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*Original Article*

# Optimization of Power Consumption in Smart Grids Using Coati Optimization Algorithm

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***Abstract*** - *The optimization of power consumption in smart grids is the subject of this article, which aims to maximize customer savings while keeping the load curve near 90% of system capacity. The study employs a mathematical model integrating Coati Optimization, a bio-inspired algorithm mimicking the natural behaviors of coatis, to determine optimal load shifting strategies. The methodology is applied to residential, commercial, and industrial areas, considering diverse load characteristics and varying energy prices. The paper presents the problem formulation, methodology, and data description, followed by the analysis of results and discussions on energy consumption disparities across different sectors. The findings underscore the significance of tailored load management strategies for industrial processes and highlight the potential for optimizing energy efficiency through Coati Optimization.*

***Keywords*** - *Smart grid, Power consumption optimization, Load curve optimization, Coati Optimization, Bio-inspired algorithms, Energy management, Load shifting strategies, Industrial energy efficiency, Residential area, Commercial area.*

## 1. Introduction

In modern energy systems, optimizing power consumption is a critical endeavour aimed at ensuring efficiency, reducing costs, and minimizing environmental impact. With the increasing demand for electricity worldwide, coupled with the growing complexity of energy networks, the need to develop effective strategies for managing power consumption has become paramount. This paper addresses this challenge by focusing on the optimization of power consumption in smart grids, with a particular emphasis on maximizing customer savings while maintaining the load curve close to 90% of system capacity [1]. The problem statement revolves around the intricate task of balancing energy supply and demand within smart grid environments. Smart grids incorporate advanced technologies to monitor, control, and manage electricity flows in real-time, offering opportunities for optimizing energy consumption at various levels. However, achieving optimal power consumption requires overcoming several challenges, including fluctuating energy prices, diverse load characteristics, and operational constraints. The importance of optimizing power consumption cannot be overstated. Not only does it contribute to cost savings for consumers and utilities, but it also promotes sustainability by reducing carbon emissions and minimizing energy wastage. Efficient load management plays a pivotal role in enhancing grid stability, reliability, and resilience, thereby ensuring uninterrupted supply and mitigating the risk of blackouts or system failures [2].

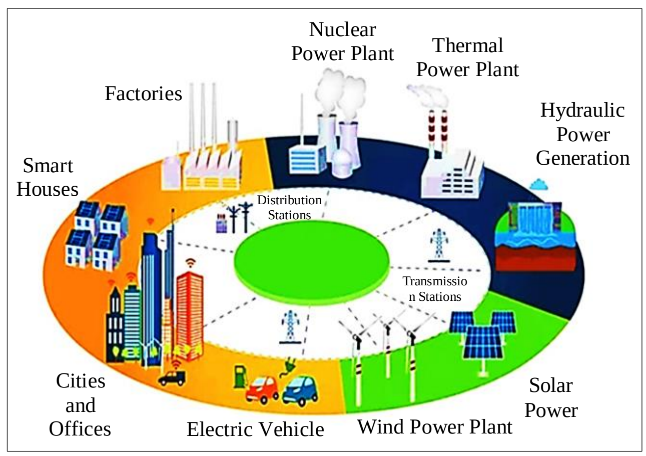


**Fig. 1 Overview of smart grid**

This study presents Coati Optimization, a bio-inspired algorithm inspired by the natural behaviors of coatis, a species of mammal native to Central and South America, to address the challenges connected with power consumption optimization. Coati Optimization harnesses the inherent capabilities of coatis in foraging and escaping predators to develop innovative approaches for solving optimization problems. By simulating coatis' hunting and escape strategies, Coati Optimization offers a promising avenue for tackling the challenges of load curve optimization in smart grids. This paper aims to present a thorough analysis of the problem statement, emphasize the significance of power consumption optimization, present Coati Optimization as a viable solution, and delineate the study's organizational framework. In order to determine if Coati Optimization is effective in maximizing customer savings while attaining optimal power consumption, this study will systematically explore various load management strategies in residential, commercial, and industrial locations [14].

## 2. Background and Problem Context

### *2.1. Overview of Load Management in Smart Grids*

Smart grids represent a transformative evolution in the management of electricity distribution and consumption. Advanced sensing, communication, and control technologies are incorporated into smart grids to enable continuous monitoring and optimization of energy distribution. Essential to smart grid functionality is load management, which entails strategically regulating and coordinating electricity usage to align with supply and demand effectively. Smart grid technologies enable various load management techniques, including demand response, dynamic pricing, and distributed energy resource integration.

Demand response programs enable utilities to adjust electricity use in response to market signals or system circumstances, relieving pressure during periods of peak demand. By using dynamic pricing models, consumers are incentivized to shift their energy consumption to off-peak hours, which reduces costs and overall strain on the system. Optimization of localized energy output and consumption is also made possible by the integration of distributed energy resources, such as solar panels and batteries. In order to better understand the potential advantages of increased grid flexibility, dependability, and resilience, numerous studies have examined various load management strategies in smart grids. By effectively managing electricity consumption, smart grids can mitigate the risk of grid instability, reduce energy wastage, and support the integration of renewable energy sources [4-6].

### *2.2. Significance of Load Curve Optimization*

Load curve optimization (Figure 2) is a fundamental aspect of load management in smart grids, aiming to maintain the load curve as close to 90% of system capacity as possible. The load curve represents the variation in electricity demand over time, with peaks indicating periods of high consumption and valleys representing low-demand intervals. Optimizing the load curve involves flattening peaks and valleys, thereby ensuring efficient utilization of grid resources and minimizing the need for costly infrastructure upgrades.

Efficient load curve optimization offers several significant advantages, including improved grid reliability, reduced operational costs, and enhanced energy efficiency. By smoothing out demand fluctuations, utilities can better anticipate and respond to grid conditions, thereby avoiding overloads and reducing the likelihood of power outages. Moreover, optimizing the load curve allows for more effective utilization of renewable energy resources, as grid stability is essential for integrating intermittent sources like solar and wind power [8, 9].

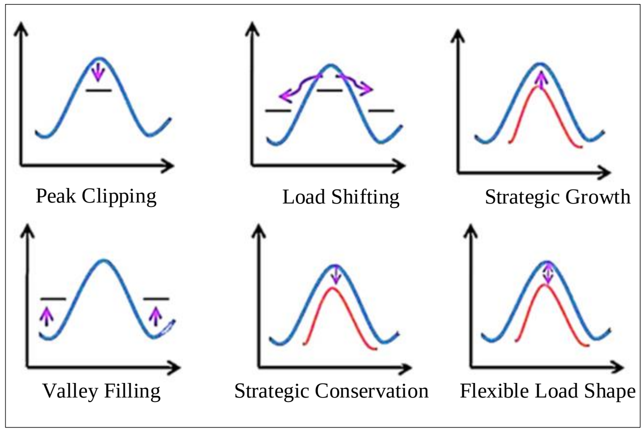


**Fig. 2 Load curves in DSM**

Several optimization techniques have been proposed for load curve optimization, ranging from traditional mathematical programming approaches to advanced heuristic algorithms. These approaches strive for equilibrium between the availability of energy and its demand, taking into account variables like energy costs, consumer choices, and limitations within the grid network. Although several techniques are utilized in smart demand-side management, including reinforcement learning, fuzzy logic, ant colony optimization, simulated annealing, genetic algorithms, and particle swarm optimization, each has limitations. Genetic algorithms may suffer from slow convergence and scalability issues, especially when dealing with large-scale systems or complex optimization problems [13].

Particle swarm optimization may struggle with premature convergence and may require fine-tuning of parameters to achieve optimal performance. Simulated annealing's effectiveness heavily depends on the initial temperature and cooling schedule, and it may converge slowly if not properly configured. Ant colony optimization may struggle with the "exploration vs. exploitation" trade-off, potentially leading to suboptimal solutions. Reinforcement learning algorithms often require significant computational resources and extensive training data, and they may be sensitive to changes in the environment or reward structure [6, 7].

Fuzzy logic controllers may lack interpretability and transparency, making it challenging to understand and validate their decision-making process. Identifying and addressing these drawbacks is crucial for developing more efficient and reliable optimization techniques in smart demand-side management [8]. By focusing on addressing these limitations, proposed optimization methods can offer improvements in terms of convergence speed, scalability, robustness, interpretability, and adaptability, ultimately enhancing the effectiveness of demand-side management systems [11]. The following research gaps are identified in the optimization of power consumption in smart grids.

#### *2.2.1. Scalability of Algorithms*

Problem: Many optimizations' algorithms struggle with scaling to large, complex smart grid networks involving millions of devices and consumers.

Research Gap: There is a need for scalable, efficient optimization techniques that can handle large-scale grid operations in real-time, particularly as grids grow more complex with distributed generation and increased electrification.

#### *2.2.2. Integration of Renewable Energy*

Problem: Renewable energy sources like solar and wind are intermittent, making it difficult to balance power supply and demand.

Research Gap: Optimization algorithms need to better handle the variability and uncertainty in renewable energy production to ensure grid stability and efficient energy distribution.

#### *2.2.3. Consumer Behavior and Demand Response*

Problem: Current optimization algorithms often neglect consumer behavior and preferences, which are critical for demand-side management.

Research Gap: Incorporating human factors and dynamic consumption patterns into optimization algorithms is essential for more accurate demand response strategies.

#### *2.2.4. Cybersecurity Concerns*

Problem: Optimized power consumption systems may introduce vulnerabilities to cyberattacks, which can disrupt grid operations.

Research Gap: Developing algorithms that not only optimize power consumption but also ensure robust security against potential cyber threats is an important research direction.

#### *2.2.5. Decentralized Optimization*

Problem: Centralized control of optimization in smart grids is increasingly impractical due to the decentralized nature of energy production (e.g., rooftop solar, electric vehicles).

Research Gap: More research is needed into decentralized or distributed optimization algorithms that can manage power consumption across distributed energy resources while maintaining overall grid efficiency.

#### *2.2.6. Real-Time Optimization*

Problem: Many optimization algorithms are designed for offline use and cannot adapt to real-time changes in the grid, such as sudden load fluctuations or unexpected outages.

Research Gap: There is a growing demand for real-time optimization algorithms that can adjust to instantaneous changes in both supply and demand within milliseconds.

#### *2.2.7. Multi-Objective Optimization*

Problem: Smart grids need to optimize multiple conflicting objectives such as cost, energy efficiency, carbon emissions, and system reliability.

Research Gap: Developing multi-objective optimization frameworks that can simultaneously address these conflicting goals in real-world scenarios is still an area lacking effective solutions.

#### *2.2.8. Interoperability of Different Technologies*

Problem: Smart grids involve a mix of technologies (e.g., IoT sensors, smart meters, energy management systems), and current optimization methods often fail to ensure seamless integration across these platforms.

Research Gap: Improved algorithms that can operate efficiently across different technology standards and protocols are necessary for future smart grid optimizations.

#### *2.2.9. Energy Storage Integration*

Problem: The integration of energy storage systems (e.g., batteries) into the optimization process is often suboptimal despite its potential to enhance grid reliability.

Research Gap: More research is required to create optimization algorithms that efficiently integrate and manage energy storage alongside renewable energy resources in smart grids.

Addressing these gaps would significantly advance the effectiveness and reliability of smart grids using optimization algorithms.

### *2.3. Introduction to Coati Optimization*

Coati Optimization is a computational technique inspired by the cooperative foraging and predator evasion tactics observed in coatis, which are small mammals. The algorithm simulates the hunting and escapes behaviors of coatis to solve optimization problems efficiently. During the hunting phase, coatis collaborate to locate and capture prey, exhibiting exploratory behavior to search for optimal solutions. Conversely, during the escape phase, coatis scatter and move to safer locations to evade predators, demonstrating exploitative behavior to refine existing solutions. Coati Optimization offers several advantages for solving optimization problems, including robustness, scalability, and adaptability.

By mimicking natural behaviors, the algorithm can effectively explore solution spaces, identify promising regions, and converge to optimal solutions quickly. Additionally, Coati Optimization demonstrates capability in addressing intricate optimization challenges across multiple dimensions with nonlinear constraints, rendering it applicable across various fields, such as optimizing load curves within smart grid systems [10-14].

### *2.4. Challenges in Industrial Energy Management*

Industrial energy management presents unique challenges due to the high energy demands and complex operational requirements of industrial facilities. Industrial processes often involve the operation of heavy machinery, such as induction motors, welding machines, and arc furnaces, which consume large amounts of electricity. Additionally, industrial operations typically run continuously or for extended periods, leading to constant energy consumption and minimal opportunities for load shifting.

Furthermore, industrial facilities may have diverse load types with varying power requirements, making load management and optimization more challenging. The presence of specific operational needs, such as continuous production schedules and stringent quality control requirements, further complicates energy management efforts. As a result, industrial energy managers must develop tailored strategies to optimize energy consumption, minimize costs, and ensure operational efficiency [9, 10].

Addressing these challenges requires a comprehensive understanding of industrial processes, energy consumption patterns, and operational constraints. Moreover, it necessitates the adoption of advanced optimization techniques, such as Coati Optimization, to develop effective load management strategies tailored to industrial environments. Overall, the background and problem context provides insights into the complexities of load management in smart grids, the importance of load curve optimization, the introduction of Coati Optimization as a promising solution, and the challenges associated with industrial energy management. By addressing these challenges and leveraging innovative optimization approaches, it is possible to enhance energy efficiency, reduce costs, and promote sustainable industrial practices [9-12].

## 3. Problem Formulation

An overview of potential research novelties in applying the Coati Optimization Algorithm to optimize power consumption in smart grids is given below.

- Hybrid Optimization Algorithms: Combining multiple algorithms to balance convergence speed and solution accuracy.
- Deep Learning-Assisted Optimization: Integrating deep learning models with optimization algorithms to improve accuracy based on historical and real-time data.
- Blockchain-Assisted Optimization: Using blockchain technology to enable decentralized, secure, and transparent optimization in energy management.
- Multi-Agent Systems (MAS) for Decentralized Optimization: Implementing decentralized optimization, where multiple agents autonomously optimize energy usage and collaborate for overall grid efficiency.
- Federated Learning for Demand-Side Management: Applying federated learning for decentralized data training, improving demand-side management while maintaining privacy.
- Quantum Computing in Power Optimization: Exploring quantum computing’s potential for faster solutions to large-scale grid optimization problems.
- Game-Theoretic Models for Load Balancing: Employing game theory to optimize interactions between various entities in the grid for efficient load balancing.
- Artificial Immune System (AIS) for Power Grid Security: Developing AIS-based algorithms to enhance security while optimizing power consumption.
- Event-Driven Optimization: Triggering optimization algorithms based on specific grid events to dynamically adjust power usage.
- Edge Computing for Real-Time Optimization: Using edge computing for real-time optimization at the local level, improving response times.
- Swarm Intelligence-Based Energy Management: Applying swarm intelligence algorithms inspired by biological systems to optimize distributed energy management.

Adaptive Optimization for Real-Time Grid Management: Developing algorithms that adapt optimization strategies based on changing grid conditions in real-time.

### *3.1. Description of the Objective Function*

This research aims to enhance power utilization efficiency and increase customer cost savings by aligning the load curve to approximately 90% of the system's capacity. This goal is measured through an objective function that combines the average consumption rate throughout a 24-hour timeframe (P_avg) and the maximum system capacity (P_max). The objective function seeks to reduce power usage and enhance savings by factoring in anticipated load and electricity prices during various consumption periods [13].

$$Objective\ function = \frac{P_{avg}}{P_{max}} \times \sum_{t=1}^{24} Forecasted\ Load \times \frac{1}{P(t)} \tag{1}$$

$$\sum_{t=1}^{M}(P_{load}(t) - objective(t))^2 \quad (2)$$

At a specific time "t," the planned load consumption is denoted as $P_{load}(t)$, which takes into account the expected load along with attached and detached loads before any load shifting occurs. The total load is computed using the provided formula.

$$P_{load}(t) = P_{forecast}(t) + P_{connected} + P_{diconnected} \quad (3)$$

The parameters Connection(t) and Disconnection(t) factor in load increments and decrements resulting from device connections and disconnections. These are modelled by taking into consideration the power consumption and duration of devices, enabling forecasts regarding potential network overload or inadequate service.

$$Connection(t) = \sum_{j=1}^{t-1}\sum_{m=1}^{N} U_{mjt}.C_{1m} + \sum_{k=1}^{l-1}\sum_{j=1}^{t-1}\sum_{m=1}^{N} U_{mj(t-1)}.C_{(1+k)m} \quad (4)$$

The variable Disconnection(t) represents a decline in load attributed to delays in device connection schedules, as well as the decrease in load resulting from delayed activation of devices that were initially expected to start consuming before the designated time "t".

$$Disconnection(t) = \sum_{x=t+1}^{t+y}\sum_{m=1}^{N} U_{mtx}.C_{1m} + \sum_{k=1}^{l-1}\sum_{x=t+1}^{t+y}\sum_{m=1}^{N} U_{m(t-1)x}.C_{(1+k)m} \quad (5)$$

$$U_{mjt} > 0\forall j, l, m \quad (6)$$

$$\sum_{t=1}^{M} U_{mjt} < C_t(j) \quad (7)$$

The research examines a scenario in which all devices consume power at every time step, depicted through a finite time-step model. The aim is to modify the number of regulated devices by applying different optimization techniques, beginning at a specific time point "j".

# 4. Methodology

## *4.1. An Overview of the Phases of Coati Optimization*

A bio-inspired technique known as the Coati Optimization Algorithm (COA) mimics the innate behaviors of coatis, a mammal species known for its cooperative hunting and avoidance strategies. COA comprises two primary phases, each mirroring distinct behaviors observed in coatis within their native environment.

### *4.1.1. Phase 1: Iguana Hunting and Attack Tactics (Exploration Phase)*

The first stage of updating the coati population in the search space is designed to mimic their iguana-hunting technique. In this tactic, a group of coatis climb a tree to confront and agitate an iguana while other coatis wait beneath the tree for the iguana to drop. The coatis will jump and chase after the iguana once it has fallen. This method asks coatis to go across the search space in different spots, demonstrating the global exploration capabilities of COA in domains where problems need to be solved.

According to COA's structure, the status of the best-performing population member is comparable to that of an iguana. It is also thought that half of the coatis scale the tree, with the other half waiting for the iguana to come down. Consequently, Equation (8) is used to calculate the mathematical simulation of Coatis' position ascent up the tree [14].

$$X_i^{P1}: x_{i,j}^{P1} = x_{i,j} + r \cdot (\text{ iguana }_j - I - x_{L,j}),$$
$$\text{for } i = 1,2,\dots,\left\lfloor\frac{N}{2}\right\rfloor \text{ and } j = 1,2,\dots,m. \quad (8)$$

When the iguana reaches the ground, it is moved at random anywhere in the search area. Equations (9) and (10), which show how Coatis, which are on the ground, move through the search space depending on this randomized position, are then displayed.

$$\text{Iguana}^{C}: \text{Iguand}_j^{C} = Ib_j + r \cdot (ub_j - Ib_j), j = 1,2,\dots,m,$$
$$x_i^{P1}: x_{i,j}^{P1} = \{x_{i,j} + I \cdot I \cdot x_{i,j}), \quad F_{\text{lyain}} << F_i, \quad (9)$$

$$\text{for } i = \left\lfloor\frac{N}{2}\right\rfloor + 1, \left\lfloor\frac{N}{2}\right\rfloor + 2, \dots, N \text{ and } j = 1,2,\dots,m. \quad (10)$$

If the new position determined for each coati increases the value of the objective function, then the update mechanism accepts it; if not, the coati stays in its original position. For the simulated values of $i$=1, 2, ..., $N$, this update condition is for Equation (11).

$$X_i = \begin{cases} X_i^{P1}, F_i^{P1} < F_i, \\ X_i, \text{ else.} \end{cases} \quad (11)$$

Here, the $i$th coati's newly computed position is represented by, $X_i^{P1}$. Its jth dimension is shown by, $x_{ij}^{P1}$, and its objective function value is indicated by $F$-$i$-$P1$. The variable r represents a real number at random in the interval [0,1]. "Iguana" represents the location within the search space, which is effectively the best member's position. Its $j$th dimension is represented by $Iguana_j$.

An integer selected at random from the collection {1,2} is the variable l. " Iguana $^{C}$ " denotes the randomly generated position of the iguana on the ground. The expression "Iguana $_j^{C}$" indicates its jth dimension. The symbols $F_{\text{lguang}}{}^{C}$ signify its objective function value. The floor function, also referred to as the biggest integer function, is represented by the symbol $\lfloor\cdot\rfloor$ [14].

*4.1.2. Phase 2: The Behavior of Running Away from a Predator (Exploitation Phase)*

The second phase is revising coatis' placements in the search space, which is modeled mathematically after how they naturally flee from predators when they come across them. A coati quickly flees to a nearby area that is safer when it encounters a predator. Using Equations (12) and (13) [14], a random position is created close to each coati's present location in order to imitate this behavior.

$$lb_j^{\text{local}} = \frac{lb_j}{t}, ub_j^{\text{local}} = \frac{ub_j}{t}, \text{ where } t = 1,2,\dots,T. \quad (12)$$

$$X_i^{p2}: x_{i,j}^{p2} = x_{i,j} + (1-2r)\cdot\left(lb_j^{\text{local}} + r\cdot\left(ub_j^{\text{local}} - lb_j^{\text{local}}\right)\right), \quad i = 1,2,\dots,N, j = 1,2,\dots,m \quad (13)$$

The position is deemed appropriate if the newly computed value increases the objective function. Equation (14), when applied to this criterion, is evaluated.

$$X_i = \begin{cases} X_i^{P2}, F_i^{P2} < F_i, \\ X_i, \text{ else}, \end{cases} \quad (14)$$

The new position (referred to as $X_i^{P2}$) for the dt coati is computed in the second phase of COA. $X_{i,j}^{P2}$ denotes its $j^{th}$ dimension, and $F_i^{P2}$ denotes its objective function value. These values are used to calculate this position. Within the interval [0,1], the variable r denotes a random number. "t" represents the number of iterations. Indicating the local lower and upper bounds of the th decision variable, respectively, are $lb_j^{local}$ and $ub_j^{local}$. Similarly, the lower and upper boundaries of the j, $i^{th}$ decision variable are represented by $lb_j$ and $ub_j$ respectively [14].

### *4.2. Pseudocode, Flowchart, and Repetition Process of COA*

After the phases of exploration and exploitation, the COA algorithm completes one iteration when all coatis' positions in the search space have been updated. Up until the algorithm's last iteration, the population update process is iterated under the direction of Equations (8) through (14). The COA algorithm is implemented iteratively, with each iteration modifying coatis' locations in the search space according to the phases of exploration and exploitation. The following pseudo-code describes the stages involved in determining the optimal solution found so far, updating coatis' positions, and calculating the objective function value.

### *4.3. Explanation of the Repetition Process*

The repetition process indicates the COA algorithm's repetitive nature. The method evaluates the objective function value for each possible solution after updating coatis' positions based on the phases of exploration and exploitation. This procedure is reiterated for a predetermined number of iterations or until meeting a termination criterion, such as convergence or reaching the maximum number of iterations. The method repeatedly searches and utilizes the search space to find the best answer to the optimization problem through this iterative approach.

## 5. Data Description

### *5.1. Wholesale Energy Prices and Load Demands*

Data on load demands and forecasted wholesale energy costs for various time periods are shown in Table 1. It includes data for household power supply, commercial power supply, and industrial power supply. Each time period is associated with a specific market price (in ct/kWh) and estimated hourly usage (in kWh) for the respective sectors.

The load demands and wholesale energy prices table enable an understanding of the variability in energy consumption patterns throughout the day and the corresponding fluctuations in energy prices. This information is crucial for developing effective load management strategies and optimizing power consumption to maximize cost savings while ensuring efficient utilization of resources.

### *5.2. Industrial, Commercial, and Residential Controllable Device Data*

Table 2 offers comprehensive information on controllable devices in commercial, industrial, and residential settings. It includes the number of appliances and the hourly consumption (in kW) of each item. Each device type is associated with its hourly consumption pattern across three consecutive hours. For the residential area, the controllable devices include appliances such as dryers, dishwashers, washing machines, ovens, irons, vacuum cleaners, fans, kettles, toasters, rice cookers, hair dryers, blenders, frying pans, and coffee makers. The data show the overall number of appliances available as well as the hourly consumption of each type of device.

In the commercial area (Table 3), controllable devices include water dispensers, dryers, kettles, ovens, coffee makers, fans/air conditioners, air conditioners, and lights. Similar to the residential area, the data provide the hourly consumption patterns and quantities of appliances for each device type.

Controllable equipment includes water heaters, welding machines, fans and air conditioners, arc furnaces, induction motors, and DC motors in the industrial area (Table 4). The data include the hourly consumption of each device type and the total quantity of appliances available. This comprehensive information on controllable devices across many industries makes it easier to create load shifting plans that are suited to the unique needs and features of each region. Efficient load management solutions can be applied to maximize cost savings and optimize power consumption by comprehending the energy consumption patterns of various devices and sectors.

**Table 1. Predicted load demands and wholesale energy prices**

| Period | Market Price (ct/kWh) | Estimated Hourly Usage (kWh) | | |
|---|---|---|---|---|
| | | Household Power Supply | Commercial Power Supply | Industrial Power Supply |
| 08:00-09:00 | 12.00 | 729.4 | 923.50 | 2045.50 |
| 09:00-10:00 | 9.19 | 713.5 | 1154.40 | 2435.10 |
| 10:00-11:00 | 12.27 | 713.5 | 1443.00 | 2629.90 |
| 11:00-12:00 | 20.69 | 808.7 | 1558.40 | 2727.30 |
| 12:00-13:00 | 26.82 | 824.5 | 1673.90 | 2435.10 |
| 13:00-14:00 | 27.35 | 761.1 | 1673.90 | 2678.60 |
| 14:00-15:00 | 13.81 | 745.2 | 1673.90 | 2678.60 |
| 15:00-16:00 | 17.31 | 681.8 | 1587.30 | 2629.90 |
| 16:00-17:00 | 16.42 | 666.0 | 1558.40 | 2532.50 |
| 17:00-18:00 | 9.83 | 951.4 | 1673.90 | 2094.20 |
| 18:00-19:00 | 8.63 | 1220.9 | 1818.20 | 1704.50 |
| 19:00-20:00 | 8.87 | 1331.9 | 1500.70 | 1509.70 |
| 20:00-21:00 | 8.35 | 1363.6 | 1298.70 | 1363.60 |
| 21:00-22:00 | 16.44 | 1252.6 | 1096.70 | 1314.90 |
| 22:00-23:00 | 16.19 | 1046.5 | 923.50 | 1120.70 |
| 23:00-24:00 | 8.87 | 761.1 | 577.20 | 1022.70 |
| 24:00-01:00 | 8.65 | 475.7 | 404.00 | 974.00 |
| 01:00-02:00 | 8.11 | 412.3 | 375.20 | 876.60 |
| 02:00-03:00 | 8.25 | 364.7 | 375.20 | 827.90 |
| 03:00-04:00 | 8.10 | 348.8 | 404.00 | 730.50 |
| 04:00-05:00 | 8.14 | 269.6 | 432.90 | 730.50 |
| 05:00-06:00 | 8.13 | 269.6 | 432.90 | 779.20 |
| 06:00-07:00 | 8.34 | 412.3 | 432.90 | 1120.10 |
| 07:00-08:00 | 9.35 | 539.1 | 663.80 | 1509.70 |

**Table 2. Controllable device information in the residential sector**

| Product Type | Device's Hourly Usage (kW) | | | Quantity of Appliances |
|---|---|---|---|---|
| | C1 | C2 | C3 | U |
| | 1st Hour | 2nd Hour | 3rd Hour | U |
| Dryer | 1.2 | 0 | 0 | 189 |
| Dishwasher | 0.7 | 0 | 0 | 288 |
| Washing Machine | 0.5 | 0.4 | 0 | 268 |
| Oven | 1.3 | 0 | 0 | 279 |
| Iron | 1 | 0 | 0 | 340 |
| Vacuum Cleaner | 0.4 | 0 | 0 | 158 |
| Fan | 0.2 | 0.2 | 0.2 | 288 |
| Kettle | 2 | 0 | 0 | 406 |
| Toaster | 0.9 | 0 | 0 | 48 |
| Rice Cooker | 0.85 | 0 | 0 | 59 |
| Hair Dryer | 1.5 | 0 | 0 | 58 |
| Blender | 0.3 | 0 | 0 | 66 |
| Frying Pan | 1.1 | 0 | 0 | 101 |
| Coffee Maker | 0.8 | 0 | 0 | 56 |
| Total | - | | | 2604 |

**Table 3. Controllable device information in commercial area**

| Product Type | Device's Hourly Usage (kW) | | | Quantity of Appliances |
|---|---|---|---|---|
| | 1st Hour | 2nd Hour | 3rd Hour | |
| Water Dispenser | 2.5 | 0 | 0 | 156 |
| Dryer | 3.5 | 0 | 0 | 117 |
| Kettle | 3 | 2.5 | 0 | 123 |
| Oven | 5 | 0 | 0 | 77 |
| Coffee maker | 2 | 2 | 0 | 99 |
| Fan/AC | 3.5 | 3 | 0 | 93 |
| Air conditioner | 4 | 3.5 | 3 | 56 |
| Lights | 2 | 1.75 | 1.5 | 87 |
| Total | 0 | 0 | 0 | 808 |

**Table 4. Controllable device information in industrial area**

| Product Type | Hourly Consumption of Device (kW) | | | Quantity of Appliances | | | |
|---|---|---|---|---|---|---|---|
| | 1st Hour | 2nd Hour | 3rd Hour | | | | |
| | C1 | C2 | C3 | C4 | C5 | C6 | U |
| | 1st Hour | 2nd Hour | 3rd Hour | 4th Hour | 5th Hour | 6th Hour | Total Quantity of Appliances |
| water Heater | 12.5 | 12.5 | 12.5 | 12.5 | 0 | 0 | 39 |
| Welding Machine | 25 | 25 | 25 | 25 | 25 | 0 | 35 |
| Fan/AC | 30 | 30 | 30 | 30 | 30 | 0 | 16 |
| Arc Furnace | 50 | 50 | 50 | 50 | 50 | 50 | 8 |
| Induction Motor | 100 | 100 | 100 | 100 | 100 | 100 | 5 |
| DC motor | 150 | 150 | 150 | 0 | 0 | - | 6 |
| Total | 0 | 0 | 0 | 0 | 0 | 0 | 109 |

## 6. Results and Discussion

### *6.1. Analysis of Optimal Load Shifting Strategies*

The analysis of optimal load shifting strategies reveals insights into effective approaches for managing power consumption in smart grids. Using Coati Optimization and accounting for the various load parameters and energy costs, the research finds ways to move loads to off-peak times while reducing expenses and optimizing savings. The results highlight the importance of considering factors such as device usage patterns, energy demand fluctuations, and price variations in developing optimal load shifting strategies.

### *6.2. Comparison of Results across Different Areas*

Comparing the results across residential, commercial, and industrial areas, as per Figure 3, provides valuable insights into the unique challenges and opportunities for load management in each sector. The analysis reveals differences in energy consumption patterns, peak demand periods, and potential for load shifting. Residential areas may exhibit more flexibility in load shifting due to the presence of multiple appliances with intermittent usage patterns. In contrast, industrial areas may face challenges in load management due to continuous operation and high-power requirements of heavy-duty machinery.

Figure 4 depicts a line chart showing energy consumption (in kWh) over 20 hours for a single sector labelled "AA". The consumption starts at around 6000 kWh and gradually decreases to around 1000 kWh. The second image shows a stacked bar chart displaying energy consumption (in kWh) for three sectors ("Residential", "Commercial", and "Industrial") over the same 20-hour period. Each sector is represented by a different colour, and the total height of each bar represents the total energy consumption for all sectors at that point in time. Both visualizations illustrate the variations in energy consumption over time and across different sectors, providing insights for load shifting and optimizing energy consumption patterns.


**Fig. 3 Illustrations of the residential, commercial and industrial smart grids**

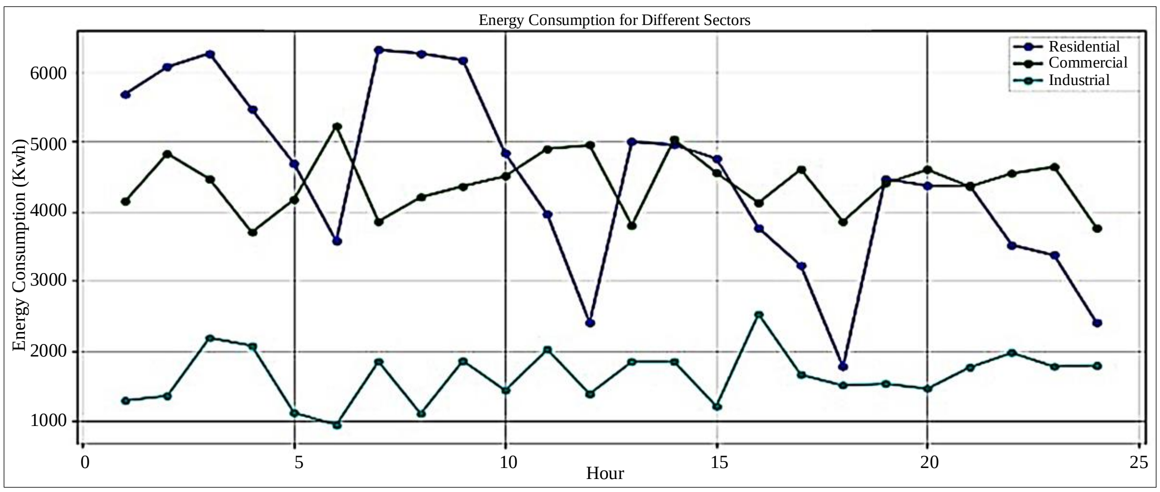


**Fig. 4 Energy consumption at residential, commercial and industrial**

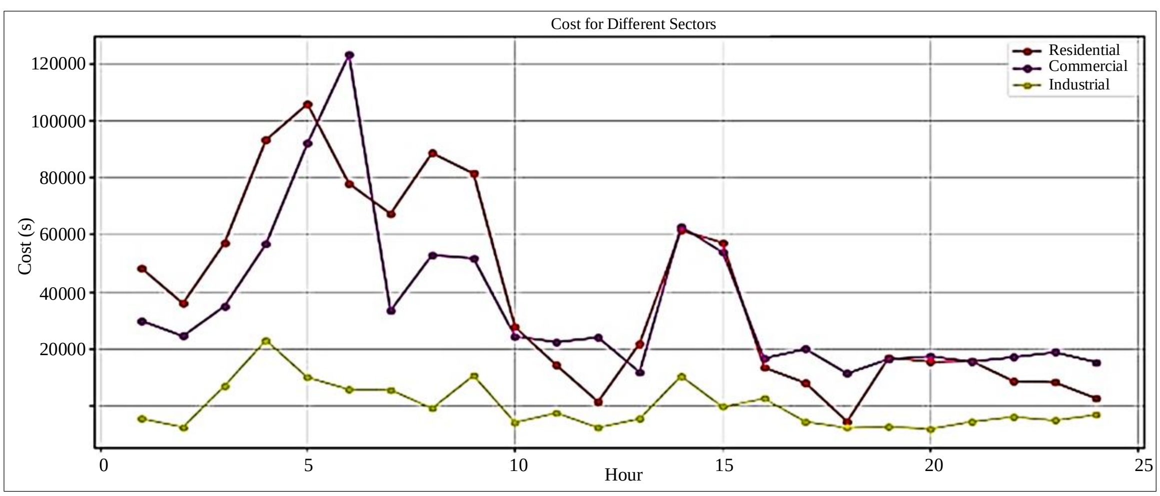


**Fig. 5 Cost variation at residential, commercial and industrial**

Figure 5 is a line chart showing the costs over time for a single sector labelled "AA" over a 20-hour period. The costs start at around $140,000 and decrease to around $20,000 by the end of the period. The second image is a stacked bar chart showing costs by sector (Residential, Commercial, and Industrial) over the same 20-hour period. Each sector is represented by a different colour, and the total height of each bar represents the total costs for all sectors at that point in time. Both images illustrate variations in costs over time and across different sectors.

The line chart provides a clear view of the cost trend for a single sector, while the stacked bar chart allows for a comparison of costs between different sectors. These visualizations can help identify opportunities for cost savings and optimizing cost patterns. The costs shown in the visualizations are likely related to energy consumption, which is a significant component of many organizations' operating expenses. However, the specific costs and their causes are not specified in the images, so further analysis would be needed to understand the underlying factors driving the cost trends. Figure 6 presents a comparison between the load after moving and the predicted load for the residential area. The red dashed line shows the load after shifting, whereas the blue line shows the anticipated load. Peak load occurs during the hours of 6hrs-7hrs and 19hrs-20hrs, with values of 269.6 kW and 1331.9 kW, respectively. After load shifting, peak load remains consistent during these hours, albeit slightly reduced, with adjusted values of 316.79 kW and 1100 kW, respectively. The predicted load for the business sector is shown in Figure 7, along with the load after shifting. The blue line shows the forecasted load, and the red dashed line shows the load after shifting. Peak load occurs during the hours of 19hrs-20hrs, with a value of 1818.2 kW in the forecasted load. After load shifting, the peak load remains around the same hour, albeit slightly reduced, with an adjusted value of 1425.4 kW.

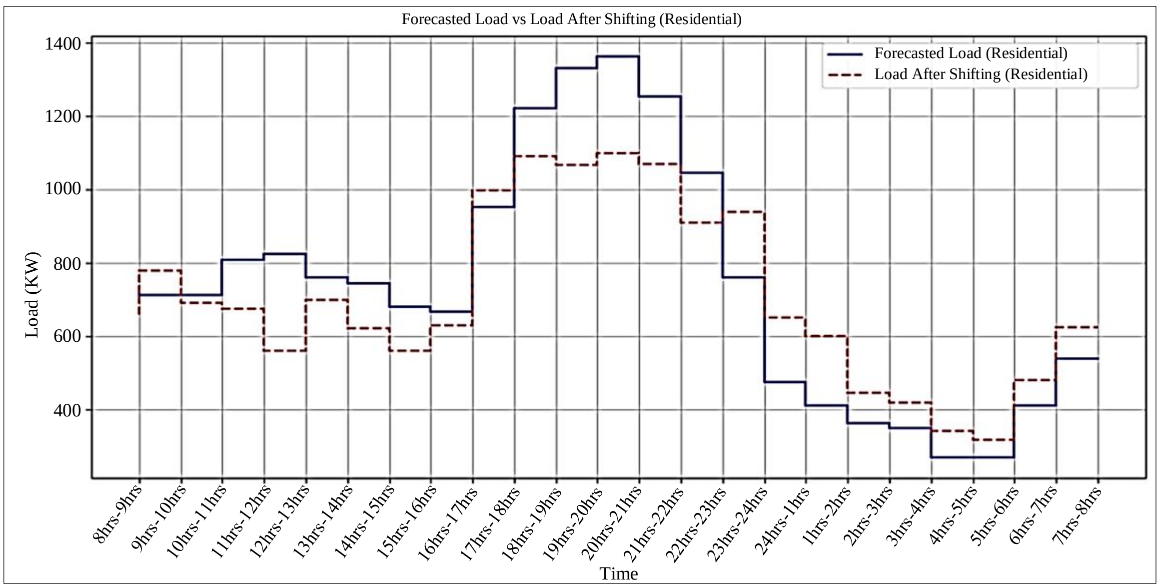


**Fig. 6 Load profiles using coati optimization algorithm (residential)**

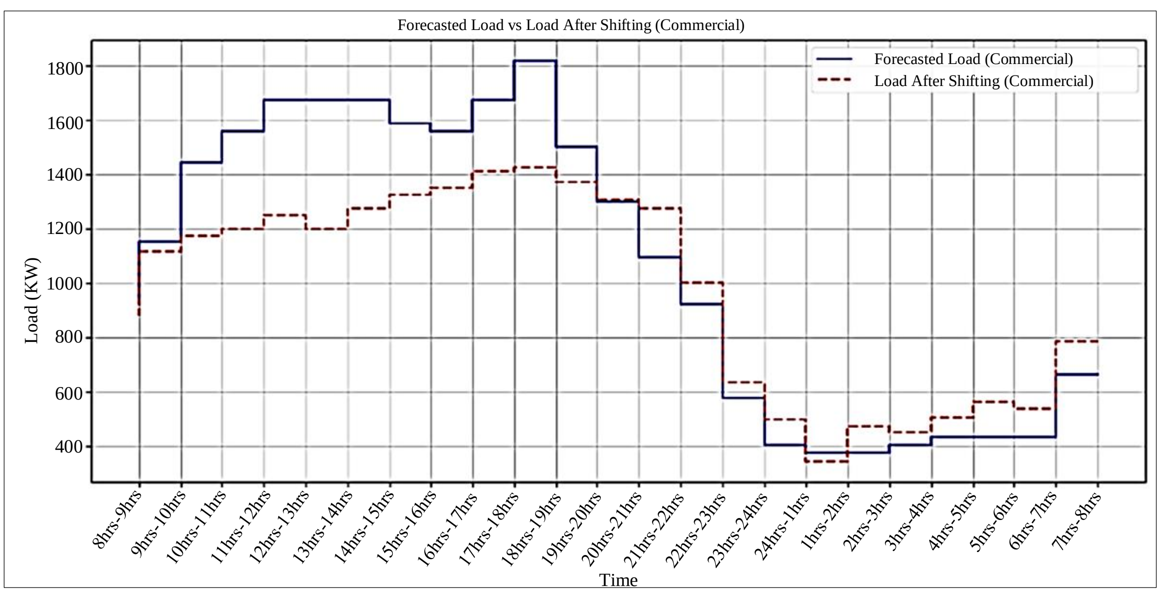


**Fig. 7 Load profiles using coati optimization algorithm (commercial)**

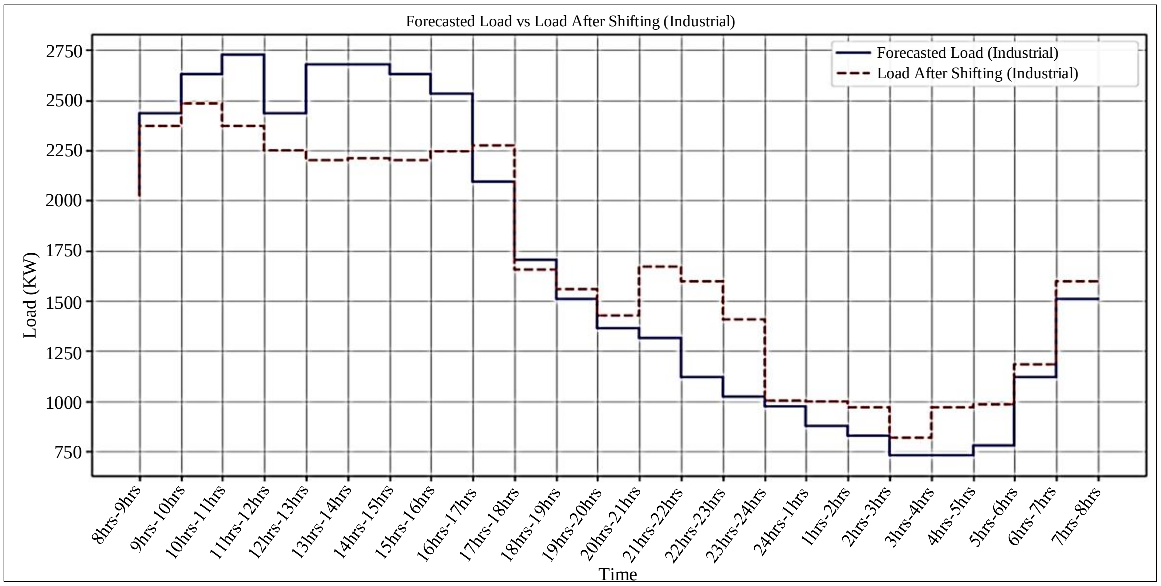


**Fig. 8 Load profiles using coati optimization algorithm (industrial)**

For the industrial sector, Figure 8 shows the predicted load and the load after relocation. The red dashed line shows the load after shifting, and the blue line shows the anticipated load. Notably, the peak load occurs during the hours of 10hrs-11hrs, with a value of 2629.9 kW in the forecasted load. Post load shifting, the peak load shifts slightly to the hours of 9hrs-10hrs, with an adjusted value of 2485.03 kW.

### *6.3. Discussion on Energy Consumption Discrepancies*

The discussion on energy consumption discrepancies explores the reasons behind the observed differences in energy consumption across different sectors. Factors such as higher power requirements, continuous operation, large-scale operations, diverse load types, and specific operational needs contribute to discrepancies in energy consumption between residential, commercial, and industrial areas. Understanding these discrepancies is crucial for developing targeted strategies to optimize energy consumption and enhance efficiency in each sector.

Table 5 presents a comparison of peak load reduction achieved by different algorithms, particularly focusing on the application of Demand Side Management (DSM) in various consumer types. The peak load reduction is expressed both in absolute terms (kW) and as a percentage reduction compared to the peak load without DSM. The table illustrates the effectiveness of the proposed algorithm (GA) in reducing peak loads across different consumer types. In general, the application of DSM results in significant reductions in peak loads, with an average reduction of 16.93%, is depicted in Figure 9.

Table 6 compares the reduction in utility bills achieved through different algorithms, emphasizing the impact of DSM on cost savings for consumers. The cost reduction is presented both in absolute terms (USD) and as a percentage reduction compared to the cost without DSM. This table highlights the effectiveness of DSM in reducing utility bills for different consumer types. The application of DSM, particularly through the proposed algorithm (GA), leads to notable cost savings, with an average reduction of 6.93%. The results demonstrate (Figure 10) the potential benefits of employing DSM strategies in energy management systems to optimize consumer costs and enhance overall efficiency.

**Table 5. Comparing utility bill reductions**

| Consumer Type | Without DSM | GA [13] | | Proposed COA [14] | |
|---|---|---|---|---|---|
| | Peak Load (kW) | Peak Load (kW) | % Reduction | Peak Load (kW) | % Reduction |
| Residential | 1363.6 | 1114.4 | 18.3 | 1100.6 | 19.3 |
| Commercial | 1818.2 | 1485.2 | 18.3 | 1425.7 | 21.5 |
| Industrial | 2727.3 | 2343.6 | 14.2 | 2370.8 | 13.1 |
| Average Peak Load Reduction | | 1314.4 | 16.93 % | 1299.03 | 18.3 |

**Table 6. Algorithms comparing with peak Load**

| Consumer Type | Cost without DSM | GA [13] | | Proposed COA [14] | |
|---|---|---|---|---|---|
| | | Cost With DSM ($) | Percentage Reduction | Cost With DSM ($) | Percentage Reduction |
| Residential | 2302.90 | 2188.30 | 5.0 | 2186.9 | 5.5 |
| Commercial | 3636.60 | 3424.30 | 5.8 | 3381.48 | 7 |
| Industrial | 5712.00 | 5141.60 | 10.0 | 5026 | 12 |
| Average Cost Reduction Bill | | 3584.7 | 6.93 % | 3531.46 | 8.17% |

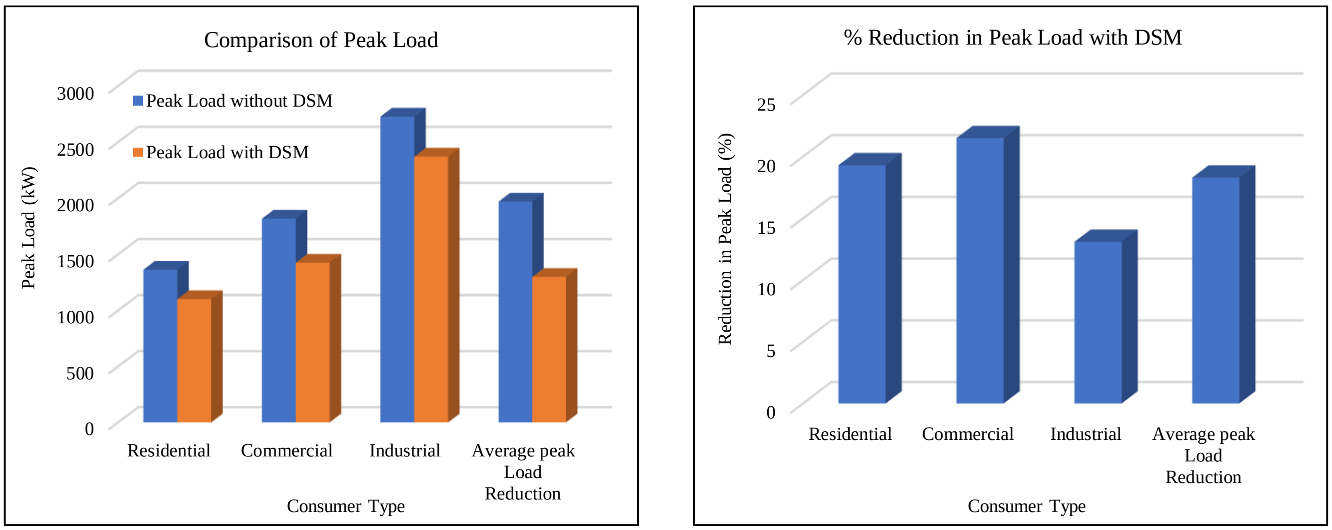


**Fig. 9 Comparison of peak load and reduction percentage**

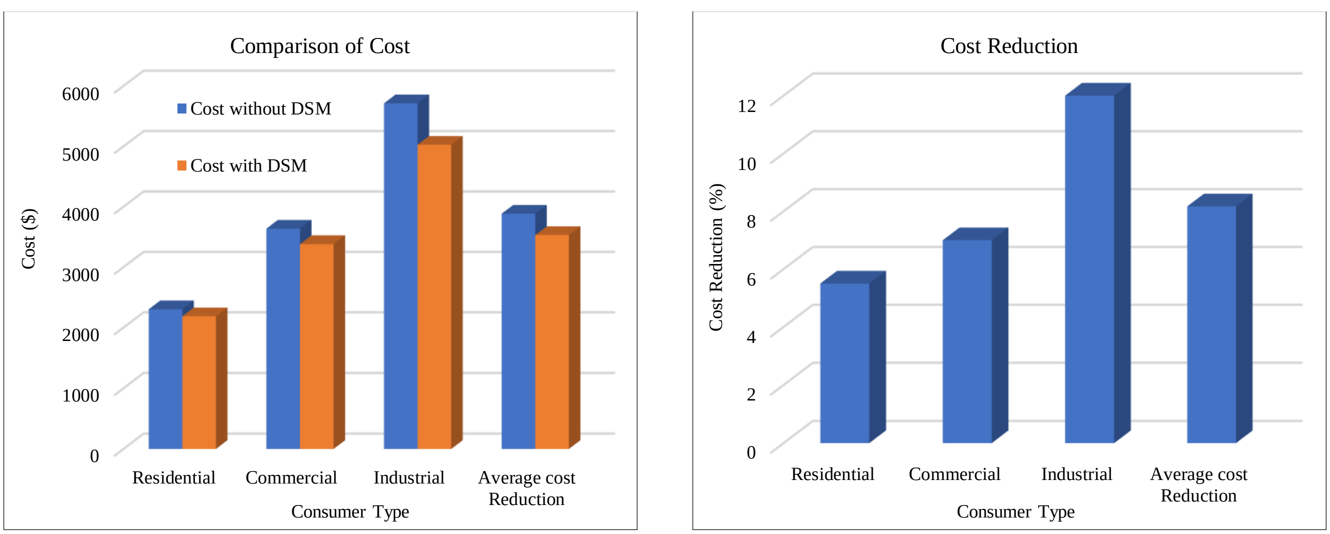


**Fig. 10 Comparison of utility bill and reduction percentage**

### *6.4. Implications for Industrial Energy Management*

The implications for industrial energy management underscore the importance of tailored approaches to optimize power consumption in industrial settings. By leveraging Coati Optimization and considering the unique requirements and operational constraints of industrial processes, significant improvements in energy efficiency can be achieved. Implementing advanced load management strategies, investing in energy-efficient technologies, and conducting regular energy audits are essential steps towards optimizing industrial energy consumption and reducing operational costs. Overall, the results and discussion highlight the significance of adopting holistic approaches to optimize power consumption in smart grids. By integrating advanced optimization techniques, considering sector-specific requirements, and addressing energy consumption discrepancies, significant improvements in energy efficiency and cost savings can be realized across residential, commercial, and industrial sectors. The practical impacts of optimizing power consumption in smart grids can be substantial, affecting various aspects of grid operation and management as provided below.

Optimizing power consumption in smart grids has significant practical impacts for both consumers and utility providers. It enhances energy efficiency by reducing wastage and improving the utilization of available resources, which in turn lowers operational costs. Consumers benefit from reduced energy bills through demand-side management and time-of-use pricing, particularly during peak demand periods. The improved balance between power supply and demand increases grid stability and reliability, minimizing the risk of overloads, blackouts, or brownouts.

This is especially crucial with the integration of intermittent renewable energy sources, which become more feasible and efficient through optimization. As a result, there is a reduction in carbon emissions, helping to meet environmental goals by decreasing reliance on fossil fuels. Optimized demand response management also allows for better flexibility in energy consumption, reducing the need for expensive peak power plants while extending the lifespan of grid infrastructure by preventing overload and stress on components.

Additionally, optimizing power consumption increases energy security by enhancing the grid's resilience to outages and system failures. It also facilitates the growing adoption of Electric Vehicles (EVs), helping manage the increased demand for electricity without causing grid congestion. Real-time adjustments and dynamic optimization based on changing grid conditions enable more responsive energy management while empowering consumers with data and control over their energy usage. This fosters consumer engagement in energy conservation and encourages smarter decisions. Overall, the optimization of power consumption in smart grids contributes to sustainability, cost-effectiveness, and reliability, positioning power grids for a more electrified and renewable energy-dependent future.

## 7. Conclusion

In-depth research on intelligent demand-side management techniques and their effects on the industrial, commercial, and residential sectors has been done in this study. It has been possible to get important insights into energy consumption patterns, peak load reduction, and cost reductions by comparing the outcomes of different optimization techniques, such as Coati Optimization and genetic algorithms.

The findings underscore the importance of tailored approaches to energy management in different sectors, considering the unique challenges and opportunities inherent in each. Moreover, the discussion on energy consumption discrepancies emphasizes the need for targeted strategies to optimize power consumption and enhance efficiency. By integrating advanced optimization techniques, investing in energy-efficient technologies, and conducting regular energy audits, significant improvements in energy efficiency and cost savings can be achieved across smart grids.

Overall, this study highlights the importance of adopting holistic approaches to energy management and underscores the potential benefits of advanced optimization techniques in optimizing power consumption and reducing operational costs in residential, commercial, and industrial settings. The analysis reveals significant reductions in peak loads across different consumer types, with an average reduction of 16.93% achieved through the proposed Coati Optimization Algorithm. Furthermore, notable cost savings are demonstrated, with an average reduction of 6.93% in utility bills achieved through demand-side management strategies. These findings underscore the efficacy of advanced optimization techniques in achieving tangible improvements in energy efficiency and cost savings across diverse sectors.

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