AREA BASED EFFICIENT AND FLEXIBLE DEMAND SIDE MANAGEMENT TO REDUCE POWER AND ENERGY USING EVOLUTIONARY ALGORITHMS

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ABSTRACT

Evolutionary algorithms are stochastic that reflects the biological evolution to reach optimal solutions to optimization problems where mathematical techniques may fail. Demand Side Management (DSM) are designed to reduce electricity consumption or to shift the consumption from peak to off – peak hours depending on consumers' lifestyle and behaviour. DSM is a flexible consumer driven activity in which the consumer has voluntarily changed his energy usage pattern during peak demand so to maintain the reliability and stability of power system and the performance of an electrical grid. In this aspect we have explored the impact of an efficient and flexible DSM which can reduce the power demand and energy in different areas like rural, urban and villa there by utilizing the device power rating and its activation time. The defined problem was solved with evolutionary based – genetic (GA), particle swarm (PSO) and differential evolution (DE) optimization algorithms. Simulation results show the better outcome in terms of power demand and energy reduction and the results are compared to know the better performing algorithm as on applied to DSM.

Keywords: ***Genetic algorithm, Particle Swarm, Differential Evolution, Optimization, Demand Side Management, Power Demand, Energy***

1.0 INTRODUCTION

The usage of an electric power system is there for a century but without much changes in the infrastructure [2]. In recent times the power sector is facing various challenges in terms of carbon emission level, depletion of resources, utility and security management. Major revolution in this sector is most needed. The future power system is expected to be a reliable and intelligent system with an environmental concern. Smart grid can be the eventual solution to the issue. DSM plays a major role in the smart grid energy management. The main goal of demand side management in smart grid is to have consumer cooperation to consume electricity more efficiently. The different DSM techniques [2] are load shifting, peak clipping, flexible load shape, strategic load growth, strategic energy conservation and valley filling. The paper deal with a new idea of flexible load shape-based DSM.

The major smart grid domains like energy management, and infrastructure related issues are discussed in [1] – [10]. The intention of this work is on power consumption scheduling called demand side management. DSM work either by reducing or shifting the energy consumption. Reducing the consumption is by means of energy aware patterns and shifting is usually by an appliance shift at the cost of consumer comfort to reduce peak. Scheduling of appliances may not be feasible with all devices. The paper work on reducing the energy consumption [1].

In literature [4] author proposed integer linear programming to handle the consumption scheduling of shiftable and non-shiftable appliances in terms of optimal power and time to achieve an effective DSM. K. Hamilton and N. Gulhar [5] in their paper have taken a next step with demand response by enabling customer choice at time of high pricing. The authors in [6] presented an analytical model with cost benefit analysis by shifting the load with the help of smart appliances from peak hours to off peak hours. Comparisons were done and analysed. Authors in [7] have focused to develop and create flexible and efficient DSM with residential distribution system with direct load control methods using load curves. Physical load models were constructed and the impact on power and energy demand observed. Giorgio et al [8] controlled shiftable loads directly in a distribution system as a real valued optimization problem with heuristic based nature inspired algorithms. The authors [9] have dealt optimized operation and dynamic distribution household appliance management. Heuristic based algorithms satisfy customer need and by reducing the cost. In future hybrid renewables can also be integrated. Paper [10] used advanced metering infrastructure to investigate an encoding system with pre-processed load shape with the help of electricity segmentation methodology.

As inspired from the literatures flexible DSM is tried implemented with evolutionary based algorithms. The contributions of this paper are as follows:

- Flexible DSM is proposed with an objective to reduce power demand and energy.
- Initially the system model was categorized in three areas: rural, urban and villa
- Furthermore, smart meters are deployed to record the device activation time and its power ratings.
- Especially load centres are considered to be school, hospital, social club and mall data along with house data.
- With all the observations and as per the device scheduling power demand and energy values are calculated.
- Finally, extensive simulations were carried out to find the effectiveness of evolutionary algorithms in terms of power demand and energy reduction to the objective.

The paper is organized as follows. The three evolutionary algorithms as implemented to the work are reviewed in Section 2. The proposed model for DSM is described in Section 3. Section 4 presents a case study details and Section 5 compares the system simulation results of the implementation of evolutionary algorithms. Section 6 discusses the results of the work. The paper is concluded in Section 7 with future research ideas.

2.0 EVOLUTIONARY ALGORITHMS

Evolutionary algorithms follow a common approach for their application to a problem. They are nature inspired with computational intelligence to make decisions with the concept of exploitation and exploration. These algorithms converge faster towards the desired solution and are applicable to the DSM problem. Formulated problem is solved with the evolutionary techniques like: GA, PSO and DE. A brief description of the algorithms which are used in the work is presented in the subsections.

2.1 Genetic Algorithms

As explained by Goldberg [11] Genetic Algorithm works on increased fitness solution through evolution which is inspired by biological systems. GA work with chromosomes which are random population represented in the form of string. Chromosome includes genes which can keep the optimization variable values. Fitness function selects the chromosome to the objective function. Selected chromosomes share the information through the process of cross over and mutation to have a better offspring. The process gets repeated for more iteration to a near optimal solution. The algorithm used to the problem is given as steps below:

Step 1. Initialize population of loads X i , operating time and power

Step 2. Generate random population of time duration combined on load demand at corresponding hour with connect and disconnect of appliances

Step 3. The GA crossover evaluates the fitness of population

Step 4. Iteration is assigned & repeated

Step 5. The mutation phase produces the best combinational solution on load within the time constraints – Maximum Power Demand & Daily Energy Demand

Step 6. The worst solutions are ignored and then the arbitrary elite solutions are saved with the acceptance and replacement

Step 7. If the terminating condition is achieved the search process is stopped

Step 8. The new population is then allocated for new solutions and the steps are repeated

If the test condition is satisfied the algorithm is stopped to return the best solution to be the current population. The main parameters to use with GA are size of population, generation numbers along with mutation and cross over rates.

2.2 Particle Swarm Algorithms

As introduced by Kennedy and Eberhart PSO [12] work on the inspiration of social behaviour on migrating birds' group to an unknown destination. In PSO each bird in the group represents a solution and is termed as a particle. Birds in the group communicate with each other as they fly and follow the path of the bird which takes up the best location in specific direction. Each bird takes up different velocity depending on their current position towards the destination. The process involves both the intelligence and the social interaction from their local search (own experience) and global search (experience from others). The algorithm to the work is given in steps below:

Step 1. Initialize population of loads X i , operating time and power
Step 2. Generate random population of time duration combined on load demand at corresponding hour with connect and disconnect of appliances
Step 3. The PSO algorithm evaluates the fitness of particle
Step 4. Individual and global bests are updated
Step 5. The velocity update & position update on each particle produces the best combinational solution on load within the time constraints – Maximum Power Demand & Daily Energy Demand
Step 6. The worst solutions are ignored and then the arbitrary elite particles are saved with the acceptance and replacement
Step 7. If the terminating condition is achieved the search process is stopped
Step 8. The new best solutions are then allocated for other newer solutions and the steps are repeated

2.3 Differential Evolution Algorithms

As introduced by Storn and Price in evolutionary computation Differential Evolution [13] [14]is a method that optimizes a problem by iteratively trying to improve a candidate solution to a given measure of quality. The algorithm given in steps below and the procedure is shown in Figure 1.

Step 1 Initial parameters are randomly chosen uniformly within the range of lower and upper bounds

Step 2 Each parameter undergoes the process of mutation recombination and selection as shown in fig.

Step 3 Mutation expands the search space within the boundary

Step 4 Recombination incorporates best solutions from the last generation

Step 5 Best solution gets randomly selected in accordance to the mutation factor

Step 6 Iterations continue until some stopping criterion is reached

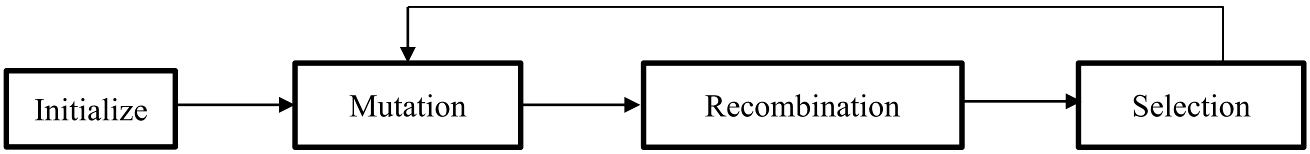


Fig 1: Differential Evolution Procedure

3.0 PROPOSED MODEL FOR DSM

3.1 Model Description

Figure 2 shows the proposed load management system. Smart appliances are the main component of the model. They are the interface between the user and the energy management unit with the details on consumer power consumption plan and choice and display the activation time. The appliances work with request on permission criteria. Based on the information available with the unit the model will optimize the hourly consumption and schedule the appliances. The model can further be extended to the different categories of devices and to the areas.

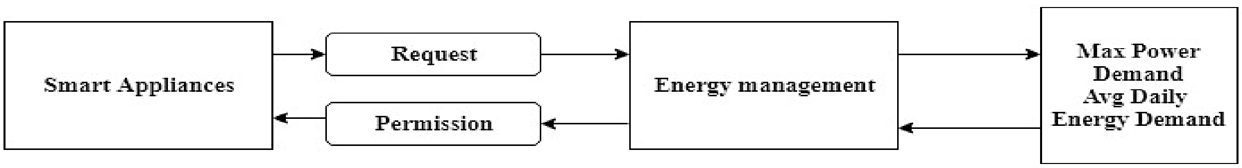
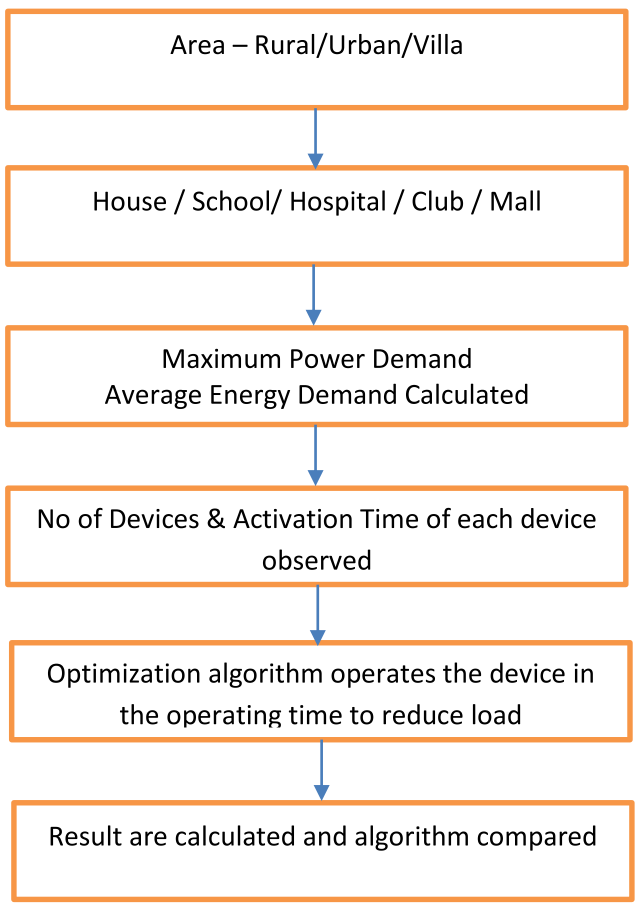


Fig 2: Proposed Load Management System

The implementation of the proposed problem is done with the following steps



3.2 Mathematical Description of the Model

The model aims to reduce power demand and energy demand by using the appliance scheduling to the priority of the user. Let the number of consumers be N.

The equation to minimize demand is ‘D’

$$Minimize\ D = \sum_{a \in h} \sum_{n \in N} d_a^h L_n^N / T a \qquad (1)$$

within the limits of power demand (D) and individual appliance power consumption (d_h) where ‘D’ is the power demand with appliance scheduling along with their energy consumption.

An individual appliance scheduling is denoted as

$$d_h = [\, d_{a,1}, d_{a,2} \ldots\ldots\ldots\ldots\ldots\ldots d_{a,24}]^T \qquad (2)$$

which means the device operation for appliance ‘a’ in a particular hour of a day. The overall consumption in a day is

$$d_h = \sum_{n \in N} d_n^h \qquad (3)$$

The average and peak consumption are

$$L_{peak} = \max d_h \qquad (4)$$

h€H

$$L_{avg} = \frac{1}{H} \sum_{n \in N} d_h \qquad (5)$$

Also household demand is an aggregation of load

$$D_h^i = \sum_{m \,\varepsilon\, M^I}^{N} d_h^{i,m} \text{ where } l^h \qquad (6)$$

$d_h^{i,m}$ is different operating device in various time slot

M^i set of Idevices in different areas

If an appliance can complete a task at various level of power, then the amount of energy also varies continuously.

3.3 Implementation Steps

An analytical case study is done and the procedure followed is given below.

Step 1 Area based devices with their activation time are chosen randomly.

Step 2 Areas which are considered includes Rural, Urban and Villa category.

Step 3 Under each area loads like houses social club, hospital and a mall are considered. In this house are dealt separately and the remaining loads are combined together as a load centre.

Step 4 Maximum power demands and average daily energy demand is calculated for a week.

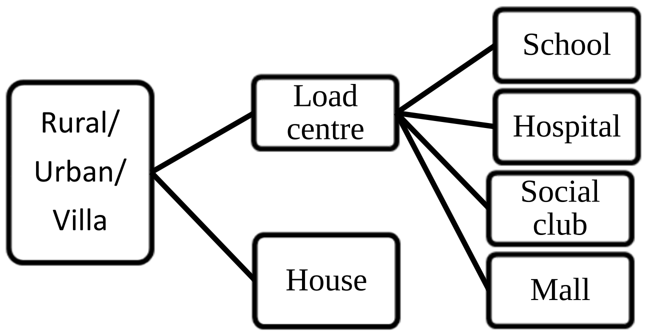
Step 5 With DSM MATLAB coding is done for load management using GA /PSO / DE algorithms and simulation plots are obtained with load reduction.

Step 6 Comparison of three algorithms is done.

4.0 CASE STUDY

The proposed work deal with flexible load shape DSM technique for the randomly chosen load data from three areas like rural, urban and villa. The categorization of different areas and loads are shown in Fig. 3.

Fig 3 Categorization of Different Areas and Loads



The simulation study was done using the data from a randomly selected 12 devices which are from rural households and load centre. Number of devices with their power and its activation time are tabulated in Table 1 below.

Table 1: Device Table in Rural Area

	Device Considered	Quantity	Power watts	Activation time hrs
House	Lamp	3	8	19:22
	Washing M/C	1	90	22.23
	Dishwasher	1	60	10:12
Load Centre				
Hospital	F. Lamp	10	8	09:16
	Fan	2	55	01:24
	Autoclave	1	1900	13:00
Store	F. Lamp	4	8	09:19
Club	F. Lamp	4	8	19.20
	TV	1	48	12.23
School	F. Lamp	6	8	09:14
	TV	1	48	10:11
	DVD	1	8	13:14
Total Devices		**12**	**2249**	

Similarly, the simulation study was done using the data from a randomly selected 21 devices which are from urban households and load centre. Number of devices with their power and its activation time are tabulated in Table 2 below.

Table 2: Device Table in Urban Area

	Devices Considered	**Quantity**	**Power watts**	**Activation Time hrs**
House	Lamp	3	8	19:22
	Washing M/C	1	90	10:12
	DC motor	1	580	20:21
	Geezer	1	122	10:20
	Fan	1	55	14:18
Load Centre				
Hospital	F. Lamp	10	8	09:16
	Fan	2	55	01:24
	Autoclave	1	1900	13:00
	Water pump	1	580	05:06
	freezer	4	90	09:16
Store	F. Lamp	4	8	09:19
	Fridge	1	37.5	01:24
	Fan	1	90	09:18
Club	F. Lamp	4	8	12:13
	TV	1	48	18:21
	DVD	1	8	18:21
School	F. Lamp	6	8	09:14
	TV	1	48	10:11
	DVD	1	8	10:11
	Fan	4	90	09:15
	Water pump	1	580	02:00
Total Devices		**21**	**4421.5**	

The simulation study was done using the data from a randomly selected 26 devices which are from villa households and load centre. Number of devices with their power and its activation time are tabulated in Table 3 below.

Table 3: Device Table in Villa Area

	Devices Considered	**Quantity**	**Power watts**	**Activation time hrs**
House	Lamp	3	8	19:22
	Washing M/C	1	90	10:12
	Dc motor	1	580	20:00
	Geyser	1	122	20:21
	Fan	1	55	14:18
	Rice cooker	1	700	11:00
	DVD	1	8	20:21
Load Centre				
Hospital	F. Lamp	4	8	09:16
	Fridge	4	55	01:24
	Autoclave	1	1900	13:00
	Water pump	4	580	05:06
	freezer	1	90	09:16
	AC	1	1450	09:16
Store	F. Lamp	4	8	09:19

	Fridge	1	37.5	01:24
	freezer	1	90	01:24
	AC	1	1450	09:18
Club	F. Lamp	4	8	12:23
	Projector	1	285	18:21
	AC	1	1450	12:18
	DVD	1	8	18:21
School	F. Lamp	6	8	09:14
	projector	1	285	10:11
	DVD	1	8	13:11
	AC	1	90	09:15
	Water pump	1	580	02:00
Total	**269953.5**			

The consolidated table of devices chosen in different areas with their power ratings are shown below in Table 4

Table 4: Consolidated Table on Selected Devices in Different Areas with their Power Ratings and Quantity

Different Centres	**Rural Area**		**Urban Area**		**Villa Area**	
	Devices considered	**Device Power (w)**	**Devices considered**	**Device Power (w)**	**Devices considered**	**Device Power (w)**
Single House	Lamp-3 Washing M/C-1 Dishwasher-1	8 90 60	Lamp-4 Washing M/C-1 Geyser-1 Fan-1 Dc motor-1	8 90 122 55 58	Lamp-1 Washing M/C-1 Geyser-1 Fan-1 Fridge-1 DVD-1 Ricecooker-1 DC motor-1	8 90 122 55 37.5 8 700 58
Hospital	F. lamps-10 Fans-2 Autoclave-1	8 55 1900	Lamps-4 Fan-1 Autoclave-1 Pump-1 Freezers-4	8 55 1900 58 90	F. lamp-4 Fridge-1 AC-1 Lamp-4 Pump-4	8 37.5 1450 8 58
Stores	F. lamp-4	8	Lamp-4 Fridge-1 Fan-1	8 37.5 55	F. lamp-4 Fridge-1 Freezer-1 AC-1	8 37.5 90 1450
Social Club	F. lamp-4 TV-1	8 48	Lamp-4 TV-1 DVD-1	8 48 8	F. lamp-4 Projector-1 DVD-1 AC-1	8 285 8 1450
School	F. lamp-6 TV-1 DVD-1	8 48 8	F. lamp-6 TV-1 DVD-1 Fan-4 Lamp-4 Pumps Lights-8	8 48 8 55 8 58 48	F. lamp-6 Projector-1 DVD-1 Lamp-4 AC-1 Pump-1 Public lights-16	8 285 8 8 1450 58 48

5.0 COMPARISON OF SYSTEM SIMULATION RESULTS FROM EA'S

All three evolutionary algorithms explained in the previous section have been coded in MATLAB. The simulation results of the three algorithms on three areas are shown below.

5.1 GA outcome in all three areas

Figures 4 (a) (b) (c) depicts the MATLAB simulation outcome to the problem mentioned using GA for a week. It is evident that the consumption is more on weekends than a weekday.

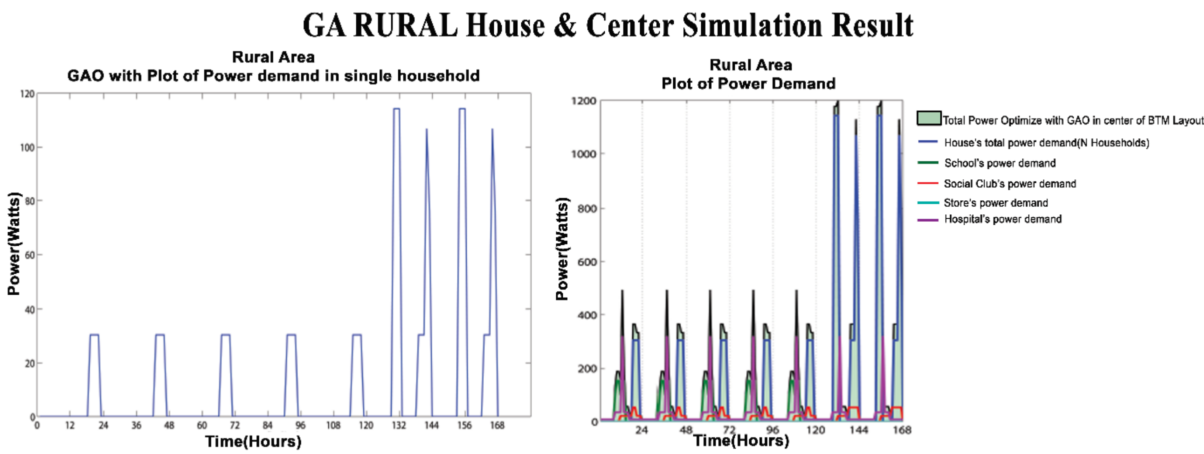


Fig. 4 (a)

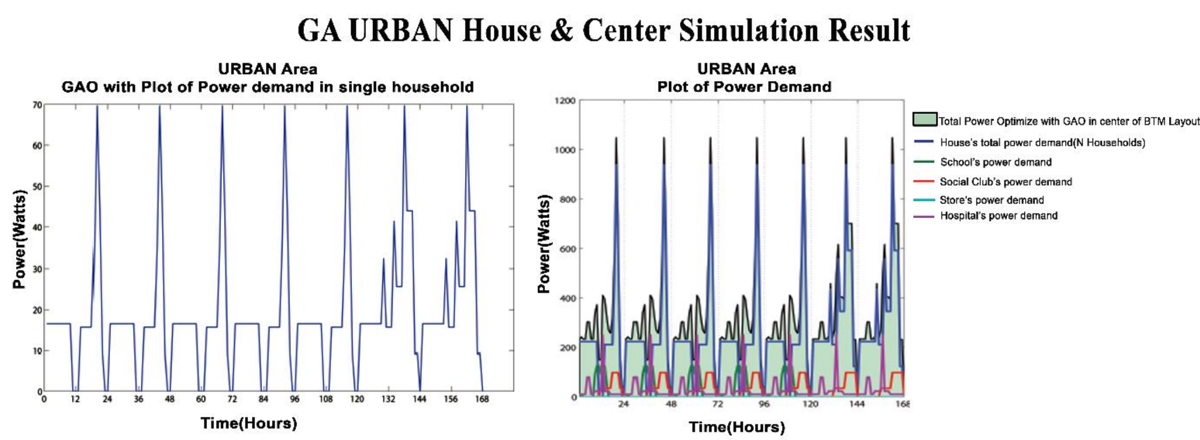


Fig. 4 (b)

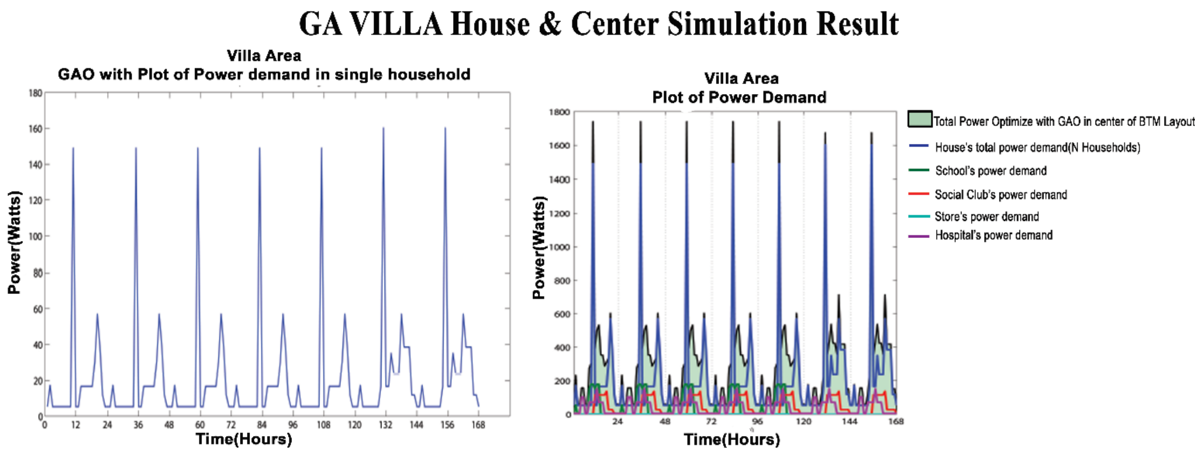


Fig. 4 (c)

The simulation parameters in GA are given below

Number of Variables = 3

Population Size = 10

Initial Population Range = [-1 0; 1 2]

5.2 PSO outcome in all three areas

Figures 5 (a) (b) (c) depicts the MATLAB simulation outcome to the problem mentioned using PSO for a week.

The simulation parameters in PSO are given below

```
w  =  2                          Inertia weight
wMax  = 0.9                      Max inertia weight
wMin  = 0.4                      Min  inertia weight
Vmax  = 6
c1=2   &  c2=2
Velocity=zeros(noP, noV) Velocity vector
Position=zeros(noP, noV)  Position vector
```

Cognitive component

pBestScore=zeros(noP)
pBest=zeros(noP, noV)

Social component

gBestScore=inf
gBest=zeros(1,noV)

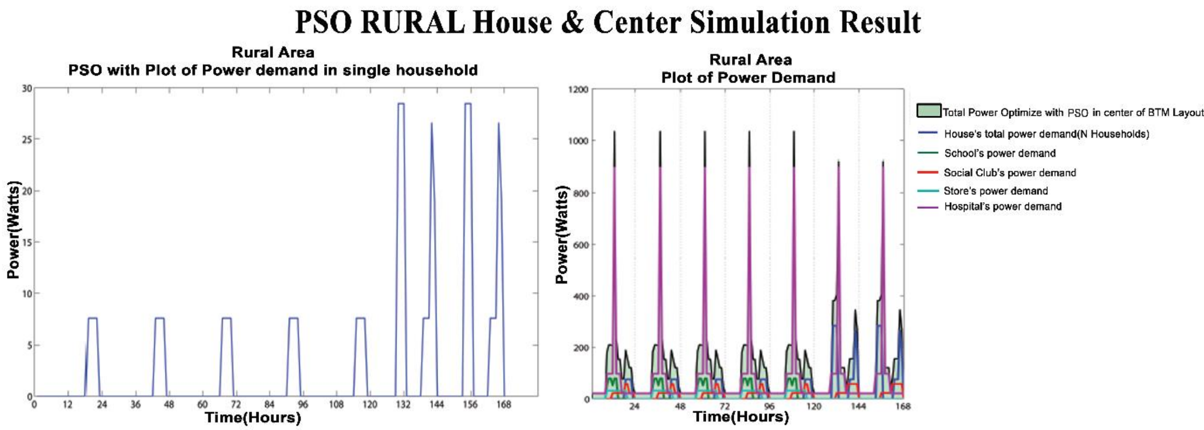


Fig. 5 (a)

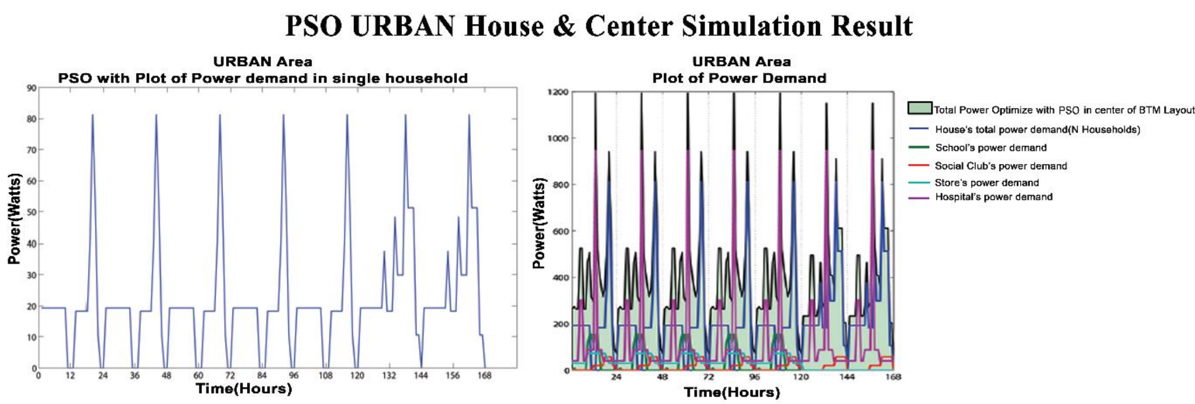


Fig. 5 (b)

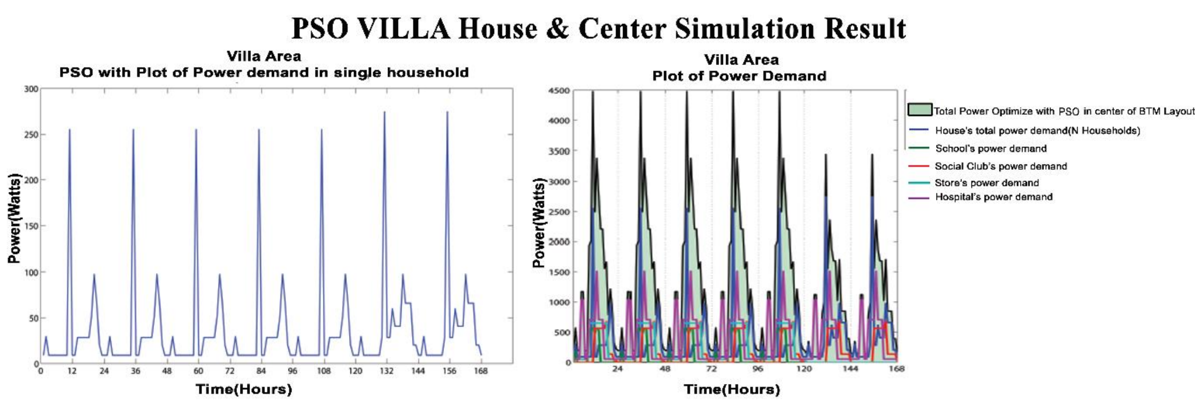


Fig. 5 (c)

5.3 DE outcome in all three areas

Figures 6 (a) (b) (c) depicts the MATLAB simulation outcome to the problem mentioned using DE for a week.

The simulation parameters in DE are given below:

Criteria = 400
D = 32 number of parameters
F = 0.5 DE-step size F ex [0, 2]
CR = 0.4 crossover probability constant
itermax = 400 maximum number of iterations strategy =1 DE/best/1

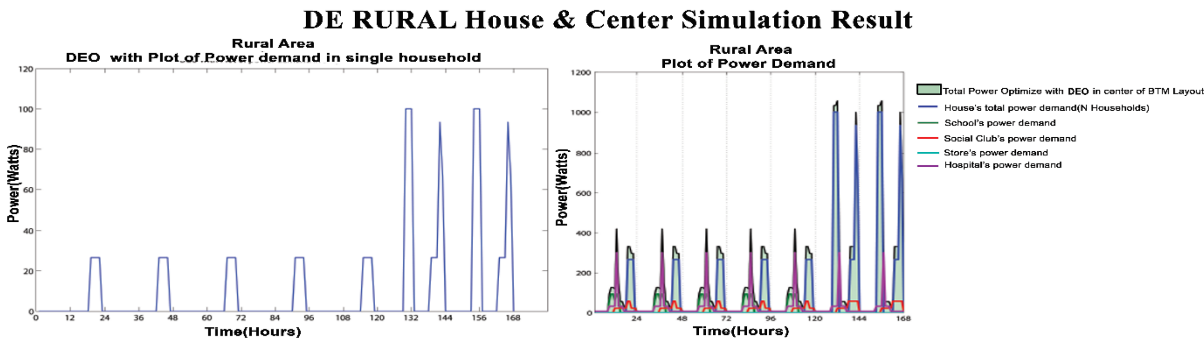


Fig. 6 (a)

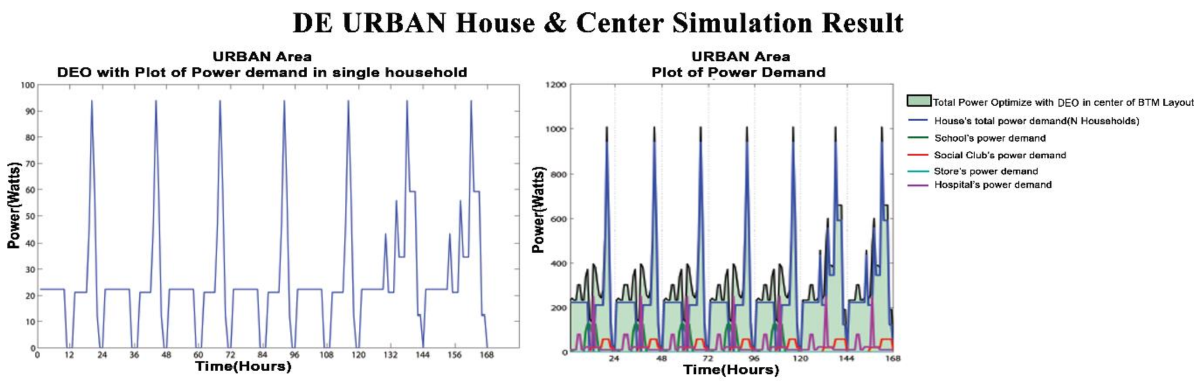


Fig. 6 (b)

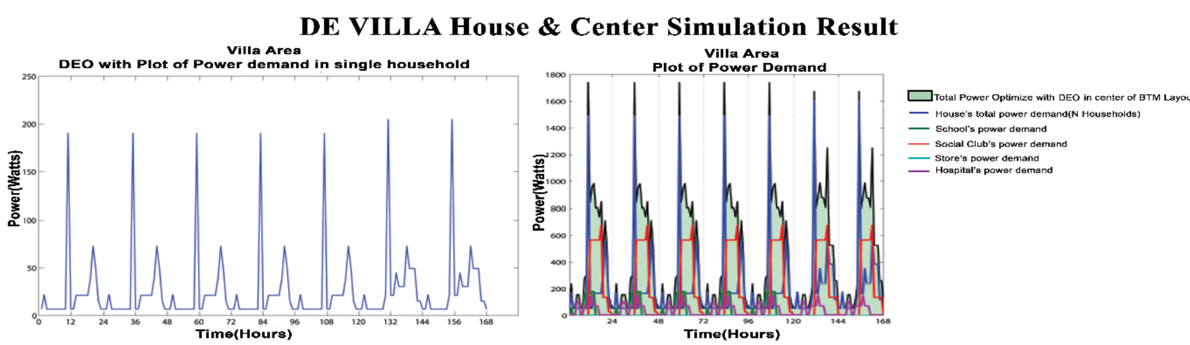
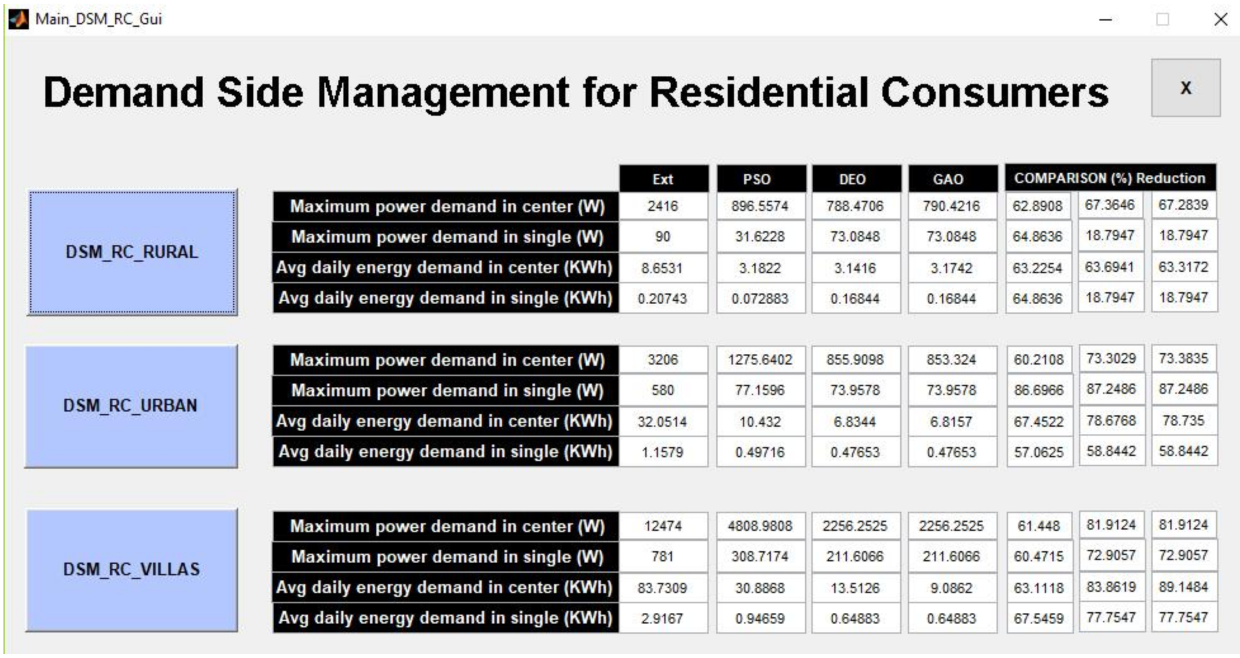


Fig. 6 (c)

The performance evaluation of three algorithms to the problem is compared and a comparison table is given below.


Main_DSM_RC_Gui

Demand Side Management for Residential Consumers

		Ext	PSO	DEO	GAO	COMPARISON (%) Reduction		
DSM_RC_RURAL	Maximum power demand in center (W)	2416	896.5574	788.4706	790.4216	62.8908	67.3646	67.2839
	Maximum power demand in single (W)	90	31.6228	73.0848	73.0848	64.8636	18.7947	18.7947
	Avg daily energy demand in center (KWh)	8.6531	3.1822	3.1416	3.1742	63.2254	63.6941	63.3172
	Avg daily energy demand in single (KWh)	0.20743	0.072883	0.16844	0.16844	64.8636	18.7947	18.7947
DSM_RC_URBAN	Maximum power demand in center (W)	3206	1275.6402	855.9098	853.324	60.2108	73.3029	73.3835
	Maximum power demand in single (W)	580	77.1596	73.9578	73.9578	86.6966	87.2486	87.2486
	Avg daily energy demand in center (KWh)	32.0514	10.432	6.8344	6.8157	67.4522	78.6768	78.735
	Avg daily energy demand in single (KWh)	1.1579	0.49716	0.47653	0.47653	57.0625	58.8442	58.8442
DSM_RC_VILLAS	Maximum power demand in center (W)	12474	4808.9808	2256.2525	2256.2525	61.448	81.9124	81.9124
	Maximum power demand in single (W)	781	308.7174	211.6066	211.6066	60.4715	72.9057	72.9057
	Avg daily energy demand in center (KWh)	83.7309	30.8868	13.5126	9.0862	63.1118	83.8619	89.1484
	Avg daily energy demand in single (KWh)	2.9167	0.94659	0.64883	0.64883	67.5459	77.7547	77.7547

Fig. 7: Simulation Outcomes with Comparison on Three Algorithms

6.0 RESULTS AND DISCUSSIONS

6.1 Rural area outcome

The simulation results are observed and compared. Table 5 shows the comparison effectiveness of all three algorithms which are considered in rural area. The proposed algorithms have effectively reduced the maximum power demand and average daily energy demand in houses and load centres.

The simulation results show that by using PSO algorithm along with DSM reduces maximum power demand in a load centre by 67.1469% and house by 66.7129%. It also shows that an average daily energy demand in a load centre get reduced by 65.8181% and house by 66.7129%.

The results also show that by using DE algorithm along with DSM reduces maximum power demand in a load centre by 58.1544% and house by 65.7781%. It also shows that an average daily energy demand in a load centre get reduced by 58.688% and house by 68.64%.

The simulation also concludes that by using genetic algorithm along with DSM reduces maximum power demand in a load centre by 57.9404% and house by 67.7781%. It also shows that an average daily energy demand in a load centre get reduced by 57.70% and house by 69.96%.

Table :5 Maximum Power Demand & Energy Demand without and with DSM in Rural Area

Without DSM		**With DSM**			**Reduction Percentage**		
DSM in Rural Area		PSO	DEO	GA	PSO	DEO	GA
Max. Power Demand (W) – centre	2416	793.7299	1010.99	1016.1606	67.1469	58.1544	57.9404
Max. Power Demand (W) – house	90	29.9584	30.7997	28.997	66.7129	65.7781	67.7781
Average daily Energy Demand (kwh) – centre	86531w	2958w	3573.9w	366.03w	65.8181	58.68888	57.7002
Average daily Energy Demand (kwh) – house	207.43w	69.047w	65.03w	63.02w	66.7129	68.64	69.96

6.2 Urban area outcome

Table 6 shows the comparison effectiveness of all three algorithms which are considered in an urban area. The proposed algorithms have effectively reduced the maximum power demand and average daily energy demand in houses and load centres.

The simulation results show that by using PSO algorithm along with DSM reduces maximum power demand in a load centre by 66.9652% and house by 84.349%. It also shows that an average daily energy demand in a load centre get reduced by 68.5274% and house by 62.79%.

The results also show that by using DE algorithm along with DSM reduces maximum power demand in a load centre by 73.2041% and house by 86.9287%. It also shows that an average daily energy demand in a load centre get reduced by 78.9732% and house by 68.9288%.

The simulation also concludes that by using genetic algorithm along with DSM reduces maximum power demand in a load centre by 73.3422% and house by 86.9287%. It also shows that an average daily energy demand in a load centre get reduced by 79.073.70% and house by 68.92%.

Table 6: Maximum Power Demand & Energy Demand without and with DSM in Urban Area

Without DSM		With DSM			Reduction Percentage		
DSM in Urban Area		**PSO**	**DEO**	**GA**	**PSO**	**DEO**	**GA**
Max. Power Demand (W) - center	3206	1059.0973	859.0776	854.6482	66.9652	73.2041	73.3422
Max. Power Demand (W) - house	580	90.776	75.8136	75.8136	84.349	86.9287	86.9287
Average daily Energy Demand (kwh) – center	32051.4w	10087.4w	6739.4w	6707.4w	68.5274	78.9732	79.073
Average daily Energy Demand (kwh) – house	1572.1w	584.89w	488.48w	488.48w	62.7967	68.9288	68.9288

6.3 Villa Area

Table 7 shows the comparison effectiveness of all three algorithms which are considered in villa area. The proposed algorithms have effectively reduced the maximum power demand and average daily energy demand in houses and load centres.

The simulation results show that by using PSO algorithm along with DSM reduces maximum power demand in a load centre by 64.118% and house by 66.7129%. It also shows that an average daily energy demand in a load centre get reduced by 65.1467% and house by 72.6702%.

The results also show that by using DE algorithm along with DSM reduces maximum power demand in a load centre by 84.573% and house by 77.4737%. It also shows that an average daily energy demand in a load centre get reduced by 86.7926% and house by 81.5052%.

The simulation also concludes that by using genetic algorithm along with DSM reduces maximum power demand in a load centre by 84.573% and house by 77.4737%. It also shows that an average daily energy demand in a load centre get reduced by 90.3122% and house by 81.505%.

As the number of devices considered is limited, the percentage reduction of power and energy is more and if the algorithm implemented in real time there can be substantial reduction too.

Table 7: Maximum Power Demand & Energy Demand without and with DSM in Villa Area

	Without DSM	**With DSM**			**Reduction Percentage**		
DSM in Villa Area		**PSO**	**DEO**	**GA**	**PSO**	**DEO**	**GA**
Max. Power Demand (W) – centre	12474	4439.2694	1924.3623	1936.23	64.118	84.573	84.573
Max. Power Demand (W) – house	781	259.9725	175.9306	175.9306	66.7129	77.4737	77.4737
Average daily Energy Demand (kwh) – centre	83730.9w	29182.9w	11058.7	8111.7w	65.1467	86.7926	90.3122
Average daily Energy Demand (kwh) – house	2916.7w	797.13w	539.44w	539.44w	72.6702	81.5052	81.5052

7.0 CONCLUSION

The paper proposed three evolutionary algorithms for different areas of load with randomly selected appliances in the view of demand side management in smart grid. The proposed algorithms can effectively reduce the power demand and average energy consumption to the user choice of activation time. Simulation results demonstrated the effectiveness of these evolutionary algorithms with limited appliance connectivity. In future when this DSM technique is extensively available the technique can be further applied with different types of appliances (uncontrollable, controllable and interruptible and controllable and uninterruptible) for all the consumer connected in the grid. With more integration of different loads, the effective implementation of DSM in the grid can be achieved. DSM constantly reduces the average cost of consumers in turn satisfying the global constraints on emissions.

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