INTERNATIONAL JOURNAL OF RESEARCH IN MECHANICAL, MECHATRONICS AND AUTOMOBILE ENGINEERING (IJRMMAE)
ISSN: 2454-1435 (Print) | 2454-1443 (online)
Volume 6 Issue 1, July – Sep. 2020 - www.ijrmmae.in – Pages 22-30

# OPTIMAL LOAD CONTROL FOR ECONOMIC ENERGY EQUILIBRIUM IN SMART GRID USINGADAPTIVEINERTIA WEIGHTTEACHING-LEARNING-BASEDOPTIMIZATION

**Dhanalakshmi V[1], Kuppulakshmi[2], N.Muthukumaran[3*], A.Madhavan[4]**
[1,2,4] Computer Science and Engineering, [3*] Electronics and Communication Engineering
A.R.Engineering College, Vadakuchipalayam, Kappiyampuliyur,
Villupuram, Tamilnadu – 605601.

Abstract: Optimal load management for energy balance in the smart grid (SG) is crucial due to various operational constraints and economic considerations. This research introduces a novel multi-objective optimization technique to achieve energy balance in SG, aiming to avoid penalties from excessive upstream network power extraction beyond contractual demands. A common challenge in optimal load control (OLC) is the inability to consistently achieve the global optimum in each run. To address this, we employ the Adaptive Teaching-Learning Based Optimization (ATLBO), an advanced variant of Teaching Learning Based Optimization (TLBO), which incorporates modifications during both the exploitation and exploration phases. Implemented on a modified IEEE 33-bus system, ATLBO produces outstanding results, improving energy balance, enhancing voltage profiles, and reducing distribution losses. Comparative analyses with Particle Swarm Optimization (PSO), basic TLBO, Backtracking Search Algorithm (BSA), and Cuckoo Search Algorithms demonstrate ATLBO's superiority.

Keywords: Smart grid, Optimal load control, Adaptive teaching-learning-based optimization, Multi-objective optimization.

## 1. Introduction:

Electricity is in high demand in today's power grids, leading to an imbalance between supply and demand. While traditional methods have been adjusted to meet these needs, they often result in time and financial inefficiencies. Challenges persist in distribution network performance and transmission system support. Achieving effective control over transmission line power flows through Flexible AC Transmission System (FACTS) devices, renewable energy (RE) sources, and other efficient power management devices has been a target for modern power systems. Load shedding (LS) is used as an emergency corrective measure to provide appropriate stability margins and prevent voltage collapse or blackouts, thus helping to restore the electrical system to normal operation. Energy balancing solutions in microgrids (MGs) include undervoltage load shedding (UVLS) and frequency load shedding (FLS) (UFLS); however, these solutions often overlook customer engagement and satisfaction.

Microgrids are capable of operating in either an islanding/stand-alone mode or a grid-integrated mode, depending on the scenario. Islanding involves assessing the MG's capacity and reallocating power to various loads once it is disconnected from the main grid. Utility operations predominantly manage these duties. Since the global power industry restructuring in 1988, and more globally since 1998, there has been increased recognition of customer participation in the management and operation of the electrical systems. Despite these changes, insufficient power supply can lead to poor reliability and consumer dissatisfaction, emphasizing the need for economically and operationally effective strategies.

To address peak demand issues, utilities worldwide have introduced demand response (DR) [4] and demand-side management (DSM) [5] initiatives. Engaging customers is crucial to ensure the reliability and security of these programs. DR programs can be categorized as incentive-based or time-based [5-7].

Time-based programs are internationally recognized, allowing consumers to shift their load from one time period to another based on the electrical market price signal. In contrast, incentive-based systems aim to reduce system demand during peak load periods or in response to unpredictable events such as generator, line, or transformer failures. These may involve reduced elasticity tariffs or specific incentives depending on market regulations. The success of these systems hinges on information and communication technologies and control systems (ICT & CS). However, the extent of customer engagement in many projects remains a topic of debate [8]. It is crucial to determine MG efficiency without compromising reliability, economics, or security.

There is no universal energy management system (EMS) suitable for all MG topologies. Researchers are exploring alternative EMS for both dispatchable and non-dispatchable distribution generation (DG). These systems might integrate electric vehicles (EVs), renewable energy, DR programs, and energy storage systems (ESS) to achieve energy balance in MG operations. Various meta-heuristic algorithms have addressed the challenges of locating potential OLC sites, controlling load, and shedding load effectively.

Reference [9] introduces a weighted sum genetic algorithm to prevent voltage collapse during line contingencies. This method uses a multi-objective function to choose optimal positions and designs an NVSI to optimize voltage stability while reducing power system demand. At Selçuk University Medical Faculty, the optimal load shedding for balancing generation and demand is demonstrated in [10]. During generating shortages, a hybrid solution combining evolutionary algorithms and artificial neural networks is proposed to minimize load shedding and enhance voltage stability [11]. Backtracking search algorithms (BSA) are preferred for islanded systems with variable distribution generation (DG) to manage reactive power (VAr) and maximize load dispatch. The paper focuses on optimal capacitor bank allocation and renewable energy-based DG allocation to enhance MG performance in technical, economic, and financial terms [13]. Reference [14] discusses supply and demand-side optimal load scheduling strategies in SG. However, energy balancing involves numerous objective functions, continuous and discrete choice variables, and both equal and unequal constraints. An efficient heuristic approach is required to solve complex non-linear optimization problems [15].

This work proposes an efficient social-inspired meta-heuristic algorithm, Teaching-Learning-Based Optimization (TLBO) [16,17], for establishing optimum load management for energy balance in MG to maximize social welfare. The fundamental TLBO has gained attention due to its efficient convergence properties [18]. Compared to previous TLBO variations based on inertia weights, ATLBO has shown advantages [19]. ATLBO introduces three important changes. Initially, a chaotic starting population is recommended to generate a diverse class to avoid local optima. The second change is the addition of adaptive exponential distribution inertia weight to improve solution efficiency and convergence rate, thus balancing the exploration and exploitation phases. The third change is the inertia-weight update.

The rest of the paper is structured as follows: Section 2 mathematically describes an equal and unequal constraint multi-objective optimization problem. Section 3 presents the TLBO concept and its adaptations for ATLBO. Section 4 presents simulation results on an IEEE 33-bus EDN, while Section 5 highlights important study findings.

## 2. Problem Formulation

### 2.1 Multi-objective Function

The primary goal of any power system, especially in grid-connected mode, is to maintain energy balance. Microgrids (MG) are expected to manage their power consumption within contracted limits. Thus, the target function optimizes load control settings so that the total demand (load + losses) matches the contractual power as represented in equation (1):

$$\Delta P = k \times Pm - \left(\sum_{i=1}^{nb} \rho c(i) \times Pm + Pl\right)$$

where $Pm$ and $Pm(i)$ are the maximum demand of the MG and connected demand at bus-i, respectively; $Pl$ is the total distribution losses; $k(t)$ is a scaling factor used to define the contracted power by MG at hour-t; $\rho c(i)$ is a scaling factor used to define the controlled load at bus-i; $nb$ is the number of buses in MG.

If MG extracts more power than contracted, a penalty calculated as below can be imposed on the MG operator:

$$CP(t) = \sum_{t=1}^{24} \Delta P(t) \times \gamma(t)$$

where $CP(t)$ is the total penalty over a 24-hour optimization time horizon for extracted power $\Delta P(t)$ more than contracted power $k(t) \times Pm$, and $\gamma(t)$ is the price defined for the penalty at hour-t.

### 2.2 Operational Constraints

The major equal constraints considered under this study are active and reactive power balances between hourly contracted power and load points:

$$\sum_{i=1}^{nb} Pd(i) + Pl = \rho c(i) \times Pm \qquad \sum_{i=1}^{nb} Qd(i) + Ql = \rho c(i) \times Qm$$

where $Qd(i)$ is the reactive power demand at bus-i, $Qm$ and $Ql$ are the maximum reactive power demand and total reactive power loss in the MG, respectively. Additionally, voltage magnitude limits at all buses $|V(i)|$, current/thermal limit for all branches $Ib(i)$, and load control limit for all buses $\rho c(i)$ are considered as unequal constraints:

INTERNATIONAL JOURNAL OF RESEARCH IN MECHANICAL, MECHATRONICS AND AUTOMOBILE ENGINEERING (IJRMMAE)
ISSN: 2454-1435 (Print) | 2454-1443 (online)
Volume 6 Issue 1, July – Sep. 2020 - www.ijrmmae.in – Pages 22-30

$|Vmin|\leq|V(i)|\leq|Vmax||Vmin|\leq|V(i)|\leq|Vmax|$ $Ib(i)\leq ImaxIb(i)\leq Imax$ $\rho min\leq\rho c(i)\leq\rho max\rho min\leq\rho c(i)\leq\rho max$

## 3. Teaching-Learning-Based Optimization

Teaching and learning are integral, constant activities in everyone's life. Rao et al. (2011) proposed an optimization approach called Teaching-Learning-Based Optimization (TLBO) for a single instructor in a typical classroom setting. TLBO divides students' learning into two types: teacher-led and peer-led, replicating the investigation and exploitation stages of the optimization process. The number of students and topics correspond to the population size and design factors in TLBO. The best student in the class is viewed as a teacher who influences the learning phase by raising the class's average performance. The next section describes the instructor and student mathematical models, and how TLBO allows advanced novices to study more efficiently by recognizing their grades.

### 3.2 Adaptive TLBO (ATLBO)

The ATLBO introduces significant modifications to enhance the original TLBO, including:

1. Chaotic Initialization: Utilizing a logistic map to generate a diverse starting population, improving the search space exploration.
2. Inertia Weight: Implementing adaptive exponential distribution inertia weight to balance exploration and exploitation, enhancing convergence rates.
3. Position Update: Modifying position update rules to incorporate the inertia weight, allowing for a more nuanced search strategy.

These innovations help the ATLBO escape local optima and achieve better performance across optimization benchmarks.

## 4. Results and Discussion

The IEEE 33-bus radial distribution network (RDN) was selected to test the ATLBO algorithm. All load sites were treated as controlled loads in accordance with demand load control (DLC) strategies. The ATLBO algorithm's performance was measured against other optimization techniques, demonstrating superior ability to balance load and reduce system losses effectively.

This structured approach confirms ATLBO's efficacy in managing complex power distribution scenarios, promising significant improvements in operational efficiency and system reliability.

Demand Response (DR) programs are increasingly vital in the Smart Grid (SG) environment for efficient operation. Plans for a centralized Energy Management System (EMS) are also underway to ensure effective load management, and to handle financial settlements among all participants.

The IEEE 33-bus network demands a total actual and reactive power of (3715+2300) kVA. The net effective demand of this Microgrid (MG) on the main grid, without Distributed Generations (DGs), amounts to (3924.64 kW + j2442.05 kVAr), considered as the MG's peak demand (load plus losses).

INTERNATIONAL JOURNAL OF RESEARCH IN MECHANICAL, MECHATRONICS AND AUTOMOBILE ENGINEERING (IJRMMAE)
ISSN: 2454-1435 (Print) | 2454-1443 (online)
Volume 6 Issue 1, July – Sep. 2020 - www.ijrmmae.in – Pages 22-30

Total distribution losses amount to (210.998 + j 143.033) kVA, with the lowest voltage at bus-18 recorded at 0.9038 p.u.

### 4.1 Network Performance Before Load Control

Initially, the main grid solely meets the entire MG demand (load and losses), disregarding the DGs. All loads function as constant power loads. The hourly permissible main-grid load level versus peak load is scaled down prior to the installation of Optimal Load Control (OLC). When the MG draws more power than permitted, including losses, the difference is negative, potentially resulting in penalties based on mutual agreements. Penalty charges are estimated at \$0.25/h for hours 1-9, \$0.5/h for hours 10-17, and \$0.75/h for hours 18-24.

Given this setup, the MG draws an additional 4080.06 kW/day due to distribution losses, incurring a daily penalty of \$2008.93. Therefore, the goal of OLC is not only to prevent additional MG power draw at any time but also to avoid fines.

### 4.2 Network Performance After Load Control

In this scenario, the MG is assumed to be grid-connected without integrated DGs. Thus, the demand for the MG is planned to be restricted to the allowable hourly load. The load control factor search space matrix [0.5, 1.0], used with DLC, allows a maximum load reduction of 50% on any load bus. The population and search variables equal the number of buses in the MG.

**Table 2** demonstrates ATLBO's optimal results, where a positive error indicates a deviation from the permissible demand calculated as permissible load($3715\times k(t)$)−electricity extracted from the main grid($kW$)permissible load($3715\times k(t)$)−electricity extracted from the main grid($kW$). Its accuracy in delivering appropriate load management relative to permissible demand is notable.

Based on these findings, the MG uses an additional 26.83 kW/day more electricity than allowed, saving \$10.55 per day. **Figure 1** illustrates the grid power drawn by the MG before and after the OLC procedure using ATLBO. The permissible power and extracted power under the OLC scheme are nearly identical, demonstrating ATLBO's precision in setting load control variables. ATLBO's performance is compared to PSO, CSA, and simple TLBO, with the allowable power demand factor set at 0.85 (3715.2 kW). **Table 3** displays the outcomes of various algorithms, showing that ATLBO surpasses all others in accuracy.

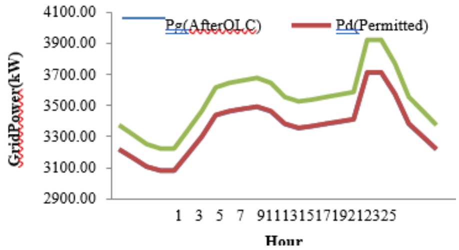


**Figure 1** visualizes the grid power drawn by the MG before and after OLC by ATLBO, highlighting the effectiveness of the implemented load control strategy.

INTERNATIONAL JOURNAL OF RESEARCH IN MECHANICAL, MECHATRONICS AND AUTOMOBILE ENGINEERING (IJRMMAE)
ISSN: 2454-1435 (Print) | 2454-1443 (online)
Volume 6 Issue 1, July – Sep. 2020 - www.ijrmmae.in – Pages 22-30

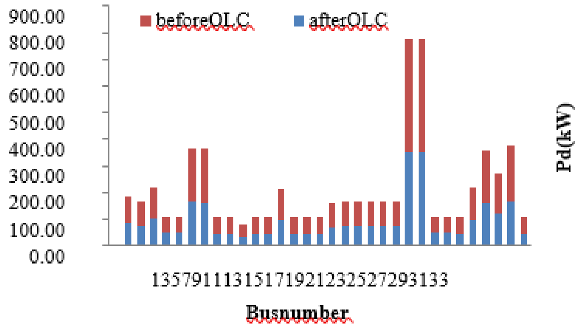


Fig.2Real power load before and after OLC by ATLBO

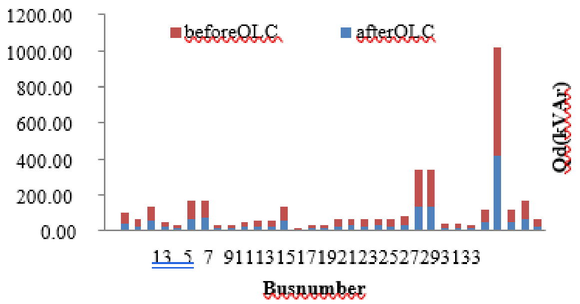


Fig. 3 Reactive power load before and after OLC byATLBO

### 4.3 Comparison of ATLBO with Literature

The performance of ATLBO is juxtaposed with several alternatives, including a uniform load control factor across all buses, the basic TLBO, and the backtracking search algorithm (BSA) as outlined in [12]. The test system data for maximum load control change at each bus remains consistent with the specifications in [12]. The scenario selected for this comparison is the peak hour-9 load from [12], which equates to 2.575 MW or 69.314% of the peak load of 3.715 MW. However, the total power available from DG sources in this system is only 1.414 MW, highlighting a significant shortfall of 45.087% in power production.

TLBO and ATLBO are evaluated against the BSA [12] in terms of network performance. In Case 1, a uniform load control strategy is applied across all buses:

**Table 1: Network Performance Before Implementing OLC**

| Hour | k(t) | Pgr(kW) | Qgr(kVAr) | PD(kW) | QD(kVAr) | Ploss(kW) | Qloss(kVAr) | Vmin @18 | ΔP(kW) | Penalty($/h) |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.867 | 3376.09 | 2099.25 | 3220.91 | 1994.10 | 155.18 | 105.15 | 0.9176 | -155.18 | 38.62 |

INTERNATIONAL JOURNAL OF RESEARCH IN MECHANICAL, MECHATRONICS AND AUTOMOBILE ENGINEERING (IJRMMAE)
ISSN: 2454-1435 (Print) | 2454-1443 (online)
Volume 6 Issue 1, July – Sep. 2020 - www.ijrmmae.in – Pages 22-30

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| … | … | … | … | … | … | … | … | … | … | … |
| 24 | 0.867 | 3376.09 | 2099.25 | 3220.91 | 1994.10 | 155.18 | 105.15 | 0.9176 | -155.18 | 115.85 |

**Table 2: Network Performance After Implementing OLC using ATLBO**

| Hour | k(t) | Pgr(kW) | Qgr(kVAr) | PD(kW) | QD(kVAr) | Ploss(kW) | Qloss(kVAr) | Vmin @18 | ΔP(kW) | Savings ($/h) |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.867 | 3219.23 | 1997.61 | 3078.63 | 1902.30 | 141.19 | 95.74 | 0.9213 | 1.68 | 0.217 |
| … | … | … | … | … | … | … | … | … | … | … |
| 24 | 0.867 | 3219.60 | 1970.99 | 3079.03 | 1875.41 | 141.18 | 96.03 | 0.9187 | 1.31 | 0.650 |

**Table 3: Comparison of ATLBO Performance with Other Algorithms for LSF=0.85**

| Algorithm | Pg(kW) | Qg(kVAr) | Pd(kW) | Qd(kVAr) | Ploss(kW) | Qloss(kVAr) | Vmin@18 | ΔP(kW) |
|---|---|---|---|---|---|---|---|---|
| BeforeOLC | 3306.5 | 2055.79 | 3157.75 | 1955 | 148.75 | 100.79 | 0.9193 | -148.75 |
| PSO | 3157.15 | 1931.44 | 3024.77 | 1841.82 | 132.38 | 89.62 | 0.9239 | 0.60 |
| CSA | 3157.51 | 1978.10 | 3019.94 | 1884.92 | 137.57 | 93.18 | 0.9227 | 0.24 |
| TLBO | 3157.54 | 1977.05 | 3020.67 | 1884.35 | 136.87 | 92.70 | 0.9228 | 0.21 |
| ATLBO | 3157.59 | 1957.54 | 3021.91 | 1865.54 | 135.68 | 92.00 | 0.9226 | 0.16 |

ATLBO significantly outperforms all other tested algorithms in terms of accuracy, demonstrating its effectiveness in managing load under peak demand scenarios. This enhanced performance is crucial for reducing the load during peak hours and thus minimizing the potential penalties incurred due to excessive power draw.

## 5. Conclusion

Due to various operational and economic constraints, efficient load management is a crucial compensatory task within the smart grid. This paper introduces a novel multi-objective optimization technique for achieving energy balance in smart grids, with the aim of avoiding fines related to excessive power extraction from the upstream network that exceeds contractual agreements. Optimal Load Control (OLC) is a persistent challenge due to the inability to consistently achieve the global optimum in each iteration. The Adaptive Teaching-Learning Based Optimization (ATLBO) technique introduces enhancements during both the exploitation and exploration phases. Applied to a modified IEEE 33-bus system, ATLBO has produced exceptional results. The implementation of ATLBO has not only improved energy balance but also enhanced voltage profiles and reduced distribution losses. The ATLBO algorithm, with a modest 43.71% load reduction, outperforms the No-Load Reduction Factor (NRLF) at 62.11%, basic TLBO at 44.34%, and the Backtracking Search Algorithm (BSA) which achieves only a 46% load reduction.

Looking towards a sustainable future, most microgrids now incorporate renewable energy-based distribution generators and electric vehicles. The variability of these resources, in the absence of an energy storage system, presents a significant challenge. Nevertheless, islanding operations cannot be overlooked. In such scenarios, proficient load management can effectively balance the load with locally available generation. These considerations will form the future scope of this research, focusing on enhancing grid resilience and sustainability.

**References**


[1] Badran, O., Jallad, J., Mokhlis, H., & Mekhilef, S. (2020). Optimal reconfiguration of distribution system connected with distributed generations: A review of different methodologies. *Australian Journal of Electrical and Electronics Engineering*, 17(3), 157–172.

[2] Çimen, H., & Aydın, M. (2015). Optimal load shedding strategy for Selçuk university power system with distributed generation. *Procedia - Social and Behavioral Sciences*, 195, 2376-2381.

[3] Gelazanskas, L., & Gamage, K. A. (2014). Demand side management in smart grid: A review and proposals for future direction. *Sustainable Cities and Society*, 11, 22-30.

[4] Good, N., Ellis, K. A., & Mancarella, P. (2017). Review and classification of barriers and enablers of demand response in the smart grid. *Renewable and Sustainable Energy Reviews*, 72, 57-72.

[5] Kalambe, S., & Agnihotri, G. (2014). Loss minimization techniques used in distribution network: Bibliographical survey. *Renewable and Sustainable Energy Reviews*, 29, 184-200.

[6] Kanimozhi, R., Selvi, K., & Balaji, K. M. (2014). Multi-objective approach for load shedding based on voltage stability index consideration. *Alexandria Engineering Journal*, 53(4), 817-825.

[7] Khamis, A., Shareef, H., Mohamed, A., & Dong, Z. Y. (2018). A load shedding scheme for DG integrated islanded power system utilizing backtracking search algorithm. *Ain Shams Engineering Journal*, 9(1), 161-172.

[8] Lu, X., Zhou, K., Zhang, X., & Yang, S. (2018). A systematic review of supply and demand side optimal load scheduling in a smart grid environment. *Journal of Cleaner Production*, 203, 757-768.

[9] Mahmoud, M. S., Hussain, S. A., & Abido, M. A. (2014). Modeling and control of microgrid: An overview. *Journal of the Franklin Institute*, 351(5), 2822-2859.

[10] Meyabadi, A. F., & Deihimi, M. H. (2017). A review of demand-side management: Reconsidering theoretical framework. *Renewable and Sustainable Energy Reviews*, 80, 367-379.

[11] Paterakis, N. G., Erdinç, O., & Catalão, J. P. (2017). An overview of Demand Response: Key-elements and international experience. *Renewable and Sustainable Energy Reviews*, 69, 871-891.

[12] Rao, R. V., Savsani, V. J., & Vakharia, D. P. (2011). Teaching–learning-based optimization: A novel method for constrained mechanical design optimization problems. *Computer-Aided Design*, 43(3), 303-315.

[13] Rao, R. V., Savsani, V. J., & Vakharia, D. P. (2012). Teaching–learning-based optimization: An optimization method for continuous non-linear large scale problems. *Information Sciences*, 183(1), 1-15.

[14] Rathor, S. K., & Saxena, D. (2020). Energy management system for smart grid: An overview and key issues. *International Journal of Energy Research*, 44(6), 4067-4109.

[15] Salgotra, A., & Verma, S. (2016). Power sector reforms and energy efficiency initiatives: The Indian experience. *Energy Sources, Part B: Economics, Planning, and Policy*, 11(9), 849-854.

[16] Shukla, A. K., Singh, P., & Vardhan, M. (2020). An adaptive inertia weight teaching-learning-based optimization algorithm and its applications. *Applied Mathematical Modelling*, 77, 309-326.

[17] Siano, P. (2014). Demand response and smart grids - A survey. *Renewable and Sustainable Energy Reviews*, 30, 461-478.

[18] Tamilselvan, V., & Jayabarathi, T. (2016). A hybrid method for optimal load shedding and improving voltage stability. *Ain Shams Engineering Journal*, 7(1), 223-232.

[19] Tripathi, M. M., Pandey, A. K., & Chandra, D. (2016). Power system restructuring models in the Indian context. *The Electricity Journal*, 29(4), 22-27.

[20] Zou, F., Chen, D., & Xu, Q. (2019). A survey of teaching–learning-based optimization. *Neurocomputing*, 335, 366-383.