recorded switching activities $R_{jk_{nom}}^{ON}$. In this case study, GA parameters are set as follows: the number of genes or the total number of installed K = 130, population size = 50, maximum generation = 1000, crossover method = single point crossover, mutation method = bit inversion, and the weight constants a and b for 'fairness' evaluation are set to 1. Figure 6 shows the assumed unallocated power $S_j^{unallocated}$ reported by each K_j.

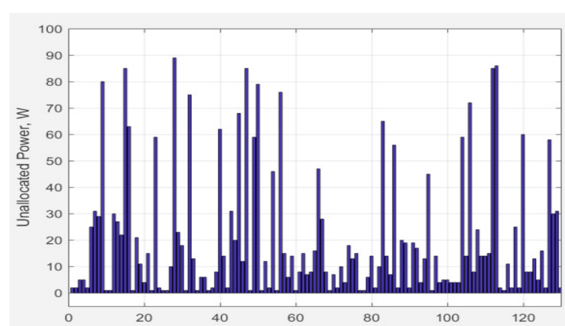

Fig. 6. Reported unallocated power from each K_j

After the GA process, there are three switching combinations obtained and evaluated by the fairness function as shown in Fig. 7. The result shows that the 2nd switching combination is the optimum combination of appliances for additional switching implementation to be communicated to each corresponding K_j to update its initially found solution during each K_j's optimization process.

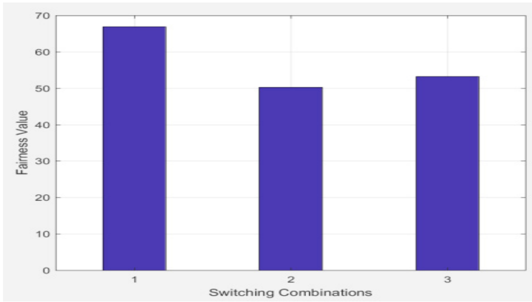

Fig. 7. Fairness values of the switching combinations

Figure 8 shows the result of the optimization process using the 2nd switching appliance combination. For the combined 2618W unallocated power $S_T^{unallocated}$, a total of 2617W load power is allocated out of 3590W total load nominated from each K_j. So the final remaining unallocated power is 1W after 30.1ms of CPU execution time.

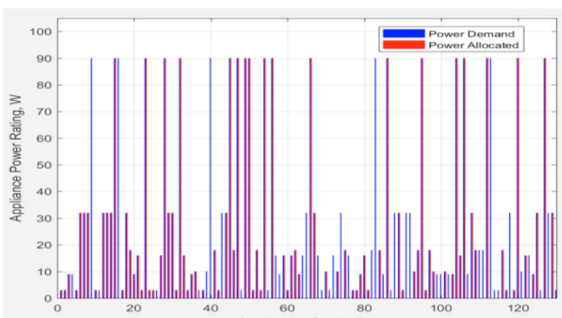

Fig. 8. Appliance power reallocation

4. CONCLUSION

In this paper, we proposed a method for real time applications to automate load shedding that gives consumers control over which appliances to deload by letting them set the appliance priority levels and avoids total blackouts while maximizing the utilization of the available power supply.

As shown in the case study, the proposed method presents promising outcomes which can be considered suitable for real-time application with substantial accuracy. The method was able to find optimum combinations of switching operations for each appliance controller quickly and accurately through two separate genetic algorithm executions, considering the varying power requirements and involving large number of consumer appliances, each with corresponding priority level and a power rating. As observed, power allocations were distributed primarily based on consumer defined priority settings, giving the consumers some degree of liberty to decide which appliances they can readily deload and not caught by surprise deloading. Also, by the implementation of the proposed method, the utilization of available supply from the grid is maximized and shutting down of the whole substation feeder can be avoided. In addition, the developed fairness function ensures that no same appliance is repeatedly deloaded at a certain time, to avoid biased load shedding operations. The final unallocated power is insignificant in actual scenario considering the total DU demand and the available power supply from the main grid. Thus the proposed method was able to maximize utilization of the available power supply signifying that more consumer appliance have power allocation. As a result, DUs will have an automated and efficient load shedding process which improves system stability, reliability and power quality.

5. ACKNOWLEDGEMENT

The researchers would like to thank and acknowledge the contribution of the Republic of the Philippines, Department of Science and Technology, Engineering Research for Development and Technology (DOST-ERDT) for the scholarship support.

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