Load Balancing in Smart Grids using Multi-Objective Evolutionary Optimization

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Abstract: The work deals with the balance between the supplied and consumed power in a residential area. An optimization task is formulated and solved. The extension of the optimization task formulation to include renewable sources is also provided. It is shown in the results that using the deployed optimization technique, a significant reduction in the energy usage cost and the waiting time of the appliances (delay) for residential consumers can be achieved. This work can be used in smart home and smart cities applications.

Keywords: Load balancing, Renewable energies, Multi-objective evolutionary optimization

1. INTRODUCTION

Utility companies are required to generate enough supply to meet the electrical demand at any given moment [1]. However, it is known that traditional resources are at their limits. Besides, according to International Energy Agency (IEA), electricity demand is expected to increase by 2% per year until 2040. In the future, utility companies may not be able to match supply with demand [2].

To remedy this issue, one solution is to implement demand side management or demand response programs to be more rationalized in the residential sector. Demand response is defined as "the changes in electric usage by end-use consumers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale prices or when system reliability is "jeopardized" [3].The reason why focus is on the residential sector to illustrate the problem at hand is that the latter accounts for 30-40% of the global energy use [4]. In addition to maintaining the balance between the supply and demand of electricity, another issue that needs to be addressed at present is the global concern over green-house emissions from traditional energy resources. There is now a need to integrate clean and renewable energy resources into the grid [4].

Unfortunately, the current electric grid does not totally accommodate renewable energy sources and the main challenge in the implementation of a DSM program is the quest for knowledge of the daily behavior of loads in the electrical system, which is generally not available from the systems based on conventional electrical meters [1,5]. Mainly for these two reasons, the need for a smart grid has emerged.

To make a power grid smart, a communication between the customer and the utility generating electricity is required. A smart grid has controls, automation, and new technologies all working together to respond to changes in electric demand. The smart grid simplifies the integration of renewable energy sources into the grid and is ready to respond to changes in the electricity demand and quickly and efficiently implement demand response programs [6].

Currently, the energy consumption of the residential sector accounts for around 30–40% of the total energy use all over the world. The residential loads often contribute significantly to seasonal and daily peak demand [3]. Thus, there is a need for practical solutions to shift the high-power household appliances to off-peak hours to reduce the peak-to-average ratio (PAR) in load demand from utility's side which will also give cost benefit to consumers as the energy usage cost is significantly lower at off-peak hours compared peak hours. Appropriate load-shifting is foreseen to become even more crucial as plug-in hybrid electric vehicles (PHEVs) become popular. Most PHEVs need 0.2–0.3 KWh of charging power for one mile of driving. This will represent a significant new load on the existing distribution system. In particular, during the charging time, the PHEVs can almost double the average household load and drastically exacerbate the already high PAR [7].

Nature inspired or evolutionary algorithms (EAs) [8-13] are efficient candidates for solving engineering problems such as the

problem of scheduling electrical appliances in a home under a demand-response program [14]. Scheduling problems may have more than one objective. In the electrical appliances scheduling problem, for example, the energy usage cost and the comfort of the user can be considered simultaneously. The two objectives in this case involve a trade-off (increase in one objective will lead to a decrease in the other and vice versa). Emulating the biological evolution mechanism and Darwin's principle on the "survival of the fittest", EAs have been a robust tool for solving multi-objective (MO) optimization problems such as the electrical appliances scheduling problem involving more than one objective that conflict with each other [15].

In [16], the main concept of the proposed approach to schedule the usage of home appliances is the aggregation of home appliances into priority classes and the definition of a maximum power consumption limit, which is not allowed to be exceeded during peak hours. The purpose is two analyze how a power consumption limit and priorities for home appliances will affect the demand peak and the user's everyday life. Reversible share (RFS) algorithm originally developed for telecommunication network is applied to verify the effectiveness of the proposed algorithm. The results have shown that the defined maximum power limit of 750 and 1000 was not exceeded and the trade-off was an average delay of 36, 1 (increment of 30% in task time) and 12, 36 (increment of 10 % in their task time).

In [17], a multi-objective mixed integer linear programming model (MOMILP) is proposed to minimize simultaneously the peak load and cost of a residential area. Constraints, including daily energy requirements and consumer preferences are considered. Its effectiveness in reducing electricity cost and electrical peak-load was verified through the simulation of the results obtained for different scenarios with different objectives. The results have shown a significant reduction in both functions.

In [14], scheduling of appliances is achieved using a genetic algorithm (GA) in order to efficiently utilize the energy available. In the proposed work, it is employed to optimize the electrical appliances energy usage cost. A comparison against the conventional approach is made. Simulation results show that the proposed genetic algorithm consistently produces better results in real time pricing (RTP) when compared to the

conventional method. User comfort was not considered in the optimization.

Similarly, in [18], GA is used to schedule the electricity usage in the home for the purpose of reducing of reducing the electricity cost and peak average rate (PAR) under RTP combined with inclined block rate model (IBR).The approach was proven to be effective in the reduction of the two parameters however as in [19], it did not consider the comfort of the user.

In [20], the paper which we based our work on used GA for the optimization of energy usage cost and waiting time of appliances to reduce the discomfort of the user. The optimization yielded improvement in the two functions.

In this work, Multi-objective evolutionary optimization based on MATLAB is used to get the results of energy usage cost and waiting time of appliances optimization and see how they compare to the paper and we'll see how we can bring modifications to these two algorithms to integrate renewable sources.

2. CHALLENGES AND SMART SOLUTIONS

The deep penetration of renewable energy sources is on the cutting edge of smart grid vision [21]. This topic is still being researched up to this day and many ways to integrate the different types of renewable sources have been developed [19]. The reason for the growing interest in better integration of renewable sources into the grid is because renewable energy offers alternative sources of energy which is in general pollution free, climate friendly, sustainable and unlimited [22]. Renewable energy sources such as wind and solar are fundamentally different from conventional generation such as coal, nuclear, natural gas. The energy production from these renewable sources is *not dispatchable* [cannot be controlled on demand], *intermittent* [exhibits large fluctuations], and *uncertain* [random or not known in advance]. The term *variability* is used to encompass these three characteristics of renewable generation. The variable nature of RE's poses significant challenges in their integration to the electric energy systems at deep penetration levels [23].

We can distinguish two types of challenges:

2.1. Technical challenges: Guaranteeing the reliability of the power system with the increase in variability.

2.2. Economic, policy, and regulatory Challenges: effectively managing the cost of RE integration and the grid investments that support it, designing policies to harness maximum value from RE, and guaranteeing that appropriate incentives are in place to encourage appropriate grid investments.

Fortunately, smart solutions exist to mitigate these challenges. The specific challenges related to the two types and the solutions that smart grid provides for their mitigation are given in the next subsection [24].

2.3. Smart solutions

Smart grid solutions emerging to manage the challenges that arise with the variability of renewable energy sources include:

• *Better forecasting.* Widespread instrumentation and advanced computer models allow system operators to better predict and manage RE variability and uncertainty.

• *Smart inverters.* Inverters and other power electronics can provide control to system operators, as well as to automatically provide some level of grid support.

• *Demand response.* Smart meters, coupled with intelligent appliances and even industrial-scale loads, can allow demand-side contributions to balancing.

• *Integrated storage.* Storage can help to smooth short-term variations in RE output, as well as to manage mismatches in supply and demand.

• *Real-time system awareness and management.* Instrumentation and control equipment across transmission and distributions networks allows system operators to have real-time awareness of system conditions, and increasingly, the ability to actively manage grid behavior.

2.4. Economic, policy, and regulatory challenges:

In addition to technical challenges, institutional challenges also arise with increasing shares of variable RE. Broadly these relate to the unique economics of variable RE, which give rise to various policy and regulatory issues. Two specific challenges are identified here: capital-intensive grid upgrades, and uncertain project costs and cash flows.

✓ ***Capital-intensive grid upgrades:*** Grid upgrades may be required to accommodate wind and solar power. For example, to the extent high quality wind and solar resources are located far from demand centers, new transmission lines or upgrades

to existing lines may be required. At the distribution level, rooftop PV may accelerate the fatigue of distribution components, such as low-voltage transformers, system reliability, translates to greater value from RE investments.

✓ ***Uncertain RE project costs and cash flows:*** Smart grid solutions are emerging to two specific issues that historically have negatively impacted RE project economics: grid upgrade costs allocated to RE project developers and energy curtailment when full RE production cannot be readily integrated into the power system. Both issues may cause cash flows of the project to diverge further from expectation. To the extent upgrades become costly or curtailments increase, the investment landscape for variable RE becomes more uncertain and can slow overall deployment [25].

In cases where policy measures and subsidies insulate project investors from these risks—for example to further enhance the investment environment for RE—costs and risks may be socialized. Smart grid investments can also play an important role in reducing those costs and risks.

Cost-effective methods of reducing curtailment and minimizing new transmission or grid upgrades can therefore capture more value from RE sources, improve the viability of individual RE projects, and maximize value to the system, enhancing the overall investment climate.

2.5. Demand side management

DSM is an initiative implemented by electricity utilities to encourage consumers to adopt procedures and practices that are advantageous to both parties. These practices include any activity that aims to change load shapes by shaping the electricity consumption behavior of consumers. Notably, the implementation of DSM increases the complexity of existing power systems because the adequate performance of DSM requires monitoring power system loads and generators. Consequently, the deployment of sensors, the provision of incentives to participants of DSM programs and the performance of the general activities of DSM will incur additional expenditures. However, the benefits of DSM far outweigh its drawback of increased power system cost.

3. MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM FOR DEMAND SIDE MANAGEMENT

The optimization of energy usage cost and waiting time of appliances during the day in a smart home is what we call a multi-objective optimization problem (MOOP). Before, beginning to describe the system used for our optimization task, it is useful present some basic knowledge about multi-objective optimization, why evolutionary algorithms are preferred over mathematical programming techniques for MOOP's and which evolutionary algorithm is most suitable to use [26].

3.1. Generalities about Multi-objective optimization:

Multi-objective optimization caters to achieving multiple goals, subject to a set of constraints, with a likelihood that the objectives will conflict with each other. It can also be explained as a multi-criteria decision-making process, in which multiple objective functions have to be optimized simultaneously. In many cases, optimal decisions may require tradeoffs between conflicting objectives. Examples of it can be found in economics (setting monetary policy), finance (risk–return analysis), engineering (process control, design tradeoff analysis), and many other applications in which conflicting objectives must be obtained. One of the prerequisites of multi-objective optimization is to determine whether one solution is better than another. However, no simple method exists for reaching such a conclusion. Instead, multi-objective optimization methods commonly adopt a set of Pareto optimal solutions (also called non-dominated solutions), which are alternatives with different tradeoffs between the various objectives. In the solution defined by a Pareto optimal set, one objective cannot be improved without degrading at least one other objective in the set [20] and the image of this set (i.e., the corresponding objective function values) form the so-called *Pareto front* [27].

3. 1.1. Multi-objective optimization problem statement

A general multi-objective optimization problem (MOOP) consists of a number of objectives and is associated with a number of equality and inequality constraints. Without loss of generality, it can be formulated in mathematical terms as follows:

$$minimize\ f(X) \qquad (1)$$

Subject to:

$$g_i(X) \leq 0, i = 1,2,\dots,m \qquad (2)$$

$$h_j(X)=0, j=1,2,\dots,l \qquad (3)$$

$$X^{(L)} \leq X \leq X^{(U)} \qquad (4)$$

Where:

- $X = [x_1, x_2, \dots, x_n]^T$: is the vector of design variables, defined in the design space $\mathbb{R}^n$ and $X^{(L)}$ and $X^{(U)}$ are respectively the lower bounds and upper bounds of the design variables.

- $f(X) = [f_1(X), f_2(X), \dots, f_k(X)]^T$, $X \in \mathbb{R}^n$: is the vector of objective functions to be minimized.

- $g_i(X)$ and $h_j(X)$ are the ith and j^{th} inequality and equality constraint functions of the problem respectively.

The three equations (2.2)-(2.4), define the region of feasible solutions, $\mathbb{S}$, in the design space $\mathbb{R}^n$. The constraints $g_i(X)$ are of types "less than or equal" functions in view of the fact that "greater or equal" functions may be converted to the first type if they are multiplied by -1.Similarly, the problem is the "minimization" of the functions $f_i(X)$, given that functions "maximization" can be transformed to the former by multiplying them by -1.

3. 1.2. Multi-objective optimization using evolutionary approach:

In spite of the fact that a wide variety of mathematical programming techniques have been developed to tackle MOPs since the 1970s, such techniques present a number of limitations, from which the most remarkable are that these algorithms are quite susceptible to the shape and/or continuity of the pareto front and that they usually generate one element of the Pareto optimal set per algorithmic execution. Additionally, some mathematical programming techniques require that the objective functions and the constraints are provided in algebraic form and in many real-world problems we can only obtain such values from a simulator. These limitations have motivated the use of alternative approaches, from which meta-heuristics have been a very popular choice, mainly because of their flexibility (i.e., they require little domain specific information) and their ease of use. From the many meta-heuristics currently available, evolutionary algorithms have certainly been the most popular in the last few years in this area,

giving rise to a field now known as evolutionary multi-objective optimization (EMO).The first Multi-Objective Evolutionary Algorithm (MOEA) was called Vector Evaluated Genetic Algorithm (VEGA) and was proposed by Schaffer in 1985.Something interesting is that there was not much interest in EMO research for almost a decade. However, in the mid-1990s, this area started to attract a lot of attention from several research groups around the world, and has maintained a high research activity since then [27]. In order to find multiple Pareto-optimal solutions, evolutionary algorithms are the best, because it deals with a population of solutions. It allows for finding an entire set of pareto-optimal solutions in a single run of the algorithm. In addition to this, evolutionary algorithms are less susceptible to the shape or continuity of the pareto-front [28].

Evolutionary based techniques use the concept of genetic algorithm and solve the multi-objective optimization problem. Following are the steps of multi- objective evolutionary algorithms:

Step 1 Initialization: Initialize a random population based on the population size.

Step 2 Fitness assignment: Assign a rank by considering each individual of the population for generating a mating pool.

Step 3 Variation: Apply variation operator (crossover, mutation) on the mating pool to generate new solutions.

Step 4 Environmental selection: Select best solutions according to the size of mating pool for next generation.

Step 5 Repeat above procedure until termination criterion meets or maximum number of generations reach [29].

3.2. Problem solution

To solve the problem, the Non-Dominated Sorting Genetic Algorithm-2 (NGSA-2) which is an elitist multi-objective evolutionary algorithm is used [ ]. It is the improved version of NGSA proposed by Deb and Srivinas []. The rank of every solution is computed based on how many number of solutions it dominates. In order to maintain the diversity of a population the algorithm finds average distance of two neighbors on either side of a solution. Along each of the objectives (as shown in figure 1), the distance is called crowding distance of that solution. For generating mating pool for next generation, selection of solutions is performed based on rank and crowding distance. When two solutions have the same rank then a solution that has higher crowding

distance is selected for mating pool. To implement elitism, the best parents are combined with the best offspring obtained and then select best solutions (according to fitness and spread), so it does not require extra memory (archive) to preserve elite solutions [29].
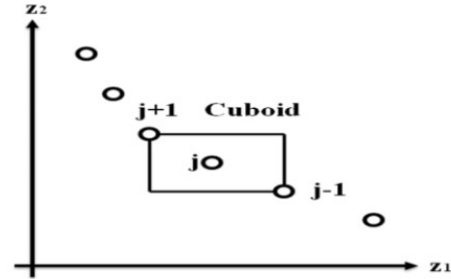

Fig. 1 Crowding distance calculation points in circles are solutions of the non-dominated front ([29])

The problem consists of the two objective functions:

a. $T(C)$:total cost of power

b. D_{avg} :average delay time of the appliances(average waiting time for electrical appliances execution)

The optimization using NGSA-2 produces the set of solutions to minimize both the objective functions.

Generally, electrical appliances fall under one of two categories: schedulable and non-schedulable appliances. A schedulable device can stop running and resume later while a non-schedulable device is always connected or involves only non-preemptive operations. Contrary to non-schedulable devices, schedulable devices are preemptive in nature. Thus, only schedulable devices can participate in the DSM mechanism.

3.2.1. Tariff details

Real time pricing program with ToU rate is applied as follows:

Table 1 Tariff details([20])

S. no.	Time period	Cost in cents
1	12 AM to 7 PM (Off-peak hours)	3
2	7 AM to 11 AM (Peak hours)	7
3	11 AM to 17 PM(Mid-peak hours)	5
4	17 PM to 9 PM (Peak hours)	7
5	9 PM to 12 AM (Off-peak hours)	3

3.2.2. MOEA algorithm

The steps of the MOEA algorithm for our problem are given as follows:

✓ Set values: set the parameter values (p), (m), (o), (Cp), (Cm), and (Co).
Where: p: peak hour, m: mid-peak hour, o: off-peak hour, Cp: peak-hour cost, Cm: mid-peak hour cost, and Co: off-peak hour cost.
✓ Initialize: set all the initial parameters (Xp), (Yp), (Zp), and (Aa).
Where: Xp: the population for peak power usage values, Yp: the population for mid-peak power usage values, Zp: population for off-peak power usage values, and Aa: starting time of appliance.
✓ Evaluate the fitness function T(C) and Davg (cost and delay).
✓ Build the pareto-front based on the dominance.
Apply G.A:-Apply genetic algorithm operations like selection, crossover and mutation.
✓ Stop:-check counter values to perform the stop operation. If the counter value has reached maximum number of iterations then print the solution otherwise calculates the fitness function for a new set of input population.

3.2.3. Problem formulation

The energy consumed by an individual home appliance A_p:

$$A_p = P \times T/M \qquad (5)$$

Where: P: power consumed by the appliance, T: operating time of the appliance in hour, and M: energy measurement units in terms of kWh.
The cost of the energy consumed by the appliance is computed using the formula:

$$A_c = C \times A_p \qquad (6)$$

Where, C: power usage cost per unit
The total consumed power of a home for a day is computed using the formula:

$$T_p = X_p + Y_p + Z_p \qquad (7)$$

Where, $X_p, Y_p,$ and Z_p represent the power consumed by a set of appliances during peak, mid-peak and off-peak hours, respectively.
The same way the time of a day can fall under one of three categories (peak, mi d-peak, and off-peak). A device priority can be one of three: high (H), medium (M), or low (L). If $D_p = H$ and the request to execute is received at peak hour then the cost of energy usage at the time is computed using the formula:

$$X_c = C_p \times X_p, \qquad p_s \leq t \leq p_e \qquad (8)$$

Where, C_p: energy cost at peak hour, p_s: peak hour start time period, and p_e: peak hour end time period.

If D_p=M and the delay time parameter of the device, $D_t = 0$ then the request to execute arrives at mid-peak hours. Thus, cost of energy usage at the time is computed using the formula:

$$Y_c = C_m \times Y_p, \qquad m_s \leq t \leq m_e \qquad (9)$$

Where, C_m: energy cost at mid-peak hour, m_s: mid-peak hour start time period, and m_e: mid-peak hour end time period.
Finally, if $D_p = L$ and $D_t = 1$ then the request to execute is received at off-peak hour. Thus, cost of energy sage at the time is computed using the formula:

$$Z_c = C_o \times Z_p, \qquad o_s \leq t \leq o_e \qquad (10)$$

Where, C_O: energy cost at off-peak hour, o_s: off-peak hour start time period, and o_e: off-peak hour end time period.
Combining the three equations (8)-(10), we obtain the total energy consumption cost usage cost per day. The formula is given below:

$$T(C) = X_c + Y_c + Z_c \qquad (11)$$

3.2.4. Objective function

From equation (11), the objective function to minimize the energy usage cost per day is given by:

$$minimize\ T(C) = X_c + Y_c + Z_c \qquad (12)$$

At off-peak time, priority based approach is applied by the load-balancing mechanism for the appliances execution arrival time. The delay or average waiting time of an appliance in a queue can be calculated using a delay function. The delay function results from subtracting the active state start time from the off-peak hour start time. If a critical or high priority appliance interrupts the execution of a running appliance, the appliance is admitted in the waiting queue and the waiting time of the latter is added to the calculated delay time. D_{avg} is the average delay time for n appliances, A_a is the transition delay time between waiting state and running state for appliance a, w_a is running state end time or waiting state start time of appliance a and ϵ_a is the deferred time of appliance a.

$$minimize\ D_{avg}$$

$$= \begin{cases} \sum_{a=1}^{n} (A_a - p), o_s \leq t \leq o_e \\ \qquad if\ not\ deferred \qquad (13) \\ \sum_{a=1}^{n} (A_a - p) + (\epsilon_a - \omega_a), \\ \qquad o_s \leq A_a \leq \omega_a < o_e \end{cases}$$

Using the two equations (12) and (13), we can optimize the cost and delay time

respectively by using the multi-objective evolutionary algorithm.

3.2.5. Admission control states

Under the assumption that threshold based power usage pattern is adopted by a residential home. Additional charges are applied in the electricity bill if the consumer's energy usage exceeds the threshold. To prevent the occurrence of this scenario, the algorithm that we propose keeps the energy usage under this threshold. Anytime the service provider implements a power budget scheme in TOU pricing model for peak and off-peak hours and to smoothly achieve the load balancing mechanism, we introduce some states in the proposed system. They are: Wait, Power ON, Running, Power OFF, Interrupt, Deferred and Update. Similarly, the three queues (scheduling, waiting and processing) are maintained by the system.

We refer to the execution state of an electrical appliance as running or active state. If a high priority appliance has to execute while a schedulable appliance is in running state, the latter is deferred until the critical appliances completes the execution. when this is achieved, the deferred appliance resumes its execution. Finally, the appliance is turned off and the power allocated to it is released. The presently available power is calculated by the system and it is allocated to the next waiting home appliances in the scheduling queue.

The admission control mechanism (i.e.) selection of the running process to interrupt can be based on the following categories: i) Random selection of the currently running process, ii) Least recently entered appliance in the running state and iii) the appliances in running state which takes longest running time. If the available power is less than the total required power for the present request, then the suggested system may involve any of the following admission control mechanisms:

1) Random selection: The software based system randomly selects appliance among the presently running state from the set. The state changes from running to deferred.

2) Least recently entered: The system finds the least recently entered appliance in running state and it removes from the list.

3) Longest running time: This method searches for the longest execution time of appliance and it is involved in the admission control mechanism.

The suggested method gives an admission control mechanism with the help of the values collected from smart meter. A random selection admission control mechanism is tested.

3.2.6. Algorithm for Home appliance scheduling and load balancing:

The algorithm begins by requesting the power consumption values of the appliances and saves it for future use. In case, one or more appliance is in the running state, the available energy is computed as follows:

$$A_e = Th - \sum_{a=1}^{n} \Pr(a) \qquad (14)$$

Where, $P_r(a)$: is the power consumed by appliance a, a=1, 2, … ,n.
T_h: is the threshold value of power.

If an appliance requests to operate, the algorithm will check the request time of appliance, level of priority and compare its power consumption with the available energy. If the appliance is requesting to operate during off-peak time, has high priority and its power consumption is less than available energy, request is granted directly and appliance executes its operation. Available energy is updated as follows:

$$A_e = A_e - P_r(a) \qquad (15)$$

If the available energy is not enough to operate the appliance, the appliances that are running at the time are stopped one by one until there is sufficient energy to run the high priority appliance. The interrupted appliances enter into deferred state. After the deferral of an appliance a, available energy is updated as follows:

$$A_e = A_e + P_r(a) \qquad (16)$$

When the operation of the high priority application is completed, the operation of the deferred appliances is resumed. Here, the system compares available energy at the time with power consumption of deferred. If available energy is greater, the appliance resumes its operation and on its successful completion, available energy is updated as follows:

$$A_e = A_e + W_q(a) \qquad (17)$$

Where,
$W_q(a)$: is the power consumption value of appliance in the waiting/ deferred queue.
Waiting state appliances are processed the same way as deferred appliances. At last, the power consumption of appliance in scheduling queue is compared with available energy. If available energy is sufficient to run

the appliance, request is granted directly else the algorithm periodically checks the available energy and grants the request when there is enough energy at hand.

$$A_e = A_e + S_q(a) \tag{18}$$

Where,

$S_q(a)$: is the power consumption value of appliance in the scheduling queue.

3.2.7. Admission control mechanism

For home appliances with high level of priority, energy is required during the peak or off-peak time. The request of these appliances is handled by the algorithm using the admission control states mentioned above. The appliance waits in the scheduling queue until it gets response for its power requirement. After the controller checks the feasibility of execution, it sends a signal to the appliance and it enters into powerON state followed by Running state.

The proposed algorithm sets a maximum deferred count for the appliances so that the delay time doesn't become too high which on certain situations may cause the appliance to enter into starvation state. If an appliance reaches maximum deferred count, it becomes a high priority appliance and in the next allocation, it will be granted power immediately;

4. RESULTS AND DISCUSSIONS
The appliances used in the simulation along with their power usage are shown below:

Table 2 Electrical Appliances Details

S.No	Appliance Name	Power Rating(w)
1	Heater	750
2	Television	200
3	Clothes Dryer	1000
4	Heat pump	500
5	Toaster	750
6	Washing machine	700
7	Pump motor	740
8	Kettle	750
9	Oven	1500
10	Coffee maker	1000

The settings for NGSA-2 are also provided in the table below:

Table 3 parameter settings for NGSA-2

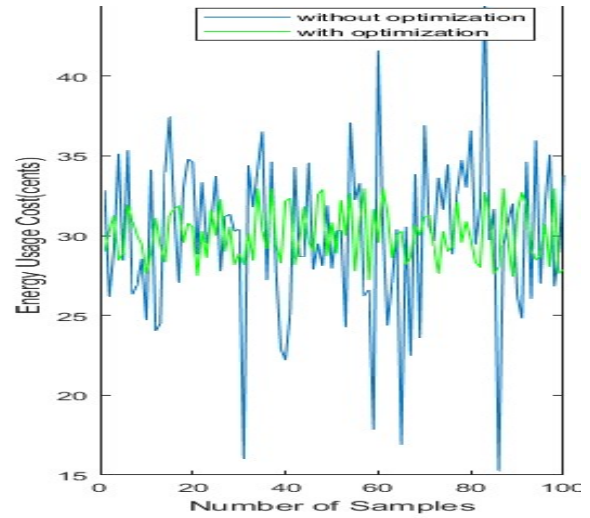| Parameter	Value
Population size	100
Distribution index for crossover (etac)	20
Distribution index for mutation (etam)	20
Mutation probability(pm)	1/problem dimension

a- With respect to cost

Fig. 2 Energy usage pattern for cost

The result shows that the proposed optimization technique reduces the energy usage cost up to a certain level when compared to normal execution. Without the proposed optimization, the energy usage cost can reach as far as 45 cents and is generally in the range [26.5, 37.5] while with it, energy usage cost is in the range [26.5, 32.5].
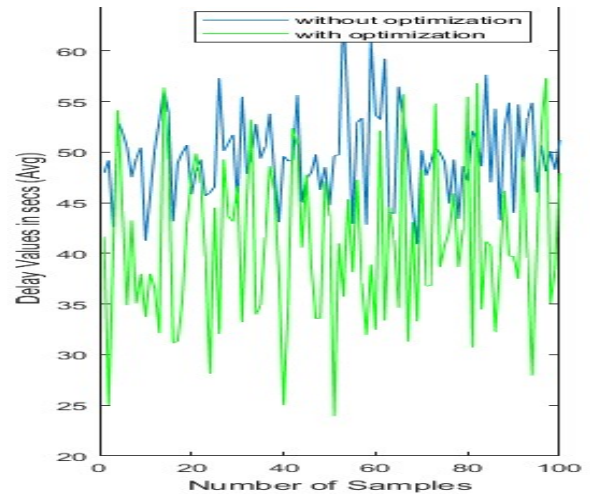
b- With respect to Delay

Fig. 3 Effect of waiting time

It can be clearly seen that the delay values without optimization exceed those with the optimization. Without the proposed optimization, delay is in the range [40, 60] while with the optimization, the delay is in the range [20, 57.5].
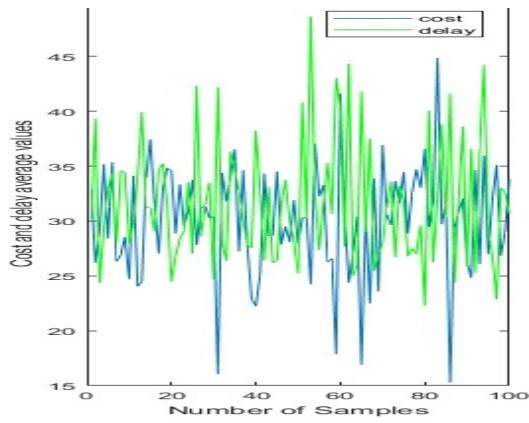
c- Cost vs Delay

Fig. 4 Tradeoff between cost vs delay

It can be clearly seen that there exists a tradeoff between cost and delay, i.e., reducing the cost will lead to higher delay and vice versa. The two objective functions are inversely related.

d- Results on Deferred State:

Figure 4 shows clearly that if the appliances are deferred, the waiting time will increase automatically and can get as high as 52.5 while if the appliances work normally, the delay didn't reach 50. Further, by setting a maximum deferred count, the occurrence of high peaks can be controlled.
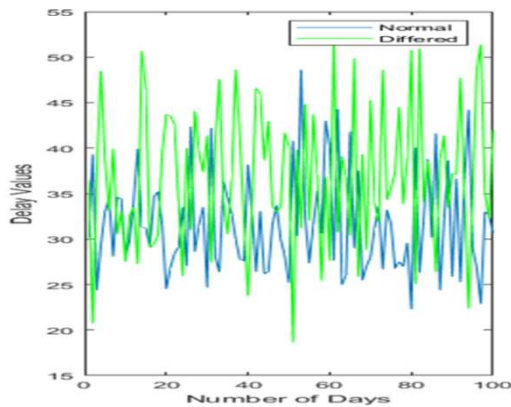

Fig. 4 Comparison of Delay time

e- Energy Usage Pattern per Day

The values of energy usage cost in a day (Fig. 5) with the proposed optimization are less than without the proposed optimization for all hours of the day except at the last hour of the day but as it corresponds to off-peak hours, it does not have much influence and the mean value of mean energy usage cost after optimization is still less than its value without it.
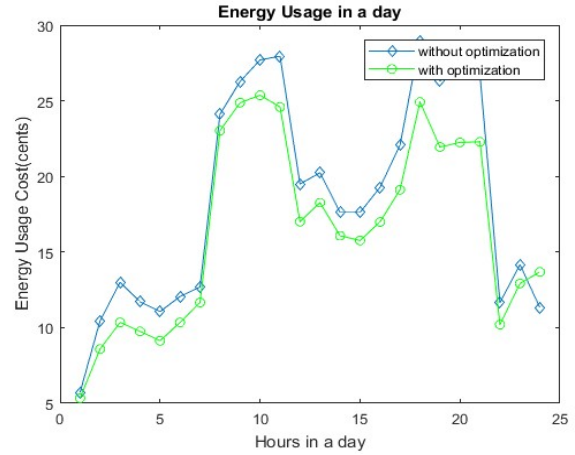

Fig. 5 Energy Usage in a Day

5. CONCLUSIONS

In this work, an optimization task together with MOEA is implemented to optimize the energy usage cost of the consumer and perform the load balancing mechanism so as to minimize the delay for the execution of the electrical appliances. The algorithm also gives an idea to select the admission control method to manage home appliance load. It also suggests the service provider to manage the load requirement during off-peak hour.

The obtained result reveals that the consumer can use the power within the threshold level to avoid additional pay to the service provider, which also helps to consume more power with minimum cost effectively. Further, it is used to analyze the electricity usage cost and waiting time in different conditions. The output shows that the proposed method minimizes both electricity cost and delay time of execution of electrical appliances for consumer.

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