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MICROGRID BSS SCHEDULING USING TEACHING LEARNING BASED OPTIMIZATION ALGORITHM

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ABSTRACT

Energy storage serves as a crucial hub for the entire grid, supplementing resources such as wind, solar, and hydropower, as well as nuclear and fossil fuels, demand side resources, and system efficiency assets. It can function as a generation, transmission, or distribution asset — all in one unit. Storage is, in the end, an enabling technology. It has the potential to save consumers money while also improving reliability and resilience, integrating power sources, and reducing environmental impacts.

Battery storage system design is now important for microgrids to prepare a day-ahead schedule for steady operation. This article discusses the scheduling of BSS, which helps to reduce the average cost imposed on microgrid consumers in the context of dynamic pricing. For minimizing, a cost function is created and subjected to optimization based on the restrictions. The search space magnification is $50*(D_C - D_D + 1)$*, where* D_C *and* D_D *are the maximum charge and discharge depths in an hour in percentage for a specific BSS, respectively. The programming is done by combining daily load, generated energy, and grid price forecasts with a microgrid size as specified in the article and implementing Teaching Learning Based Optimization (TLBO) for achieving an average cost reduction when compared to Net Power Based Algorithm and Particle Swarm Optimization for a planned BSS.*

KEYWORDS: *Important for Microgrids, Implementing Teaching Learning Based Optimization (TLBO)*

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INTRODUCTION

An algorithmic approach for the Optimization of Day-Ahead Energy Storage System Scheduling in Microgrid problem by using Genetic Algorithm and Particle Swarm Optimization. Both GA and PSO fared well compared to the Net Power Based Algorithm[1].

A grid is a system for transferring electricity from sources to consumers. With the aid of contemporary smart technologies, traditional power grids, which can only transport energy in one direction, from producer to consumer, are rapidly developing into a two-way power flow system [2]. A smart grid is a bi-directional energy transmission and data communication network that is smart and dispersed [3]. The smart grid is expected to develop as a result of the plug-and-play integration of smart microgrids [4].

A microgrid is like a mini version of a power grid [5]. According to the US Department of Energy, a microgrid is a collection of interconnected loads and distributed energy resources that operate as a single regulated body in respect to the grid within correctly established electrical limitations [6].

When technical or economic conditions warrant it, a microgrid is a distributed group of energy resources and loads that is mainly associated to and synchronized with the conventional broad range synchronous grid (macro-grid), but can unplug from the interconnected grid and execute autonomously in island mode. By transitioning between island and connected modes, microgrids improve supply security within the microgrid unit and can offer backup energy. An off-grid microgrid, also known as an autonomous, stand-alone, or solitary microgrid, is another use.

Battery storage systems (BSSs) play an important and diversified function in microgrids. A voltage source is required to synchronize solar PV and other renewable distributed generation (DG) systems. Customarily, a backup generator has been used for this. An BSS, on the other hand, provides an equivalent energy supply without the pollution that a diesel generator produces.

BSSs are commonly used to store and utilize electricity generated at various periods. A important concern is that a BSS in a microgrid deteriorates with time due to frequent charging/discharging cycles [7].

To prolong the length of life of a BSS, a microgrid may undertake the following actions:

Optimal SoC

As per traditional power storage standards, Li-ion batteries are most useful between 10-20% and 80-90% State of Charge (SoC). Excessive or insufficient use of these restrictions may decrease the battery's life cycle and reduce energy production.

Depth of Charging / Discharging Limit

The Depth of Charge/Discharge is a proportion of the battery's total capability that reflects the amount of electricity that is cycled in and out of the battery in a particular time interval. Most batteries have a physical limit on how many times they can charge and discharge in a particular length of time.

However, to improve battery life, it is recommended that you keep well below this number. For example, a battery's maximum depth of discharge for one hour may be 30 percent. Any discharge level that is higher than this may harm the battery.

Dynamic energy pricing is developing traction as a way to promote peak shaving and load levelling by charging premium rates amid periods of high demand, incentivizing consumers to reduce their consumption and changing the load curve. Lowering peak demand and levelling demand profiles benefits producers since it decreases overall plant and capital costs [3]. TOU pricing is a kind of dynamic pricing in which the cost of an electrical unit is influenced by the time of day.

Consumers are likely to devise ingenious ways to take advantage of changing tariffs [8]. One such technique is to use the BSS to store electricity while the tariff is low and then use the energy when the tariff is higher. Efficient BSS schedule, or choosing when the BSS charges or discharges, is required for this. Moving particular loads to a various time points during the day, typically when the grid cost is lowest, is another way to capitalize from dynamic pricing. Load shifting is a demand response strategy that has been explored in numerous papers [9]-[11].This, like the preceding approach, is a tough optimization problem. Consider a typical microgrid model that is coupled to a classic one-way-power grid or classic grid. This is connected to a BSS for the purpose of studying the model.

In this article, the first problem will be acknowledged: optimizing the BSS schedule in a microgrid with dynamic pricing in order to minimize the overall cost charged by consumers. We utilized TLBO [12] to optimize a day-ahead BSS schedule in a microgrid connected to a conventional one-way-power-flow grid with dynamic pricing. A day-ahead hourly load, generated electricity, and grid price forecast are required for this optimization problem. Despite the reality that load and generation energy forecasting is a difficult problem [14], numerous studies have given a variety of strategies for predicting with reasonable accuracy [15]-[18].

Problem Formulation

An objective function is developed and bounds are provided in this work. We use greedy selection to discover the most optimal solution to our optimization issue.

Consider a micro-grid comprised of a diverse array of solar panels, wind turbines, and (if necessary) additional energy generators. The micro-grid also has an unified BSS with capacity CBSS (in kWh). The microgrid is linked to a normal one-way-power-flow grid (called Utility). The microgrid is subjected to hourly dynamic power pricing by the traditional grid (also known as the main grid). The load in a micro-grid is the sum of all the loads in the micro-grid. In order to decrease the cost paid by micro-grid customers, we optimize the BSS charge/discharge schedule for a single day divided into distinct intervals of time.

Let X_t indicate the microgrid's cumulative load (in kWh), G_t represent the non-conventional energy produced by the microgrid (in kWh), and Ah denote the unit price for power generation pulled from the power grid (in cents/kWh) even during hourly interval h where $1 \leq t \leq 24$.

Let D_C be the greatest depth of charge achieved by the BSS in one interval. Set D_D to the maximum depth of discharge in the same way. Then we construct a battery schedule vector as follows. A battery planned vector is a 24-dimensional real-valued vector [S1, S2,...,S24] that represents the day-ahead planning of a microgrid battery. Each S_t indicates the depth of charging/discharging in the hour period h and must adhere to the restrictions.

$$S_t \in \begin{cases} \left[\max\left(-1 * \frac{(X_t - G_h)}{C_{BSS}} * 100, D_D\right), D_C\right] X_t > G_t \\ [0, D_C] X_t \leq G_t \end{cases} \tag{1}$$

$$10 \leq \sum_{t=1}^{n} S_t \leq 90 \; \forall \, n \in [1,24] \tag{2}$$

The limitation in Equation 1 ensures that the cell does not discharge much beyond $|D_D|$ percent and does not charge much more than $|D_C|$ percent in an hour. The types of batteries used determine the D_D and D_C values. It also protects the battery from being discharged if the quantity of power generated is more than the load required. The limitation in Equation 2 ensures that the battery's SoC does not fall below 10% or climb over 90% to maintain an optimal state of charge. To determine the costs associated with a battery scheduling vector, we first create the power consumption vector.

Each E_{ct} in an energy consumption vector, which is a 24-dimensional valued vector [E_{c1}, E_{c2},........,E_{c24}], represents the amount of energy taken by the microgrid from the grid system (in kWh). Eh comes from the following sources:

$$E_{ct} = max(X_{ct} - G_t + (0.01 * C_{BSS} * S_t), 0) \tag{3}$$

Using Equation 3, the whole input or outflow of energy from the batteries during the time t is approximated by $0.01*C_{BSS}*S_t$ (depending on the value of S_t). When $X_t > G_t$, $X_t - G_t$ represents the remaining energy required to fully power the load, or the additional energy left (possibly to charge the battery) after G_t has been used to power the load (when $X_t < G_t$).

Because we assume that electricity only flows into the grid and not out of it, the'max' ensures that E_{ct} does not go below zero (when X_t>$G_t$and the battery is unable to entirely conserve the surplus power due to the constraints in Equations 1 and 2).

Minimizing the consumer's total cost, TC, which is the total of the product of E_{ct} and the unit electricity prices during period t, A_t, over all intervals, becomes the optimization problem.

$$minimize\ TC = \sum_{t=1}^{24} E_{ct} * A_t \tag{4}$$

The problem's search space has now been specified. It's worth mentioning that we're expecting that charging and discharging depths advance or decrease in 0.01 increments. In our example, the BSS's SoC can range from 30% to 30%.01 percent, but there is no number in between. In the real world, changes in the SoC of batteries have corresponding minimal step values. This is referenced to as the charging/discharging minimum depth.

The search space is specified as a set of all 24-dimensional vectors, such as TC = [S1; S2,......, S24], where S_t is a real integer in the range [D_D, D_C], and D_D and D_C, respectively, represent the highest depth of discharging and charging in an hour period.

The price of any random search element, such as TC = [S_1, S_2,......, S_{24}], is defined as Cost(TC).

$$Cost(TC) = \begin{cases} \sum_{i=1}^{24} E_i * A_i\ If\ U\ satisfies\ constraints\ in\ eq.(1)\ and\ (2) \\ \infty\ Otherwise \end{cases} \tag{5}$$

DESCRIPTION OF TLBO ALGORITHM

We discovered that all evolutionary and swarm intelligence-based optimization approaches are probabilistic, with similar controlling parameters such as population count, number of generations, elite size, and so on,[12]. In addition to these common elements, each algorithm has its own set of controlling parameters. The TLBO simply requires common regulating parameters, and as a result, it has attracted the attention and acceptance of the research community.

The TLBO algorithm is a teaching-learning approach that is derived from the phenomena of the teacher's influence on the learners' results. It represents two phases for the purpose of learning:

- From the teacher (called as teacher phase)
- From the interacting of learners with another learners (called learner phase)

The learning set is considered as a population in this approach, and non-identical subjects provided to learners are treated as divergent design factors for the optimization, and the learner's output is regarded as the issue's 'fitness value' [12].

The best solution obtained from the entire population is referred to as a teacher. The variables of design are those that are incorporated in an objective function in order to arrive at the best solution, which is the best value obtained from the objective function. This is a simple method that creates the simulation process's class room process. It frequently necessitates common control parameters rather than algorithm-specific control criteria [12]. [13] is the enhanced version of TLBO. This approach does not require gradient information or an error function. The major benefit of TLBO is that it does not need any parameter tweaking. The artistic depiction of the procedure is represented in Figure 1.

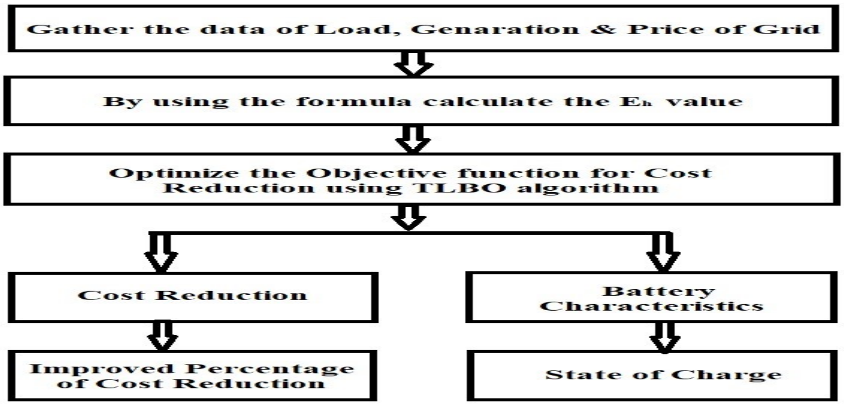

Figure 1: Schematic Diagram Depicting the Order of Proposed Methodology

CASE STUDY

Over a 24-hour period, we acquired the hourly load (X_t), produced energy (G_t), and grid pricing (A_t) profiles from [1]. Microgrids of size 8 houses with a total battery capacity of 43.44kWh are included in this data set. In this simulation, we assume that in each microgrid, the cumulative batteries constitute a centralized BSS. We also assume that each BSS's SoC is 30% at the beginning of the day. D_D, the greatest depth of discharge, has a value of -23. (which means SoC can fall by at most 23 percent in an hour interval). D_C, the greatest depth of charge, is also +23. As a result, the search space has a total of $100(D_D - D_C + 1)^{24} = 4700^{24} \approx 2288$ items.

Parameters Applied

Table 1: Parameter Values for PSO and TLBO

PSO Parameters		TLBO Parameters	
Parameter	**Value**	**Parameter**	**Value**
Number of iterations	50	Termination Criteria	50
Number of design variables	1	Number of Subjects	1
Population	24	Number of Students	24
Inertia of weight, w	0.88-0.38	Rand	0-1
Constant C1	2	Upper bound	90
Constant C2	2	Lower bound	10
Rand 1	0-1		
Rand 2	0-1		
Upper bound	90		
Lower bound	10		

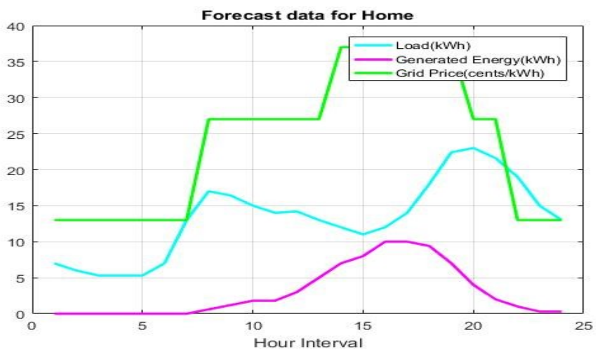

Figure 2: Data Forecast for 8 Homes in 24 Hours.

Cost Reduction Using PSO

The PSO method is used to optimize a cost function with provided restrictions, as shown in Eq. 5, and the outcome is shown in Figure 3. In Figure 3, the greatest cost is 4995.60 cents, while the lowest cost is 4688.68 cents.

When comparing the PSO and NPBA algorithms, the PSO method costs less, whereas the NPBA cos is 5471.22 cents [1]. It compares its efficacy to that of NPBA and calculates the improvement percentage. PSO hourly SoC is shown in Figure 4. The SOC using PSO is 70 %, indicating that the battery is working well and is in good health.

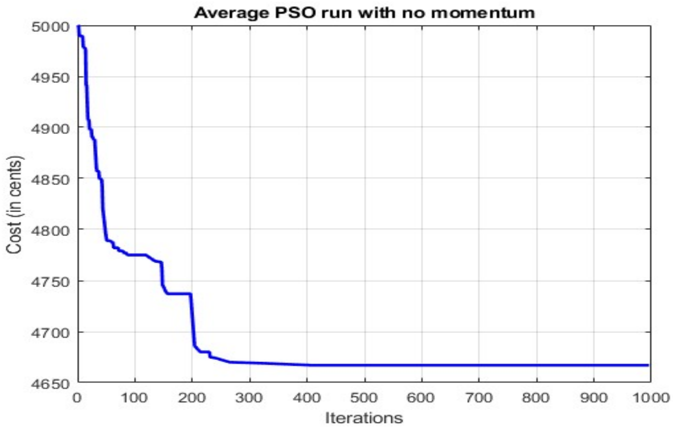

Figure 3: Cost Reduction Using PSO.

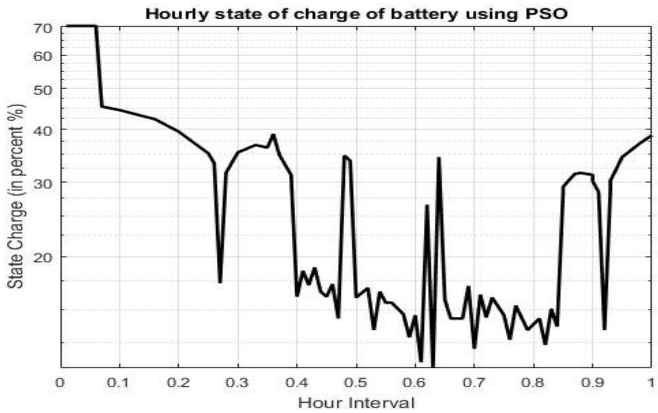

Figure 4: Hourly SoC by PSO.

Cost Reduction Using TLBO

The TLBO method was used to optimize a cost function with provided restrictions, and the highest cost was 4775.63 cents and the minimum cost was 4407.53 cents, as shown in fig. 5. When compared to NPBA and PSO, the cost of the TLBO algorithm is significantly lower.

It compares its efficacy to NPBA and PSO and calculates the gain percentage. It compares its efficacy to NPBA and PSO and calculates the gain percentage. The hourly SoC for TLBO is 79 percent while we applied the TLBO algorithm, as shown in Figure 6. It clearly demonstrates the superiority of the TLBO algorithm over the PSO method.

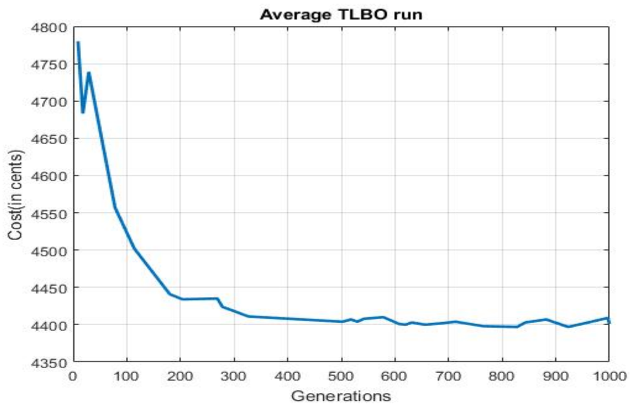

Figure 5: Cost Reduction Using TLBO.

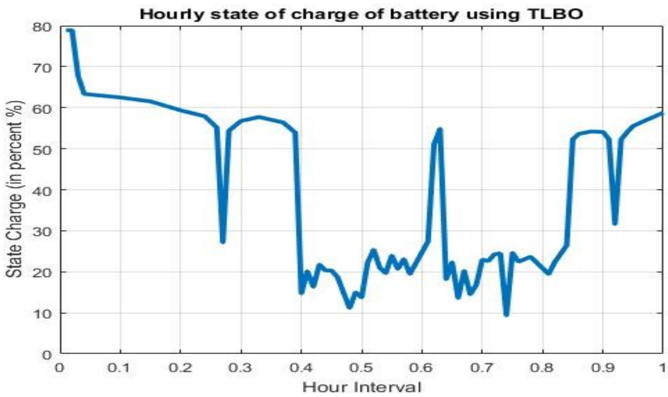

Figure 6: Hourly SoC by TLBO.

COMPARISON ANALYSIS

The NPBA cost for eight houses is 5471.22 cents. With this in mind, The outcomes shown above are for an 8-home microgrid. The algorithms were then run on the 16-home and 32-home microgrids, with similar results, as shown in Table 2. It's worth noting that the last column, Avg. Above all three data sets, Cost Reduction is an unweighted average of the percentage improvement over NPBA delivered by the individual method. It's worth noting that the performance of our suggested algorithms is highly reliant on the parameters used. Parameter settings that are effective for our data sets may or may not be effective for other data sets. As a result, it's crucial to experiment with various parameter values until you find one that works well for the data set in question.

Table 2: Comparison Analysis

	Algorithm	Cost Obtained	Cost Reduction %
8 Homes	PSO	4688.68	14.31
	TLBO	4407.53	19.45
16 Homes	PSO	9373.69	14.34
	TLBO	8810.2	19.49
32 Homes	PSO	18754.92	13.9
	TLBO	17724.22	19.02

CONCLUSIONS

The findings of the entire article are presented in this section. Real-time pricing, sometimes referred to as dynamic pricing, is a utility rate structure in which the per-kWh fee fluctuates every hour based on the utility's current production prices. Real-time pricing makes retail energy prices more expensive during peak hours than during shoulder and off-peak hours since peaking facilities are more expensive to run than base load plants. The cost is reduced using the PSO and TLBO algorithms, with PSO achieving a cost of 4688.98 cents. The price is 4407.53 cents according to TLBO. The cost reduction percentages are calculated using the basic NPBA cost as a benchmark, which is 5471.22 cents. Using PSO results in a 14.31 percent cost decrease. The cost savings from utilizing TLBO is 19.45 percent. In comparison to the PSO, it is apparent that TLBO has a higher cost reduction percentage. We then applied the algorithms to forecast data obtained from [19].As a result, it is obvious that the TLBO method is more productive than the PSO algorithm. The greatest SOC attained with TLBO is 79%, while the PSO is 70%. This clearly demonstrates the precision of the TLBO algorithm when used in a microgrid to determine the battery's level of charge. When compared to PSO, the efficacy of TLBO may be expressed as the number of iterations considered being 100, which results in higher performance. PSO and TLBO's performance will be almost identical after 100 cycles, making comparison impossible.

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