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Research paper

Performance analysis of heuristic optimization algorithms for demand side energy scheduling with TOU pricing

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Abstract

The major objective of the paper is to find a suitable optimization algorithm which can manage the energy consumption behaviour of a consumer in presence of time of use (TOU) pricing tariff so that the demand for energy during peak hours as well as the cost of energy for the consumer is minimized. A mathematical model has been presented to describe the proposed demand management system and a comparative assessment of the performance of different heuristic optimization algorithms for optimization of daily energy consumption of a household has also been made. The algorithm PSO and some of its variants are taken for comparison. The comparative assessment of the algorithms reveals that the NQPSO optimization algorithm which is a quantum based variant of PSO is the best among the discussed algorithms and can be implemented in a residential sector for energy optimization. From the comparison of energy costs with or without optimization it becomes apparent that the projected heuristic based optimization should be used to have an optimized schedule for the operations of the appliances at a household. As a result the individuals are motivated to be a part of the demand side energy management programs which finally leads to a reliable and stable grid system.

Keywords: *APSO; IQPSOS; NQPSO; PSO; TOUP.*

1. Introduction

Electricity is the most universally used form of energy and due to growing requirement most of the sources depend on fossil fuels to generate electricity which increases the level of carbon dioxide in the atmosphere making a negative effect on the environment. These sources are also very expensive which increases the cost of energy when demand is increased. However a smart grid can be used to increase the energy efficiency by increasing the reliability and quality of power supplies with the help of new technologies that make use of energy storage devices and low carbon energy sources.

Smart grid has demand response capacity through which it can maintain a balance between electricity demand and supply. It employs different Demand Side Management (DSM) techniques that help the consumers to manage their usage in such a way that the demand during peak hours is reduced which in turn reduces the pressure on expensive sources of electricity making the system more stable and reducing the cost of electricity.

The DSM programs encourage users to reduce their electricity consumption during peak hours by shifting it to off-peak hours, which help flatten the demand curve resulting in a more reliable, and qualitative grid system. The DSM can be implemented efficiently when the individuals and organizations use more energy-efficient appliances and try to reduce their electricity use on a regular basis. Overall load reduction in conjunction with low demand during peak hours is necessary to have a robust grid system, because if the demand is high during peak hours the electricity suppliers may depend on expensive sources to meet such high demand which as a result increases the electricity cost. Therefore the consumers should be motivated to reduce their energy use during peak times. The DSM programs can induce short-term diminution in peak load demand by shifting a part of the energy consumption to a lower-demand time which is otherwise referred as off-peak hours in literature. Electricity is charged at a cheaper price during off-peak hours, which can encourage people to reduce the use of electricity during peak hours. Off-peak times typically refer to early morning, night time or weekends. Shifting some of the daily peak demand to non-peak time flattens the load curve which allows more electricity to be provided by less expensive energy source. The reduction in demand or shifting of demand from high peak hours to low peak hours enable the energy supplier to use the available generation capacity more efficiently and effectively so that new generation and transmission infrastructure will not be required. To motivate the consumers to reduce their energy consumption during peak hours the energy suppliers use different pricing tariffs. For example, time of use pricing (TOU), real time pricing (RTP) and critical peak pricing (CPP) etc. In TOU the rate for electricity depends on the time of the day without using a fixed rate. For example, the electricity may cost more in the afternoon than in the morning, encouraging people to use the clothes dryers and air conditioners less in the afternoon when the power companies have to produce electricity more expensively. In RTP electricity prices change from hour to hour determined from wholesale market prices. In this pricing scheme, the entire time of operation is divided into some time slots. The exact cost for each slot is decided in real-time. Some random events and the reactions of consumers to the prices of preceding time slots affect the price placed in future operation slots. It lets consumers manage their electricity consumption in such a way that they have to pay less. In CPP the price of electricity is higher during periods of high energy use called CPP events and during all other times the CPP rate offers lower prices. CPP offers customers less electricity rates under normal circumstances and increased rates for some particular hours every year when the total demand for energy is high. For example CPP events may occur when extremely hot weather requires high air-conditioning use or access to electricity resources is cut, straining the electric grid. Thus the DR programs can be considered as complementary to the DSM programs. Both of them help to manage the energy usage of the consumers so that their overall energy consumption as well as their demand during peak hours is reduced which helps to reduce the cost of electricity and make the grid system more efficient and reliable.

2. Literature review

Recently a lot of research has been made on different scheduling methods applied in DSM programs in residential grid networks. Even if they are different in their methodologies their main aim is to reduce the consumers' expense of energy and demand during peak hours, because increase in peak load leads to higher production costs and shortages in electricity supply. The scheduling methods help to guide the consumption pattern of the users so that the peak load can be reduced. Some the methods are discussed here. A dynamic programming based method is presented by Hsu and Su (1991) to reduce the peak load by cycling off consumers' air conditioners. The consumers are divided into some groups. The air-conditioners for a particular group are held off for a fixed time period with their acceptance. When the control period is over their demands are restored and for some other group the loads are held off for the same time span. This procedure is repeated for all the groups for the whole day. Kurucz et al. (1996) have proposed a Linear Programming (LP) model to control the peak load by controlling the loads in commercial, industrial and residential area. By offering lower prices for electricity the utility tries to control the load during different periods. The residential load control is done for some particular appliances such as pool pumps, air conditioners and water heaters. Samadi et al. (2012) have proposed a Vickrey-Clarke-Groves (VCG) mechanism which implements the utilitarian welfare function for implementing DSM programs. It encourages efficient energy consumption among users so that social welfare may be maximized. An optimization problem has been formulated to maximize the aggregate utility and minimize the total cost for all the users. The utility function of each user is derived from its preferences and energy consumption patterns. The optimization process is based on the assumption that every user possesses a smart meter containing an energy consumption controller (ECC) unit in it. The ECC unit tries to control the user's energy consumption and maintain coordination between the user and the energy provider. All the smart meters are connected to the energy provider through a local area network. Using this network each user can share its demand information with the energy provider. By executing a centralized mechanism, the energy provider determines the optimal energy consumption level for each user, and broadcasts a specific electricity payment for the user. Bu, S. and Yu, F. R. (2013) have used a real-time pricing tariff. A real-time demand response scheme is used to manage the load demand of the consumers so that the cost of electricity can be reduced and the utility from the consumption of electricity can be maximized. The model is described with the help of a Stackelberg game. The initial stages of the game analyze how the retailer should make decisions regarding the selection of sources of electricity, the amount of electricity to be bought and the optimal retail price for the consumers, in order to get maximum profit. Then the consumers adjust their demand based on the current price to reduce the cost to be paid and maximize the utility they get from the energy consumption. A demand-side energy consumption scheduling scheme for both the time-shiftable and the power-shiftable appliances has been proposed by Liu et al. (2014). It tries to maintain a uniform load demand during the day time. In addition, the schedule generated by the optimization process takes the consumers preferred usage requirements into consideration while finding optimal energy consumption and operation time for the appliances. Similarly, a home area energy management system (HEMS) for smart homes has been proposed by Zhao et al. (2015). It can manage different load types with photovoltaic generation with energy storage. The HEMS optimizes the utilization of local renewable and reduces energy wastage due to AC and DC conversions and storage charging and discharging. The objective of the system is to minimize the total daily energy cost for all the consumers. A fully distributed DSM method presented by Barbatoa et al. (2015) is based on a game theoretic approach which minimizes the peak demand of a group of residential users. It uses a real time pricing tariff. The authors have considered two practical scenarios. In the Single-Appliance DSM case each appliance decides autonomously its scheduling time in a distributed fashion, so each appliance is a player in the game which can make independent decision regarding the starting time of its execution and the time appropriate to buy energy from the grid so that its contribution towards the overall electricity payment is minimized. In the Multiple-Appliance DSM case each user has to find schedules for all his home appliances. The householder is the player in this game who chooses the schedule of all its appliances according to its preferences with an aim to minimize its electricity payment. Zhu et al. have used integer linear programming (ILP) technique to reduce the peak hourly load of the consumers. Every house is connected with a smart meter that produces an optimal schedule for all the connected appliances in the household. The system also supports multiple users where many smart meters are connected together in order to achieve a cooperative scheduling. There is a central control node takes the information about the appliances belonging to individual houses from their respective meters and try to optimize the operation schedules for all the appliances connected to the system.

Most of the works in literature use both linear and non-linear programming method to solve the DSM problem. However these programming techniques cannot handle a large number of controllable devices which have several computation patterns and heuristics (Logenthiran et al., 2012). They may not find a feasible solution or the computational times are too high when the problems belong to non-convex programming, Mixed Integer Nonlinear Programming or NP-hard problems. For such cases, heuristic-based evolutionary algorithm can provide a fast and near optimal solution (Huang et al., 2015). The heuristic based methods like genetic algorithm, Ant Colony Optimization and Particle Swarm Optimization (PSO) can search very large spaces of candidate solutions and find globally optimal solution in polynomial time. Venayagamoorthy, G. K. (2009) has given importance on advanced computational techniques which are needed for optimization and better control of grid systems. As distributed and coordinated intelligence is required at all levels of the electric grid like generation, transmission and distribution, the authors have emphasized on the computational intelligence mechanisms that include artificial and bio-inspired intelligence paradigms that exhibit an ability to learn and adjust to new situation, generalize and abstract the existing situations and find association between different situations which in turn help to develop effective and robust algorithms for grid management.

The method proposed in this work has also adapted a computational intelligence based methodology (PSO algorithm) to manage and control the household energy with a TOU pricing tariff to reduce the daily energy cost for the user. Particle swarm optimization (PSO) (Sun et al., 2004) is a widely used population based stochastic optimization technique. It is an optimization method which is inspired by the swarming or collective action and reaction of biological population. It is more popular than other heuristic algorithms because it gives satisfactory and effective results. It is faster, economic and involves few parameters to adjust in comparison to other techniques. However PSO can easily get trapped in the local optima when solving complex problems. A lot of research has been done to improve the algorithm so that the convergence speed can be accelerated and trapping into local optima can be avoided. QPSO(Quantum-behaved PSO)(Sun et al.,2004), WQPSO(Weighted Quantum-behaved PSO)(Xi et al.,2008), APSO(Adaptive PSO)(Zhan et al.,2009), NQPSO(new Quantum-behaved PSO)(Fu et al.,2013) and IQPSOS(Hybrid Improved Quantum-behaved PSO-Simplex method)(Davoodi et al.,2014) are some variants of PSO which have been developed as a result of this research. In this paper PSO and some of its variants have been used to compare the optimization process to find the best one for implementation. The rest of the paper is structured as follows. Section 3 narrates the distinctive aspect of a demand side management technique to be implemented for a single user which helps to generate an optimized schedule for the operation of the electrical appliances belonging to the user at home. Section 4 describes the proposed optimization algorithm. Section 5 provides the results of simulation of PSO algorithm. Section 6 describes the effects of optimization on the daily energy consumption of the user. It also explains how the daily cost of energy is reduced due to the change in consumption pattern. Section 7 gives brief descriptions about the PSO variants taken for optimization. Their performance is compared based on the results of the simulation in section 8. Section 9 provides the conclusion.

3. System model

A residential energy management system for a smart home has been considered here in which the consumer possesses a smart meter, which supplies the electricity acquired from the grid to all appliances and receives information from the user about the energy requirement of each appliance. The scheduler contained in the smart meter produces an optimized operation schedule for the appliances. Every appliance is assumed to be a smart appliance which can get control signals from the smart meter to operate at the scheduled time. There are mainly two types of appliances in a household. They are time-shiftable and non time-shiftable. The time-shiftable appliances such as washing machines and dishwashers etc. can be switched to work at times when load is less or price of electricity is less. The non time-shiftable appliances have fixed operational periods such as refrigerators and air conditioning units. As the operation time of non time-shiftable appliances cannot be changed, they are not considered for optimization. An optimization problem of minimizing the energy cost has been formulated in order to find the optimal energy consumption and operation time of the shiftable appliances only. The appliances are connected to the smart meter through an interface. The typical scenario is depicted in figure 1. Through the interface the user is able to input the information about the appliances required for the proper operation of the appliances to the smart meter. The information can include the name of the appliance, allowed time period for its operation and the total energy to be consumed by the appliance for a day etc. The scheduler uses this information to calculate the schedule before the beginning of the day and the controller in the smart meter controls the operation of the appliances according to this schedule. However whenever necessary an appliance can be controlled manually. But to reduce the energy cost the user has to strictly follow the schedule. Here the energy consumption problem is considered at a single user level as the smart meter present with each user is assumed to be having same functionalities. It is again assumed that every user in the system is equipped with a smart meter and through the smart meter if the demand of every user is reduced during peak hours then the overall demand of all the users is reduced at peak time as a result of which the whole grid system becomes more efficient and reliable.

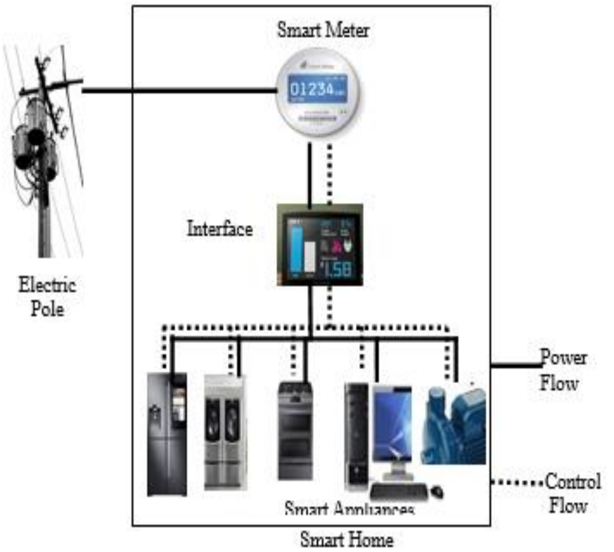

Fig. 1: Appliances at Home Are Connected to Smart Meter That Controls their Operation.

3.1. Energy demand description

The entire time of operation describes a whole day which is represented by a set T. In a day there may be 24 equal time slots and each slot is assumed to be of one hour. During a time slot t the energy consumption of a user denoted by eload(t) is described as:

$$eload\left(t\right)=\sum_{a\in A} eload_{a}\left(t\right),\ \forall t\in T=\left\{1,2,\ldots,24\right\} \tag{1}$$

Where A represents the set of all time shiftable appliances belonging to the user and eloada(t) denotes the amount of energy consumed by the appliance a during time slot t. The value of eload(t) may be equal to zero or more than zero depending on the consumption of the user during that time slot. But it can never be more than a predefined limit which is known as maximum load demand possible during a time slot. The constraint is defined as:

$$eload\left(t\right)\ \le\ Maxload,\quad \forall\ t\in T \tag{2}$$

Maxload is the maximum load demand allowed during a time slot. Generally this information is given by the utility. Every appliance has a particular time of operation which is decided by the user. Beyond this time the value of energy consumption for the appliance is zero.

$$eload_{a}(t)=0,\ \forall\ t\in T-T\left(a\right) \tag{3}$$

T (a) is the set of possible operating time slots for appliance a determined by the user. It represents the time during which the appliance can operate. Every appliance has a minimum and maximum power consumption level at a time t ∈ T denoted as minpow(a) and maxpow(a) respectively. The constraint is expressed as:

$$minpow\,(a)\le eload_{a}(t)\le maxpow\left(a\right),\forall a\in A,\ t\in T\left(a\right) \tag{4}$$

Additionally the user has a predetermined amount of daily energy consumption for every appliance denoted as ETOT(a) which is decided by the user. The following statement defines the constraint.

$$\sum_{t=1}^{24} eload_{a}(t)=ETOT\,(a),\forall a\in A \tag{5}$$

The daily energy consumption vector for an appliance a can be defined as:

$$eload = (eload(1), eload(2), ..., eload(24)) \quad (6)$$

3.2. Energy cost function

The cost that the user has to pay to the energy provider for the amount of energy consumed during a time slot t is denoted as C (eload(t)). The cost function is assumed to be an increasing function of demand. It implies that the cost of energy for a time slot is proportional to the amount of energy consumed during that slot which can control and reduce the peak demand during a particular slot. A quadratic function is generally used to define the cost function, that is, $price-coefficient * (eload(t))^2$ .The value of price coefficient is kept more during peak hours than the non-peak hours in order to control the consumption of the consumers at peak hours. In case of quadratic function, the computation time increases exceptionally when the cost function varies excessively. For example if the load is increased two times, the cost of energy is increased four times when a quadratic cost function is used. During peak hours this huge increment would pose inconvenience to the consumers. Therefore, a linear increase in the energy cost in accordance with the total load is necessary to encourage the users to participate in the energy management programme and the logarithmic function can be a great help in this regard as it gives a near linear graph. Figure 2 provides a comparison between the growth rates of quadratic function and logarithmic function. It shows that the quadratic function has a rapid growth rate than the logarithmic function. Therefore a logarithmic cost function has been used here. The energy cost function is defined as:

$$C(eload(t)) = price\ coefficient * log\ (1/(1-\phi)) \quad (7)$$

Where, ϕ =eload(t)/k and k is a constant whose value is greater than eload(t). This cost function provides an artificial cost rate which can be used by the utility to control and manage the load demand of the users.

The objective of the system is to minimize the cost of energy paid by the user. The scheduler uses a heuristic algorithm based optimization method to generate the schedule for the appliances of the user. The purpose of the algorithm is to minimize the cost of the energy during the entire time of operation (the whole day). The cost minimization function can be described as:

$$\text{minimize} \quad \sum_{t \in T} C(eload(t)) \quad (8)$$

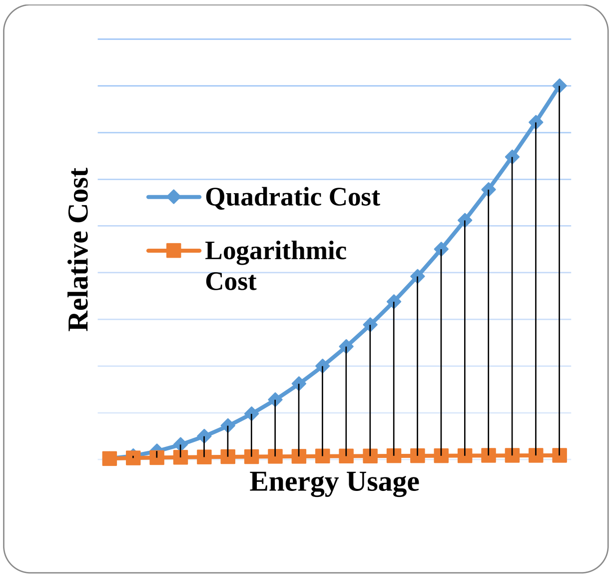

Fig. 2: Quadratic versus Logarithmic Function Growth.

4. Optimization algorithm

The scheduler generates the operation schedule for all the time-shiftable appliances for the upcoming day after getting the required information from the user. The energy consumption patterns of the appliances are taken automatically by the smart meter using the network through which all the appliances are connected to the smart meter. The basic flow of the optimization method proposed is described through the following algorithm.

Step 1: Accept input about possible operation time of each appliance and the maximum energy consumption for the next day.

Step2: Initialize the position and velocity matrices with random values using the information already stored in the smart meter and the information entered in step 1. The components of the position matrix should be within predefined (user specified) range. Every row of the position matrix represents an energy consumption schedule for the day being considered for optimization which is a possible solution for the problem. Every column represents a time slot and every element in the matrix represents energy consumption amount of an appliance for that time slot. This step describes the first step of PSO.

Step 3: For each row of the position matrix if the sum of the components present in the row is not equal to the user specified amount for maximum energy consumption (specified in step 1) then adjust the values in the row so that the row sum becomes equal to the maximum consumption amount and if possible shift values to that parts of the row which represent the non peak hours, to get better position.

Step 4: Apply rest of the steps of PSO algorithm on the velocity matrix and the updated position matrix to find the optimized schedule.

Simulation results show that the proposed scheduling scheme can achieve effective scheduling for the time-shiftable household appliances which reduces the energy cost for the user by reducing the energy demand during peak hours.

5. Simulation results of PSO algorithm

The simulation results of the PSO algorithm has been presented in this section. The time of optimization is taken as the entire day. The typical peak-demand period is assumed to be from 9:00AM to 8:00PM and remaining time in the day has been considered as low demand period. A TOU pricing tariff has been used for which the price coefficient during peak hours is assumed as 0.3 and during other time it is 0.2. As a result of which the price remains high during peak hours. The devices taken for simulation are PHEV, Heater, Well Pump, Furnace, Clothes Dryer, Humidifier, Geyser, Laptop, Dish washer, Desktop, Iron, Water Kettle, Vacuum Cleaner and Sewing Machine. The daily energy consumption details for each of these devices are given in Table-1. Time of operation says about the time period during which it can operate.

Table 1: Energy Consumption Details for the Time-Shiftable Appliances

Appliance	Energy Usage (KWh)	Time of operation	Total energy consumed/Day(KW)
PHEV	3	1am-9am	9
Heater	1.2	6am-9am,7pm-10pm	2.4
Well pump	2	1am-9am	2
Furnace	1	6pm-12am	1
Clothes Dryer	1	7am-9pm	1
Humidifier	1	12pm-4pm	1
Microwave	1.6	7am-11am,2pm-9pm	3.2
Geyser	2	3am-9pm	2

Laptop	0.08	7am-12pm	0.32
Dish Washer	1	6am-11pm	2
Washing Machine	0.25	5am-11pm	0.25
Desktop	0.21	7am-1pm	1
Iron	1.5	6am-5pm	1.5
Water Kettle	1.8	6am-9am	1.8
Vacuum Cleaner	1.5	6am-11pm	1.5

6. Effect of optimization on energy consumption and energy cost

Generally the user wants to operate most of its appliances during 9am to 8pm which is considered as peak hours of the day. During this period the price of electricity remains high according to TOU pricing tariff. If the user does not follow the optimized schedule generated by the smart meter then the overall cost of electricity for the day remains higher. In order to reduce the daily cost the user has to follow the schedule. In figure 3 it can be seen that when optimization is performed the shiftable loads are shifted to the non peak hours making the demand graph somewhat flatten. However the job is done during the allowable time of operation of the appliance which is set by the user. That means if possible the starting time of an appliance is moved to non peak hours so that some part of the job or the whole job can be done in the non peak period. As a result the loads during peak hours remain low. For example if PHEV(plug-in hybrid electric vehicle), which is a major part of the load, charged during 1am to 7am then cost of energy will be reduced to a great extent. As the appliances are assumed to be smart appliances, the appliances like PHEV can be can be operated and controlled by the smart meter according to the optimized schedule without any human interference if required. If every day some part of the load is shifted to off peak hours the user can get reduced cost for the same amount of load. When the PSO based optimization is used the daily energy consumption during peak hours is reduced which can be observed from the figure 3. Figure 4 shows the cost graphs calculated for 25 days. It provides clear information regarding the reduction of cost due to optimization. The cost graph obtained after optimization is compared with the cost graph that may result when there is no optimization followed. It is to be noted that the cost curves are calculated using the daily energy consumption amount of all the appliances used in the simulations. Motivated by the simulation results the authors have taken some variants of the PSO algorithms to test their performance and find a better one for implementation which is discussed in the next section.

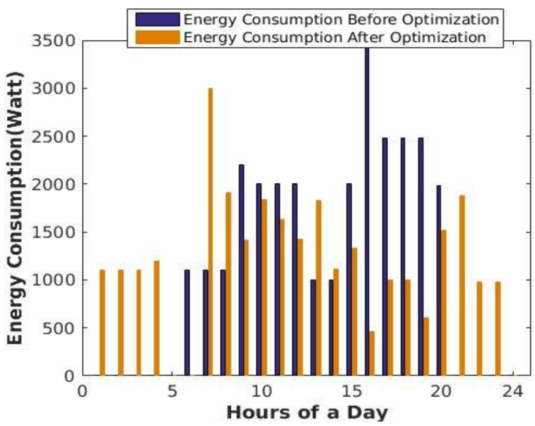

Fig. 3: Energy Consumption during Different Hours of a Day.

7. Brief description of the used optimization techniques

The optimization algorithms taken for comparison are PSO, APSO, IQPSOS and NQPSO which are described below. The common terms used for all the algorithms are w, c1, c2, pBest and gBest. w is the inertial coefficient. c1 and c2 are acceleration coefficients. pBest is a matrix in which every row represents the best position of a particular particle and gBest is a vector that represents the global best position for all particles(is the swarm's best position till current iteration).

7.1. PSO

PSO is a population-based optimization technique where a population is termed as a swarm, and each member in the swarm is termed as a particle. The direction of the search process of a particle is decided by its own previous best position and the global best position found so far by all particles.

7.2. APSO

It consists of two main steps. In the first step it evaluates the fitness of the particles in the population. After evaluating the fitness it tries to identify the state of the search process which may resemble one of the four possible states such as exploration, exploitation, convergence and jumping out. Then it updates the parameters like inertia weight and acceleration coefficients etc. In the second step an elitist learning technique is used that guides the search process so that it does not get trapped into the possible local optima and tries to find a better area than the current global best position. This step is applied if the state is identified as convergence state. If the area found is better than the previous one, then the other particles in the population follow the leader and converge to the new region.

7.3. IQPSOS

It is a hybrid algorithm that combines IQPSO and simplex algorithm. In Quantum-behaved PSO the Wave function or probability function of position describes the state of the particle in quantized search space. However it does not give any definite information about the position of a particle. Therefore the transformation of state provides the measurement of a particle's position. In this method the Quantum based PSO is used to get a solution which is refined by simplex method to reach at optimal or near optimal solution.

7.4. NQPSO

It is Quantum based PSO algorithm called new QPSO(NQPSO), which uses one local and one global neighbourhood search strategies. In the local neighbourhood search (LNS) strategy, focus is given on exploring the local neighbourhood of the current particle. This can help find more accurate solutions. In the global neighbourhood search (GNS) strategy, importance is given on searching the global neighbourhood of the current particle. This can enhance the global search and avoid premature convergence. In addition, a concept of opposition-based learning (OBL) is also employed for calculating initial population which can generate improved initial solutions and accelerate the convergence speed. In OBL, first a set of N number of random positions for N number of particles are generated. Then another set of particles is produced by generating an opposite position for each particle in the set N using some formula and then N fittest particles are selected from both the sets.

8. Performance evaluation of the algorithms

The algorithms are compared based on their convergence speed and their optimization value. Simulation results are analysed to make the comparisons. Repeated simulations have been conducted with different population size and different iteration numbers to assess the actual performance of the algorithms. The means that are used to compare the algorithms are discussed below.

8.1. Comparison in terms of convergence

Figure 5 shows values of the function upon convergence of the algorithms when the number of individuals in the population is 10 and the total number of iterations is 1000. Figure 6 shows function values with the population size as 10 and the total number of iterations as 5000. The values
in figure 7 shows a comparison between the function values calculated by the algorithms when the number of individuals in the population is 20 and the total number of iterations is 1000. It is clear from these figures that performance of NQPSO is better than others. The figures 8, 9 and 10 demonstrate that when the population size is increased the IQPSOS algorithm after some iteration behaves like NQPSO. However in different test environments the convergence characteristics of NQPSO remains stable. Therefore it can be considered better than others.

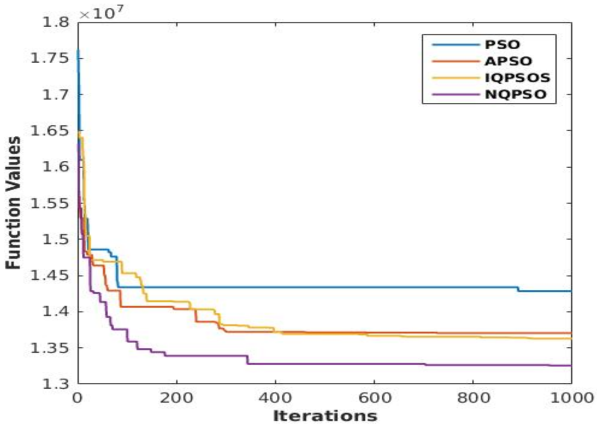

Fig. 5: Convergence with Population Size 10 and Iterations 1000.

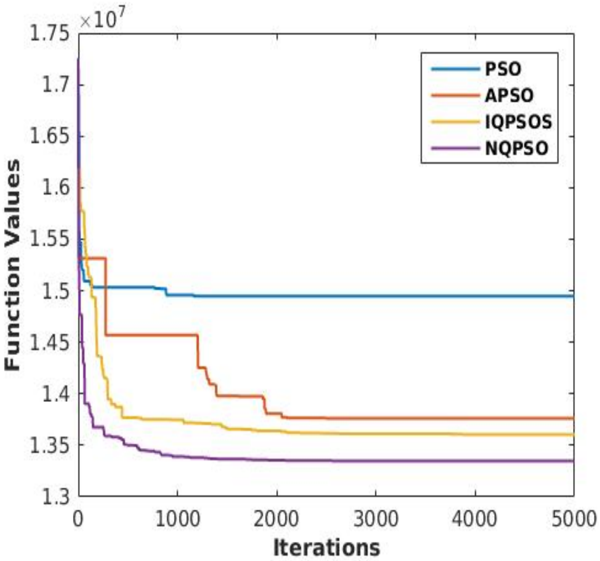

Fig. 6: Convergence with Population Size 10 and Iterations 5000.

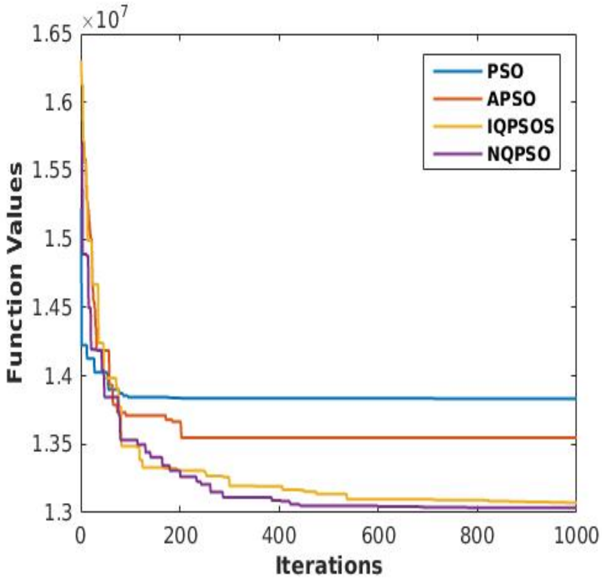

Fig. 7: Convergence with Population Size 20 and Iterations 1000.

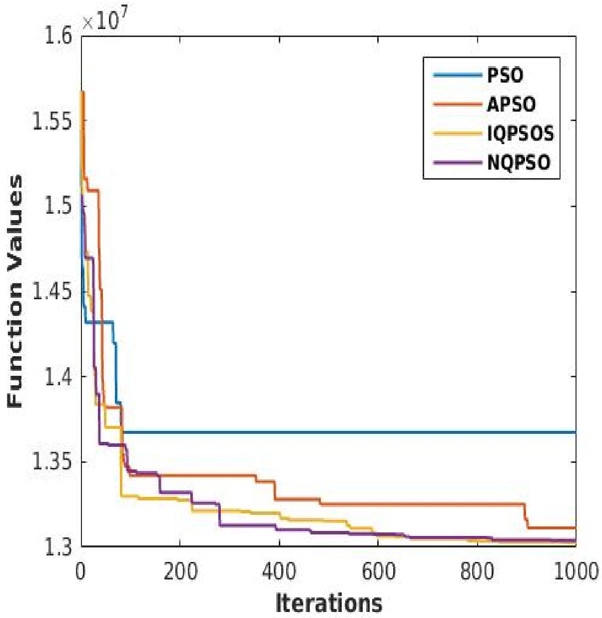

Fig. 8: Convergence with Population Size 30 and Iterations 1000.

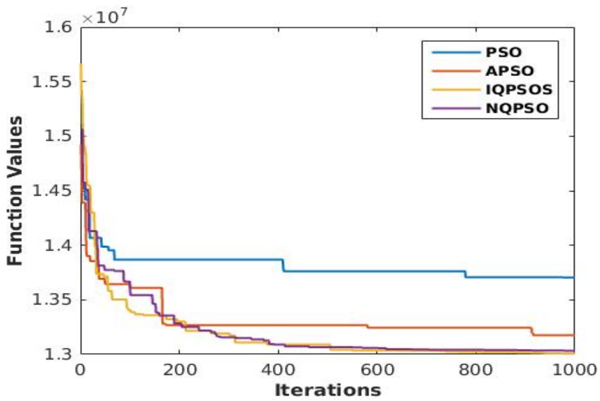

Fig. 9: Convergence with Population Size 50 and Iterations 1000.

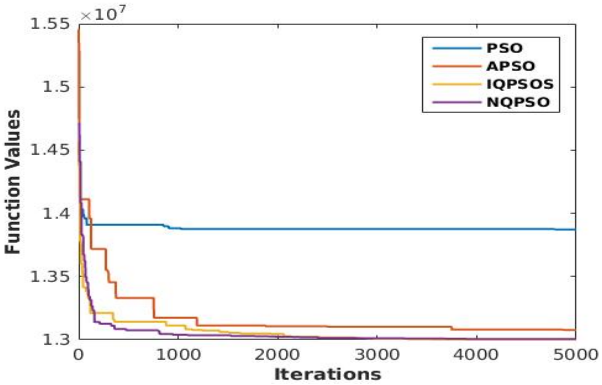

Fig. 10: Convergence with Population Size 50 and Iterations 5000.

8.2. Comparison with optimization value

Figures 11, 12, 13, 14, 15 and 16 demonstrate a comparison between the daily energy costs yielded as a result of optimization for a period of 25 days. Repeated executions are done taking different population size with different number of iterations. These figures confirm that the cost values generated from NQPSO are lower than the cost values calculated by other algorithms for most of the days.

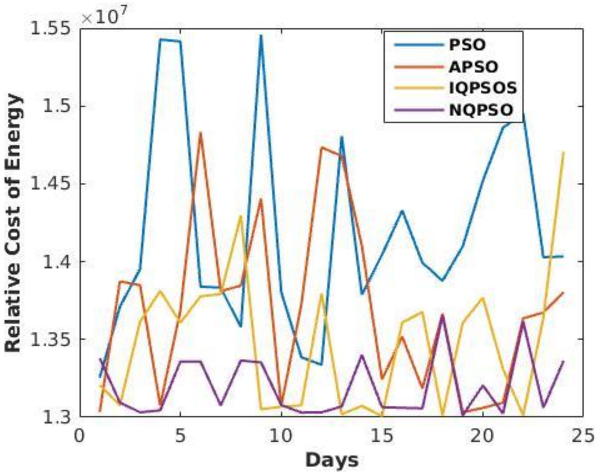

Fig. 11: Day Wise Cost Graphs with Population Size 10 and Iterations 1000.

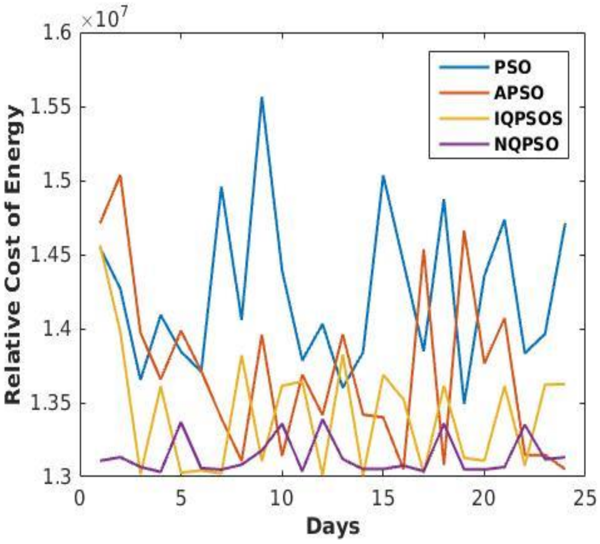

Fig. 12: Day Wise Cost Graphs with Population Size 20 and Iterations 1000.

8.3. Comparison of accuracy level

Table 2 shows the comparison among the algorithms in terms of mean fitness, variance, standard deviation and standard error of the solutions obtained from the 30 independent runs of each algorithm with different population size and for different number of iterations. From the statistical data present in the table it is comprehensible that the mean of the fitness values, standard error, variance and standard deviation for the solutions obtained from NQPSO are the lowest among all. Therefore NQPSO can be treated as the best among the discussed algorithms.

Table 2: Comparison of Search Results

Statistical Measurements	PSO	APSO	IQPSOS	NQPSO
Mean	1.41E+007	1.40E+007	1.34E+007	1.31E+007
Std. Error	1.57E005	1.42E005	0.65E005	0.39E005
Variance	4.73E011	3.83E011	0.82E011	0.29E011
Std. Deviation	6.88E005	6.19E005	2.88E005	1.72E005

9. Conclusion

The simulation results confirm that the proposed scheme can definitely benefit the users in terms of minimizing electricity cost and help the utility to reduce energy demand during peak hours making the system more stable. A logarithmic cost function along with a heuristic algorithm based optimization has been suggested which has an advantage of having cost function that supports a near linear growth even in drastic change in energy load conditions. The PSO algorithm based optimization scheme proposed here tries to generate an optimal energy consumption schedule for the appliances of a user by minimizing the cost function. Some variants of PSO have also been used for optimization. After analysing the performance of all the algorithms it seems that NQPSO is a better choice for implementation for the proposed system. The acceleration coefficients make the algorithm very effective with enhanced convergence speed. Another attractive feature of this algorithm is it uses one local neighbourhood search strategy which tries to find more accurate solutions and one global neighbourhood search strategy that avoids premature convergence. Therefore the NQPSO algorithm can be used to implement the described energy cost minimization function which can generate the optimized schedule for the operation of the appliances. If the user follows the schedule the cost of energy paid by the user can be definitely reduced. However there may be some preferred starting time of the user for each of its appliances and when the scheduled starting time for an appliance does not match with that time the user may get some dissatisfaction which should be taken in to consideration in the optimization process. In future the authors may work on an optimization process which considers the satisfaction level of the users that gets affected due to cost minimization. Several other variants of PSO could have also been taken for comparisons which can be a part of the future work for the authors.

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