Heuristic Techniques for Reducing Energy Consumption of Household

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Advanced metering system, load/appliances scheduling, heuristic techniques, genetic algorithm (GA), particle swarm optimization (PSO).

ABSTRACT

Efficient energy demand management plays an essential role in smart grid, sustainable and smart cities applications and efforts to reduce CO2 emissions. In this paper, we propose a framework for describing the household daily energy consumption and how it can be used to help residential households to perform appliance rescheduling to reduce energy consumption and hence reducing their energy bills while keeping resident's comfort. In this paper, heuristic optimization techniques such as genetic algorithm (GA) and particle swarm optimization (PSO) are used for solving the load scheduling problem. Due to its ability to deal with computational complex scenarios in less computational time using less and less computational resources, Heuristic optimization techniques are used. In the proposed model, dynamic pricing is adopted where the objective is to minimize the overall cost of electricity consumption and payments by scheduling different devices in a way that fulfil each individual's constraints and preferences. Here, MATLAB was used as the simulation platform. Simulation results showed that GA and PSO can optimize energy consumption and bills and at the same time fulfils needs and preferences of each individual customer.

INTRODUCTION

With the steady increased electricity demands in recent years, the need arises for mentoring energy usage and improving efficiency of energy use. Energy efficiency, in this regard, means using less energy to get the same job done, while cutting energy bills and reducing pollution. Smart energy metering technology is crucial for monitoring and improving energy use. Electricity smart metering become available to enormous numbers of end customers worldwide. By the end of 2020, it reached around 72% of European consumers (European Commission Joint Research Centre, 2021). In Norway, 100% of electricity consumers have received smart meters by 1 January 2019 (NVE-RME, 2022). Advanced metering system (AMS) allows the consumers to track their power usage and receive information about their electricity consumption and enables the distribution companies to move to a smart distribution system depending on current energy demands (Istad, 2019).
As power consumption is continuously increasing, the need arises for understanding consumption patterns, i.e., measurement and analysis of consumption overtime, and consumer's behavior. There are several load management strategies, which allow both utility companies and consumers to detect and control overloads (Gaur et al. 2017). Demand-side management (DSM) in Smart Grid (SG) is a strategy that enables a more efficient and reliable grid operations. In this approach, there are two main functions: energy management and demand-side control activities for end-users.
In a residential area, every smart home is equipped with energy management controller (EMC) and smart meters to provide stable and reliable bi-directional communication between utilities and consumers. The communication between EMC and electrical appliances, sensors, local generation, and energy storage systems (ESSs) is done through home area network (HAN). After each data collection, EMC Sends it to SG domain. Figure 1 shows a simple architecture of DSM architecture.

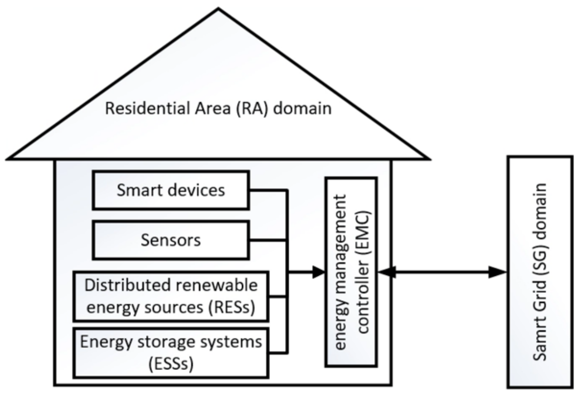

Figure 1: Simple Architecture of DSM

With an objective of contributing residents' awareness on efficient energy consumption we have investigated energy demand and how this affects electricity prices dynamically. More specifically we have looked closer at two popular heuristic optimization techniques: genetic algorithm (GA) and particle swarm intelligence (PSO) to solve the appliances' scheduling problem due to their capabilities in solving this kind of complex problems (Haupt and Haupt, 2004). With an objective of minimizing the overall cost of electricity payment by scheduling different devices according to their individual constraints, dynamic pricing was adopted. MATLAB was used as our simulation platform.
The rest of the paper is organized as follows: Related work is described in the next section. Then we explain the load scheduling model developed, followed by a discussion of simulation results. Finally, conclusions are drawn, and future work suggested.

RELATED WORKS

In recent years, smart grid played a significant role in designing sustainable systems that promotes energy efficiency and reducing CO2 emissions. A smart grid is an electrical grid which includes a variety of operation and

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energy measures including: AMSs, smart appliances, RESs, and energy efficient utilizing (Nejad et al. 2013; Saleh et al. 2015; Rahim et al. 2016). Electronic power conditioning and control of electricity production and distribution are important aspects of smart grid technology (Benysek, 2011).
In the demand side, using smart home concepts using smart devices, sensors, RESs, ESSs, and EMC will lead to better demand side management, as it is shown in Figure 1. There have been many attempts to optimally schedule smart appliances in a way that enhances energy efficiency. Rahim et al. (2016), evaluated the performance of home energy management controllers designed based on a set of heuristic algorithms; GA, binary PSO, and ant colony optimization (ACO) algorithms. They solved the load scheduling problem as a non-deterministic polynomial-time NP-hard scheduling problem. Mehrshad (2013) considered the problem as a multi-objective optimization problem and provided a solution based on GA. Heuristic algorithms were widely used by many researchers to solve the appliance scheduling problem using GA (Cardenas et al. 2009; Yogyong and Audomvongseree 2011; AboGaleela et al. 2012; Chen et al. 2013; Mehrshad et al. 2013; Zhao et al. 2013; Oladeji and Olakanmi 2014; Rahim et al. 2016; Rasheed et al. 2016), PSO (Pedrasa et al. 2009; Zhou et al. 2014; Mahmood et al. 2016), and ACO (Liu et al. 2011; Hazra et al. 2012; Dethlefs et al. 2015).
In optimizing load scheduling, beside cutting energy costs for the end customers, other objectives have been considered. For instance, AboGaleela (AboGaleela et al. 2012) considered a load distribution scheme by applying one of following load control strategies: load shifting, peak clipping, valley filling, or load building over time. Minimizing the peak to average ratio (PAR) (AboGaleela et al. 2012; Zhao et al. 2013; Rahim et al. 2016; Rasheed et al. 2016), and load scheduling over multiple consumers in a defined neighborhood area (Mohsenian-Rad et al. 2010) are also considered.
In our proposed model, the objective is to minimize the energy consumption bill while keeping the resident's comfort. The proposed objective function in this model can easily be modified to accommodate other objectives and needs.

SYSTEM MODEL

Residents are an essential element of the smart energy consumption model. In this model, the aim is to increase the customers' awareness of their energy consumption by analyzing their historical energy consumption data that is recorded by AMS. Then, a load scheduling model is designed incorporating the use of heuristic optimization algorithms such as GA and PSO with the aim to enable the customers to efficiently control their energy consumption. The proposed method will be described in detail in the below sections.

Energy consumption model

Let $A = \{a_1, a_2, a_3, \dots, a_m\}$ be the set of appliances in the house, where m is the total number of appliances. Then, by dividing the day to small time slots (e.g., hours), the daily energy consumption of an appliance can be calculated using the equation:

$$E(a,t) = \{E(a,t_1) + E(a,t_2) + \cdots + E(a, t_{t\_max})\} \quad (1)$$

Where $E(a,t_1)$ is the energy consumption of the appliance a in the time slot t_1.
The total consumption demand for the all the appliances in one day is then calculated as follows:

$$E = \sum_{t=1}^{t_{max}} \sum_{i=1}^{m} E(a_i, t) \quad (2)$$

Where m is the number of appliances, t is the time in hours and t_{max} is 24 hours. The energy consumption of each appliance depends on the it's characteristics and the user lifestyle. To manage the energy consumption through appliance scheduling; appliances are classified into two categories: shiftable and non-shiftable appliances (see Table 1).

Load categorization

The power consumption pattern of different types of consumers depends on the kind of appliances, which is used in the consumer's house. In general, electrical appliance can be categorized into schedulable (i.e., shiftable) and non-schedulable (i.e., non-shiftable) appliances. Non-shiftable appliances are used in a specific period with non-changed power level. These appliances include essential equipment such as: lights, cooker, kettle, ventilation, etc. In contrast, shiftable appliances such as washing machine, electrical vehicle and clothes dryer can be moved to another time to use. For example, we can charge the electrical vehicle during the night to avoid the peak hours to reduce the energy costs.
Table 1 summarizes most of the used appliances in a typical Norwegian house/apartment categorized into shiftable (S) and non-shiftable (NS) appliances.

Table 1: Household Electrical Load

	Power (KW)	Quantity	Load type
Television	0.1	1	NS
PC	0.1	2	NS
Phone	0.05	2	NS
Bulbs (inside and outside)	0.025	10	NS
Iron	1.5	1	NS
Ventilation	0.5	1	NS
Refrigerator	0.160	1	S
Water heater	3	1	S
Space heater	2	1	S
Washing machine	1.5	1	S
Dish washer	3	1	S
Clothes dryer	4	1	S
Electrical car	4	1	S
Coffee machine	1.5	1	NS
Oven	3	1	NS
Freezer box	0.175	1	S
Microwave	0.8	1	NS
Cook top	3	1	NS
Hoover	0.7	1	NS
Hair dryer	0.75	1	NS

In our proposed model, we selected only four appliances in the scheduling optimizing problem, as it is shown in Table 2. We selected these four appliances for simplicity and as a proof-of-concept, but other shiftable appliances can be easily added to the model.

Table 2: Parameters of shiftable appliances

Appliance	Start time (h)	End time (h)	Power (KW)	Operational time (h)
Washing machine	7am	7pm	1.5	2
Clothes dryer	9am	9pm	4	2
Dish washer	6am	10pm	3	2
Electrical car	16pm	6am	4	4

Energy price model

Based on the daily energy demand, the time periods in the day can be classified as peak or non-peak hours (Rahim et al. 2016). During peak hours, the cost of the energy consumption is the highest. There are several tariff models that can be used to define electrical energy prices for a full day or for shorter periods during the day. Real-time electricity prices (RTEP) can change hourly reflecting the utility cost of supplying energy to consumers at that specific time. In Norway, this is called "spotpris" or spot price that follows the prices in the Nordpool which change hourly (Nordpoolgroup.com). In contrast to RTEP, ToU tariff model is defined for electricity prices depending on the time of a day and it is pre-defined in advance. Critical peak pricing (CPP) is a variant of ToU, and the price is considerably raising in the high demand (e.g., peak hours) (Oladeji and Olakanmi, 2014). In our model, we used ToU by considering the energy demand side and historical spot prices reference to Aalesund[1] region.

The total energy cost for each time slot t is the summation of the energy consumed by the ON appliances at this time slot, multiplied by the price at this time slot.

Problem statement

To reduce the energy consumption cost, the user can schedule the shiftable appliances to perform their jobs on non-peak hours. The non-shiftable devices must operate at any time depending on their characteristics or the user's needs and preferences. Then the reduction of electricity bill is not possible with non-shiftable appliances. But the electricity usage cost can still be reduced by scheduling the shiftable appliances. In this model, heuristic algorithms such as GA and PSO, will be used to solve the scheduling problem in a way that minimizes the defined cost function.

Objective/cost function

The overall objective/cost function is to minimize the electricity bill by scheduling the shiftable devices to perform their jobs at optimal time where energy cost is minimum. The multi-objective cost function has two parts: minimizing the electricity bill and minimizing the waiting time to keep the user's comfort. Each shiftable appliance has start time (st), end time (et), and operation time (ot) as it is shown in Figure 2.

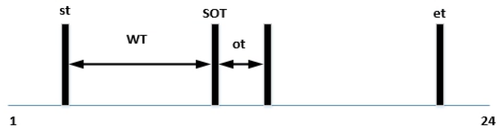

Figure 2: Parameters of appliance

The total electrical energy consumption cost at each hour is the total energy consumption at this hour multiplied by the electricity price at this hour as follows:

$$Cost_i = p_i \sum_{k=1}^{m} E(a_k, t_i) \tag{3}$$

where $Cost_i$ is the total electricity consumption cost of an hour i , p_i is the electricity price of an hour i, $E(a_k, t_i)$ is the energy consumption by an appliance k at an hour i. m is the total number of appliances. Then the daily cost is the summation of the cost of each hour as follows:

$$Cost = \sum_{i=1}^{24} Cost_i \tag{4}$$

To keep residents' comfort, we consider the user's wish to switch on the appliance at the given start time (st), as it is shown in Figure 2. Then, we schedule the shiftable appliances in a way that minimizes the waiting time, as it is shown in Eq. (5):

$$\mathrm{WT} = \sum_{k=1}^{m} (SOT_k - st_k) \tag{5}$$

where WT is the total waiting time for all the shiftable appliances, SOT_k is the start operation time for device k, and st_k is the given possible start time by the user for the appliance k.

Then the objective function to select better or optimized solution can be modeled as follows:

$$min\left(w_1\left(\sum_{i=1}^{24} Cost_i\right) + w_2\left(\sum_{k=1}^{m}(SOT_k - st_k)\right)\right) \tag{6}$$

where w_1 and w_2 are weights of two parts of objective function and their values are between 0 and 1, and $w_1+w_2 = 1$.

Genetic Algorithm

Genetic algorithm (GA) is the most popular heuristic technique. GA is an optimization and search technique based on the principles of genetic and natural selection (Haupt and Haupt, 2004). A GA allows a population composed of many individuals to evolve under specified selection rules to a state that maximize the fitness (i.e., minimizes the cost function). Genetic algorithms (GAs) were invented by John Holland in 1960s and were developed by him and his students in 1960s and 1970s (Holland, 1975). GA belongs to the larger class of evolutionary algorithms, which generate solutions to optimization problems using techniques inspired by natural evolution such as selection (reproduction), crossover (recombination) and mutation (altering). The evolution process starts from a population of individuals generated

[1] Aalesund, is a municipality in Møre og Romsdal County, western cost of Norway.

randomly within the search space and continues for generations. In each generation, fitness of every individual is evaluated, and multiple individuals are randomly selected from the current population based on their fitness and modified by recombination and mutation operation to form a new population. Then this new population will be used for the next generation of the evolution. In general, the search process ends when either a maximum number of generations have been produced or a fitness level has been reached for the population. The flowchart of GA is shown in figure 3.

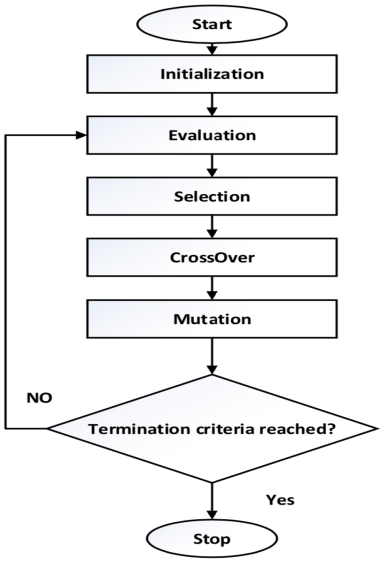

Figure 3: Flowchart of GA

GA for appliances' scheduling problem

In this scheduling problem, the objective is to find the optimal start operation time for the shiftable appliances. Then, the chromosome length is the number of shiftable appliances, and the variables are the start operation times ($SOPs$) for the appliances as follows:

$$chromosome = [SOT_1, SOT_2, \dots, STO_m] \quad (7)$$

Where m is the number of shiftable appliances. and the $SOTs$ take only integer values.

Particle Swarm Optimization

Particle swarm Optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution regarding a given measure of quality. Kennedy and Eberhart introduced PSO in 1995 (Kennedy and Eberhart, 1995). PSO was originally used to solve non-linear continuous optimization problems, but more recently it has been used in many practical, real-life application problems. For example, PSO has been successfully applied to track dynamic systems (Eberhart and Shi, 2001) and evolve weights and structure of neural networks (Zhang et al. 2000). PSO draws inspiration from the sociological behavior associated with bird flocking. It is a natural observation that birds can fly in large groups with no collision for extended long distances, making use of their effort to maintain an optimum distance between themselves and their neighbors.

The PSO methodology operates by placing a group of individual particles into a continues search space, wherein each particle is initialized with a random position and a random initial velocity in the search space. The position and velocity are updated synchronously in each iteration of the algorithm. Each particle adjusts its velocity according to its own flight experience and the other's experience in the swarm in such a way that it accelerates towards positions that have high fitness values in previous iterations. In other words, each particle keeps track of its coordinates in the solution space that are associated with the best solution that has achieved so far by itself. This value is called personal best (pbest), Another best value that is tracked by the PSO is the best value obtained so far by any particle in the neighborhood of that particle. This value is called (gbest). So, the basic concept of PSO lies in accelerating each particle toward its pbest and the gbest locations, with a random weighted acceleration at each time step. Figure 4 shows the flow chart of a standard PSO algorithm.

The modification of the particle's position can be mathematically modeled according to following equations:

$$\vec{v}(k+1) = w\vec{v}(k) + c_1\overrightarrow{R_1}\left(\overrightarrow{pbest} - \vec{s_i}(k)\right) + c_2\overrightarrow{R_2}\left(\overrightarrow{gbest} - \vec{s_i}(k)\right) \quad (8)$$

Where,

$\vec{v}(k)$ is the velocity of a particle at iteration k.

$\overrightarrow{R_1}$ and $\overrightarrow{R_2}$ are random numbers in the range of [0,1] with the same size of the swarm population.

c_1 and c_2 are learning factors which will be fixed through whole the process.

w is the inertia weight, and it is calculated as:

$$w = w_{start} - \frac{w_{start} - w_{end}}{K} k \quad (9)$$

Then the new position for the particles is the addition of the position at k iteration and the distance that the particles will fly with the new velocity $\vec{v}(k+1)$. The position is updated by:

$$\vec{s_i}(k+1) = \vec{s_i}(k) + \vec{v}(k+1) \quad (10)$$

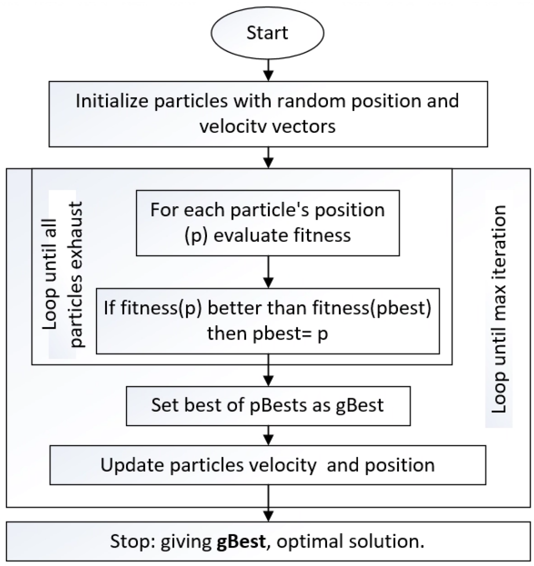

Figure 4: Flowchart of general PSO algorithm

PSO for appliances' scheduling problem

As it is described in GA, PSO can also applied to find the optimum start operation time SOP for each shiftable appliance. The particle position vector includes the start operation times as the following:

$$particle\ position = [SOT_1, SOT_2, \ldots, STO_m] \qquad (11)$$

SIMULATIONS AND RESULTS

In order to study the power consumption patterns; we analyzed the data we got from Mørenett[2]. We got data for 1112 meters in Sunnmøre region, Norway. Table 3 summarizes the data; the consumptions are in hourly rates from 18 November 2018 to 25 November 2019. Figure 5 shows the total consumption for all the 1112 meters/consumers.

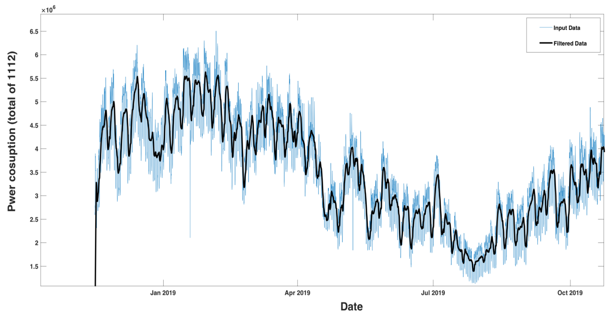

Figure 5: Energy consumption of 1112 meters

Table 3: Data from Mørenett

Apartments and houses	**960**
Industry	**114**
Cabin	**38**
Total	**1112**

Scheduling scenario

For scheduling, we have selected the week 47 (18 – 24 November 2019) to test and validate the proposed scheduling model. We have selected one of the customer's meters, then we added 4 appliances (washing machine, clothes dryer, dish washer and vehicle charger) randomly within time limits (Table 2). Figure 6 shows the original power consumption during week 47 and the consumption after adding the shiftable appliances.

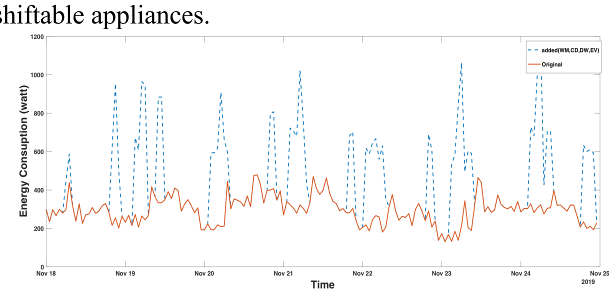

Figure 6: Week 47 (sample), added shiftable appliances

Scheduling by GA

For scheduling, we got the "spotpris" or spot prices for this region in week 47, as it is shown in Figure 7. Then, we counted the bill for this end-user for week 47 which was 300.67 NOK. After that, we optimize it by finding an optimized/better scheduling.

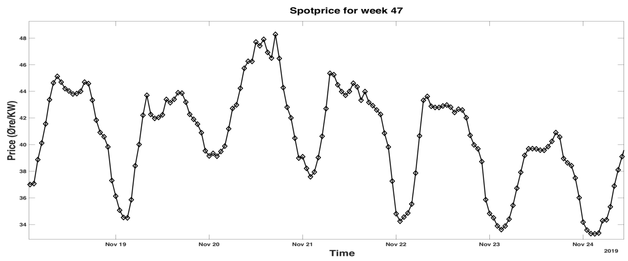

Figure 7: Week 47 spotprise from Nordpool AS (Nordpoolgroup.com)

We used GA with defined parameters in Table 4. The objective function defined in Eq. (6) is used with $w_1 = 0.7$ and $w_2 = 0.3$. The choice of weight values reflects the importance of energy cost compared to end-users' comfort.

Table 4: GA Parameters

Number of optimisation variables	4
Upper limit on optimisation variables	[19,21,22,28]
Lower limit on optimisation variables	[7,9,6,16]
Maximum iteration	100
Population size	100
Selection rate	0.8

Figure 8 shows our results. Upper part shows the original energy consumption and the optimized one. The middle figure shows the prices on hourly-based. The bottom figure shows the consumption cost for both original consumption and optimized consumption by applying scheduling.

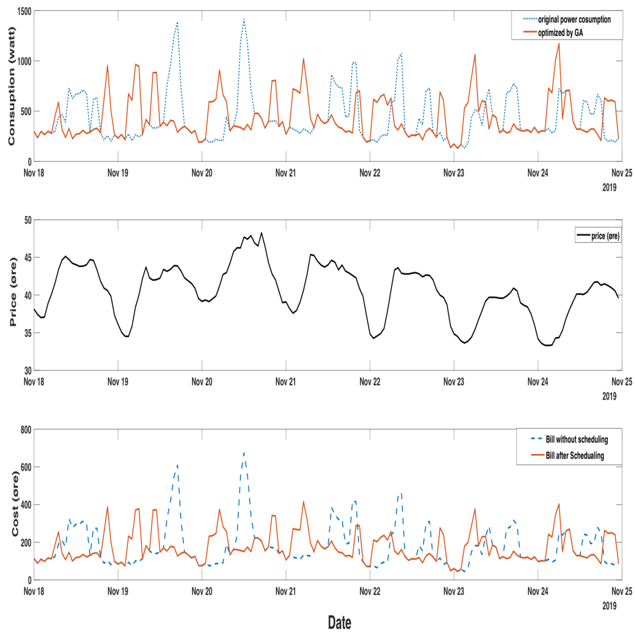

Figure 8: GA week-47 2019

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[2] Mørenett is a network company in Sunnmøre and parts of Nordfjord

Table 5: Result for week 47-2019

Weekly bill without scheduling (NOK)	Weekly bill with scheduling (NOK)
300.67	**291.17**

Daily price model

To test our scheduling optimization model, we have designed a daily price model shown in Figure 9. We have considered the historical prices and the daily usage patterns.

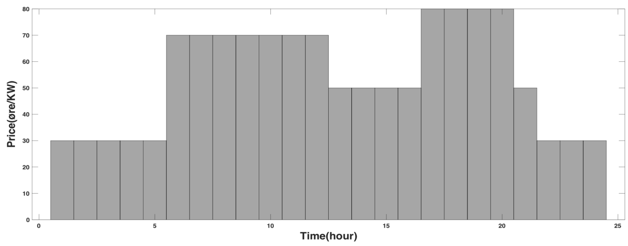

Figure 9: Daily prices

We used the shiftable appliances with defined parameters in Table 2. The schedule for each appliance is optimized by GA to minimize the objective function defined in Eq. (6). Table 6 summarizes the obtained results that shows that 9.5NOK could be saved daily, then 285NOK monthly and 3467.5NOK annually.

Table 6: Optimization Results

	Washing machine	**Clothes dryer**	**Dish washer**	**Electrical vehicle**	**Daily cost of the shiftable appliances**
Start time without GA	17	19	18	16	21.6 (NOK)
Start time with GA	7	13	13	22	12.1 (NOK)
Monthly saved = 285 NOK					
Annually saved = 3467.5 NOK					

Scheduling by PSO

In this section, we applied PSO algorithm in the same manner as it is in the previous section. A customized PSO toolbox has been developed from scratch in MATLAB environment since existing PSO in the optimization toolbox can't be modified to incorporate integer PSO. The PSO parameters are summarized in Table 7.

Table 7: PSO Parameters

Swarm size	200
Dimension of the problem	4
Maximum iteration	100
c1 (cognitive parameter)	1.5
c2 (social parameter)	1.5
C (constriction factor)	1
Inertia start	0.9
Inertia end	0.4
Upper limit on optimisation variables	[19,21,22,28]
Lower limit on optimisation variables	[7,9,6,16]
Maximum velocity	3

PSO provided very similar results to that obtained by GA. Figure 10 shows the convergence of PSO algorithm which shows that it can converge faster than GA.

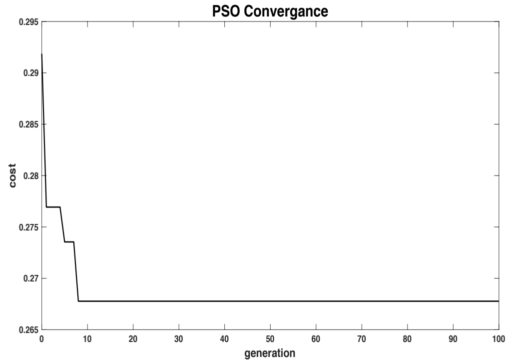

Figure 10: PSO convergence

CONCLUSIONS

The objective of this article is to increase the user awareness of energy efficiency and how optimization algorithms can be very beneficial in appliance scheduling in a way that minimizes consumption and at the same time keep customer's satisfaction. Demand side management is an essential part in design smart grids and sustainable energy systems. Residents can reduce the energy consumption considerably by using smart appliances that can be operated optimally. Also, scheduling the shiftable appliances by taking into consideration the varying electricity prices and the resident's comfort; would you reduces the electricity bill and consequently, reduce the electricity prices leading to smart grids and sustainability.
We have successfully used GA and PSO for scheduling four shiftable appliances. For GA, we used the MATLAB optimization toolbox, while we have developed a PSO-based optimization toolbox in MATALB that can handle integer decision variables. The simulation results for the defined scenario showed a cut in electricity bill up to 285NOK monthly on average.

Future work

This work can be extended in many different ways. For instance, developing a visualization tool that can be used by residents to increase their awareness of how to manage their energy consumption. The objective function can be extended to include different aspects of the problem such as including load control strategies (e.g., load shifting), and minimizing the peak to average ratio. Additionally, solving the problem as a multi-objective optimization problem should be investigated.

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