ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 2, Issue 4, October 2012

Artificial Intelligence Based Optimization Algorithm for Demand Response Management of Residential Load in Smart Grid

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Abstract— Demand response is gaining a growing focus of attention now a days in electrical distribution systems with several advantages for the reliable distribution system functioning and for electricity prices. In this paper a scheduling strategy for Demand Response Management is present. The methodology is implemented in MATLAB for technical validation of solutions and Particle Swarm Optimization (PSO) for solution optimization. The validity of the tool is illustrated through an example case study for various household scenarios.

***Index Terms*- Demand-Side Management, Home Automation, Home Energy Management, Particle Swarm Optimization, Simulation Tool, Smart Grid.**

I. INTRODUCTION

According to the Ministry of Power, India's transmission and distribution losses are amongst the highest in the world, averaging 26 per cent of total electricity production, and as high as 62 per cent in some states. These losses do not include non-technical losses like theft etc.; if such losses are included, the average losses are as high as 50 per cent. India losses money for every unit of electricity sold, since India has one of the weakest electric grids in the world. Some of the technical flaws in the Indian power grid are - it is a poorly planned distribution network, there is overloading of the system components, there is lack of reactive power efficiency and bill collection, etc. The basic concept of Smart Grid is to add monitoring, analysis, control and communication capabilities to the national electric grid in order to improve reliability, maximize throughput, increase energy efficiency, provide consumer participation and allow diverse generation and storage options. Demand Side Management (DSM) introduced by Electric Power Research Institute (EPRI) in the 1980s. DSM consists of a series of activities that governments or utilities design to change the amount or time of electric energy consumption, to achieve better social welfare or some times for maximizing the benefits of utilities or consumers. In fact, DSM is a global term that covers activities such as: Load Management, Energy Efficiency, Energy Saving and so on [1]. Energy savings is often cited as a significant potential benefit to developing the smart grid. Yet little attention has been paid to how this will happen. The strategy currently receiving the most attention is installation of smart meters in homes and businesses. A handful of utilities across the country have moved quickly to install Advanced Metering Infrastructure, selling consumers on the idea that these energy monitoring devices that communicate with the utility will save them energy and money. But smart meters are only tools for collecting information on how our buildings use energy. Installing them does nothing to cut energy consumption or reduce greenhouse gas emissions. It's what we do with that information that matters. The smart grid can be designed to maximize energy savings and we must adopt policies and technologies that achieve this goal. On the demand side, buildings hold great potential for cost-effective energy savings made possible by smart grid infrastructure and applications. But buildings must have functional control systems to be able to hook into the smart grid. In other words, for the smart grid to maximize energy savings, we need buildings to work. And further, the cost-effectiveness of the smart grid as a whole will rely on the materialization of building energy savings. Unfortunately, this nation's building stock isn't ready for the smart grid. Just as buildings need to be commissioned for building systems to work together properly, commissioned buildings that work properly will be able to take advantage of smart grid infrastructure. The energy efficiency and commissioning industries will lead the way in actually designing and implementing smart grid integration with building systems. Smart grid capabilities, in turn, could change the energy efficiency market. Widespread adoption of smart grid infrastructure will affect how energy efficiency programs are structured and implemented and will potentially magnify the energy savings achieved with such programs [2-6].

II. ARTIFICIAL INTELLIGENCE

The term "Artificial Intelligence" (AI) is used to describe research into human-made systems that possesses some of the essential properties of life. Actually, there are already lots of computational techniques inspired by biological systems. For example, artificial neural network is a simplified model of human brain; genetic algorithm is inspired by the human evolution. Here we discuss another type of biological system - social system, more specifically, the collective behaviors of simple individuals interacting with their environment and each other. Someone called it as swarm intelligence. All of the simulations utilized local processes, such as those modeled by cellular automata, and might underlie the unpredictable group dynamics of social behavior. Some popular examples are bees and birds. Both of the simulations were created to interpret the movement of organisms in a bird flock or fish school. These simulations are normally used in computer animation or computer aided design. There are two popular swarm inspired methods in computational

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intelligence areas: Ant colony optimization (ACO) and particle swarm optimization (PSO). ACO was inspired by the behaviors of ants and has many successful applications in discrete optimization problems. The particle swarm concept originated as a simulation of simplified social system. The original intent was to graphically simulate the choreography of bird of a bird block or fish of a fish school. However, it was found that particle swarm model could be used as an optimizer.

III. PARTICLE SWARM OPTIMIZATION

PSO simulates the behaviors of bird flocking. Suppose the following scenario: a group of birds are randomly searching food in an area. There is only one piece of food in the area being searched. All the birds do not know where the food is. But they know how far the food is. The best strategy to find the food is to follow the bird, which is nearest to the food. PSO learned from the scenarios [7-9] is used to solve the optimization problems. In PSO, each single solution is a "bird" in the search space and is called "particle". All of the particles have fitness values, which are evaluated by the fitness function to be optimized, and have velocities, which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles.

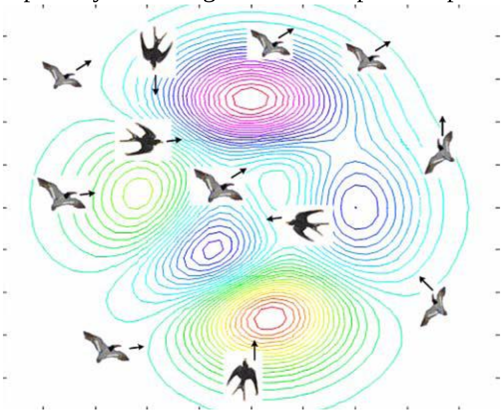

Fig. 1 Particle Swarm Optimization

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In all iterations, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called *pbe*. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called *gbe*. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called *pbe*. After finding the two best values, the particle updates its velocity and positions.

IV. PROBLEM FORMULATION FOR APPLIANCE SELECTION

This section presents how PSO can solve the demand response problem, using a multi-objective approach. First, we define the optimization problem; following, the modified implementation of the PSO algorithm, which in combination with the smart home cognition, can provide promising performance.

A. The Optimization Problem

It is of great importance to distribute loads properly, such that one can obtain the highest profit out of the smart home system. Thus, we define the optimization problem as follows: Given a set of appliances A = { , , , ..., }, where each appliance consumes a total of watts. Such appliances are considered to be connected to the smart grid. The cost of electricity in the smart grid is based on the time, and varies according to peak hours and off-peak hours; it is common that in peak hours the price is relatively high. Hence, our objective is to manage the load according to an imposed set point, such that the price of using the smart grid is minimized. To achieve such minimization, it is sufficient to select the optimal combination of appliances for peak loads, such that

$$Fk = \sum_{i \in |a_i|} a_i * w_i < W, a_i \in \{0, \quad (1)$$

is maximized. Equation 1 resembles the well-known combinatorial 0/1 Knapsack problem [10], with k = 1. However as k increases, the complexity of the problem increases fast enough, because it transforms into a Multidimensional Knapsack problem, with the additional constrain that the capacity of the knapsacks are not equal. This causes problems, because the Knapsack solution has to be found for each dimension, and their solutions are not mutually independent. The Knapsack problem has a solution of the form m(i) = max{ + |a − , *w*} (2)

Using the concept of dynamic programming, this problem can be expressed as a matrix on which the equation 2 is evaluated for 1 ≤ w ≤ W. Given that the range of total watts is in the order of kilowatts, this yields problems because most of the entries on such a matrix are computed unnecessarily, increasing the complexity of the problem. Hence a new solution is needed, for which we have proposed to use Evolutionary Computation, particularly the Particle Swarm Optimization. The next subsection covers the implementation of PSO and data flow of optimization procedure.

B. Data Flow of Two Dimensional Binary Particle Swarm Optimization

For the utilization of the BPSO algorithm in the tool, the population size was set to 30 particles, the dimension *d* was set to the total number of appliances present at the time of calculation, and the maximum number of iterations was set to 100. The minimum velocity *vm* and maximum velocity *vm* were set as –1.0 and 1.0 respectively. Acceleration constants and were chosen as 1. The inertia weight factor *w* was set to 0.99. The value of decreases as the iteration number increases [11]:

= *wm* – (*wm* – *wm*)* *it* / *iterm* (3)

Where *iterm* is the maximum number of iterations, *it* is the current iteration number, *wm* is the maximum value of , which is set to 1 and *wm* is the minimum value of , which is set to 0. The possible solution space is the defined as 0 or 1 which relates to the appliance operational state of switched off and switched on respectively. The

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 2, Issue 4, October 2012

computational procedure of the proposed method is laid out as follows:

• Step 1: Determine the value of the present cost rate, the total number of appliances, the total duration of operation of the appliance and the appliance power consumption.

• Step 2: Randomly generate the particles $\{x_i^0, i = 1,2,..., N\}$, where $x_i^0 = [x_{i1}^0, x_{i2}^0, ..., x_{id}^0]$, d is the dimension, x_{id}^0 is either 0 or 1.

• Step 3: Generate the initial velocities of all particles randomly, { , i = 1,2,...., N }, here = [1, 1 ,..., 1]. v is generated randomly with 1= v_n + (v_m - v_n) * rand, rand is a random real number between 0 and 1.

• Step 4: For each particle i in the swarm, set individual best solution $pbest_i^0 = x_i^0$ and using (5), calculate the best fitness value $pbestvalue_i = Zs\,(pbest_i^0)$, where i = 1, 2…….. N.

• Step 5: Determine the $pbest_i^0$ having the best fitness value and assign to global best solution $gbest$.

• Step 6: Increase the iteration number by one.

• Step 7: Update the member velocity v of each particle based on the following equation:

$$v_i^{t+1} = w * v_i^t + c_1 * r_1 * (pbest_i^t - x_i^t) + c_2 * r_2 * (gbest_i^t - x_i^t)$$

Where i = 1,2,….,N is the number of particles, t is the iteration number, $r1$ and $r2$ are real random numbers between 0 and 1.

• Step 8: Determine the normalized velocity of each particle using the sigmoid function:

$$v_i^{t+1} = \frac{1}{1+e^{-v_i^{t+1}}}$$

Where i = 1, 2,…, N is the number of particles and t is the iteration number. The value of v_i^{t+1} is limit according to the following condition:

$$v_i^{t+1} = \begin{cases} v_{max}, & if\, v_i^{t+1} > v_{max} \\ v_{min}, & if\, v_i^{t+1} < v_{min} \end{cases}$$

• Step 9: Update the member position x of each particle based on the following equation:

$$x_{id}^t = \begin{cases} 1, & if\, v_i^{t+1} > rand \\ 0, & otherwise \end{cases}$$

Where i = 1, 2,….,N is the number of particles, t is the iteration number, and $rand$ is a random real number between 0 and 1.

• Step 10: Calculate values of the design objective (1) and evaluate the fitness of each particle.

• Step 11: If the fitness of the particle is better than the value stored in $pbest$, update $pbest$ with the present values of the particle.

• Step 12: Repeat step 4 for each particle.

• Step 13: Determine the best solution for all the particles and update $gbest$.

• Step 14: Update the inertia weight factor w.

• Step 15: If the maximum number of iterations reaches the predefined limiting factor, then exit PSO algorithm, else repeat step 4.

V. SIMULATION RESULTS

For evaluating the tool, we considered sample household appliances shown in Table I. The properties (number of appliances, time of operation, and power consumption) of the appliances were set as shown in Table I.

Table I. Household Appliances, Power Consumption and Operating Time

Appliance Name	Code	Time of Operation without DSM	Kilowatts
Air Conditioner1	A1	6 AM to 10 PM	3
Air Conditioner2	A2	10 PM to 6 AM	2.5
Cloth Dryer	A3	7 AM to 9AM	0.65
Refrigerator	A4	12 AM to 12 AM	0.6
Microwave Oven	A5	12 PM to 1 PM	1.2
Washing Machine	A6	7 AM to 9AM	0.8
Computer system	A7	6 PM to 9PM	0.36
Television 25’’	A8	9 PM to 12 PM	0.3
Vacuum Cleaner	A9	10 AM to 11 AM	0.5
Sump Pump ½ hp	A10	7 AM to 8 AM	1.05
Light Load	A11	5 PM to 1 AM	0.25
Fan	A12	12 AM to 12 AM	0.5
Water Heater	A13	8-9 AM & 9-10 PM	1

Where i = 1,2,….,N is the

The daily cost-rates for consumption of electricity were assumed to be part of a cost-rate structure plan as shown in Table II.

Table II.Cost-Rate Plan

TIME	RS./KWH
7 AM to 9 AM	4.56
9 AM to 4 PM	3.04
4 PM to 6 PM	3.75
6 PM to 10 PM	4.56
10 PM to 7 AM	3.04

Scenario 1: Based on the cost-rate plan shown in Table II, the tool was initially evaluated for different conditions and the results obtained are shown in Table III.

Table III.Results of Cost of Consumption for Scenario 1

	Cost (Rs/day)
Without DSM and optimized appliance selection	378
With DSM and without optimized appliance selection	367.20

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
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Percentage cost saving per day by utilizing DSM (378.00-367.20)/378.00=2.88%

Scenario 2: The proposed PSO methodology has been used to optimize load management, developed in MATLAB R2009 32bits software, aiming at reducing the initial consumption in scenario 2 to the specified Set Point. Table IV shows the initial load conditions in different time periods when price in higher i.e. in the price at peak loads according to table I and table II

TABLE IV. Initial Load Conditions on Peak Rate Timings

	AM		PM					
	7-8	**8-9**	**4-5**	**5-6**	**6-7**	**7-8**	**8-9**	**9-10**
A1	3	3	3	3	3	3	3	3
A2								
A3	0.65	0.65						
A4	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
A5								
A6	0.8	0.8						
A7					0.36	0.36	0.36	
A8								0.3
A9								
A10	1.05							
A11				0.25	0.25	0.25	0.25	0.25
A12	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
A13		1						1
Total	**6.6**	**6.55**	**4.1**	**4.35**	**4.71**	**4.71**	**4.71**	**5.65**

The initial energy consumptions at different time periods are described in table IV. These vary between 4.1 kW to 6.6 kW. For optimization, the energy consumption limits (Set Point) changes to 1 kW for peak rates 4.56 Rs. /KWH and 1.5 kW for peak rates 3.75 KWH.

The PSO results were chosen after 35 run trials; the most common result has been selected and is shown in Table V.

TABLE IV.Scenario 2 Optimization

	AM		PM					
	7-8	8-9	4-5	5-6	6-7	7-8	8-9	9-10
A1								
A2								
A3								
A4			0.6	0.6	0.6	0.6	0.6	0.6
A5								
A6	0.8	0.8						
A7					0.36	0.36	0.36	
A8								0.3
A9								
A10								
A11				0.25				
A12			0.5	0.5				
A13								
TOTAL	**0.8**	**0.8**	**1.1**	**1.35**	**0.96**	**0.96**	**0.96**	**0.9**

Based on the cost-rate plan defined in Table II, the results obtained for Scenario 2 are shown in Table V.

TABLE V. Results of Cost of Consumption for Scenario 2

	Cost (Rs/day)
Without DSM and optimized appliance selection	378
With DSM and without optimized appliance selection	367.20
With DSM and optimized appliance selection	230.26

Percentage cost saving per day by utilizing DSM & optimized appliance selection (378-230.26/378) = 39.1%

Scenario 3: The results presented in scenario 2 followed an actual reduction or disconnection of some loads. Let us consider that, after that, the consumer turns on some loads that were turned off by PSO approach. If this happens, a new optimization is undertaken, considering the consumers' actions. The user decided to turn on some loads in the different peak rate periods. Table VI shows the loads turned on by user.

TABLE VI. Different Loads Turns On By User

	AM		PM					
	7-8	8-9	4-5	5-6	6-7	7-8	8-9	9-10
A1			3	3				
A2								
A3	0.65							
A4			0.6	0.6	0.6	0.6	0.6	0.6
A5								
A6	0.8	0.8						
A7					0.36	0.36	0.36	
A8								0.3
A9								
A10								
A11				0.25	0.25	0.25	0.25	0.25
A12			0.5	0.5				
A13		1						
TOTAL	**1.45**	**1.8**	**4.1**	**4.35**	**1.21**	**1.21**	**1.21**	**1.15**

Table VII shows the results obtained with PSO approach. It was possible to maintain the loads fixed by the user, while respecting the imposed power limits.

TABLE VII .Scenario 3 Optimization Results

	AM		PM					
	7-8	8-9	4-5	5-6	6-7	7-8	8-9	9-10
A1			3	3				

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 2, Issue 4, October 2012

A2								
A3	0.65							
A4					0.6	0.6	0.6	0.6
A5								
A6								
A7								
A8								
A9								
A10								
A11					0.25	0.25	0.25	0.25
A12								
A13		1						
TOTAL	**0.65**	**1**	**3**	**3**	**0.85**	**0.85**	**0.85**	**0.85**

It was possible to maintain the loads fixed by the user, but the total consumption was higher than the Set-Points. This is considered acceptable as it directly results from a consumer's decision. Based on the cost-rate plan defined in Table II, the results obtained for Scenario 2 are shown in Table VIII.

TABLE VIII .Results of Cost of Consumption for Scenario 3

	Cost (Rs/day)
Without DSM and optimized appliance selection	378
With DSM, optimized appliance selection & consumer's preference	242.06

Percentage cost saving per day by utilizing DSM, optimized appliance selection & consumer's preference (378-242.06/378) = 36%

VI. CONCLUSION

This paper proposes a PSO methodology applied to residential load management. The proposed methodology manages load consumption when the consumption is above an imposed power consumption limit. Load management takes into account consumers' preferences. The proposed methodology has been illustrated using three scenarios. The tool simulates a household environment, thereby providing the customer a real-time analysis of optimized appliance selection. The utilization of DSM and optimized appliance selection form appliance selection helps to achieve a cost saving of 39.1% for the end-user. The results also show that DSM, optimized appliance selection and consumer's preference lead to cost savings of about 36%. These results show significant annual savings for the customer. The tool can be used for extending research on improving DSM and for educational purposes. The tool can be enhanced such that prior data regarding household electricity usage can be considered for probabilistic determination of present and future consumption of electricity. The concept of using Plug-in Hybrid Electric Vehicle (PHEV) for storing energy can be integrated into the tool along with the concept of selling back excess energy to the grid.

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ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 2, Issue 4, October 2012

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