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Demand Management in a Microgrid Using Particle Swarm Optimization (PSO)

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Abstract: *Microgrid has an economic incentive due to avoiding energy purchases during peak periods and creation of carbon benefits through low-carbon/low-pollutant generation and co-production of heat and power, which has higher energy efficiency. In this paper a new DSM program based on load shifting and dynamic pricing for electricity consumption for controllable appliances is proposed. The main objective of proposed algorithm is to reduce load peak demand in microgrid. The objective load curve is chosen inversely proportional to the wholesale electricity price in the residential area.*
Key words: *Demand Side Management, Microgrid, Particle Swarm Optimization, Load Shifting*

INTRODUCTION

Considering Smart grid has brought many benefits for both utility companies and electricity customers through various demand side management programs. According to the annual report of U.S. Department of energy in 2014, approximately 74% of energy consumption occurs in buildings and residential areas [4]. This magnificent portion of energy onsumption in residential areas results large costs for both customers and utilities in a power grid which can be reduced up to 36% in customers' electricity bill and up to 55% in utility costs by a suitable DSM program [5]. Due to the increase of energy demand and rising global emissions of greenhouse gases, the current centralised generation system is challenged. The future electricity distribution system will be integrated, intelligent and better known as smart grid, which includes advanced digital metres, distribution automation, communication systems and distributed energy resources. Environmental problems, high cost of energy, shortage of fossil fuels and a vital need for a fast communication between components' [1]. Smart grid uses decentralized energy resources such as such as photovoltaic panels, wind power, fuel cell as its main power supply. Smart grid uses sensors and advanced metering systems which enables customers to manage their energy accurately and also they can participate in Demand Side Management (DSM) programs to decrease their cost of energy consumption[2]. DSM program involves actions carried out by the suppliers on the customer side to manage the customers' electrical consumption, mainly by shifting load demands from peak hours to off- peak periods[3].
The desired smart grid functionalities include self-healing, optimising asset utilisation and minimising operations and maintenance expenses [1]. Microgrid is a relatively small-scale localised energy network, which includes loads, network control system and a set of distributed energy resources (DERs), such as generators and energy storage devices. Microgrid has an economic incentive due to avoiding energy purchases during peak periods and creation of carbon benefits through low-carbon/low-pollutant generation and co-production of heat and power, which has higher energy efficiency. It also provides secure and reliable energy supply during serious blackout period as a back-up energy supplying system.
The optimal decisions, including the use of generators for power and heat production, storage system scheduling, proper load management and local grid power selling and purchasing for next day, are

determined by maximising the profit. A generalised formulation to determine the optimal strategy and cost optimisation scheme for a microgrid is shown in [9], accounting for emission cost, startup costs, operation cost and maintenance costs. Optimal economic operation scheduling of a microgrid in an isolated load area is obtained by mixed integer linear programming (MILP) model in [10], and a Virtual Power Producer (VPP) is used to operate the generation units optimally and the methodology is applied to a real microgrid case study. A short-term DER management methodology in smart grids is presented by [11], which involves as short as 5 min ahead scheduling and the previously obtained schedule is rescheduled accordingly. A Genetic Algorithm (GA) approach is used for optimisation. Hawkes and Leach [12] present a linear programming (LP) model to minimise the cost for the high level system design and corresponding unit commitment of generators and storages within a microgrid. Compared with centralised generation, the sensitivity analysis of results to variations in energy prices indicates a microgrid can offer an economic proposition. This model can provide both the optimal capacities of candidate technologies and the operating schedule. Several studies have considered how to design the capacity of a microgrid system to minimise the annual cost. Comprehensive review of the research on microgrid technology, the current research projects and the relevant standards is given by [3], in which pilot projects and further research are discussed. Asano et al. [5] develop a methodology to design the number and capacity of each equipment in a microgrid with combined heat and power (CHP) system considering partial load efficiency of a gas engine and its scale economy are considered to minimise the annual cost. A baseline analysis estimating the economic benefits of microgrids is performed by King and Morgan [6], and the examined results indicate that better overall system efficiency and cost savings can be achieved from a good mix of customer types. A computer program that optimises the equipment arrangement of each building linked to a fuel cell network and the path of the hot-water piping network under the cost minimisation objective has also been developed in [7], where operation plan of each piece of equipment is considered. Bagherian and Tafreshi [8] present energy managementsystems and optimal scheduling of microgrid. DSM programs are classified into two main categories and some subcategories as follows [5] :

Incentive Based Programs

- Direct Load Control
- Interruptible/Curtailable Service
- Demand Side Bidding/Buyback
- Emergency Demand Response Programs
- Capacity Market Programs
- Ancillary Service Market Programs

Time Based Rate Programs

- Time Based Rate Programs
- Time of Use
- Real Time Pricing
- Critical Peak Pricing

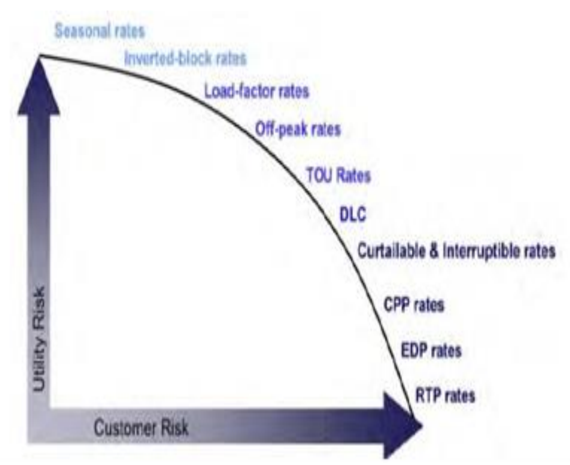

Figure 1: DSM program on the utility and the customer[6].

The main objective of proposed algorithm in this paper is to reduce load peak demand an also electricity bill with respect to the customers' welfare. The objective load curve is chosen inversely proportional to the wholesale electricity price in the residential area. In order to have an optimized load curve pattern, particle swarm optimization (PSO) algorithm is applied to the proposed DSM technique.

DETAILS OF THE TEST SYSTEM

In this article, demand side management program is carried out on a smart residential micro grid. The entire grid operates at a voltage of410 V. Smart pricing [23] in taken into consideration as well as smart metering and energy consumption scheduler (ECS) units for each residential building. The devices subjected to control in the residential area have small power consumption ratings and short durations of use. There are over 2600controllable devices from 14 different types of devices with a total of 1.5 MW. Table I shows devices types and their consumption which are subjected to control.

Table I: Data of Controllable Devices

Device Type	*Hourly Consumption Of Devices (kW)*			*Number of Devices*
	1st Hour	*2nd Hour*	*2rd Hour*	
Dryer	*1.2*	-	-	*189*
Dish Washer	*0.7*	-	-	*288*
Washing Machine	*0.5*	*0.4*	-	*268*
Oven	*1.3*	-	-	*279*
Iron	*1.0*	-	-	*340*
Vacuum Cleaner	*0.4*	-	-	*158*
Fan	*0.2*	-	-	*288*
Kettle	*2.0*	*0.2*	*0.2*	*406*
Toaster	*0.9*	-	-	*48*
Rice Cooker	*0.85*	-	-	*59*
Hair Dryer	*1.5*	-	-	*58*
Blender	*0.3*	-	-	*66*
Frying Pan	*1.1*	-	-	*101*
Coffee Maker	*0.8*	-	-	*56*
Total	-	-	-	*2604*

PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) algorithm is based on the evolutionary computation technique first was proposed by Kennedy and Eberhart in1995[24]. This method is based on simulation of social behavior and movement dynamics of a group of animals such as a flock of birds, a school of fish or a group of people who search a common goal. Each bird or fish is defined as a particle or intelligent particle in search space. Search space is determined byD dimension space based on the problem space or problem variables that all particles are seeking on this space for finding food (goal). The algorithm is initialized with random position and velocity for each particle in D dimension search space. Each particle interacts with another one in its neighborhood. In other words, social sharing of information (i.e., best position) among all particles offers an evolutionary advantage for faster convergence to the goal. By adding a new inertia weight into PSO, a new version of PSO is introduced in [18]. In PSO, instead of using genetic operators, each particle (individual) adjusts its "flying" according to its own flying experience and its companions' flying experience. Each particle is treated as a point in a D –dimensional space. The ith particle is represented as XI=(xi1 ,xi2 , … , xiD). The best previous position (the position giving the best fitness value) of the ith particle is recorded and represented as PI=(pi1,pi2 , … , piD). The index of the best particle among all the particles in the population is represented by the symbol g. The rate of the position change (velocity) for particle i is represented as VI = (vi1 ,vi2 , … , viD). The particles are manipulated according to the following equation:

$$v_{id} = \omega * v_{id} + c_1 * rand\left(\ \right) * \left(p_{id} - x_{id}\right) + c_2 * rand\left(p_{gd} - x_{id}\right) * \quad (1)$$

$$x_{id}\left(new\right) = x_{id}\left(old\right) + v_{id} \quad (2)$$

Where c1 and c2 are two positive constants, rand() is a random function in the range of [0,1], and w is the inertia weight. Equation (1) is used to calculate the particle's new velocity according to its previous velocity and the distances of its current position from its own best experience (position) and the group's best experience. Then the particle flies toward a new position according to equation (1). The performance of each particle is measured according to a pre - defined fitness function, which is related to the problem to be solved. The inertia weight ω is employed to control the impact of the previous history of velocities on the current velocity, thus to influence the trade-off between global (wide-ranging) and local (nearby) exploration abilities of the "flying points". A larger inertia weight w facilitates global exploration (searching new areas) while a smaller inertia weight tends to facilitate local exploration to fine tune thecurrent search area. Suitable selection of the inertia weightω can provide a balance between global and local exploration abilities and thus require less iteration on average to find the optimum. In this paper, an analysis of the impact of this inertia weight together with the maximum velocity allowed on the performance of PSO is given, followed by experiments that illustrate the analysis and provide someinsights into optimal selection of the inertia weight and maximum velocity allowed [25]. Figure 2 shows the operation flowchart of PSO.

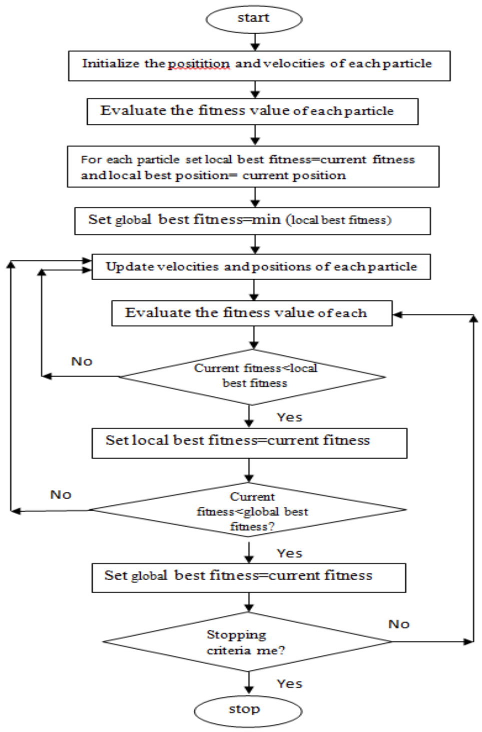

Fig2 : Particle Swarm Optimization Flowchart.

PROPOSED DEMAND SIDE MANAGEMENT TECHNIQUE

The principle of the proposed DSM technique is based on load shifting considering time of use price and customers' welfare. The objective load curve is chosen to be inversely proportional to electricity price in different hours of the day and is set as a day-ahead input of the system . Equation (1) shows the mathematical formulation for objective load consumption at different time of the day. The shifting algorithm runs a quadratic program and finds best possible load scheduling considering the problem's constraints.

$$objective\,(t) = \frac{1}{Electricity\ \ price\,(t)} \quad (1)$$

The proposed demand side management strategy schedules the connection moments of each controllable device within the system in a way that brings the total load consumption curve as close as possible to the objective load consumption curve. Equation (2) shows the objective of proposed DSM program.

The problem is mathematically formulated as follows:

$$Minimize : \sum_{t=1}^{N} \left[Pload\,(t) - objective\,(t) \right]^2 \quad (2)$$

Where, Objective(t) is the value of the objective curve at time t, and PLoad(t) is the actual consumption at time (t),which is given by,

$$PLoad\,(t) = Forecast\,(t) + connect\,(t) - Disconnect\,(t) \quad (3)$$

Where, Forecast(t) is the forecasted consumption at time (t),and Connect(t) and Disconnect(t) are the amount of loads connected and disconnected at time (t) respectively during the load shifting.

The term Connect(t) is made up of two parts: the increment in the load at time t due to the connection times of devices shifted to time (t), and the increment in the load at time (t) due to the device connections scheduled for times that precede(t) . Connect(t) is given by the equation (4).

$$connect(t)=\sum_{i=1}^{t-1}\sum_{k=1}^{D}X_{kit}.P_{1k}+\sum_{l=1}^{j-1}\sum_{i=1}^{t-1}\sum_{k=1}^{D}X_{kit(t-1)}.P_{(1+l)k} \quad (4)$$

Where, Xkit is the number of devices of type k that are shifted from time stepi to t, D is the number of device types,P1k and P(1+l)k are the power consumed at time steps 1 and 1+lrespectively for device typek, and j is the total duration of consumption for device of type k.

Similarly, the term Disconnect(t) also consists of two parts: the decrement in the load due to delay in connection times of devices that were originally supposed to begin their consumption at time step t, and the decrement in the load due to delay in connection times of devices that were expected to start their consumption at time steps that precede(t).Disconnect(t) is given by the equation (5).

$$Disconnect(t) = \sum_{q=t+1}^{t+m}\sum_{k=1}^{D}X_{ktq}.P_{1k} + \sum_{l=1}^{j-1}\sum_{q=t+1}^{D}\sum_{k=1}^{D}X_{k(t-1)q}.P_{(1+l)k} \quad (5)$$

Where, Xktq is the number of devices of type k that are delayed from time step (t) to (q), m is the maximum allowable delay.

This minimization problem is subject to the following constraints:

The number of devices shifted cannot be a negative value.

$$X_{kit} > 0 \quad \forall i,j,k \quad (6)$$

The number of devices shifted away from a time step cannot be more than the number of devices available for control at the time step.

$$\sum_{t=1}^{N}X_{kit} \le ctrlable(i) \quad (7)$$

Where, Ctrlable(i) is the number of devices of type k available for control at time stepi.

SIMULATION RESULTS AND DISCUSSION

The proposed demand side management algorithm is applied to the system by PSO algorithm and then the results are compared with two different approaches, multi agent system [17] and Genetic Algorithm(GA)[20].

The numerical analysis of the proposed DSM algorithm with other well-known methods for reduction of peak load demand and cost for the residential smart micro grid are shown in Tables II and III, respectively. The results show that PSO algorithm can save a great amount of power and therefore can reduce the electricity bill of customers. Figure 3 illustrates the model development workflow.

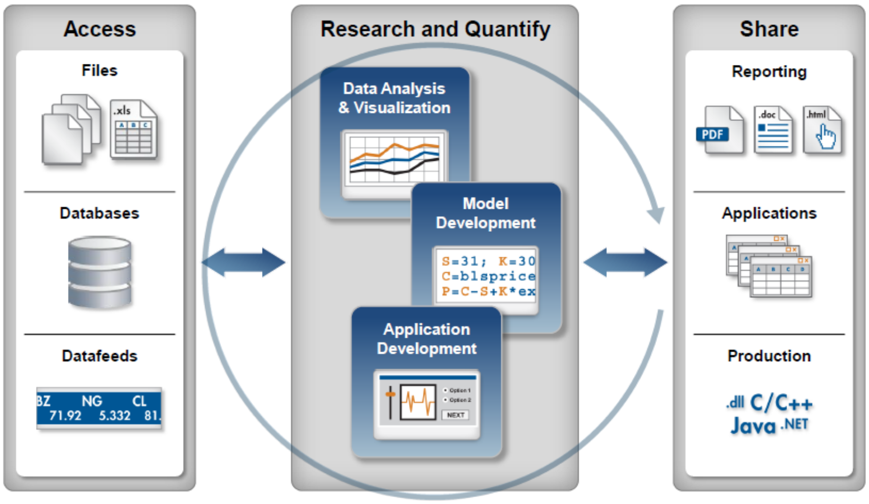

Figure 3: Model development workflow

TABLE II: Peak Load Reduction Results

	Peak Load Before DSM (kW)	*Peak Load After DSM (kW)*	*Peak Reduction (kW)*	*Percentage Reduction (%)*
GA [20]	*1363.6*	*1114.4*	*249.2*	*18.27*
Multi Agent System [17]	*1363.6*	*1121.2*	*242.4*	*17.77*

Table III: Cost Reduction Result

	Cost Before DSM ($)	*Cost After DSM ($)*
GA [20]	*2302.9*	*2188.3*
Multi Agent System [17]	*2302.9*	*2161.21*
PSO	*2302.9*	*2049.7*

CONCLUSION

The proposed demand side management technique takes both electricity bill reduction and peak load reduction into consideration with respect to customers' welfare and utility's limitations. In this paper a new demand side management program based of load shifting is applied to a smart residential micro grid. Particle swarm optimization (PSO) algorithm is applied to the proposed DSM program in order to find the best possible load consumption pattern.

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