

Load Responsive Based Demand Response in Smart Grid Environment using Meta-Heuristic Techniques

Margaret. V, Uma K. Rao

Abstract: Rapid growth of information and communication technology benefits both the consumers and utilities for efficient utilization of the available power. A smarter grid has the potential to make our electricity system more efficient and cleaner. Imbalance in supply and demand can also be effectively taken care with the inclusion of demand response programs such as load based and price based without addition of generation which in turn is a long-term process. If the utilities fail to predict or balance the system during the power deficit it may lead to black outs and disturbs the operation of power grid. At present, in order to obtain the system stability in a short span of periods and to address the variable demand conditions of the consumers the utilities are mainly concentrating on the meta-heuristic algorithms which provides the solutions very quickly and brings the grid into stable condition. The performance of three well recognized population based meta-heuristic algorithms such as GA, ACO and PSO, to solve load management at the consumer level in the smart grid environment were examined in terms of their efficiency, effectiveness and consistency in obtaining the optimal solution.

Index Terms: Load Management, Load Shedding, Smart Grid.

I. INTRODUCTION

Demand response began as an economical approach for utilities to manage things wherever the generation or transmission capacity was not sufficient to service customer loads during peak usage periods (Tariq 2012). Recent advances in information and communication technologies made the two way communication between energy provider and end user lead to greater Demand Response capabilities as discussed by Zahir (1998).

Zhong Fan (2011) proposed load management as sets of objectives which are used to control and change the demand patterns of various consumers connected to the power utility. It is one of the ways for implementing Demand Response. The control and modification of demand patterns will enable the utilities to satisfy the consumer demands at all times in an economic manner. Consumer load management when implemented efficiently can provide benefits which could have resulted from capacity addition. Load management can be achieved in a number of ways like direct intervention of the utility in real time or by introducing special tariffs to influence the consumer behavior. The main benefit of load management is that it can reduce the need for new capacity and can also defer any planned capacity addition aimed to meet the increased demands of the consumers. They also help the utilities to reshape the load curve and reduce the peak demand on the system. By altering the energy use patterns we can

Revised Manuscript Received on July 10, 2019.

Margaret V, Department of Electrical & Electronics Engineering Faculty of Engineering, CHRIST (Deemed to be University) Bengaluru, India.

Uma K Rao, Department of Electrical & Electronics Engineering, RV college of Engineering, Bengaluru, India.

change the demands on the system and also the loading of the distribution system equipment's as proposed by Farookh et al (2013).

Load shedding (Direct Load Control) is a strategy adopted by electric utilities whenever they are faced with an disparity between supply and demand. The situation of generation deficiency can result in the decline of power system frequency. Similarly faults or disturbances can result in voltage instability problems within the power system which requires sudden reduction in load. Load shedding becomes important in this context in order to preserve power system stability as discussed by Amraee (2006).

In the existing grid system, load shedding takes place at the feeder level with the help of "Round Robin" technique. In this method, feeders whose consumption equals the amount of load to be shed are disconnected in a cyclic manner in blocks of an hour or less. It is difficult to shed the exact amount of load to meet the load shedding requirement with this method. A feeder may contain loads belonging to different categories such as industrial, residential, commercial etc. Each of them has a different priority time of usage of power. Since load shedding takes place at the feeder level effective distribution of power to the consumers does not takes place.

When load shedding takes place both the consumers and the utilities suffer from revenue loss. It would be beneficial if power can be supplied to a consumer when he needs it the most as quoted by Peqas (1999).

This paper mainly concentrates on the application of meta heuristic optimization techniques such as Genetic Algorithm (GA), Ant colony optimization (ACO) and Particle Swarm Optimization (PSO) for load management techniques such as Direct Load Control and curtailable load which is one of the demand response program adopted by the utilities at the time of power deficiency or during the peak demand periods. The paper has also introduced the concept of relating load shedding to the grade point of a consumer, at the time of shedding. Loads with least grade points are shed, instead of randomly shedding them. The details are discussed in the following sections.

II. PRIORITIZATION OF LOADS

The different consumers connected to the smart grid are given priority at each time during load management. Grading of loads is a strategy by which we assign priorities to loads belonging to different categories and also those falling under the same category. The idea behind grading is to allocate some values or grade points to loads which indicates the importance of that load in a specified time of the day. With the adoption of such a scheme selective control of loads is possible at the feeder level. Here we consider a sample feeder system of 100 loads belonging to various categories. Loads are graded by considering certain

factors and assigning weightages to those parameters. The factors considered for grading and the weightages allotted to each of them are shown Table 2.1 below:

Table 2.1: Factors considered for grading the loads

Factors	Weightage
Number of units of power consumption	10%
Severity of impact of load shedding	20%
Revenue loss to the end-user	30%
Revenue loss to the utility	30%
Other considerations if any	10%

Any other parameters can be included for grading depending on the requirements of the distribution company. A consumer should be assigned high grade value during his priority time. For example, consumers belonging to residential category should be assigned with high grade points between 6:00 AM – 9:00 AM in the morning and during late evenings as residential consumer uses the power mostly during this time.

Grade points assigned to a load lies in the range of 0-100 and changes at each and every hour of the day depending on its priority time of usage. High values should be assigned to critical loads like hospitals, data centers to signify their importance. Therefore we create a priority table describing the grade points for 100 loads on an hourly basis for a day. This will be taken as an input while running the algorithm. At no point of time is any consumer completely cut off without power. The issue in the approach proposed is to supply each consumer with partial power, to meet atleast the important loads of the consumer. The amount of load to be shed is decided by the grade point of that particular consumer. the different ranges of grade values and load shedding limits for execution of partial load shedding is as shown in Table 2.2.

Table 2.2: Load Shedding Limits

Range	Limits
0-20	70-80%
21-40	60-70%
41-60	40-60%
61-80	20-40%
>80	10-20%

III. META-HEURISTICS TECHNIQUES

Meta-heuristics are problem-independent techniques that can provide solution for a broad range of problems. The main objective function of the algorithms used is to shed partial load to each consumer, based on their grade, so as to reduce the error between the amount of load that needs to be shed and the actual amount of load being shed. The three Meta heuristic algorithms GA, ACO and PSO techniques are used for achieving the objective function.

A. Meta-heuristics Optimization techniques:

Genetic algorithm is the most commonly used optimization techniques for solving both constrained and unconstrained optimization problems. It searches for the global optimum value of the objective function through a search space called ‘population’. ‘population’ constitutes a number of possible

solutions known as individuals and each individual is known as a ‘chromosome’. Initially, a set of chromosomes is randomly generated as initial population. Individuals are ranked based on their fitness and a suitable fitness value is assigned. Depending on the position of the individuals the fitness value is calculated ignoring their distinct performance. Maximum and minimum limits between the fitness values are calculated with fixed incremental steps and assigned to the ranked individuals. In the next step, each individuals are subjected to crossover and mutations and the best solution is obtained.

In 1992, M. Dorigo et al. proposed a meta-heuristic technique known as Ant Colony Optimization which can be applied to any optimization problems. This optimization algorithm is inspired by the real ants behavior on how they forage for food. A finite size colony of artificial ants is created and each ant builds its own possible solution to the problem. Each ant collects and stores information while building its own solution based on the problem characteristics and on its own performance on the pheromone trails. In the whole ant search process the pheromone trails plays the important role of a distributed long term memory. Updation of the pheromone trail is done by the algorithm using all solutions produced by the ant colony at the end of their tour.

Particle Swarm Optimization (PSO) is predicated on the collective behavior of a colony of insects. For example, a bee in a colony or a fish in a school represents the word particle. Random population of particles is generated initially and each particle represents the possible solution of the system. Position, velocity and fitness are the three indicators represented by each particle. At start each particle with random velocity travels dynamically by adjusting the velocity and position through its own experience which is termed as ‘personal best’ and also their neighbor’s termed as ‘global best’. Through continuous learning and updating the entire group of particles will travel in the search region with higher fitness. Until it reaches the maximum iterations or the set minimum fitness, this process will be repeated.

B. Implementation of the algorithm

The algorithm for load shedding is developed based on the following assumptions:

- Utility considered each electrical connection as one lumped load.
- Information regarding the power consumption, voltage, power factor to the control center is sent through the Smart meters installed within the customer premises continuously.
- Loads installed at the consumer site are controlled by the utilities from a remote control center.
- The Load Dispatch Centers communicate with the substations regarding the amount of load that has to be shed in case of power deficit to deal with the situation.
- Substations shed the loads in blocks of 1 hour duration.
- We consider a test system of 100 loads which belongs to different categories and grade them based on their priority. MATLAB R2017a of Mathworks is used to develop the code. Time of day is taken as the input and the corresponding grade points of the loads are extracted from the database. The objective function ‘F’ defined in this algorithm is as follows:



F = Minimization of P_E

Where, P_E is the error in load shedding and is given by,

$$P_E = (\text{Amount of load to be shed } 'P_L') - (\text{Amount of load being shed } 'P_S')$$

IV. RESULTS AND DISCUSSIONS

To test the efficiency of the different algorithms a test system of 100 loads is considered. Based on the real time data obtained from an Indian Substation the test system is generated. The Loads are classified as High Tension (HT) and Low Tension (LT) depending on the voltage levels. For example, in the test systems LT2a1 and LTa2 represents Low Tension loads such as residential loads, educational institution, etc., with maximum power consumption 5 kW. Similarly, HT1 and HT2 represent High Tension commercial and industrial loads.

Table 4.1 gives the information of Power Consumption 'P' assumed for each load at the time of load shedding. Power consumption of each lumped load is given in each column. Based on the tariff the loads are categorized which is proportional to substation data.

Table 4.1: Power Consumption of each load connected to the utility

LT1	LT2a1	LT2a2	LT2b	LT3	LT4	LT5	LT6	LT7	HT1	HT2	HT3				
0.9	1.62	0.04	1.5	0.63	3.89	3.63	13.28	9.61	6.58	74.51	21.16	35.42	56.46	68.26	85.36
0.95	1.5	1.84	0.46	1.62	3.06	4.46	12.4	7.82	13.58	33.01	24.39		79.24	102.36	160.58
	0.24	1.3	0.12	1.58	4.99	3.77	11.96	12.44		72.27	18.54			138.25	
	1.05	1.86	1.53	1.7	2.67	3.56	12.5	13.88		30.82	19.1				
	0.65	0.32	1.34	1.01	3.96	4.58	9.06	6.24		60.77	24.84				
	1.09	1.84	1.43	1.27	3.82	4.02	10.94			65.26					
	0.8	1.58	1.28	1.9	3.16	4.49	10.6			54.03					
	0.83	1.15	0.84	0.88	2.42	4.08	10.24			69.84					
	0.36	0.88	0.78	2.18	2.08		8.2			70.46					
	0.51	0.52	1.63	4.6	3.26		7.98			58.16					

A. Partial load shedding solution using GA, ACO and PSO

The efficiency of the different proposed algorithm is tested for partial load shedding of the test system; power consumption of loads is taken from Table 4.1. The priority time usage for a residential consumer is usually between 6: 00 AM - 9: 00 AM in the morning and during late evenings, whereas industrial and commercial consumer's priority time usage will be during 9: 00 AM to 5: 00 PM and 6: 00 PM to 10: 00 PM respectively. For example, at 7:00 AM the priority is given to residential consumers and at 11: 00 AM industrial consumers will have more priority. The commercial consumers will have more priority between 6:00 PM to 10:00 PM. The grade points assigned for each load depending on the priority time usage lies in the range of 0 - 100 and it varies at each and every hour of the day.

The priority table describing the grading values for each load at 7: 00 AM and 11: 00 AM are as shown in Table 4.2 and 4.3 respectively.

Table 4.2: Grade values of the loads at 7:00 AM

LT1	LT2a1	LT2a2	LT2b	LT3	LT4	LT5	LT6	LT7	HT1	HT2	HT3				
10	19	22	29	24	19	59	52	87	61	66	11	38	67	86	80
10	22	37	32	33	24	55	49	83	31	67	20		39	73	74
	27	22	16	18	13	55	68	77		63	56			76	
	18	31	19	17	19	52	66	34		68	53				
	26	34	12	23	30	51	64	70		66	43				
	23	15	42	21	17	46	50			54					
	32	19	29	31	46	49	68			68					
	22	27	41	28	14	49	60			68					
	27	28	26	19	11		84			63					
	18	23	21	21	32		80			46					

Partial load shedding solution for 'Ps' of 600 kW at 7: 00 AM and 11: 00 AM given by the ACO is as shown in Figure 4.1 and Figure 4.2 respectively.

Table 4.3: Grade values of the loads at 11:00 AM

LT1	LT2a1	LT2a2	LT2b	LT3	LT4	LT5	LT6	LT7	HT1	HT2	HT3				
10	53	49	51	38	50	29	25	53	51	35	11	52	51	83	78
10	40	44	55	57	48	20	28	58	49	35	20		65	73	73
	56	46	50	52	60	24	35	52		36	27			75	
	40	52	53	51	55	29	39	52		48	45				
	45	46	53	57	60	15	33	44		31	45				
	49	48	22	50	47	27	32			36					
	58	57	19	51	41	28	33			43					
	45	47	31	58	11	29	45			31					
	49	47	13	47	25		53			26					
	49	51	26	57	38		54			67					

From the solution obtained we can know that no load is completely shed and also minimum amount of load is available to all the connected loads depending on the grading values at that particular time. During morning the higher priority is given to domestic consumers and from the figures we can know that this requirement is met and at 11: 00 AM the industrial and commercial loads along with the critical loads have been given priority which is as shown in figures.

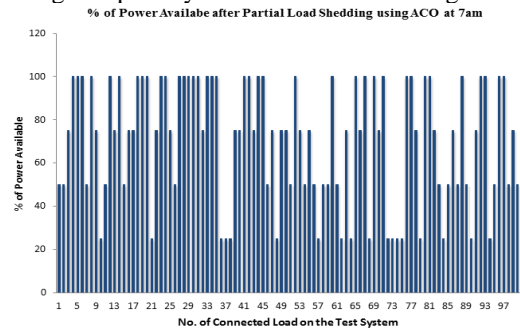


Figure 4.1: P_S for 600 kW at 7:00 AM using ACO

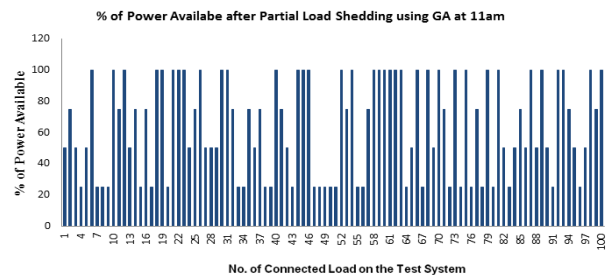


Figure 4.2: P_S for 600 kW at 11:00 AM using ACO

Similarly, the partial load solutions given by the GA and PSO at 7: 00 AM and 11: 00 AM are depicted in Figure 4.3, Figure 4.4, Figure 4.5 and Figure 4.6 respectively.

The results shows that the consumers load is being partially shed based on the priority time usage and also we can observe that the no load is completely shed a partial amount of power is supplied to each consumers.

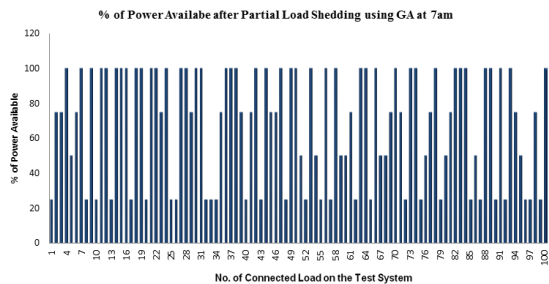


Figure 4.3: PS for 600 kW at 7:00 AM using GA

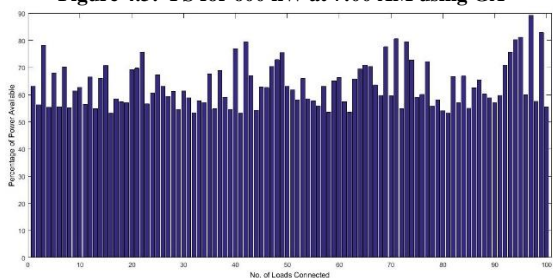


Figure 4.4: PS for 600 kW at 11:00 AM using GA

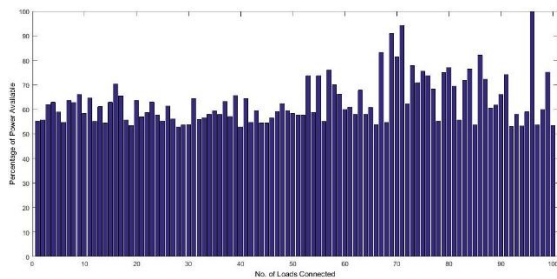


Figure 4.5: PS for 600 kW at 7:00 AM using PSO

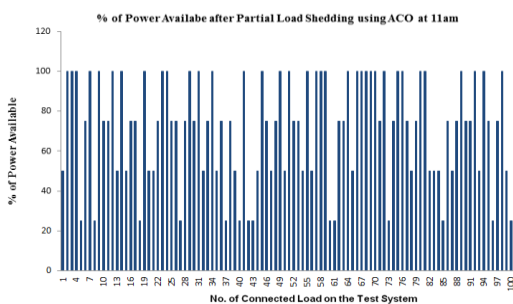


Figure 4.6: PS for 600 kW at 11:00 AM using PSO

Solutions show that the loads are given priority based on the grade points and each consumer is given a partial load instead of shedding the complete load. For partial load shedding the loads which are having the minimum grade values at the time of the load shedding is considered. From this, it can be seen that the proposed algorithm optimizes load shedding based on priority assigned to each load. The algorithms are also capable of handling the dynamic constraints assigned.

B. Different load shedding requirement at same time of the day using GA, ACO and PSO

Main objective of proposed partial load shedding is to provide ensure that no consumer is fully shed and a small amount of power is always available to satisfy their basic demands. In this section, partial load shedding using GA, ACO and PSO for different load shedding requirements are considered. As the priority for residential loads and industrial loads are mostly during the morning and in the forenoon here we consider the load shedding at 7: 00 AM and 11: 00 AM for testing algorithm efficiency in minimizing the load shedding error. Based on the priority time usage of each consumer the proposed algorithm computes the grade points and partial amount of power is being shed. In the Table 4.4 and Table 4.5, load shedding error and the % error partial load shedding 'P_E' for different load shedding requirements at 7: 00 AM and 11: 00 AM using ACO, GA and PSO are shown in detail.

Table 4.4: Comparison of % P_E of a consumer at 7: 00 AM using ACO, GA and PSO

Sl. No.	Amount of Load to be Shed in kW	Error in Partial Load Shedding in kW at 7 am using ACO	% Error in Partial Load Shedding at 7 am using ACO	Error in Partial Load Shedding in kW at 7 am using GA	% Error in Partial Load Shedding at 7 am using GA	Error in Partial Load Shedding in kW at 7 am using PSO	% Error in Partial Load Shedding at 7 am using PSO
1	100	5.2225	5.2225	2.7881	2.7881	16.907	16.907
2	200	18.1175	9.05875	0.1309	0.06545	20.9009	10.45045
3	300	0.345	0.115	2.458	0.819333333	16.8517	5.617233
4	400	0.5525	0.138125	1.5059	0.376475	3.9212	0.9803
5	500	0.0225	0.0045	0.2639	0.05278	0.7302	0.14604
6	600	0.5425	0.090417	5.4181	0.903016667	0.162	0.027
7	700	1.6925	0.241786	1.301	0.185857143	0.2005	0.028643
8	800	1.9325	0.241563	10.7088	1.3386	0.1558	0.019475
9	900	4.43	0.492222	0.6026	0.066955556	0.0269	0.002989
10	1000	0.37	0.037	158.8622	15.88622	0.4956	0.04956
11	1100	51.545	4.685909	284.3379	25.8489	0.0417	0.003791
12	1200	87.3075	7.275625	535.7789	44.64824167	102.7656	8.5638

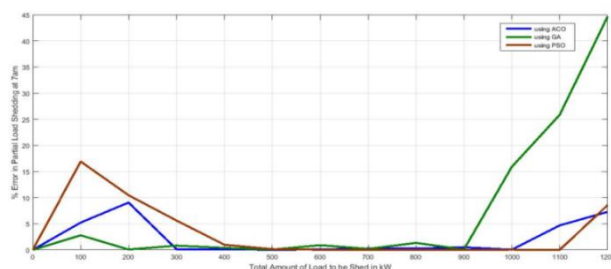


Figure 4.7: Comparison of % P_E of a consumer at 7: 00 AM using ACO, GA and PSO

Table 4.5: Comparison of % P_E of a consumer at 11: 00 AM using ACO, GA and PSO

Sl. No.	Amount of Load to be Shed in kW	Error in Partial Load Shedding in kW at 11 am using ACO	% Error in Partial Load Shedding at 11 am using ACO	Error in Partial Load Shedding in kW at 11 am using GA	% Error in Partial Load Shedding at 11 am using GA	Error in Partial Load Shedding in kW at 11 am using PSO	% Error in Partial Load Shedding at 11 am using PSO
1	100	1.945	11.50411	0.3251	0.3251	18.8758	18.8758
2	200	1.85	17.70259	2.219	1.1095	29.5934	14.7967
3	300	0.5175	9.21272	0.4489	0.149633	31.525	10.50833
4	400	2.205	224.9311	1.6967	0.424175	10.1152	2.5288
5	500	0.1975	135.2369	1.7679	0.35358	4.751	0.9502
6	600	0.5325	1972.222	2.9361	0.48935	1.5074	0.251233
7	700	0.635	2216.958	1.9202	0.274314	0.4804	0.068629
8	800	1.035	5314.506	0.87	0.10875	0.1592	0.0199
9	900	2.7325	91421.93	0.8846	0.098289	0.1816	0.020178
10	1000	1.695	3420.097	126.3477	12.63477	0.2314	0.02314
11	1100	34.92	921151.1	264.3393	24.03085	0.0847	0.0077
12	1200	87.3075	1019.495	384.3668	32.03057	132.7249	11.06041



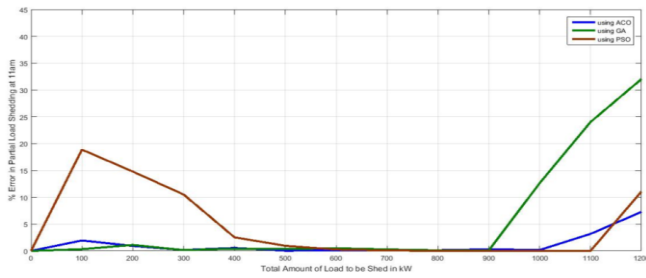


Figure 4.8: Comparison of % P_E of a consumer at 11: 00 AM using ACO, GA and PSO

The result shows that the % P_E is around 20% when the load required to be shed is less than 10% of the total load connected and the % P_E is less than 1% when the load shedding requirement is in the range of 20% to 60% of the total load connected. The comparative performance of the three algorithms at 7: 00 AM and 11: 00 AM is depicted in Figure 4.7 and figure 4.8. From this, it can be observed that PSO gives the best results when the amount of load to be shed is more than 300 kW and using GA algorithm the best results can be obtained when the amount of load to be shed is lesser than 300 kW. Using PSO algorithm the % P_E is close to zero when required amount of load to be shed is the range of 20% to 60% of the total load connected.

The advantages of partial load shedding when compared to completer shedding of consumer is greater flexibility in controlling the consumer load and reduced impact of load shedding. Further, it also reduces revenue loss to the utility, by ensuring that there is no under shedding or over shedding.

V. CONCLUSIONS

In smart grid environment, the Meta heuristic techniques applied for intelligent load shedding gives a distinctive opportunity to treat an individual load as single lumped load and tries to decrease the effect of load shedding to the feasible extent by taking into account of priority time usage of each load and the grade points assigned to each load. This new approach of intelligent load shedding can be applied to the substation with large number of loads connected more efficiently. With respect to efficiency, GA is the fastest among the three algorithms to find the optimum result, followed by PSO and then by ACO. In terms of minimization of load shedding error PSO yields the best result compared with GA and ACO.

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AUTHORS PROFILE



Dr. Vijaya Margaret presently working as Assistant professor in the Department of Electrical & Electronics Engineering, Faculty of Engineering, CHRIST (Deemed to be University). Received the B.E. degree in electrical engineering from the Bangalore University, Bangalore, Karnataka, India, in 2003, M.Tech. in Computer Applications in Industrial Drives from the National Institute of Engineering (VTU), Mysore, Karnataka, India, in

2006 and Ph.D. degrees in electrical engineering from, CHRIST (Deemed to be University) Bangalore, Karnataka, India, in 2018. Current research interests include power systems, smart grid, demand response and power quality.



Dr. Uma K Rao, presently working as Professor in the Department of Electrical & Electronics Engineering, RV College of Engineering, Bangalore, India. PhD in Power Engineering from Indian Institute of Science. More than 30 years of UG and PG teaching experience in Electrical, Electronics and Management. Current research interests include power systems, renewable energy,

smart grid, demand response and power quality.