Optimal Load Control for Social Welfare Maximization in a Smart Distribution System using ATLBO Algorithm

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Distribution utilities incur heavy penalties when the grid utilization exceeds the permitted demand levels. This is in turn translates into higher tariffs and customer bills, reduced customer satisfaction and adverse impacts on social welfare. To achieve energy balance, load shedding becomes inevitable under circumstances when the demand on grid exceeds permitted levels. The advent of smart distribution systems has made possible accurate, distributed load control approach instead of bulk load shedding. Small amounts of acceptable load sheds than larger tariffs improve household social welfare in poorer economies. In this paper a novel load control approach has been proposed using the recent variant of Teaching Learning Based Optimization (TLBO) algorithm, called Adaptive Inertia Weight Teaching-Learning-Based Optimization (ATLBO) which uses an adaptive inertia weight strategy. The method has been tested on the IEEE 33 bus test system and has yielded exceptional results in terms of energy balance, reduced losses and reduced penalties for power overdraw from grid. Penalties to be paid by utilities can percolate into increased energy costs for the customers, affecting social welfare. The performance of the approach has been compared with the performance of PSO, CSA and basic TLBO in finding efficient solutions to the load control problem.

Keywords: Energy Balance, Load Control, Smart Grid, Social Welfare, ATLBO.

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1 Introduction

Deficiencies in generation can lead to drop in power system frequency and voltage collapse. Load shedding becomes the only feasible solution in such emergency situations. Conventional load shedding strategies involved the shedding of pre-decided bulk loads when the system passed through decided frequency thresholds. This leads to excess or lesser load sheds. As distribution systems became smarter, the possibility to shed optimally calculated loads at optimal locations became a possibility. With restructuring initiations in the power industry [1], customer participation in demand side management [2] and demand side programs [3], load shedding, without compromising customer satisfaction became relevant. Demand for power varies based on hour of the day, season, changes in climate, and a host of other factors. Utilities deal with changed demands in different ways. During peak periods, utilities may use peaker plants which are carbon intensive and expensive to install and operate. But with the large acceptance of demand side management and the implementation of smart grids, utilities are now better able to manage the short term energy situation crisis without compromising on the reliability expectations of customers. This requires the calculation of optimal amounts of load shed and the best locations for load shed ensuring voltage stability and frequency stability of the system. The emergence of smart grids has given rise to selective and accurate load sheds. Accurate and selective load sheds makes feasible brown outs instead of black outs. Distribution companies (DisCos) purchase power from system operators and are liable to pay penalty if the demand exceeds the contracted power. This in turn percolates to higher customer bills, and customer dissatisfaction. With selective sheds DisCos can curtail less priority loads during peak demand periods if the demand exceeds the contracted demand from grid.

Towards determination of optimal amounts and locations of load sheds, Meta heuristic algorithms have found wide acceptance in literature. The study in [4] demonstrates the use of GA in minimizing the sum of curtailed load and losses to determine optimal load shed. This was demonstrated by the authors with and without the use of Distributed Generation sources (DGs) in the system. GA has also been used in [5] to implement a load shedding method to provide voltage stability with and without DG when demand exceeds generation. Application of Bacterial Foraging Algorithm optimization application to determine the best load shedding method with the goal of minimizing total power losses, voltage stability index value, and total load shed cost can be seen in [6]. The authors in [7] have used an optimal load shedding algorithm which was implemented in two parts. The first part identifies the buses for load shed based on the sensitivity of minimum eigenvalues of load flow Jacobian with respect to load shed. The second part determines the amount of load shed using differential evolution. In [8] an optimal load shedding scheme has been proposed to balance the electricity demand and the generated power of DGs with a hybrid of Firefly algorithm and PSO. Artificial Bee Colony (ABC) algorithm is applied to a renewable energy populated islanded micro grid in [9]. Load shedding considering priorities for loads aimed to minimize the square of difference between available power and demand has been proposed in [10]. Though many solutions with heuristic algorithms have been proposed in literature, the research field is still open to try recent and more efficient algorithms to the problem for efficient solutions. The Teaching Learning Optimization (TLBO) algorithm was introduced by Rao et al in [11]. The algorithm's computational ease stems from the fact that it does not depend on the tuning of any algorithm specific parameters unlike the swam based and evolutionary algorithms. TLBO has been competently used in solving power system problems [12]. Many improved versions of TLBO have been proposed and a comprehensive survey of the different variants can be found in [13]. The Adaptive Inertia Weight TLBO (ATLBO) introduces adaptive exponential distribution inertia weight for updating the position vector (AEDIW) and has shown its superiority over other existing inertia weight basic TLBO variants [14].

This paper proposes a novel method using ATLBO algorithm to determine accurate load shedding amounts and locations to nullify grid imposed penalties for peak load demands exceeding contracted demands from grid. The method is based on ATLBO algorithm and backward forward load flow method [15].

2 Problem Formulation

The primary objective of any type of power system is to obtain energy equilibrium at all times. By load shedding the utilities strive to achieve this objective. Therefore the objective function is formulated as in (1)

$$OF = min[P_G - \{(1-\beta_i) \times P_{di}\} + P_{loss}] \quad (1)$$

where, P_G is the contracted power from the grid by the utility, β_i is the fraction of load shed at every bus, P_{di} is the peak load at each bus and P_{loss} is the total distribution loss in the system.

2.1 Constraints

The voltage and current should be maintained within limits as given by (2) and (3). The permitted demand level from the grid at each hour is limited by β_i as in (4).

$$|V_{i,min}| < |V_i| < |V_{i,max}| \qquad \forall\{i = 1,2, \dots n_b\} \quad (2)$$

$$I_{j,min} < I_j < I_{j,max} \forall_j \{j = 1,2, \dots n_{br}\} \quad (3)$$

$$\beta_i < \beta_{i,max} \forall_i \{i = 1,2, \dots n_b\} \quad (4)$$

3 Adaptive Inertia Weight Teaching Learning Based Optimization (ATLBO) Algorithm

ATLBO is a recent variant of the TLBO algorithm. A description of basic TLBO is given in this session along with the improvement in ATLBO.

3.1 TLBO Algorithm

TLBO algorithm which was introduced by Rao et al in 2011 has the advantage of the non usage of any algorithm specific parameters unlike in the case of popular swarm based and evolutionary algorithms. Low computational burden and less memory rate are also plus points of the basic TLBO algorithm. Students learn in the TLBO algorithm in two ways: (i) from an instructor and (ii) from their classmates. The first mode is known as the teacher phase, while the second is known as the learner phase, and they both replicate the optimization process' exploration and exploitation stages respectively. In the teacher phase the teacher is considered as the best learner and tries to bring the learner's performance to match his performance using (5).

$$X'_{j,k} = X_{j,k} + r_i(X_{j,kbest} - T_F M_j) \quad (5)$$

where, $X'_{j,k}$ is modified student performance , T_F is teaching factor and r_i is a random number between 0 and 1 and M_j, the mean value. In the learner phase peer learning is encouraged to increase learner's knowledge using (6) and (7).

$$X'_{j,m} = X_{j,m} + r_i(X_{j,m} - X_{j,n}) \quad (6)$$

if m th learner's performance is better than n th learner's performance, else if n th learner's performance is better than m th learner's performance

$$X'_{j,n} = X_{j,n} + r_i(X_{j,n} - X_{j,m}) \tag{7}$$

TLBO has been successfully used to solve optimization problems [16]. But every optimization algorithm is open to scope for improvement and inertia has been found to be a crucial measure to control the exploration and exploitation by preserving a balance in their capabilities. ATLBO uses an adaptive inertia weight strategy. It monitors the search situation and adapts the inertia weight value based on one or more feedback parameters. The three aspects introduced in ATLBO are chaos-based initialization, new inertia weight strategy and position-updating equation.

3.2 ATLBO Algorithm

The computational efficiency of any heuristic algorithm is mainly dependent on generation of its initial population and it plays a key role in ATLBO also. Logistic-map, a chaos based method, is employed for initialization of random population, because it can map the present population value at any time step to its value at the next time step. It is given by the equation as in (8).

$$x_{t+1} = r.x_t(1 - x_t) \tag{8}$$

where x_t denotes the t^{th} chaotic variable, generated for a set of specific periodic static points (0, 0.25, 0.5, 0.75 and 1); r represents the growth rate or bifurcation coefficient by a fixed continuous set of 4. The adaptive exponential distribution inertia weight (AEDIW) is suggested to improve the efficiency of solution and convergence rate. Equations (9) to (11) represent the inertia weight calculation.

$$\omega = -\rho_1 e^{-\rho\lambda} + \rho_2 e^{\rho\lambda},\ L_b < U_b \tag{9}$$

$$\rho_1 = \omega_2 e^{-\lambda} + \omega_1 e^{\lambda} \tag{10}$$

$$\rho_2 = -\omega_1 e^{2\lambda} + \omega_2 \tag{11}$$

where ω_1 and ω_2 are positive real numbers. In contrast to simple TLBO, this inertia weight is employed to update the position of all students at once, and so equation (5) is modified as in (12). The value of ρ is the parameter of the distribution in TLBO algorithm in the range of [L_b,U_b] for each learner.

$$X'_{j,k} = \omega \times X_{j,k} + r_i(X_{j,kbest} - T_F M_j) \tag{12}$$

The steps involved in ATLBO algorithm has been represented using a flowchart in Fig. 1.

4 Results and Discussions

The proposed approach has been tested on IEEE 33 bus system with a total connected load of 3715 kW + j 2300 kVAR. The contingency considered here is the overload situation where the system draws more than the contracted power from the grid. The hourly contracted demand from grid is represented as a fraction of the total connected load in Fig 2. The distribution system's net effective demand on the main grid, including losses, is calculated as (3925.99 kW + j 2443.03 kVAR), and it is used as the peak demand (load + losses) in further calculations. Total distribution losses are (210.998 + j 143.033) kW, with bus-18 experiencing the lowest voltage magnitude of 0.9038 per unit (pu). The results have been presented without and with implementation of load control. Without load control the system draws more power than permitted level from the grid. With the hourly permitted level as in Fig. 3, the additional power from grid has been calculated as the difference between hourly permitted and the actual power drawn from grid (ie, permitted demand plus losses). The mismatch in the case without optimal load control (OLC) amounts to the losses and is negative since the drawn power is greater than the sanctioned power. Fig 4 represents this. With OLC it has been possible to reduce this error to a negligible value. The mismatch with OLC is represented in Fig. 5.

The penalty prices are assumed as 0.25 $/h for hours 0 to 8, 0.5 $/h for hours 9 to16, and 0.75 $/h for hours 17 to 23, respectively. The hourly penalty to be paid by the DisCo for additional power drawn from grid is presented in Fig 5.With OLC, this penalty has been nullified. The total load curtailment in kW with implementation of OLC is as in Fig 6. The maximum load shed happens for the peak hours 18 th and 19 th hour. The load shed at each bus is represented during these hours in Fig 7. The maximum load shed happens at bus no. 24 and 25. The amount of load shed is distributed across the feeders instead of bulk load sheds and any excess or less load sheds are avoided. By optimal load control shedding at each bus, the load demand is made as close as possible to the available demand. This shows the effectiveness of the ATLBO method. The active and reactive power demand on the grid before and after implementing load control and comparison with the contracted demand is presented in Fig. 8 and Fig. 9. With load shed the losses reduce which contributes to reduction in power drawn from the grid. The losses are shown in Fig. 10. The voltage profile is maintained with the minimum voltage above 0.9 pu as in Fig. 11.

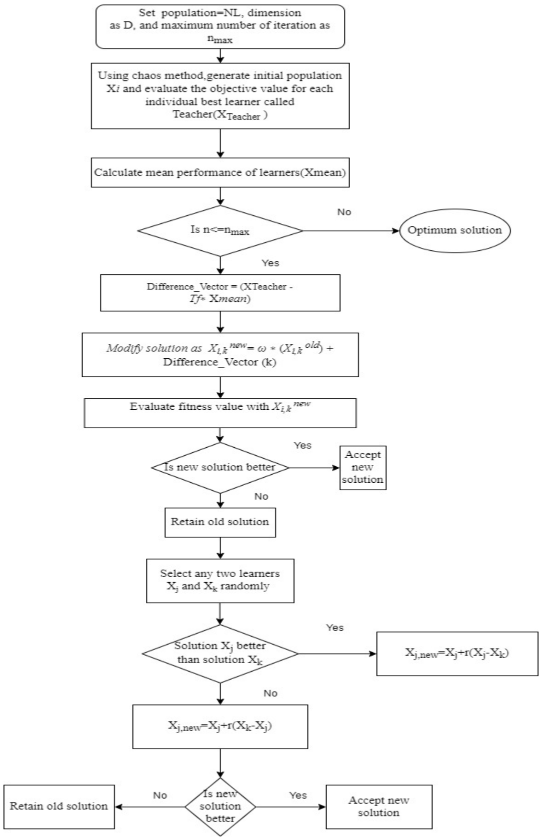

Fig. 1. Flowchart of ATLBO Algorithm

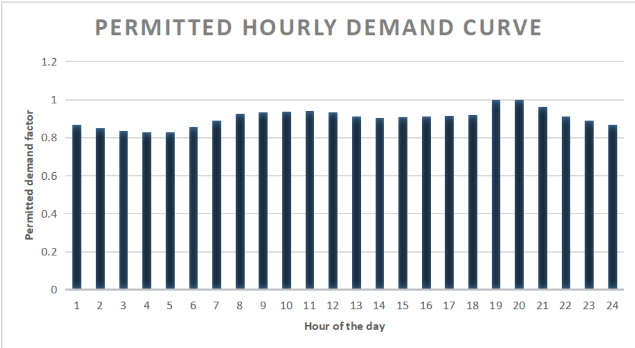

Fig. 2. Hourly permitted demand from grid

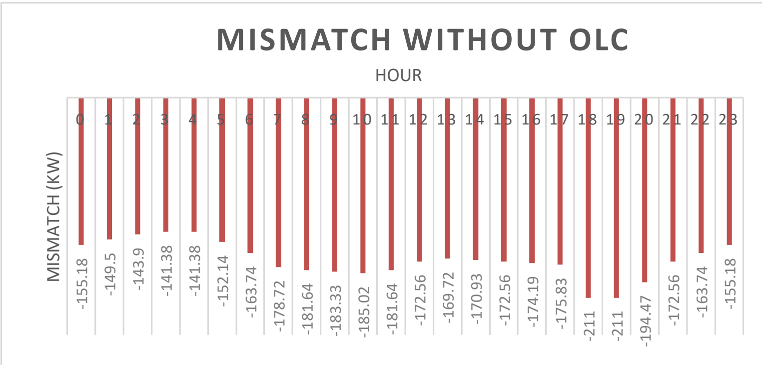

Fig 3. Power mismatch without load control

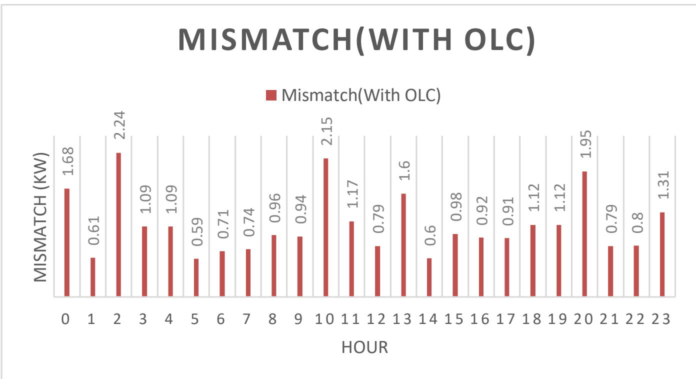

Fig.4. Power Mismatch with Load Control

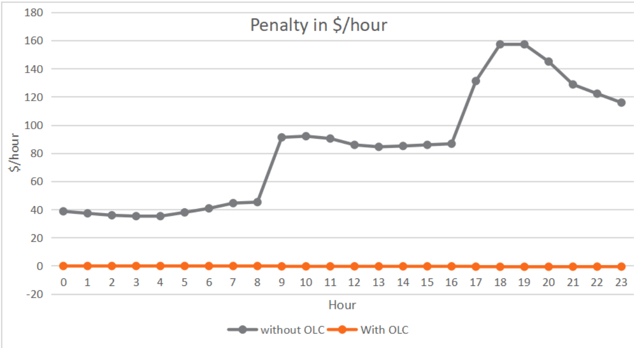

Fig. 5. Penalty to be paid by the distribution utility with and without OLC

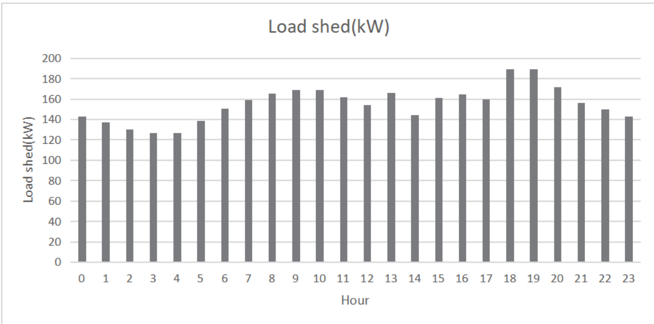

Fig. 6. Hourly load shed (kW) with OLC

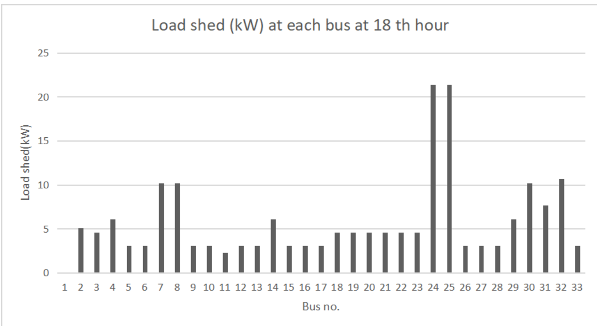

Fig. 7. Peak hour load shed (kW)

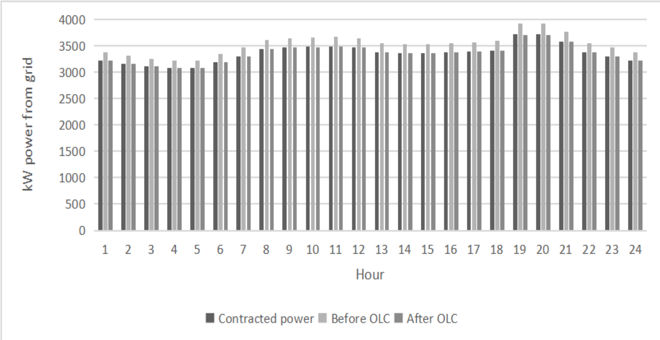

Fig. 8. Active Power (kW) demand from grid

As a comparative performance analysis with other algorithms, the performance of ATLBO is compared with Particle Swarm Optimization (PSO), Butterfly Optimization Algorithm (BOA) and basic TLBO. The control parameters for the ATLBO algorithm have been detailed in [14]. The control parameters for the compared algorithms are as listed in [16]. For the comparison, a permitted power demand factor of 0.85 is chosen. The results obtained by different algorithms are given in Table 1. The results show the superior performance of ATLBO with least mismatch.

Table 1. Comparative performance with other algorithms

Method	**Mismatch(kW)**	**Power drawn from grid(kW)**	**Power drawn from grid(kVar)**	**Loss-es(kW)**	**V_{min} (pu)@ bus 18**
Before OLC	-148.75	3306.5	3157.75	148.75	0.9193
PSO	0.6	3157.15	3024.77	132.38	0.9239
BOA	0.24	3157.51	3019.94	137.57	0.9227
TLBO	0.21	3157.54	3020.67	136.87	0.9228
ATLBO	0.16	3157.59	3021.91	135.68	0.9226

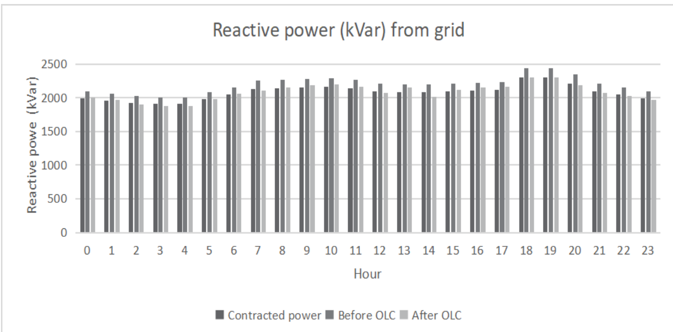

Fig 9. Reactive Power (kVar) Demand from grid

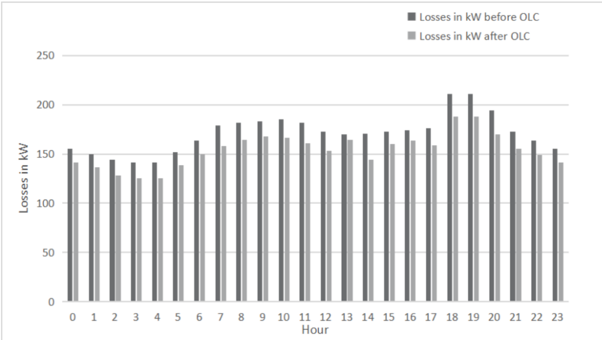

Fig. 10. System losses (kW) before and after OLC implementation

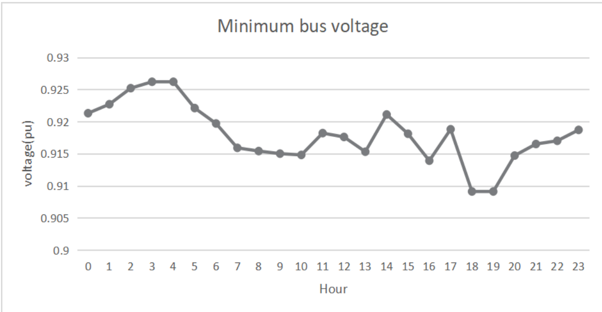

Fig.11. Bus Voltage profile with OLC

5 Conclusion

In this study, a novel optimization approach for achieving energy balance in a distribution system has been proposed using the ATLBO algorithm, which uses an adaptive exponential distribution inertia weight (AEDIW)for updating the position vector towards achieving global optima. The method has been able to nullify penalties to be paid by the distribution utilities for exceeding permitted power utilization from the grid. Simulations run on the IEEE 33 bus test system has produced excellent results in achieving the energy balance when load demand exceeds sanctioned demands. The results have achieved zero penalties which otherwise would have percolated to the customers bills reducing customer satisfaction and adversely affecting social welfare. The effectiveness of ATLBO has been compared with PSO, CSA and basic TLBO for solving the energy balance problem and the finding demonstrates the superior performance of ATLBO.

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