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Original Article

A Stackelberg Game-Based DSM Framework for Residential Energy Management in Oman: A Comparative Analysis of PSO and Optuna Optimizations

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Abstract - *Nowadays, the power system networks are facing some crucial problems due to the Lack of resources and rising household energy demands. The conventional Demand-Side Management (DSM) techniques are often inflexible and unresponsive, limiting their capacity to maximize energy consumption efficiency. In this research work, a Non-Cooperative model of Stackelberg Game-Theoretic (SGT) strategy is proposed for a residential energy management system with a highly effective and flexible Metaheuristic optimization algorithm, Particle Swarm Optimization (PSO), and a novel method of the Optuna optimization framework. Based on the monthly loads record of 2023 in the Ad Dakhliyah region, Oman, the proposed algorithms have proven to be efficient and flexible in the smart grid application domain. The historical data have been applied to the SGT-DSM framework with the proposed optimization methods. This comparative analysis shows a 35.08% decline in energy consumption using the existing method of PSO strategy and a 45.45% decline when applying a novel Optuna technique annually. From the results, the cost-saving opportunities and the levels of accuracy in RMSE (Root Mean Square Error) and MAE (Mean Average Error) metrics are observed with both approaches. Finally, the results have been compared and proved from the analysis that Optuna exhibits a more profitable economic outcome, better grid reliability, and good performance in balancing loads, even PSO's better performance in grid reliability and load balance system.*

Keywords - *Stackelberg Game Theory, Non-Cooperative model, Demand-Side Management, Particle Swarm Optimization, Optuna, Energy Performance Metrics, Grid reliability, and Load balancing metrics.*

1. Introduction

Because of the increase in population and changes in environmental conditions, there is a change in the demand for power and also in its price within the market. Due to the actions of the users, there is a fluctuation in energy usage patterns during the course of the day at the customers' places. The generation capability should be such that it can cater to the peak energy demand. The smart grid employs Information and Communication Technologies (ICT), real-time monitoring systems, and Distributed Energy Resources (DERs) to facilitate two-way communication between the utilities and customers [1].

The interactions between utility suppliers (Leaders) and consumers (Followers) are not represented in traditional DSM approaches, and their responsiveness is yet to be improved. Thus, for sustainable and reliable power grids, the optimization of domestic energy use is essential [2]. The DSM techniques aim at making consumers more efficient by ensuring that they remain comfortable. While the previous approaches, such as time of use, have been fairly successful, they have remained fairly rigid and are unable to adjust according to changes in consumer behavior and grid changes. The advent of Smart Grids has made advanced demand response technologies emerge, but these technologies often fall short of understanding different consumer behaviors.

Most conventional DSM approaches rely on rule-based or time-invariant scheduling mechanisms, which are inadequate for handling the nonlinear, stochastic, and strategic nature of residential electricity consumption. Consequently, these approaches fail to capture the interactive decision-making process between utility providers and consumers, resulting in suboptimal load scheduling and inefficient energy utilization. Despite extensive research into the utility-consumer relationship using game theory approaches, the implementation of such models within the DSM paradigm has seen relatively little progress. It is common to see that most research studies fail to utilize any actual residential consumption data, possess no real-time adaptability, and inadequately consider the problem of maximizing the utility function of the consumers in the context of dynamic pricing.

Some of the major problems pointed out by this research study include the following:

a. Centralized and static DSM systems lacking substantial real-time engagement among utility service providers and domestic users.
b. Inadequate DSM systems that lack an adaptive approach and use game theory decision-making process, specifically, Stackelberg game models, to model interactions between utilities and customers.
c. Lack of a GT Non-cooperative mechanism for utility-customer collaboration that ensures grid stability and minimizes costs without compromising on consumer welfare.
d. Also, many of the existing models utilized in the DSM approach do not make use of state-of-the-art optimization techniques that solve multi-objective optimization problems.

Consequently, utility companies continue to encounter challenges in terms of adopting adaptive prices and optimizing demands while taking into account stability, peak shaving, and customer satisfaction. Thus, there is a gap in the current literature regarding the Lack of an adaptive and dynamic DSM system that integrates Stackelberg Game hierarchical interactions between energy suppliers and customers can be effectively modelled using game-theoretic frameworks like the recently developed SGT [3, 4].

Conventional SGT-based DSM frameworks continue to employ static optimization techniques, which are inefficient with nonlinear, time-sensitive data.

For the observed problems, this research paper focuses on an energy management system that integrates optimization methods, such as an existing PSO and a novel Optuna, with a Non-Cooperative SGT model. The goal of this integration is to enhance the residential grid's DSM performance. This study addresses important problems in current DSM systems by combining hierarchical decision modeling with real-world optimization.

This research work suggests an implementation of the non-cooperative SGT approach, which integrates DSM along with the already existent PSO and a novel Optuna optimization approach independently to achieve the objectives set by Oman Vision 2040 through increased efficiency and cost reduction. Besides, the reliability of the grid and balance of the load systems will be analysed and compared for both optimization methods. For this study, the residential load data from Al Dhakliyah, Oman, for the year 2023 have been utilized. Figure 1 shows the Conceptual diagram of the supply-consumer with Game Theory and Optimization scheme.

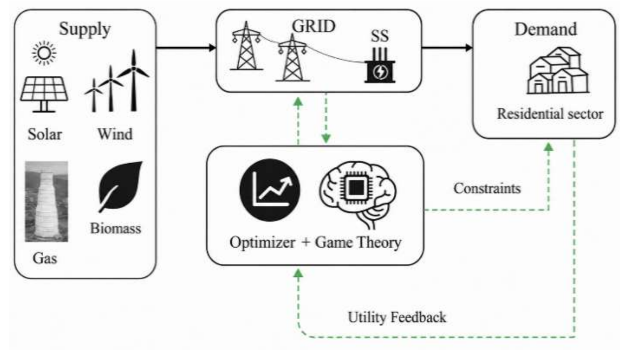


Fig. 1 Conceptual view of Supply-Consumer Optimization

So, this research work has carried out the general objectives as follows:

a. To create a SGT-non-cooperative with DSM framework model interactions between utility providers (Leaders) and consumers (Followers) using an existing method of PSO and a novel Optuna optimization method separately.
b. To analyze and compare the optimization performance results from both optimization schemes, and also grid reliability and load balancing metrics.

2. Related and Proposed Work

2.1. Challenges in DSM and Smart Grids

The instability of renewable energy sources and increased energy demand on a global scale put grid stability at risk [5]. Traditional power grids have no involvement from consumers because of the centralized DSM structure and its inefficient communication. Implementation of DSM technologies in underdeveloped countries is difficult because of factors such as high costs of implementation, Lack of governmental support, and cyber risks [6]. In Oman, implementing Smart-grid and DSM technologies is dependent on advanced communication networks, IoT devices, smart meters, and data analytics, which bring concerns such as data privacy, communication networks, and cyber-attacks [7-9].

As is common in research into smart grids, it is stated that there is high vulnerability to cyber-physical attacks in Oman. The cloud-based smart grid market in Oman faces the same problem mentioned above as a significant market barrier, where "High initial investment costs" is one of the biggest barriers for the development of cloud-based smart grid technology [34]. Getting the participation of consumers in Oman might prove difficult.

2.2. Game-Theoretic DSM Framework

The interaction between the utility and its consumers could be strategically captured via the use of game theory. In Stackelberg games, followers adjust their energy consumption to minimize their expenditure, whereas the leader introduces Time of Use (ToU) or Dynamic pricing schemes. Some studies have applied Stackelberg models to incorporate renewable Energy, decrease peak load, and react to changes in demand. However, most of today's models are based on static optimization, making them unsuitable for the rapidly evolving nature of the grid [10, 11]. In the modern power system, the DSM paradigm has started integrating game theory models (Non-Cooperative or Cooperative) with optimization methods [12]. Non-cooperative game theory models scenarios in which the players (Leaders/Followers) act independently and aim to optimize their individual payoff without cooperating with one another. Nash equilibrium denotes the stable point at which none of the players can unilaterally alter their strategy and obtain better payoffs, assuming that the other players do not change their strategies [13]. In DSM, the non-cooperative game theory models the practical behaviour of consumers wherein each house adjusts its energy consumption according to the price signal generated by the utility.

The use of game theory, especially Evolutionary game theory, Metaheuristic game, Bayesian games, or other types of games, has been insightful in analysing the strategy used by players in the market. Game theory has enabled us to gain a deeper insight into the strategies that power purchasing firms and power generating firms adopt in reaction to changes in the market environment [14, 15].

The method presented ensures effective contribution from users towards managing the issue of peak demand management and off-peak energy usage through effective pricing mechanisms. The combination of game theory modelling and optimization leads to significant savings in grid investments and costs associated with consumption by consumers, thus providing a win-win situation for both parties involved [16].

2.3. Optimization

Optimization is a core tool in game theory-based DSM to minimize total energy cost, reduce peak demand, and improve load distribution across consumers. It determines optimal load scheduling, energy allocation, or price signals by balancing consumer comfort, system constraints, and grid stability.

When compared with other optimization methods like Genetic Algorithm (GA), Simulated Annealing (SA), and Gradient-Based optimization, PSO is characterized by faster convergence, reduced computational complexity, and high adaptability in addressing nonlinear demand-side management issues [17, 18].

Regarding the applicability of DSM, there are various traditional optimization methods, such as GA, SA, and LP, that have some drawbacks. GA or SA are even effective global optimization algorithms; however, those models might take some time to converge, and the parameter setting could be rather difficult. Moreover, Gradient-based optimization algorithms work well for smooth problems; on the other hand, they cannot be used for the DSM problems where the decision variable is either not differentiable or discrete (e.g., scheduling of electrical appliances). In addition, fuzzy logic and rule-based optimization algorithms, despite being simple and intuitively appealing, do not provide enough flexibility for DSM problems. Out of these traditional methods, PSO has a more effective result with respect to the Energy and cost reduction, as well as the speed performance.

PSO is extensively applied in DSM in order to achieve load and cost optimization due to its scalability and usability. With respect to the PSO algorithm, each particle stands for a certain way to consume Energy, adjusting its path based on the best local and global positions [19]. However, the problem with PSO lies in the fast convergence that occurs in the case of a nonlinear dynamic system. Such a problem can be resolved by applying the technique offered by a relatively new hyperparameter optimization method called Optuna.

Optuna is a hyperparameter optimization algorithm [31] that is based on probability modelling with an aim to provide an efficient exploration of a set of optimal parameter combinations aimed at optimizing the energy consumption and cost. The main difference between Optuna and the classical PSO algorithm is that it employs adaptive hyperparameters, which are learned through probabilistic modelling.

In contrast, PSO uses predefined parameters in the search for an optimal solution, but Optuna makes the process of learning dynamic, resulting in more efficient convergence and better results with regard to energy and cost savings. Table 1 shows the summary of the comparison between PSO and Optuna optimization.

Table 1. Comparison – PSO Vs Optuna

Aspect	PSO	Optuna
Optimization type	Metaheuristic	Bayesian / TPE-based
Search nature	Population-based	Probabilistic, adaptive
Convergence speed	Moderate	Fast
Parameter tuning	Manual	Automatic
Multi-objective support	Limited	Strong
DSM performance	Improved	Best
Computational cost	High	Low
Adaptability	Low	High

2.4. Regional Context

The model's practical significance is demonstrated by applying it to Oman's residential sector. According to actual load statistics from 2023, the average household consumption is 44.50 kWh per day (See Table 2) [32], mostly due to air conditioning loads in the summer season. These loads can be controlled directly by using novel optimization algorithms [20].

Table 2. Typical Residential Load (Per Consumer) in Oman

Appliances	Energy Consumption Per Day (kWh)
Washing machine	1.00
Hair dryer	0.50
Vacuum cleaner	0.50
Cooker	2.50
Water heater	3.00
Television	1.50
Motor (Water Pump)	1.00
Iron	0.50
Microwave / Kettle/ Toaster	2.50
Air Conditioner (AC)	20.00
LED / CFL Bulb	2.00
Refrigerator	3.50
Freezer	1.50
Miscellaneous (Fan, PC, Chargers, etc.)	4.50
Total	44.50 kWh/Day

In Oman, the electricity price structure has been implemented as a block rate level for residential Load. Oman's tariff structure (Block Rate) for the residential sector with Omani Baisa (1 OMR = 1000 Baisa) [33] is shown in Figure 2.

In line with Oman Vision 2040's sustainability objectives, this research work suggested SGT-based DSM with an existing model of PSO and a novel model of Optuna optimization structure in order to increase energy efficiency, cost savings, and system adaptability. Its main contributions are: Utilize dual optimizers with SGT separately; striking a balance between cost and precision.

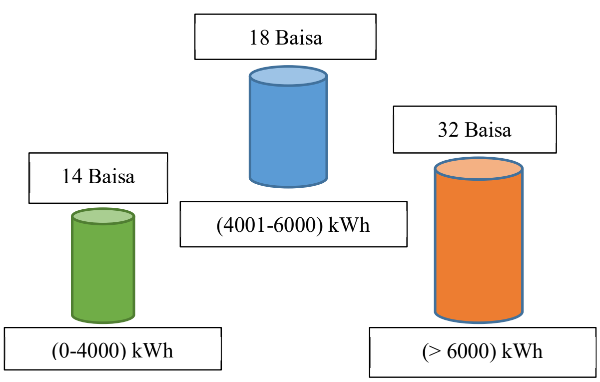


Fig. 2 Residential Load Tariff Structure
(Source: APSR, Oman)

The optimization of block rate pricing is concerned with finding the appropriate sizes and differences between blocks so that two objectives are fulfilled; one objective is to make sure that consumers benefit from the pricing, and secondly, to ensure that the utilities get maximum benefit from their services and deal with any changes in demand [20].

2.5. Proposed System

Most of the existing researchers showed the energy consumption in the range of 15% - 45% using the Game theory model with different optimization algorithms. The load reduction showed 33% using the SGT model with MATLAB Simulink [3], showed 49% energy savings using IoT/cloud-based methods [7], and has shown 40% energy reduction using RL optimization in the SGT-DSM model [8].

The cost savings have been achieved 28% using Reinforcement Learning (RL) optimization under a type-based approach [11]. Apart from the energy and cost reduction factors, the grid reliability and Load balancing systems like PAR, CRI, were also implemented with different traditional or AI-based schemes [29] in the existing research works.

Based on the literature reviews, this research work has proposed and implemented with SGT (Non-Cooperative)-DSM framework with an existing PSO and a novel Optuna Optimization method independently, as shown in Figure 3, in order to show that the novel method of Optuna optimization will achieve better energy and cost performance grid reliability.

A non-cooperative approach is one whereby the residential consumers make their decisions individually in an attempt to meet their own objectives, such as reducing their costs of using electricity or increasing their comfort level [21].

The residential energy consumption and cost data of Oman (Ad Dakhliyah region) for 2023 have been collected and applied to the SGT-DSM framework.

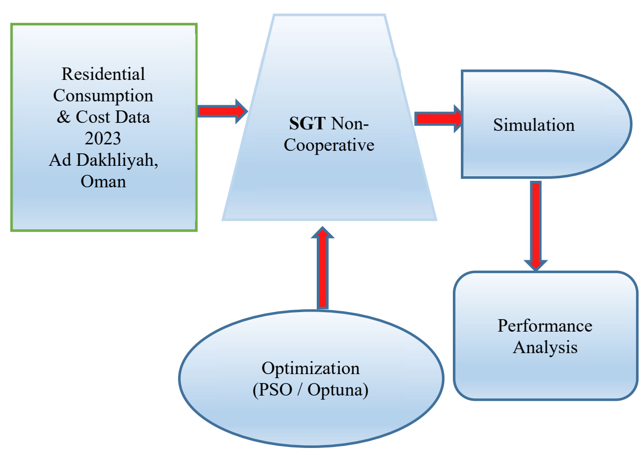


Fig. 3 Block Diagram – Proposal

Figure 4 shows the SGT (Non-Cooperative)-DSM Framework for this research work. It has the primary objectives on the Leader and Follower sides. This interaction converges to a Stackelberg equilibrium, balancing system efficiency and user cost.

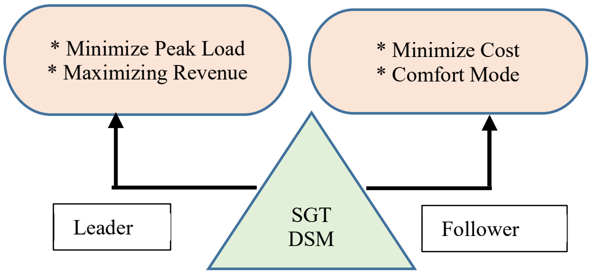


Fig. 4 SGT Framework

3. Methodology

The research design establishes a structured framework for developing and analyzing a DSM optimization model focused on energy consumption and cost reduction in residential sectors. Figure 5 shows that the methodological structure ensures that the research remains aligned with its objectives while offering reproducible and scalable insights for energy optimization in the context of Oman's electricity demand patterns.

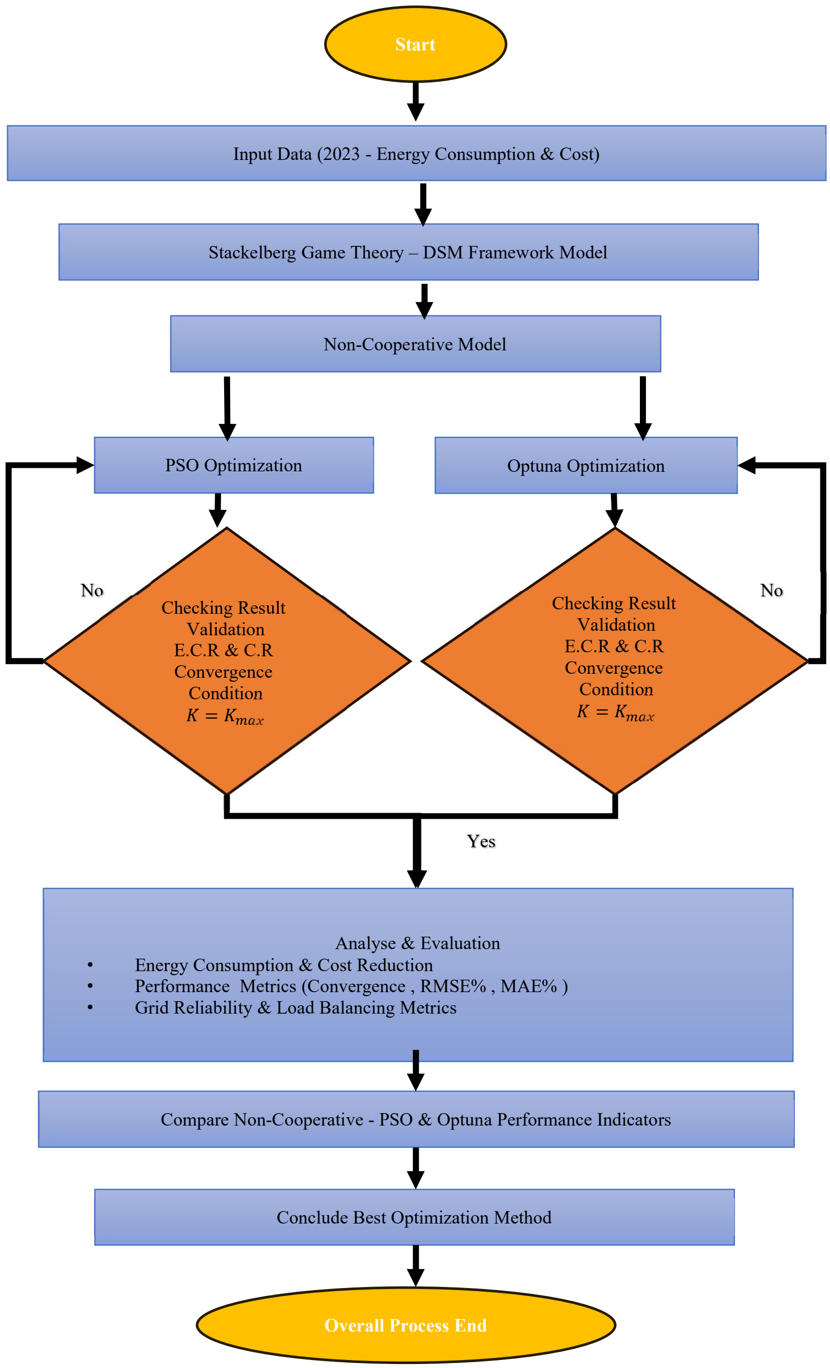


Fig. 5 Flow Chart - Methodology

3.1. Data Collection

The Ad Dakhliyah region of Oman's actual domestic electricity usage data for the months of January through December of 2023 is used in this research analysis. The dataset (See Appendix 1) shows differences in demand between summer and winter by providing monthly and seasonal consumption numbers in GWh. Due mostly to summertime air conditioning loads, peak consumption happens between 11:00 AM and 5:00 PM. With an average per-consumer consumption of 16.2044 MWh (16,204.44 kWh), the total energy consumption for 2023 was 1643.02 GWh per year [32]. A tiered tariff structure with different charges for different use categories is used to bill consumers. The Utility-Consumer interactions are modelled using this data with SGT, which are also used as input for existing PSO and novel Optuna optimization.

3.2. Stackelberg Game-Theoretic Model

In this model, the Leader-Follower framework sets electricity prices to maximize revenue and minimize peak demand, while consumers adjust consumption to minimize cost. The leader typically maximizes profit or minimizes system cost [3]:

3.2.1. Leader's Objective

The leader's objective function is mentioned as follows:

$$\max_{p} UL = \sum_{t=1}^{T} p_i . X_t - \lambda . P_{Pk} \tag{1}$$

Where *UL* is the Utility function of the leader, p_i is the electricity price per unit of electricity consumption for consumer i, X_t is the total power consumption at the time period t, λ is the penalty factor for exceeding the peak load limit, P_{Pk} is peak load or peak demand, and T is the total number of time slots. $p_i . X_t$ is the utility revenue. The equations for X_t and P_{Pk} are as follows.

$$X_t = \sum_{i=1}^{N} x_i \tag{2}$$

$$P_{Pk} = \max_{t} X_t \tag{3}$$

3.2.2. Follower's Objective

The Follower's objective function is mentioned as follows:

$$\min_{x_i} UF = \sum_{i=1}^{T} p_{iB} . x_i \tag{4}$$

For the feasibility constraint,

$$x_i^{min} \leq x_i \leq x_i^{max} \tag{5}$$

Where *UF* represents the function (cost) of Follower, p_{iB} indicates the electricity slab tariffs for customer *i* belonging to the threshold block band x_i denotes the Energy consumed by customer *i, and* T represents the total number of time slots.

3.3. Optimization Algorithms

In this study, two optimization algorithms: PSO and the novel method of Optuna, are used to solve the Stackelberg-based bi-level optimization problem for the utility (Leader) and consumers (Followers). Both methods are used to optimize energy consumption and minimize energy consumption cost under Block rate pricing for a 12-month data set.

3.3.1. PSO Method

PSO is a population-based algorithm inspired by social behaviour. A swarm of particles represents potential consumption schedules $x = [x1, x2\ldots xn]$. Each particle updates its velocity and position according to personal and global best experiences [22-24], as shown below:

$$v_i(k+1) = wv_i(k) + c_1 r_1 \left(p_{best_i} - x_i(k)\right) + c_2 r_2 \left(g_{best} - x_i(k)\right) \tag{6}$$

$$x_i(k+1) = x_i(k) + v_i(k+1) \tag{7}$$

Where $v_i(k)$ is the particle velocity during iteration k, $v_i(k+1)$ is the updated velocity, $x_i(k)$ is the particle position during iteration $k, x_i(k+1)$ is the updated position, p_{best_i} represents the best position of particle i, g_{best} represents the optimal position by the swarm, i is the particle index, k is the iteration index, w is the inertia weight, c_1, c_2 are acceleration coefficients, and r_1, r_2 are random numbers in the range (0,1).

3.3.2. Optuna Method

Formulation of Energy Optimization for Optuna can be achieved using the Tree-structured Parzen Estimator (TPE). Probability model of Optuna for DSM decisions with respect to energy optimization E is shown below [31]:

$$Pd(\theta|E) = \begin{Bmatrix} l(\theta), E \leq E^* \\ g(\theta),\ E > E^* \end{Bmatrix} \tag{8}$$

Where Pd (θ|E) denotes the conditional probability density of the vector of parameters θ conditional upon the value of the objective E, E^* represents a critical level (or quantile) dividing solutions into good and poor ones, l(θ) is the probability density function of good solutions, that is, those for which objective values are small (E ≤ E^*), g(θ) is the probability density function of poor solutions, for which objective values are large (E > E^*).

3.4. Energy Consumption Reduction

Efficient energy reduction is when energy usage is reduced in an optimal manner without compromising reliability and consumer comfort. Efficient energy reduction is achieved by optimizing and controlling flexible loads. Therefore, efficient energy reduction not only favours the consumer by saving on costs but also increases the efficiency of the power system as a whole [25, 30].

Generally, the Average Daily Consumption (ADC) and Average Monthly Consumption (AMC) are computed as:

$$ADC = \frac{\sum_{d=1}^{D} x_{id}}{D} \tag{9}$$

$$AMC = x_{id}.D \tag{10}$$

Where D is the number of days in the month, and xid is the energy consumption on day d.

Each consumer acts independently:

$$x_t\ base \le \Delta x_t \le \gamma_{NC}\ x_t^{\wedge} \tag{11}$$

Where, x_t Base is the energy consumption at time, $\Delta.x_t$ is the energy consumption reduction decision, γ_{NC} is Non-cooperative flexibility limit (0.5), x_t^ is the Optimized Energy consumption.

The optimization of energy consumption can be expressed as:

$$x_t^{\wedge} = x_t\ base - \Delta x_t \tag{12}$$

3.5. Cost Reduction

In the present research, the cost of energy consumption is taken from the existing dataset. The objective function to be minimized is: Minimize individual customers' energy cost under the block rate tariff with restricted load flexibility [17]. The energy cost at time *t* is,

$$C_t = \sum_{k=1}^{K} \lambda_k . \max(0, \min(P_t^{\wedge}, B_k) - B_{k-1}) \tag{13}$$

Where, C_t: Total electricity cost (OMR) during time period t, t: Time index (Hour/Day/Month), *K*: Total number of tariff blocks in the block-rate pricing model, *k*: Tariff block index, λ_k: Unit electricity price per kWh in tariff block k (OMR/kWh), $P_t^{\wedge}$: Optimized energy consumption at time t by PSO/Optuna, B_k : Maximum consumption capacity of tariff block *k*, B_{k-1}: Minimum consumption capacity of tariff block *k*.

The optimized cost ($C_i^{\wedge}$) is,

$$\min_{x} \quad C_i{}^{\wedge} = \sum_{t=1}^{T} C_t \tag{14}$$

The constraints of the cost function are,

$$c_{t\ base} \le \Delta c_t \le \gamma\text{NC}\ c_i^{\wedge} \tag{15}$$

Where, c_t Base is the energy consumption cost, Base at time, $\Delta.c_t$ is the energy consumption cost reduction decision, γ_{NC} is Non-cooperative flexibility limit (0.5), C_i^ is the optimized energy consumption cost. Generally, each household's total electricity cost function is computed based on the Block Rate tariff as:

$$C_i = \begin{cases} p_1 x_i & x_i \le B_1 \\ p_1 B_1 + p_2(x_i - B_1) & B_1 < x_i \le B_2 \\ p_1 B_1 + p_2(B_2 - B_1) + p_3(x_i - B_2) & x_i > B_2 \end{cases} \tag{16}$$

Where C_i is the total cost incurred by the energy consumption of household i, $p_1, p_2, p_3,$ are the slab rates of electricity, x is the energy consumption for household i, and B_1, B_2, B_3 These are the energy consumption blocks.

3.5.1. PSO - Algorithm

S1: Initialize: Energy consumption base value x_i / Energy consumption cost Base value c_i, and constraints.
S2: Leader Stage: T Utility establishes DSM policy and flexibility threshold γ_{NC}.
S3: Follower Stage: Consumer makes changes in its energy consumption level x_i to reduce the cost at the expense of comfort.
S4: PSO Iteration: Velocity and position updating; function evaluation; iteration continues until the solution converges.
S5: Output: Optimized energy consumption x_{ipso}^ / cost of consumption C_{ipso}^.

3.5.2. Optuna - Algorithm

S1: Import datasets: Energy consumption base value x_i / Energy consumption cost Base value c_i , and constraints.
S2: Define: Leader (Utility) and Follower (Consumer) objectives with flexibility limit γ_{NC}.
S3: Optuna Iteration: Update TPE distribution. Update the best and worst trials.
S4: Pruning: Eliminate poor-performing trials. Continue the trials to convergence or max iterations, then choose the trial that achieves maximum cost saving.
S5: Output: Power consumption optimization x_{iopt}^ / cost of consumption C_{iopt}^.

Based on the optimization results obtained using PSO and the Optuna methods applied to the base dataset, the Energy and cost reduction % can be calculated as follows:

The percentage of energy consumption reduction is

$$(\Delta E^{\wedge}\%) = \frac{\Delta E^{\wedge}}{x_i} \times 100 \tag{17}$$

$$\Delta E^{\wedge} = (x_i - x_i{}^{\wedge}) \quad (18)$$

The percentage of energy consumption cost reduction is,

$$(\Delta C^{\wedge}\%) = \frac{\Delta C^{\wedge}}{C_i} \times 100 \quad (19)$$

$$\Delta C^{\wedge} = (c_i - c_i{}^{\wedge}) \quad (20)$$

Where, x_i is the total base value of energy consumption, $x_i{}^{\wedge}$ is the optimized (PSO/Optuna) total energy consumption, C_i is the total energy consumption cost (Base), $C_i{}^{\wedge}$ is the optimized (PSO/Optuna) total energy consumption cost, $\Delta E^{\wedge}$ is the optimized (PSO/Optuna) energy consumption reduction, and $\Delta C^{\wedge}$ is the optimized (PSO / Optuna) energy consumption cost reduction.

3.6. Performance Metrics

3.6.1. Convergence

The term convergence is used to refer to the point where the objective function reaches a constant value, and subsequent iterations do not lead to any significant improvements [26].

Mathematically,

$$|f^{k+1} - f^{k}| \rightarrow 0 \; or \; K = K_{max} \quad (21)$$

Where f is the objective function, k is the number of iterations, f^{k} is the objective value at iteration k, and f^{k+1} is the objective value at the next iteration. When,

$|f^{k+1} - f^{k}| \approx 0$ means that the algorithm has converged.

3.6.2. RMSE% and MAE%

Model accuracy is evaluated using RMSE and MAE with respect to the energy consumption:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - x_i{}^{\wedge})^2} \quad (22)$$

$$MAE = \frac{1}{N}\sum_{i-1}^{N}\left|x_i - \hat{x_i}\right| \quad (23)$$

Where x_i is the total base energy consumption, $x_i{}^{\wedge}$ is the total optimized energy consumption, and N is the total number of periods.

$$\text{RMSE \%} = \frac{\text{RMSE value}}{x_i} \text{X } 100 \quad (24)$$

$$\text{MAE \%} = \frac{\text{MAE value}}{x_i} \text{X } 100 \quad (25)$$

3.6.3. Grid Reliability and Load Balancing Indicators

Grid reliability is one of the important performance criteria for smart grids, and can be determined using reliability indices and system stability indicators. Demand-side management and smart optimization methods greatly improve the reliability of the system by optimizing load sharing and removing the uncertainties associated with operations. It is very important that grid fairness be ensured among the consumers through grid reliability indicators, such as Load Balancing Factor (LBF), Peak to Average Ratio (PAR), Load Variability Index (LVI), Load Stability Index (LSI), and Customer Reliability Index (CRI) [27-29], which can be calculated according to the standard formulas (See Appendix 2).

4. Results

The simulation was carried out using Python on the Jupyter Notebook platform. PSO and Optuna algorithms optimized the consumption schedule and tuned hyperparameters. Matplotlib and Seaborn were used for plotting and DSM simulations within the context of a smart grid network.

4.1. Energy Consumption Reduction

According to the dataset (See Appendix 1), the energy consumption (Per Consumer in MWh) for each month of 2023 has been optimized by both the existing PSO and the novel Optuna approach methods individually. The findings are presented in Table 3 below, which highlights the efficiency of the suggested optimization techniques.

The consumption of Energy with respect to PSO optimization is 10.52 MWh compared to 16.20 MWh of Energy consumed in the base case scenario for a whole year. The Optuna algorithm shows better results in reducing the consumption rate to 8.84 MWh per year.

Table 3. Optimized Monthly Energy Consumption with Base (Per Consumer)

Period	x_i (MWh)	$x_i pso^{\wedge}$ (MWh)	$x_i opt^{\wedge}$ (MWh)
Jan-23	0.60483	0.37	0.34
Feb-23	0.6032	0.36	0.33
Mar-23	0.79172	0.50	0.42
Apr-23	1.0231	0.63	0.58
May-23	1.6326	1.10	0.86
Jun-23	2.0808	1.38	1.15
Jul-23	2.2211	1.45	1.22
Aug-23	2.0501	1.35	1.19
Sep-23	1.9018	1.27	0.96
Oct-23	1.5688	0.96	0.89
Nov-23	1.0312	0.70	0.55
Dec-23	0.69519	0.45	0.35
Total	16.20444	10.52	8.84

Figure 6 shows the energy consumption (Per Consumer) in MWh for a whole year. It indicates high energy consumption during the summer season from May to

September, as a result of utilizing more Air Conditioners at the residential end. The energy consumption graph shows the usual yearly load curve, which is indicated by lower values of energy consumption during the first three months from January through March (0.4-0.7 MWh), after which there is an increase until May-June. The energy consumption in July becomes maximum for the Base case, which amounts to 2.2 MWh, whereas for the other two cases (PSO and Optuna), the energy consumption reaches about 1.45 MWh and 1.25 MWh, respectively. Further on, the energy consumption decreases from September until December. The two techniques have the capability of handling load profiles efficiently. Nevertheless, Optuna proves superior in minimizing energy consumption and balancing peak demand periods.

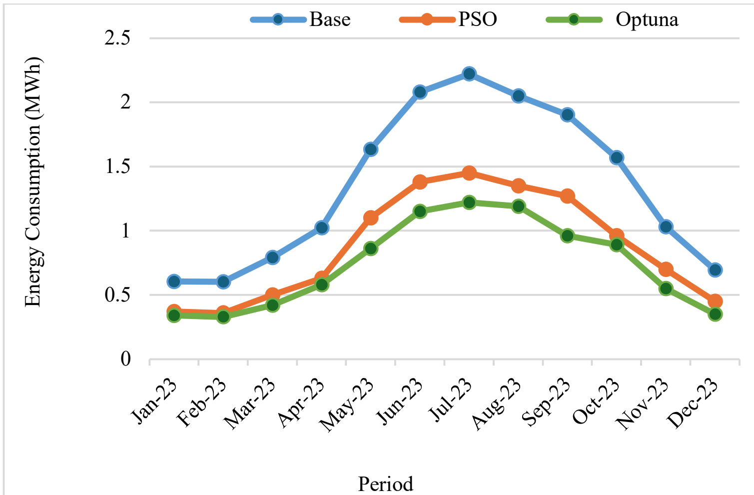


Fig. 6 Monthly Energy Consumption Curve

The energy consumption reduction percent for each month of 2023 is shown in Fig. 7, which is calculated by means of Equation (17) & Equation (18). As can be observed from the plot, PSO provides a relatively good reduction in energy consumption by 31%-40%, but the results obtained using Optuna provide significantly better energy reduction by 41%-50%. The output obtained for Optuna proves to be efficient consistently throughout all months and especially during high demands. So, it is observed that the proposed optimization method, Optuna, has produced a better energy reduction percent than the conventional PSO technique. Hence, energy savings are 35.08% in PSO and 45.45% in Optuna. From Table 4 below, one can observe that there is a definite seasonality in the pattern of energy usage, which is low in the early and late months but much higher in the middle months. The findings demonstrate that energy consumption is substantially lower than in the Base scenario for all months using the two optimization algorithms, PSO and Optuna. The largest decrease occurs in the months of peak consumption (June-Sep) when the consumption drops from 63-72 kWh per day (Base) to 42- 47 kWh per day (PSO) and 32-39 kWh per day (Optuna).

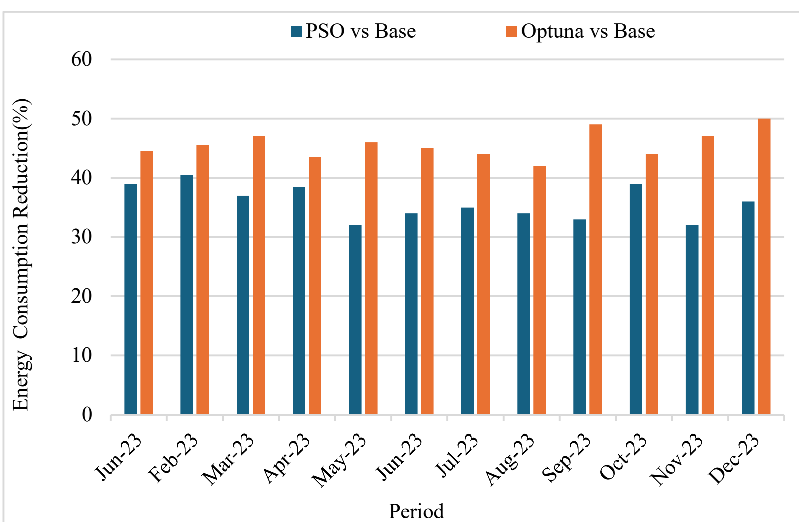


Fig. 7 Percentage of Monthly Energy Consumption Reduction Curve

Table 4. Optimized Daily Energy Consumption Values with Base (Per Consumer)

Period	x_i (kWh/Day)	$x_i pso^\wedge$ (kWh/Day)	$x_i opt^\wedge$ (kWh/Day)
Jan-23	19.51	11.94	10.97
Feb-23	21.54	12.86	11.79
Mar-23	25.54	16.13	13.55
Apr-23	34.10	21.00	19.33
May-23	52.66	35.48	27.74
Jun-23	69.36	46.00	38.33
Jul-23	71.65	46.77	39.35
Aug-23	66.13	43.55	38.39
Sep-23	63.39	42.33	32.00
Oct-23	50.61	30.97	28.71
Nov-23	34.37	23.33	18.33
Dec-23	22.43	14.52	11.29

Figure 8 shows the daily energy consumption (kWh) basis for the Base, PSO, and Optuna Optimization cases. The above results indicate that the optimization approach is able to achieve reductions in energy usage compared to the Base scenario. The peak demand is lowered from 70 kWh/Day (Base) to 47 kWh/Day using PSO (33% reduction), and to 40 kWh/Day when using Optuna (43% reduction). On average, for all months, the PSO approach was able to deliver a 30%-35% reduction, while the Optuna approach provided more significant reductions by 40%-45%. In summary, the Optuna-based approach performs better in terms of lowering energy usage/peak demands.

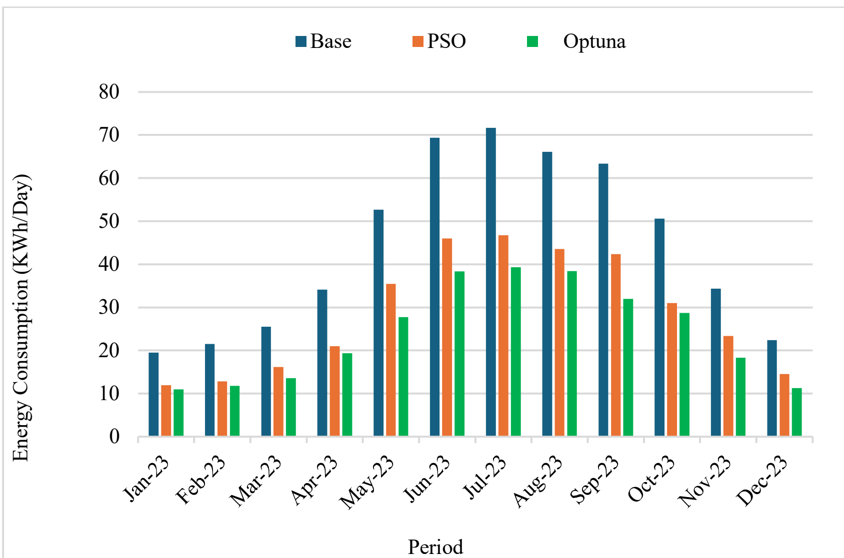


Fig. 8 Daily Energy Consumption Curve

4.2. Energy Consumption Cost Reduction

Also, Table 5 indicates the monthly energy cost per consumer for the PSO and Optuna approaches according to the findings of the optimization code implementation. The findings reveal that both optimization approaches lead to remarkable savings in energy costs. The yearly base cost of 243.07 OMR (632.18 USD) reduces to 146.3 OMR (380.50 USD) with PSO, representing a savings of 39.82%. It further reduces to 121.8 OMR (316.78 USD) with Optuna, a saving of 49.89%. The monthly energy consumption cost (Per Consumer) for the PSO and Optuna models is calculated and compared with the base dataset, as shown in Figure 9. Analysis of the cost per month shows that there is a notable decline in cost after optimizing in any month. From the base case, the cost is shown to be the highest, ranging from 9-10 OMR in January up to February and increasing to 33-34 OMR in July before declining back to 10 OMR in December.After optimization using PSO, the highest cost becomes 19-20 OMR, meaning that there is a notable decrease in cost of between 38%-42%. Using the Optuna scheme, the cost of Energy will decrease even more by between 45%-50%, as the cost will be reduced to 17-18 OMR.

Table 5. Optimized Monthly Energy Consumption Cost with Base (Per Consumer)

Period	C_i (OMR)	$C_i pso$^ (OMR)	$C_i opt$^ (OMR)
Jan-23	9.07	5.1	4.5
Feb-23	9.05	5.6	4.2
Mar-23	11.88	7.7	6.5
Apr-23	15.35	8.8	8.0
May-23	24.49	14.8	11.8
Jun-23	31.21	18.9	16.0
Jul-23	33.32	19.5	17.5
Aug-23	30.75	19.4	15.4
Sep-23	28.53	18.0	14.2
Oct-23	23.53	13.5	11.5
Nov-23	15.47	9.0	7.0
Dec-23	10.43	6.0	5.2
Total	243.07	146.3	121.8

Optuna gives a lower cost compared to PSO, showing that it makes improvements of between 5%-8%. Most importantly, there is a notable reduction in cost during peak consumption periods, i.e., May to September. This cost curve demonstrates that both PSO and novel Optuna achieve noticeable cost reductions relative to the base load profile. Figure 10 depicts the monthly percentage reduction in the cost of consumption of Energy that has been accomplished through PSO and Optuna optimization compared to the baseline scenario. PSO optimization is able to deliver moderate cost reduction percentages in the range of 35%-44% since they are based on efficient scheduling of loads and cost optimization. On the other hand, the Optuna method always outperforms PSO, producing greater cost reductions in all months, with a percentage range between 45%-55%. So, the average cost reduction is 39.82% in PSO and 49.89% in novel Optuna. From the outcomes, it can be noted that even though PSO performs reasonably well in reducing cost, the method based on Optuna performs much better and consistently in terms of savings.

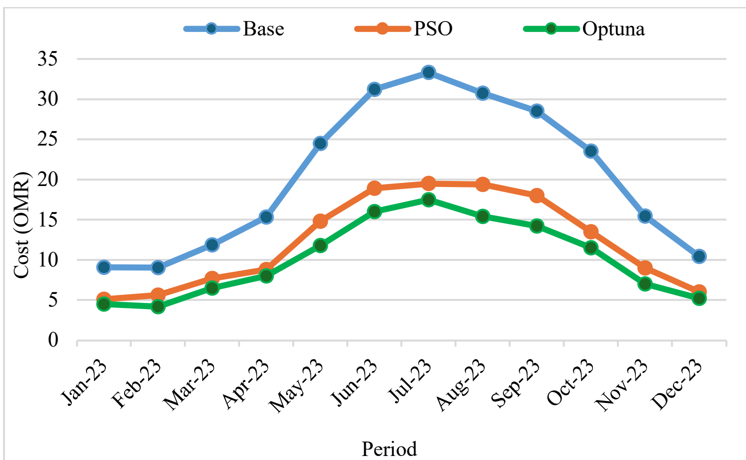


Fig. 9 Monthly energy consumption cost

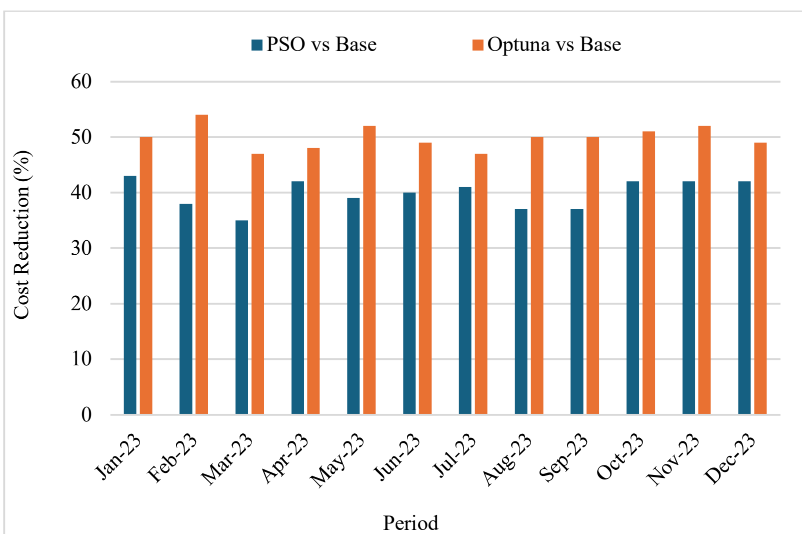


Fig. 10 Percentage of monthly energy consumption cost reduction curve

Table 6 provides data on the daily energy consumption cost for each consumer (OMR/Day) under Base, PSO, and Optuna-optimized conditions. The cost per day has been seen to be subject to the seasonality factor, showing relatively low values in the first and last months and high cost values in between. Although PSO reduces costs by about 41%-42%, the Optuna method is more effective, providing reductions of 49%.

This demonstrates its efficacy in reducing the cost of electricity during peak times. Figure 11 represents the daily energy consumption cost for each consumer (OMR/Day) under Base, PSO, and Optuna-optimized conditions throughout all months in 2023. The PSO optimization always lowers the cost approximately in the range of 35%-45%, while the best performance in cost reduction is seen at approximately 45%-55%.

Table 6. Optimized Daily Energy Consumption Cost with Base (Per Consumer)

Period	C_i (OMR)	$C_i pso$^ (OMR)	$C_i opt$^ (OMR)
Jan-23	0.293	0.165	0.145
Feb-23	0.323	0.200	0.150
Mar-23	0.383	0.248	0.210
Apr-23	0.512	0.293	0.267
May-23	0.790	0.477	0.381
Jun-23	1.040	0.630	0.533
Jul-23	1.075	0.629	0.565
Aug-23	0.992	0.626	0.497
Sep-23	0.951	0.600	0.473
Oct-23	0.759	0.435	0.371
Nov-23	0.516	0.300	0.233
Dec-23	0.336	0.194	0.168

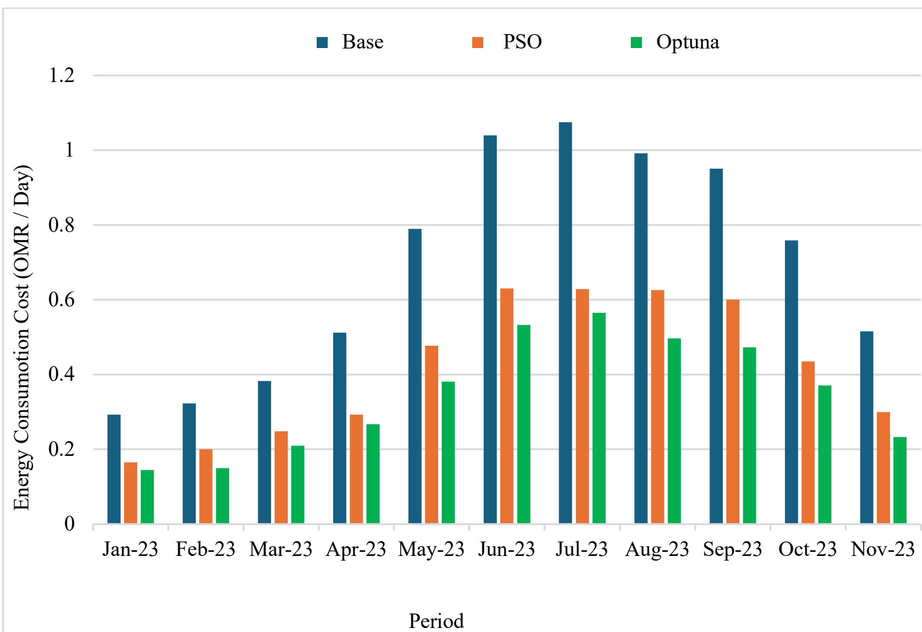
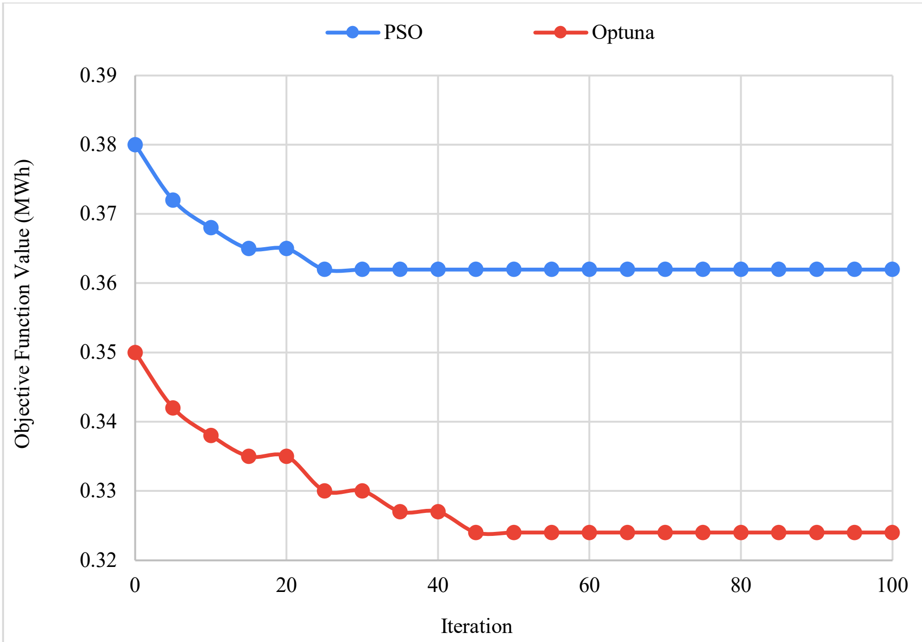


Fig. 11 Daily Energy Consumption Cost Curve (Per Consumer)

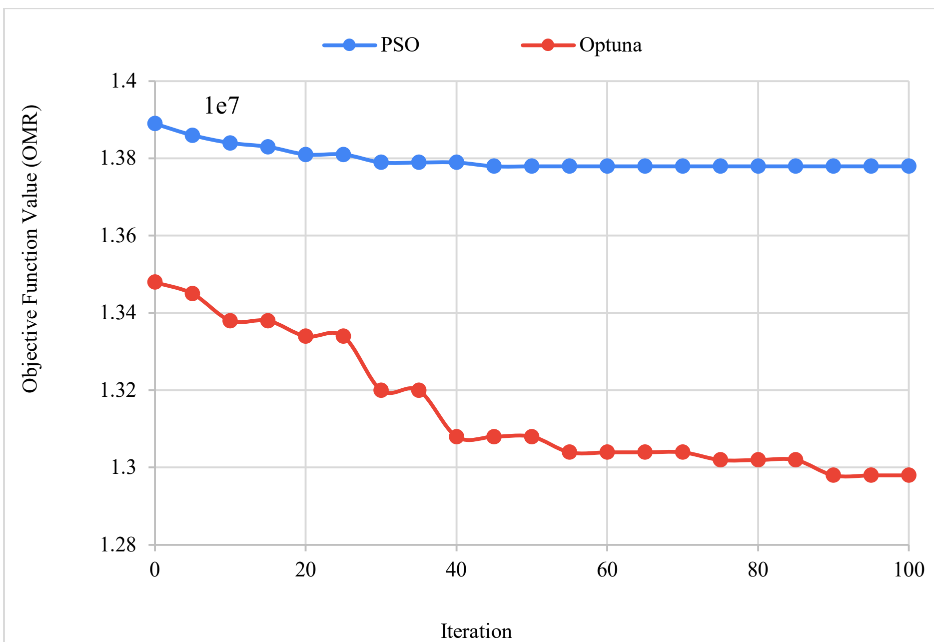
4.3. Convergence

In line with the process of optimization, the convergence graphs (See Figure 12-a and b) have been drawn regarding the values of objective functions of GWh and OMR with respect to both PSO and Optuna algorithms.

Concerning the energy function, PSO decreases Energy from approximately 0.38 MWh in its first iteration to 0.362 MWh in subsequent iterations, thereby obtaining an energy reduction of about 4.7%. On the other hand, Optuna exhibits a faster convergence rate to achieve a lower final energy state, which is 0.00035 GWh to about 0.324 GWh and consequently reduces Energy by 7.4%. In terms of cost, while PSO converges very fast to arrive at a high cost of approximately 1.378×10^7 OMR, Optuna converges slowly but achieves a relatively lower cost of around 1.29×10^7 OMR due to adaptive sampling and pruning techniques that expand search spaces for solutions.



(a)



(b)

Fig. 12 Convergence Curves (a) Energy Basis, and (b) Cost Basis.

4.4. RMSE% and MAE% Evaluation

Based on RMSE and MAE values, RMSE% and MAE% are calculated according to Equation (24) and Equation (25). Figure 13 shows the percentage of RMSE and MAE for both PSO and Optuna methods. PSO has lower error values, where the RMSE value is 1.640 MWh, while MAE has 0.4733 MWh. On the other hand, the RMSE for Optuna is 2.125 MWh, whereas the MAE is 0.613 MWh. As a result, the accuracy of PSO is found to be higher, which makes it provide more balanced loads. Nevertheless, higher accuracy by PSO implies that it requires higher costs and energy consumption. Although Optuna has lower accuracy, its costs and energy consumption are lower. These metrics are evaluated with respect to the energy consumption strategy.

This emphasizes the trade-off between optimization accuracy and economic efficiency in DSM. The PSO gives lower values of RMSE in comparison to Optuna, meaning that the accuracy is better regarding the tracking of the baseline or estimated load profile. For the MAE metric, PSO achieves a more stable level, and Optuna remains within the acceptable limit.

The overall performance of an existing optimization PSO and novelty optimization of Optuna is illustrated below (See Figure 13). The reduction of Energy achieved by Optuna is more significant at 45.45% compared to 35.08%, whereas the reduction of cost stands at 49.89% compared to 39.82% with PSO. This means that Optuna has improved on optimization. However, while its RMSE% stands at 13.12% and MAE% at 3.79%, both are a bit higher compared to those of PSO at 10.12% RMSE% and 2.92% MAE%. This means Optuna provides lower prediction accuracy. Annual Base Cost stands at 243.07 OMR ($632.18), reduced to 146.3 OMR ($380.50) with PSO (39.82%). It falls to 121.8 OMR (316.78 USD) with Optuna, a reduction of 49.89%. These results confirm that both algorithms effectively cut energy expenses in non-cooperative settings, with Optuna offering better cost efficiency for residential DSM.

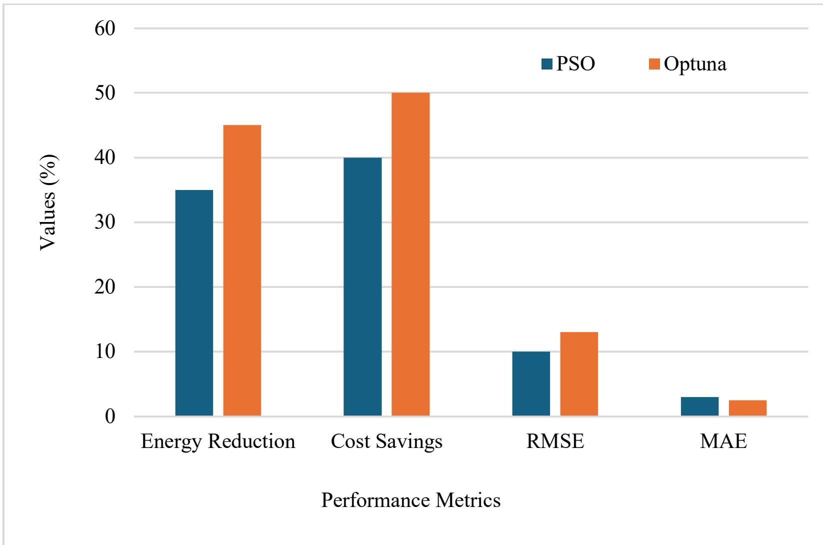


Fig. 13 Overall Performance Comparison

4.5. Grid Reliability and Load Balancing Metrics

According to the optimized results from the Base data, grid reliability and balancing Load of the grid are analyzed using the standard formulae (See Appendix 2). The indicators' values are presented in Figure 14 for one year. The findings further prove that optimization strategies play a vital role in improving the performance of grids through load balance and reliability measures.

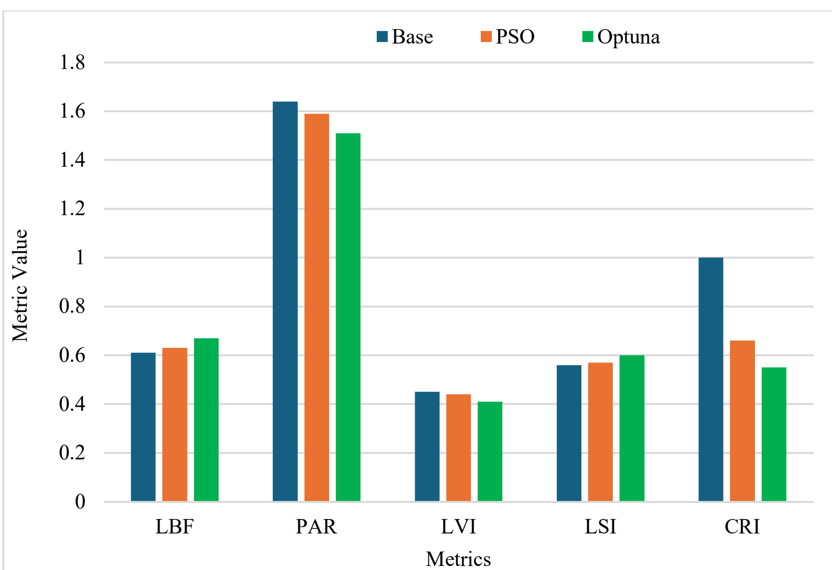


Fig. 14 Grid Reliability and Load Balancing Metrics

Although there is a significant improvement in load balance and reliability using PSO compared to the baseline system, the Optuna strategy has proved to be better with a high LBF of ≈ 0.65, low PAR of ≈1.50, reduced LVI of ≈ 0.40, increased LSI of ≈ 0.60, and minimized CRI of ≈ 0.55. From this result, the customer reliability index has performed well with Optuna.

From the performance of the grids based on the metrics, there is an apparent improvement upon optimization. The LBF increases from Base to PSO and then to Optuna, meaning the loads are distributed efficiently. The LVI declines considerably after optimization, indicating that load variability has been minimized. The LSI increases in a progressive manner, thus signifying the high level of stability in demand. There may be an insignificant change in PAR value upon optimization; however, it still shows that the loads have been balanced. Lower PAR value means that the demand peaks have decreased in relation to the average Load, leading to the stability of the grid [26]. More importantly, the CRI decreases upon optimization, implying increased grid reliability. So, the analysis shows that although PSO performs better than the Base for all the metrics, Optuna outperforms both Base and PSO in all metrics.

5. Discussion

Even though there is clear evidence of energy savings in the simulation process, the practical application of this model in residential settings might lead to minor differences because of factors like practical limitations, user behaviour actions, and demand response uncertainty. In other words, the achieved results can be seen as close to optimal and not entirely practical.

The results generated from this study have been derived based on historical data and given limitations. When practically applied, however, there will be changes in the environment of operations because of actual variations in load requirements and the effects of weather. This will cause the schedules to be implemented in a manner that differs from the expected one, which causes the difference between what is attained and what is predicted. But the novelty optimization method will achieve the most efficient system performance compared to the PSO and other optimization schemes.

Implementation of the proposed DSM approach based on the Stackelberg Game is limited by a number of issues, such as the need for infrastructure that includes smart meters, communications, and automation equipment. Moreover, there may be limitations associated with appliances, comfort needs, and policy regulations that may limit the ability to adjust the scheduling of loads. The above restrictions narrow down the optimization problem domain, impacting the performance of the optimization process. Uncertainty is an inherent part of demand response in reality, owing to fluctuations in consumer involvement and price elasticity. While the Stackelberg Game assumes that consumers respond rationally to price-based stimuli, in reality, there could be a wide variation in response between consumers. The user's conduct becomes an essential factor in ensuring that demand-side management techniques become effective. While in simulations, it is taken for granted that consumer behavior will strictly adhere to the optimized schedule provided, actual consumers may decide to ignore the recommended change in Load because of comfort issues, lifestyle, and other factors, which ultimately impacts performance.

6. Conclusion

A new technique for handling Energy within the house that integrates the Non-Cooperative SGT model with a pre-existing PSO algorithm and a novel Optuna optimization model is provided in this study. This is done to overcome the limitations of the present DSM methodologies, like delays in real-time response and inefficiency in optimization. From the RMSE% and MAE% output, it can be seen that PSO is more accurate in balancing loads. However, Optuna saves 45.45% energy and 49.89% costs annually. PSO produces more precise and consistent results, but it requires more computing power and has greater running expenses. However, the Optuna model trades off some accuracy in predicting the Load but is more economical and achieves convergence more quickly. It is stressed in the paper that it is crucial for the real-time DSM model to strike a balance between economic efficiency and optimum accuracy. Optuna outperforms PSO in situations where cost savings are a priority. However, in cases where grid stability and load balancing requirements must be met accurately, PSO becomes more suitable. This approach promotes sustainable energy management and improves DSM optimization in areas with variable demand and limited resources. Adaptive pruning in Optuna allows faster convergence, where accuracy is reached with less complexity than in PSO, especially in large and nonlinear cases. Although PSO performs well on small problems, Optuna outperforms PSO on larger problems and shows better efficiency. Moreover, Optuna has shown better grid reliability and load-balancing performance than the PSO algorithm.

This research work has illustrated that the use of the SGT-DSM framework with an existing metaheuristic algorithm and novel optimization framework methods. It has been proven that the novelty scheme improves the performance of the system as well as the grid performance compared to the existing method. From the overall results, it is evident that there is a significant compromise between the efficiency and effectiveness of optimization and prediction processes, since the PSO algorithm places a lot of emphasis on reducing errors, whereas Optuna provides a relatively stable optimization approach despite being associated with some level of acceptable error rate. So, the novelty Optuna method is more effective than PSO with its better Energy and cost savings and higher reliability for the residential sector DSM.

Conflict of Interest

The authors declare that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] S. Yilmaz, A. Rinaldi, and M. K. Patel, “DSM Interactions: What is the Impact of Appliance Energy Efficiency Measures on the Demand Response (Peak Load Management)?,” *Energy Policy*, vol. 139, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[2] Mutiu Shola Bakare et al., “A Comprehensive Overview on Demand Side Energy Management towards Smart Grids: Challenges, Solutions, and Future Direction,” *Energy Informatics*, vol. 6, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[3] Geetha Sivanantham, and Srivatsun Gopalakrishnan, “A Stackelberg Game Theoretical Approach for Demand Response in Smart Grid,” *Personal and Ubiquitous Computing*, vol. 24, no. 5, pp. 511-518, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[4] Jun Li, Tao Li, and Daoyi Dong, “Demand Response Management of Smart Grid Based on Stackelberg-Evolutionary Joint Game,” *Science China Information Sciences*, vol. 66, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[5] Jun He et al., “Application of Game Theory in Integrated Energy System Systems: A Review,” *IEEE Access*, vol. 8, pp. 93380-93397, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[6] Fahad R. Albogamy et al., “Real-Time Energy Management and Load Scheduling with Renewable Energy Integration in Smart Grid,” *Sustainability*, vol. 14, no. 3, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[7] Abhishek Tiwari, and Naran M. Pindoriya, “Automated Demand Response in Smart Distribution Grid: A Review on Metering Infrastructure, Communication Technology and Optimization Models,” *Electric Power Systems Research*, vol. 206, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[8] M. Usman Saleem et al., “Integrating Smart Energy Management System with Internet of Things and Cloud Computing for Efficient Demand Side Management in Smart Grids,” *Energies*, vol. 16, no. 12, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] Abdullah Nawaz et al., “An Intelligent Integrated Approach for Efficient Demand Side Management with Forecaster and Advanced Metering Infrastructure Frameworks in Smart Grid,” *IEEE Access*, vol. 8, pp. 132551-132581, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[10] Eity Sarker et al., “Optimal Management of Home Loads with Renewable Energy Integration and Demand Response Strategy,” *Energy*, vol. 210, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[11] Jun Li, Xiaotai Wu, and Tao Li, “Demand Response Management of Smart Grid Based on Bayesian Stackelberg Game Approach,” *Journal of Systems Science and Complexity*, vol. 39, pp. 1477-1496, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[12] Aviad Navon et al., “Applications of Game Theory to Design and Operation of Modern Power Systems: A Comprehensive Review,” *Energies*, vol. 13, no. 15, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[13] Hala Alsalloum, Leila Merghem-Boulahia, and Rana Rahim, “Hierarchical System Model for the Energy Management in the Smart Grid: A Game Theoretic Approach,” *Sustainable Energy, Grids and Networks*, vol. 21, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[14] Lefeng Cheng et al., “Optimizing Electricity Markets Through Game-Theoretical Methods: Strategic and Policy Implications for Power Purchasing and Generation Enterprises,” *Mathematics*, vol. 13, no. 3, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[15] Zhichao Zhang et al., “Prediction Accuracy of Stackelberg Game Model of Electricity Price in Smart Grid Power Market Environment,” *Energies*, vol. 18, no. 3, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[16] Li Dengfeng et al., “Optimization Method of Time-of-Use Electricity Price for the Cost Savings of Power Grid Investment,” *Frontiers in Energy Research*, vol. 12, pp. 1232-1245, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[17] Gokul Sidarth Thirunavukkarasu et al., “Role of Optimization Techniques in Microgrid Energy Management Systems - A Review,” *Energy Strategy Reviews*, vol. 43, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[18] Amit Shewale et al., “An Overview of Demand Response in Smart Grid and Optimization Techniques for Efficient Residential Appliance Scheduling Problem,” *Energies*, vol. 13, no. 16, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[19] Christoforos Menos-Aikateriniadis, Ilias Lamprinos, and Pavlos S. Georgilakis, “Particle Swarm Optimization in Residential Demand-Side Management: A Review on Scheduling and Control Algorithms for Demand Response Provision,” *Energies*, vol. 15, no. 6, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[20] José Adrián Rama Curiel, and Jagruti Thakur, “A Novel Approach for Direct Load Control of Residential Air Conditioners for Demand Side Management in Developing Regions,” *Energy*, vol. 258, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[21] Subhasis Panda et al., "Residential Demand Side Management Model, Optimization and Future Perspective: A Review," *Energy Reports*, vol. 8, pp. 3727-3766, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[22] Songhao Zhao, "Research on the Application of Swarm Behavior to Artificial Intelligence Systems," *Applied and Computational Engineering*, vol. 120, pp. 158-163, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[23] Dongshu Wang, Dapei Tan, and Lei Liu, "Particle Swarm Optimization Algorithm: An Overview," *Soft Computing*, vol. 22, no. 2, pp. 387-408, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[24] Ricardo Faia et al., "Demand Response Optimization Using Particle Swarm Algorithm Considering Optimum Battery Energy Schedule in A Residential House," *Energies*, vol. 12, no. 9, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[25] Yang You, Qianwen Xu, and Carlo Fischione, "Hierarchical Online Game-Theoretic Framework for Real-Time Energy Trading in Smart Grid," *IEEE Transactions on Smart Grid*, vol. 15, no. 2, pp. 1634-1645, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[26] Dereje Tarekegn, Surafel Tilahun, and Tekle Gemechu, "A Review on Convergence Analysis of Particle Swarm Optimization," *International Journal of Swarm Intelligence Research*, vol. 14, no. 1, pp. 1-34, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[27] Brian Tarroja et al., "Metrics for Evaluating the Impacts of Intermittent Renewable Generation on Utility Load-Balancing," *Energy*, vol. 42, no. 1, pp. 546-562, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[28] Gabriel Gómez-Ruiz et al., "A Game-Theoretic Approach to Fair and Grid-Aware Load Flexibility Allocation in Residential Distribution Networks," *Computers and Electrical Engineering*, vol. 131, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[29] A. Sunantha et al., "Smart Grid Optimization: Implementing AI and Machine Learning for Predictive Energy Load Balancing," *2025 Global Conference in Emerging Technology (GINOTECH)*, PUNE, India, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[30] Yanfang Mo et al., "Optimal Online Algorithms for Peak-Demand Reduction Maximization with Energy Storage," *e-Energy '21: Proceedings of the Twelfth ACM International Conference on Future Energy Systems*, pp. 73-83, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[31] NAMA Distribution Company - Oman / Annual Report, 2023. [Online]. Available: https://distribution.nama.om/annual-report

[32] Authority for Public Services Regulation (APSR), Oman / Annual Report, 2023. [Online]. Available: https://apsr.om/pages/home

[33] Shahid Hasan et al., "Oman Electricity Sector: Features, Challenges and Opportunities for Market Integration," *KAPSARC Discussion Paper*, Riyadh, Saudi Arabia, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[34] Optuna Development Team, Efficient Optimization Algorithms - Optuna Documentation, 2024. [Online]. Available: https://optuna.readthedocs.io/en/stable/tutorial/10_key_features/003_efficient_optimization_algorithms.html

APPENDIX 1
Grid Data Set - Ad Dakhliyah, Oman

Period	Electricity Distribution (GWh)	Residential Consumption (GWh)	Residential Consumption – Per Consumer (GWh)	Number of Residential Consumers	Total Electricity Cost (OMR)	Cost per Consumer (OMR)
Jan-23	144.20	60.4638406	6.0483×10^{-4}	99,968	906,957.61	9.072479293
Feb-23	148.61	60.44615507	6.032×10^{-4}	100,213	906,692.33	9.047651802
Mar-23	171.92	79.50892004	7.9172×10^{-4}	100,426	1,192,633.80	11.87574732
Apr-23	202.98	102.9780124	1.0231×10^{-3}	100,653	1,544,670.19	15.34648932
May-23	290.19	164.5517112	1.6326×10^{-3}	100,793	2,468,275.67	24.4885624
Jun-23	339.35	210.5474497	2.0808×10^{-3}	101,184	3,158,211.74	31.21256068
Jul-23	361.99	225.5435311	2.2211×10^{-3}	101,547	3,383,152.97	33.31612918
Aug-23	353.83	208.1437976	2.0501×10^{-3}	101,528	3,122,156.96	30.75168387
Sep-23	333.45	194.1073427	1.9018×10^{-3}	102,063	2,911,610.14	28.52757748
Oct-23	286.10	159.9667986	1.5688×10^{-3}	101,970	2,399,501.97	23.53145013
Nov-23	208.91	105.6152402	1.0312×10^{-3}	102,419	1,584,228.60	15.46811236
Dec-23	155.27	71.33411256	6.9519×10^{-4}	102,611	1,070,011.69	10.42784584
TOTAL	2,996.80	1,643.206912	0. 0162044	1,215,375	24,648,173.67	243.0662897

(Source: NAMA Company, 2023)

APPENDIX 2

Grid Reliability and Load Balancing Metrics Formula

* $LBF = \frac{1}{PAR}$; PAR is the Maximum Load to Average Load
* $PAR = \frac{x_{max}}{x_{avg}}$; x_{max} Is the Maximum of the energy consumption monthly or annually?

  x_{avg} Is the Average Energy Consumption monthly or annually
* $LVI = \frac{\sigma x}{x_{avg}}$; σx is the standard deviation of the energy consumption in a month or annual period

  x_{avg} Is the Average Energy Consumption in a month or annually
* $LSI = 1 - LVI$
* $CRI = \frac{x_{max}}{x_{max-Base}}$; x_{max} Is the Maximum of the energy consumption in a month or annually?

: $x_{max-Base}$ Is the Base-Maximum of the energy consumption in a month or annually?