A Review Study on Evolutionary Optimization Technique for Demand Side Management in Smart Grid

Nikita Medhane[1], Dr. Rahul Agrawal[2]
[1]PG Student, [2]Associate Professor
Department of Electrical Engineering,
School of Engineering and Technology, Sandip University, Nashik, India

Abstract- Most of the energy efficiency programs developed is objectified for reduction in losses and rising the efficiency and getting a generation close to base load. But with present real time controls developed, the phase is changing towards load flexibility and maintaining distributed generation to balance any rise in demands.
Demand side management has potential to provide many benefits to the entire smart grid, particularly at distribution network level. This objective of Demand side management needs to optimize for cheapest price option and highest efficiency. The strategy studied in this paper is a generalized technique based on load shifting, which has been mathematically formulated as a minimization problem. The controllability of the operation can be optimized using various control technique.

Keywords- Demand side management (DSM), Demand Side Response (DSR), Flexible Load, Distributed Generations

I. INTRODUCTION

In today's electrical market, Customers have an array of choices at their fingertips to explore rooftop solar, micro-wind turbines, biogas options, fuel cells are distributed generations, and at load side we have smart appliances, Electric Vehicle charging options, Heating and Air Conditioning (HVAC), water heating and solar plus storage. All aspects of grid-connected home can surely accommodate customer preferences and comfort. These parametric changes occurring in grid effects the real time meter readings. This data can be used to predict energy bills for customers and help in reducing it. Customer usage insights can also be used to drive additional products and services to help improve the customer experience.

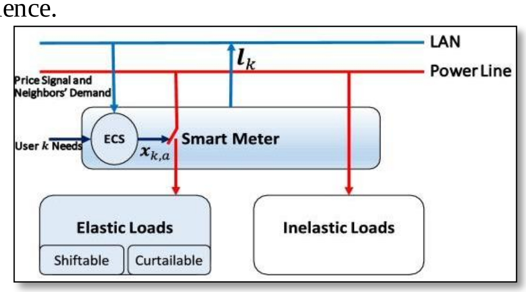

Fig.1: Grid-Customer Interaction Model

The mounting number of connected loads, self-generation mounts and energy management possibilities empowers the customers to have a central role in the future grid. So, they will no longer be viewed as passive load, but instead as flexible grid resources.

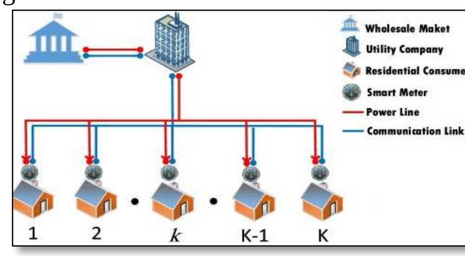

Fig.2: Architecture of Grid Communication

An integrated condition to improve DSM will ensure customers stands for an expanded role in supporting grid services, rescheduling of capital disbursement and utility revenue flows. An ensemble of technologies at grid-side helps to channelize a modern grid and dynamic pricing to optimize the experience for the customer while supporting efficient grid operations. Utilities are in an ideal position to take advantage of this shift by understanding the role of technology, customer behavior and the various business models for valuing and sourcing DERs. Additionally home power optimization, distributed energy management systems are being tested and setup created by utilities and third-party developers to control customer assets that meet a variety of grid needs. Automated metering infrastructure gives us the option to monitor any changes in the load on real time basis which powers the software to predict and analyze the system in Hour ahead or day-ahead manner.

II. PROFILE OF DEMAND SIDE MANAGEMENT

DSM amends electricity utilization patterns to fabricate desired changes in the load pattern of power distribution structures. The transformations in the resultant utilization profile depend on planning intentions and operation of utility. DSM focuses on power saving, tariff architecture, incentives, and government policies to tone down the peak load demand instead of expanding the generation capacity reinforcing the transmission and distribution network.

To tone down system instabilities raised by increasing electricity requirement, an appropriate purpose of DSM activities is to change the profile of the load demand curve by dropping the total load requirement of distribution system during peak phases, and shift these loads to be given out during more appropriate times to reduce the overall planning and functional cost of network. These proposals require a sophisticated harmonization between the network operators and clients. The load shapes which designate the regular or seasonal electricity requirements of industrial, commercial or residential consumers between peak and off peak times can be revised by means of six broad methods: Peak shortening, valley filling, load shifting, strategic conservation, strategic load growth, and flexible load shape. Generally, these are the possible demand side management techniques that can be employed in future smart grids.

Peak clipping and valley filling focus on reducing the difference between the peak and valley load levels to mitigate the burden of peak demands, and increases the security of smart grid. Peak clipping is a direct load control technique to make reduction of the peak loads, and valley filling constructs the off-peak demand by applying direct load control. Load shifting is widely applied as the most effective load management technique in current distribution networks. Load shifting takes advantage of time independence of loads, and shifts loads from peak time to off-peak time. Strategic conservation aims to achieve load shape optimization through application of demand reduction methods directly at customer premises.

The power distribution management system has to take regards of longer term repercussions of demand reduction on network arrangements and operation. Strategic load augmentation optimizes the routine responses in case large demand prefaces the valley filling directions. It works by increasing the market share of loads in conjunction with energy conversion and storage systems or distributed energy resources.

III. PROBLEM FORMULATION

The demand side management strategy under study here and scheduled the connection moments of each shift-able device in the system in adjustments that brings the load consumption curve as close as to the objective load consumption curve. Load shifting technique is mathematically formulated as follows:

$$\sum_{t=1}^{N} (PLoad(t) - Objective(t))^2$$

Where, *Objective (t)* is the value of the objective curve at time, t and $P_{Load}(t)$ is the actual consumption at time, t. The $P_{Load}(t)$ given by the following equation:

$$P_{Load}(t) = Forecast(t) + Connect(t) - Disconnect(t)$$

Where, *Forecast (t)* is forecasted consumption at time, *Connect(t)* and *Disconnect(t)* are the amount of loads connected and disconnected at time respectively during the load shifting. *Connect (t)*is made up of two parts: the increment in the load at time due to the connection times of devices shifted to time, and the increment in the load at time due to the device connections scheduled for times that precede . The *Connect (t)* is given by the following equation:

Here, X_{kit} is the number of devices of type that are shifted from time step to , D is the number of device types, P_{1k} and $P_{(1+l)k}$ are the power consumptions at time steps 1 and 1+l, respectively for device type k and j is the total duration of consumption for device of type k .

$$Connect(t) = \sum_{i=1}^{t-1} \sum_{k=1}^{D} X_{kit}P_{1k} + \sum_{l=1}^{j-1} \sum_{i=1}^{t-1} \sum_{k=1}^{D} X_{ki(t-1)}P_{(1+l)k}$$

Disconnect(t) the load due to delay in connection times of devices that were originally supposed to begin their consumption at time step, 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 . The *Disconnect (t)* is given by the following equation:

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

Where, X_{ktq} is the number of devices of type that are delayed from time step t to q, m is the maximum allowable delay. Like any optimization problem, these equations are subjected to constraints:

1. The number of devices shifted cannot be a negative value

$$X_{kit} > 0$$

2. 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.

$$\sum_{t=1}^{n} X_{kiq} <= Ctrlable(i)$$

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

IV. EVOLUTIONARY ALGORITHM

Given a population of individuals, the environmental stress causes natural selection by theme of survival of the fittest, and this origin for a rise in the suitability of the population. Given a quality function to be maximized, we can arbitrarily generate a set of candidate solutions, i.e., components of the function's domain, and make affect the quality function as an abstract fitness measure (the higher the better). Based on this fitness, a little of the better solutions are preferred to seed the next generation by applying recombination and/or mutation to them. Recombination is an operator applied to two or more selected candidates (parents) and result some or more new candidates (children).

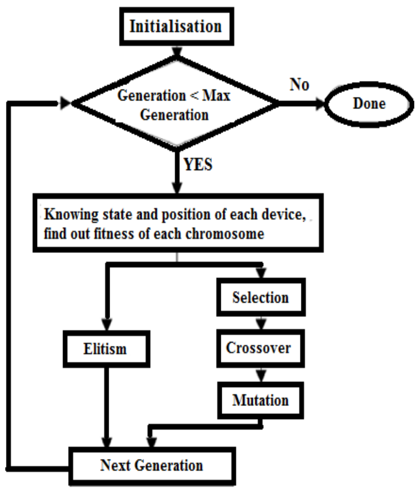

Fig.3: Process of Evolutionary Algorithm

Mutation is applied to one solution and results in one more new solution. Executing recombination and mutation results in set of new solutions (the off-spring) that competes (based on fitness and age) with the old solutions for a position in the next generation. This process can be iterated until a candidate with sufficient quality (a solution) is found or a previously set computational limit is reached. In this process, there are two fundamental forces that form the basis of evolutionary systems:

- *Variation operators (recombination and mutation) create the necessary diversity and thereby facilitate novelty*
- *Selection acts as a force pushing quality.*

The mutual application of variation and selection by and large leads to humanizing fitness value in consecutive populations. It is easy to see such a process as if the evolution is optimizing, or at least approximating, by approaching optimal values closer and closer over its course. Otherwise, evolution it is often seen as a process of adaptation. The fitness is virtual enough to treat as objective function for optimization, but an expression of environmental requirements. Matching these requirements more closely implies an increased viability, reflected in a higher number of resulted solutions. The evolutionary process makes the population adapt to the environment better and better.

V. SIMULATION AND RESULTS

The main advantage of the algorithm is the flexibility in constructing and developing the algorithm which cannot be afforded by any other conventional approaches. The adaptable nature of this algorithm permits implementation of attributes that model load demand patterns based on the lifestyles of the customers so that the inconvenience to the customers can be minimized. Certain loads may have higher priority over other loads, which can also be taken into consideration by the algorithm so that these loads are shifted to the appropriate time steps according to their importance.

The demand side management problem has characteristics such as, connection times of devices that can only be delayed and not brought forward, which can be expressed as:

$$X_{kit} = 0, \; i > t$$

The contract options stipulate the maximum allowable time delay for all devices and limit the possible number of time steps that devices can be shifted to,

$$X_{kit} = 0, \; t\text{-}i > m$$

Where, m is the maximum permissible delay. Taking the above into consideration, the maximum number of possible time steps can be found using the following equation:

$$\mathrm{N} \;=\; \left((24-\mathrm{m})\mathrm{m} + \sum_{\mathrm{n}=1}^{\mathrm{m}-1}\mathrm{n}\right)\mathrm{k}$$

Where, k is the number of different types of devices.

Chromosomes of the evolutionary algorithm represent the solutions to the problem. In this work, the chromosome is constructed as an array of bits. The length of the chromosome is directly related to the number of time steps, which is given by the following equation:

$$\textit{Length of the Chromosome} = N \times B$$

A population of chromosomes is randomly initialized by the numbers between upper and lower limits of each gene. A fitness function is chosen such that the algorithm achieves a final load curve as close to the objective load curve as possible, which is given as follows:

$$Fitness \;=\; \frac{1}{1+\sum_{t=1}^{24}\left(PLoad(t)-Objective(t)\right)^2}$$

While the algorithm is progressing, new populations of chromosomes are produced from the existing populations by genetic operators: single point crossover and binary mutation. A large cross-over rate makes sure quicker convergence of the solution. Very large mutation rate may result in loss of good solutions from previous generations, and stop the algorithm with premature convergence.

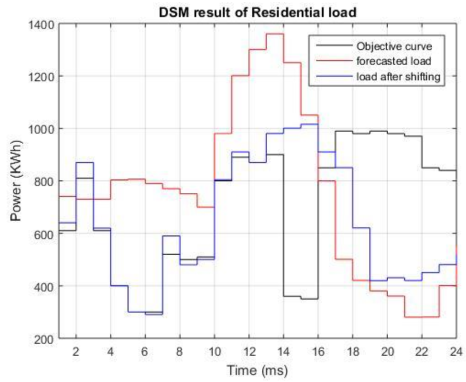

Fig.4: DSM results of the residential area

In this study, the primary objective is to reduce the utility bills of consumers in these areas. Therefore, an objective load curve was chosen to be inversely proportional to electricity market prices. The same market prices were applied to all areas in the smart grid. Simulations were carried out with a maximum allowable delay of 12hrs. It is known that the longer the delay, the better the performance of demand side management algorithm since the possible number of loads subjected to load shifting increases, resulting in improved results.

Table I summarizes the simulation results from the demand side management strategy under study for three areas of the smart grid. The approach has successfully managed to achieve the objective in all three areas, with considerable savings in the utility bills. Typically, demand side management results are better when the number of devices available for control increases, but it’s a variable parameter.

TABLE I- REDUCTION IN BILLING

Area	Reduction (%)
Residential	5.0
Commercial	5.8
Industrial	10.0

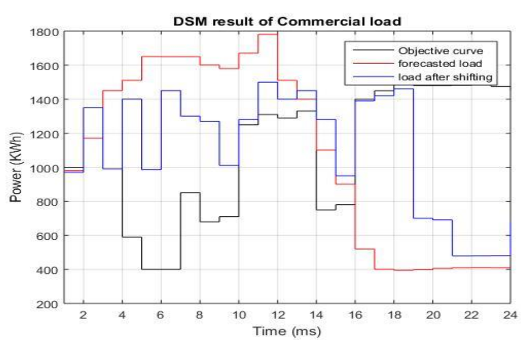

Fig.5: DSM results of the commercial area

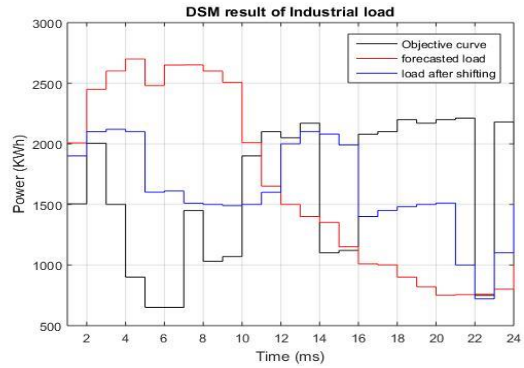

Fig.6: DSM results of the industrial area

TABLE II- DEMAND LEVELS DUE TO DSM

Type of Area	**Peak load w/o DSM (kW)**	**Peak load with DSM (kW)**	**Peak Reducti on (kW)**	**Reductio n (%)**
Residential	1363	1114	249.2	18.3
Commercia l	1818	1485	333.0	18.3
Industrial	2727	2343	383.7	14.2

Table II shows that the demand side management strategy reduces the peak load demand for each area. Reduction in the peak load demand improves grid sustainability by reducing the overall cost and carbon emission levels. Generation companies also stand to benefit, as the reduction in peak load demand results in substantial cost savings as peak load generators are not needed. This would also result in increasing reserve generation capacity of the system.

VI. CONCLUSION

Demand side management strategy under study here is implied for three different types of loads. It successfully managed to achieve considerable savings in the utility bills. It also reduced the peak load demand for each area improving grid sustainability, reduces the overall operational cost and cuts down carbon emission levels. Reduction in peak load demand results in substantial cost savings by shedding peak generators, virtually increasing reserve capacity.

VII. REFERENCES

[1]. I. Cohen and C. C. Wang, “An optimization method for load management scheduling,” *IEEE Trans. Power Syst.*, vol. 3, no. 2, pp. 612–618, May 1988.

[2]. K.-H. Ng and G. B. Sheblé, “Direct load control-A profit-based load management using linear programming,” *IEEE Trans. Power Syst.*, vol. 13, no. 2, pp. 688–694, May 1998.

[3]. F. C. Schweppe, B. Daryanian, and R. D. Tabors, “Algorithms for a spot price responding residential load controller,” *IEEE Trans. Power Syst.*, vol. 4, no. 2, pp. 507–516, May 1989.

[4]. M. Shahidehpour, H. Yamin, and Z. Li, *Market Operations in Electric Power Systems: Forecasting, Scheduling, and Risk Management*. New York: Wiley–IEEE Press, 2002.

[5]. Z. N. Popovic and D. S. Popovic, "Direct load control as a market-based program in deregulated power industries," in *Proc. IEEE Bologna Power Tech Conf.*, Jun. 23–26, 2003, vol. 3, p. 4.

[6]. N. Kurucz, D. Brandt, and S. Sim, "A linear programming model for reducing system peak through customer load control programs," *IEEE Trans. Power Syst.*, vol. 11, no. 4, pp. 1817–1824, Nov. 1996.

[7]. W. C. Chu, B. K. Chen, and C. K. Fu, "Scheduling of direct load control to minimize load reduction for a utility suffering from generation shortage," *IEEE Trans. Power Syst.*, vol. 8, no. 4, pp. 1525–1530, Nov. 1993.

[8]. M.R. Narimani, J-Y. Joo, M.L. Crow, "Dynamic Economic Dispatch with Demand Side Management of Individual Residential Loads",IEEE, North American Power Symposium (NAPS) (2015)

[9]. M.H. Alham, M. Elshahed, Khalil Ibrahim Doaa, Essam El Din Abo El Zahab, "A dynamic economic emission dispatch considering wind power uncertainty incorporating energy storage system and demand side management", Renewable Energy, 96 (2016), pp. 800-811

[10]. K.G. Di Santo, S.G. Di Santo, R.M. Monaro, M.A. Saidel, "Active demand side management for households in smart grids using optimization and artificial intelligence," Measurement (2017)

[11]. S Mohammad, A.de Gracia, C. Fernández, Martin Belusko, Dieter Boer, Luisa F. Cabez, "Optimized demand side management (DSM) of peak electricity demand by coupling low temperature thermal energy storage (TES) and solar PV Applied Energy, 211 (2018), pp. 604-616