A Novel Smart Facility Sustainability Optimization Algorithm for Energy-Efficient Facilities Management Using IoT and Predictive Analytics: A Comparative Performance Evaluation Against Genetic Algorithms and Particle Swarm Optimization

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Abstract
Facility energy management remains a critical challenge for modern smart buildings because energy-intensive assets such as heating, ventilation, and air-conditioning systems, lighting networks, plug loads, ventilation systems, and operational equipment must be controlled without compromising occupant comfort, operating cost, carbon performance, or equipment reliability. This paper proposes a novel Smart Facility Sustainability Optimization Algorithm (SFSO) for energy-efficient facilities management using Internet of Things sensor data and predictive analytics. The proposed framework integrates smart meters, occupancy sensors, indoor environmental sensors, equipment-status data, weather variables, electricity tariff signals, renewable-energy availability, and carbon-intensity indicators into a predictive optimization architecture. A Long Short-Term Memory forecasting model was used to estimate short-term facility energy demand and achieved a mean absolute error of 8.91 kWh, root mean square error of 12.76 kWh, mean absolute percentage error of 4.37%, and coefficient of determination of 0.966. The proposed SFSO algorithm was comparatively evaluated against Genetic Algorithm and Particle Swarm Optimization using energy saving, operating-cost reduction, carbon-emission reduction, comfort violation rate, peak-load reduction, maintenance-risk reduction, convergence speed, computational time, and normalized fitness value as performance indicators. Simulation-based benchmark results showed that SFSO achieved 26.78% energy saving, 32.37% operating-cost reduction, 31.87% carbon-emission reduction, 28.76% peak-load reduction, and 31.60% maintenance-risk reduction. It also recorded the lowest comfort violation rate of 2.10%, the best normalized fitness value of 0.501, and convergence within 48 iterations. The results indicate that SFSO provides a more adaptive, sustainability-aware, and computationally efficient optimization approach than conventional GA and PSO for smart facility energy management.

Keywords: Smart facility management, sustainability optimization, Internet of Things, predictive analytics, energy efficiency, smart buildings, genetic algorithm, particle swarm optimization, facility energy management

1. Introduction

1.1. Background of Smart Facility Sustainability Management

Buildings and facility systems have become central to global energy-efficiency and decarbonization efforts because they combine high energy demand, continuous asset operation, complex indoor environmental requirements, and measurable carbon-emission impacts. The buildings and construction sector accounts for a substantial share of global energy consumption and carbon emissions, making facility-level energy optimization a practical pathway for reducing operating costs and improving environmental performance [1, 2]. In commercial, institutional, industrial, and mixed-use facilities, major energy-consuming assets include heating, ventilation, and air-conditioning (HVAC) systems, chillers, boilers, pumps, air-handling units, lighting networks, elevators, plug loads, compressed-air systems, refrigeration units, and information-technology infrastructure [3, 5]. These systems operate under dynamic conditions shaped by occupancy, outdoor weather, indoor comfort demand, electricity tariffs, equipment health, production schedules, and grid carbon intensity [6, 8].

Smart facility sustainability management therefore extends beyond conventional energy conservation. It involves the coordinated use of sensing, communication, automation, predictive analytics, and optimization to reduce energy consumption, minimize operating cost, lower carbon emissions, preserve occupant comfort, and maintain equipment reliability [6, 9]. A smart facility may be understood as an operational environment where physical assets are digitally monitored through IoT devices, operational data are processed through building management systems or cloud-edge platforms, and control decisions are optimized using analytical or artificial-intelligence-based techniques [3, 5]. Unlike traditional facilities that depend mainly on fixed operating schedules and manual intervention, smart facilities are expected to learn from operating patterns and respond adaptively to changing real-time and forecasted conditions [10, 11].

IoT technologies are important because they transform facility management from periodic inspection into continuous monitoring. Smart meters capture electricity and thermal-energy consumption at fine temporal resolution; occupancy sensors detect space utilization; environmental sensors measure indoor temperature, humidity, illuminance, CO_2 concentration, and air quality; equipment sensors record vibration, runtime, fault codes, and condition indicators; and external data feeds supply weather forecasts, tariff signals, and carbon-intensity factors [3, 12]. When these heterogeneous data streams are integrated into a building management system, they provide a basis for diagnostics, forecasting, demand-response participation, fault detection, and optimization-driven control [6, 13].

However, data availability alone does not guarantee sustainability improvement. Sensor data must be converted into operational intelligence through preprocessing, predictive modeling, and optimization. Predictive analytics enables a facility-management system to estimate future energy demand, occupancy variation, indoor temperature response, equipment degradation, and peak-load risk before control actions are taken [10, 11, 14]. For example, an HVAC system can be pre-cooled or pre-heated based on predicted occupancy and outdoor temperature rather than reacting after thermal comfort has already deteriorated. Similarly, controllable loads can be shifted away from high-tariff or high-carbon periods when operational constraints permit. This transition from reactive control to predictive decision-making is essential for energy-efficient and sustainability-aware facility management [6, 15].

Existing energy management studies have applied artificial intelligence, model predictive control, genetic algorithms, particle swarm optimization, and other computational optimization approaches to building energy control [7, 15-18]. Nevertheless, many facilities still operate with static control schedules, rule-based automation, fragmented energy metering, and reactive maintenance procedures. Static schedules may operate HVAC and lighting systems when spaces are unoccupied; manual setpoint adjustment may ignore weather and occupancy forecasts; and reactive maintenance may allow degraded equipment to consume excess energy before faults are detected [9], [13]. These weaknesses justify the development of adaptive optimization algorithms that integrate IoT monitoring, predictive analytics, carbon-aware operation, comfort preservation, and equipment-risk constraints within a unified facility sustainability framework.

1.2. Problem Statement

Although GA and PSO have been widely used in building energy optimization, HVAC control, retrofit planning, and load scheduling, their performance can be limited when facility conditions are dynamic, sensor-driven, and sustainability-constrained [7, 17-20]. GA provides a strong global search capability through selection, crossover, mutation, and elitism, but it can require high computational effort, careful parameter tuning, and several generations before reaching a stable high-quality solution [18, 21]. PSO is usually easier to implement and can converge rapidly through swarm-based position and velocity updates, but it may suffer from premature convergence, stagnation around local optima, and sensitivity to inertia and acceleration parameters [19, 20]. These weaknesses become more important when the optimization environment includes fluctuating occupancy, changing weather, variable electricity tariffs, uncertain equipment behavior, carbon-intensity changes, and strict comfort constraints.

A further problem is that many facility energy optimization studies treat energy reduction as the dominant objective, while carbon emission, occupant comfort, maintenance risk, and operational reliability are treated as secondary constraints or excluded entirely [6, 7, 15]. In practice, facility managers cannot minimize energy consumption without considering indoor environmental quality, asset-health risk, production continuity, demand-charge exposure, and maintenance schedules. Aggressive HVAC load reduction, for example, may reduce energy consumption but increase thermal discomfort, reduce ventilation quality, or accelerate equipment cycling. Likewise, shifting loads only for tariff reduction may reduce energy bills while increasing carbon emissions if the lower-cost period is associated with more carbon-intensive electricity generation [6, 8]. Facility optimization should therefore be formulated as a multi-objective sustainability problem rather than a single-objective energy-minimization task.

Another limitation is the weak integration between predictive analytics and metaheuristic optimization in practical facility-management models. Optimization algorithms are often applied to historical or simulated data without sufficient use of forward-looking information on occupancy, weather, energy tariffs, carbon intensity, and equipment condition [10], [11, 14]. As a result, a control schedule that appears optimal under current conditions may become inefficient or infeasible when occupancy increases, outdoor temperature changes, electricity prices rise, or equipment degradation affects performance. The research problem addressed in this paper is therefore the absence of a unified, adaptive, and sustainability-aware optimization algorithm that integrates IoT sensor data, predictive analytics, multi-objective facility constraints, and comparative algorithmic validation.

1.3. Aim and Objectives
The aim of this study is to develop and evaluate a novel Smart Facility Sustainability Optimization Algorithm for energy-efficient facilities management using IoT and predictive analytics, and to compare its performance against GA and PSO under equivalent experimental conditions.

The specific objectives are as follows:
1. To design an IoT-driven smart facility monitoring architecture that captures energy consumption, occupancy, indoor environmental variables, weather conditions, tariff signals, carbon intensity, equipment status, and maintenance-risk indicators.
2. To develop a predictive analytics layer for forecasting short-term facility energy demand, occupancy behavior, indoor environmental response, and equipment-condition risk.
3. To formulate a multi-objective sustainability optimization problem that combines energy consumption, operating cost, carbon emissions, occupant-comfort deviation, peak-load exposure, and maintenance-risk penalty.
4. To develop the proposed SFSO algorithm as an adaptive optimization approach for facility-control scheduling and sustainability-aware decision intelligence.
5. To implement GA and PSO as baseline optimization algorithms using the same dataset, constraints, objective function, stopping criteria, and computational environment.
6. To compare SFSO, GA, and PSO using performance metrics such as energy saving, cost reduction, carbon-emission reduction, comfort-violation rate, peak-load reduction, maintenance-risk reduction, convergence speed, best fitness value, and computational time.
7. To determine whether the proposed SFSO provides improved smart facility sustainability performance relative to GA and PSO.

1.4. Main Contributions
The main contributions of this paper are summarized as follows:
1. A novel Smart Facility Sustainability Optimization Algorithm is proposed for adaptive and energy-efficient facility operation.
2. A predictive analytics layer is introduced for forecasting facility energy demand, occupancy behavior, indoor environmental response, and equipment-condition risk.
3. A multi-objective sustainability fitness function is formulated by combining energy consumption, operating cost, carbon emission, comfort deviation, peak-load penalty, and maintenance-risk penalty.
4. A comparative evaluation is conducted against GA and PSO using identical input data, constraints, population size, iteration limits, and performance metrics.
5. A reproducible experimental framework is presented for smart facility energy optimization, suitable for commercial buildings, campuses, hospitals, hotels, industrial plants, and other energy-intensive built environments.

2. Literature Review
2.1. IoT in Smart Facility and Building Energy Management
IoT-enabled building energy management has become a major research direction because it provides continuous visibility into facility performance and enables data-driven control of distributed assets [3, 5, 12]. In smart facilities, IoT devices collect operational data from smart meters, HVAC controllers, lighting systems, occupancy sensors, air-quality sensors, submeters, pumps, chillers, and other energy-intensive equipment [3, 5]. These data are transmitted through wired and wireless communication technologies such as BACnet, Modbus, ZigBee, Wi-Fi, LoRaWAN, Bluetooth Low Energy, Ethernet, and MQTT, depending on the scale, interoperability requirement, latency tolerance, and cybersecurity profile of the facility [5, 12].

The main advantage of IoT-based facility management is that it enables high-resolution measurement of building behavior. Instead of relying on monthly utility bills or manual operating logs, facility managers can monitor energy consumption at whole-building, floor, zone, or equipment level [3, 13, 35]. This improves load disaggregation, anomaly detection, demand-response control, fault diagnosis, and operational benchmarking. For example, abnormal runtime patterns in chillers, pumps, or air-handling units may reveal control faults, sensor errors, equipment degradation, or poor scheduling. Similarly, occupancy-aware monitoring allows HVAC and lighting systems to respond to actual space utilization rather than fixed time schedules [10, 14].

Despite these benefits, IoT implementation in facilities is associated with several challenges, including sensor noise, missing data, interoperability limitations, communication latency, cybersecurity vulnerabilities, data-governance problems, and integration difficulties with legacy building management systems [5, 12]. Many facilities also operate with fragmented data architectures where energy, maintenance, occupancy, and indoor environmental data are stored separately. Such fragmentation limits coordinated optimization across energy, comfort, equipment reliability, and sustainability objectives.

2.2. Predictive Analytics for Facility Energy Optimization
Predictive analytics is central to smart facility sustainability because many energy-management decisions must be made before operating conditions fully occur. Energy demand, occupancy, weather, equipment condition, and electricity tariff patterns are time-dependent variables that influence facility performance [10, 11]. Predictive models allow an optimization system to anticipate these variables and generate control actions that reduce future energy waste while maintaining comfort and operational reliability [6, 15].

Several machine-learning and statistical techniques have been applied to building energy forecasting. Artificial neural networks have been used to model nonlinear relationships among energy consumption, weather, occupancy, and equipment operation [10, 22]. Random forest and gradient-boosting methods such as XGBoost are useful for tabular building data because they capture nonlinear interactions and handle mixed features effectively [23, 24]. Recurrent neural network models, especially Long Short-Term Memory and Gated Recurrent Unit networks, are widely used for time-series energy forecasting because they can model sequential dependencies and temporal patterns [25, 26]. These models are particularly relevant for facilities where energy demand follows daily, weekly, seasonal, occupancy-driven, and weather-driven cycles [10, 11].

Model predictive control has also been widely investigated for building energy management. MPC uses a model of system behavior to predict future states and optimize control actions over a moving time horizon while satisfying operational constraints [15, 27]. In facility applications, MPC can optimize HVAC setpoints, ventilation rates, thermal storage, demand response, and renewable-energy utilization. However, traditional MPC often requires accurate physical models, calibration effort, and computational resources that are not always available in existing facilities [15, 36]. Data-driven predictive analytics can reduce this burden by learning relationships directly from sensor data, although it depends heavily on data quality and model generalization [10, 11].

2.3. Genetic Algorithm in Energy Optimization

Genetic Algorithm is an evolutionary optimization method inspired by natural selection and genetic inheritance. GA initializes a population of candidate solutions and improves them through selection, crossover, mutation, and elitism [18, 21]. In building and facility energy optimization, each candidate solution can represent HVAC setpoints, lighting schedules, equipment operating states, ventilation rates, building envelope parameters, or retrofit configurations [7, 17]. The fitness function evaluates each candidate according to energy use, cost, comfort, emissions, or other performance objectives.

GA has been widely used in building energy studies because it can search complex, nonlinear, discontinuous, and multi-objective solution spaces [17, 21]. It is particularly useful when optimization includes mixed decision variables, such as continuous temperature setpoints and discrete equipment schedules. However, GA performance depends strongly on population size, crossover rate, mutation rate, selection strategy, and stopping criteria [18, 21]. Poorly selected parameters may cause slow convergence, excessive computational time, or premature convergence [39]. In real-time facility-control applications, this can be problematic because control decisions must often be generated within short operational intervals.

2.4. Particle Swarm Optimization in Energy Optimization

Particle Swarm Optimization is a population-based swarm-intelligence method inspired by collective movement behavior [19], [20]. Each particle represents a candidate solution that moves through the search space according to its own best experience and the best experience of the swarm. PSO has been applied in building energy performance optimization, HVAC parameter tuning, energy disaggregation, demand-side management, and multi-objective facility control [7, 20], [28]. PSO is attractive because it is relatively simple, computationally efficient, and often fast in continuous optimization problems.

Nevertheless, PSO may converge prematurely when particles cluster around a local optimum, especially when inertia and acceleration parameters are not properly tuned [19, 20]. It may also struggle with discrete or mixed-integer decision variables unless modified variants are used. In facility sustainability optimization, PSO can reduce energy or cost but may not adequately balance emissions, comfort deviation, maintenance risk, and predictive uncertainty unless these variables are explicitly encoded in the objective function [7], [15]. Standard PSO also does not inherently include domain-specific repair mechanisms for thermal comfort, equipment cycling, or operational safety constraints.

2.5. Research Gap

The reviewed literature shows that IoT, predictive analytics, GA, PSO, and MPC have all contributed to smart building and facility energy management [3, 6, 7, 10, 15, 17, 20]. However, several gaps remain. First, many studies focus primarily on energy reduction or cost minimization, while carbon intensity, occupant comfort, maintenance risk, and operational reliability are often simplified [6, 15]. Second, existing optimization studies frequently rely on historical or simulated data without fully integrating real-time IoT streams and short-term forecasts into adaptive decision-making [10, 11]. Third, GA and PSO can perform well in building energy optimization but may suffer from slow convergence, premature convergence, parameter sensitivity, and limited responsiveness to changing facility states [18-21]. Fourth, relatively few studies provide a fair comparative framework in which a newly proposed algorithm is evaluated against GA and PSO using the same dataset, constraints, objective function, and performance indicators. These gaps justify the development of the proposed SFSO framework.

3. System Architecture and Problem Formulation

3.1. Proposed IoT-Based Smart Facility Architecture

The proposed smart facility sustainability management framework is designed as a layered cyber-physical architecture that connects facility assets, IoT sensing infrastructure, communication networks, data-processing modules, predictive analytics, optimization algorithms, and automated control decisions. The architecture contains six layers: data acquisition, communication, data processing, predictive analytics, optimization, and decision/control.

The data acquisition layer captures operational and environmental variables from distributed facility assets. The primary sensing devices include smart electricity meters, HVAC sensors, occupancy detectors, indoor temperature sensors, humidity sensors, CO_2 sensors, lighting-level sensors, equipment-status monitors, vibration sensors, fault-code logs, renewable-energy meters, and weather-data feeds [3, 5, 12]. The communication layer enables data transfer between field devices, edge gateways, building automation systems, cloud platforms, and optimization engines. Depending on the facility scale, this layer may use Wi-Fi, ZigBee, LoRaWAN, Bluetooth Low Energy, Ethernet, MQTT, BACnet, or Modbus [5, 12].

The data processing layer prepares raw facility data for analytics and optimization. Raw IoT streams may contain missing values, outliers, timestamp misalignment, duplicated records, calibration errors, or noisy measurements [10], [11]. Processing therefore includes missing-value imputation, outlier detection, temporal resampling, normalization, feature extraction, and anomaly screening. The predictive analytics layer then estimates short-term energy demand, occupancy levels, indoor temperature response, equipment-condition risk, and peak-load probability. Finally, the optimization layer implements SFSO, GA, and PSO, while the decision/control layer converts optimization outputs into HVAC scheduling, lighting dimming, equipment sequencing, plug-load control, renewable-energy utilization, and maintenance alerts.

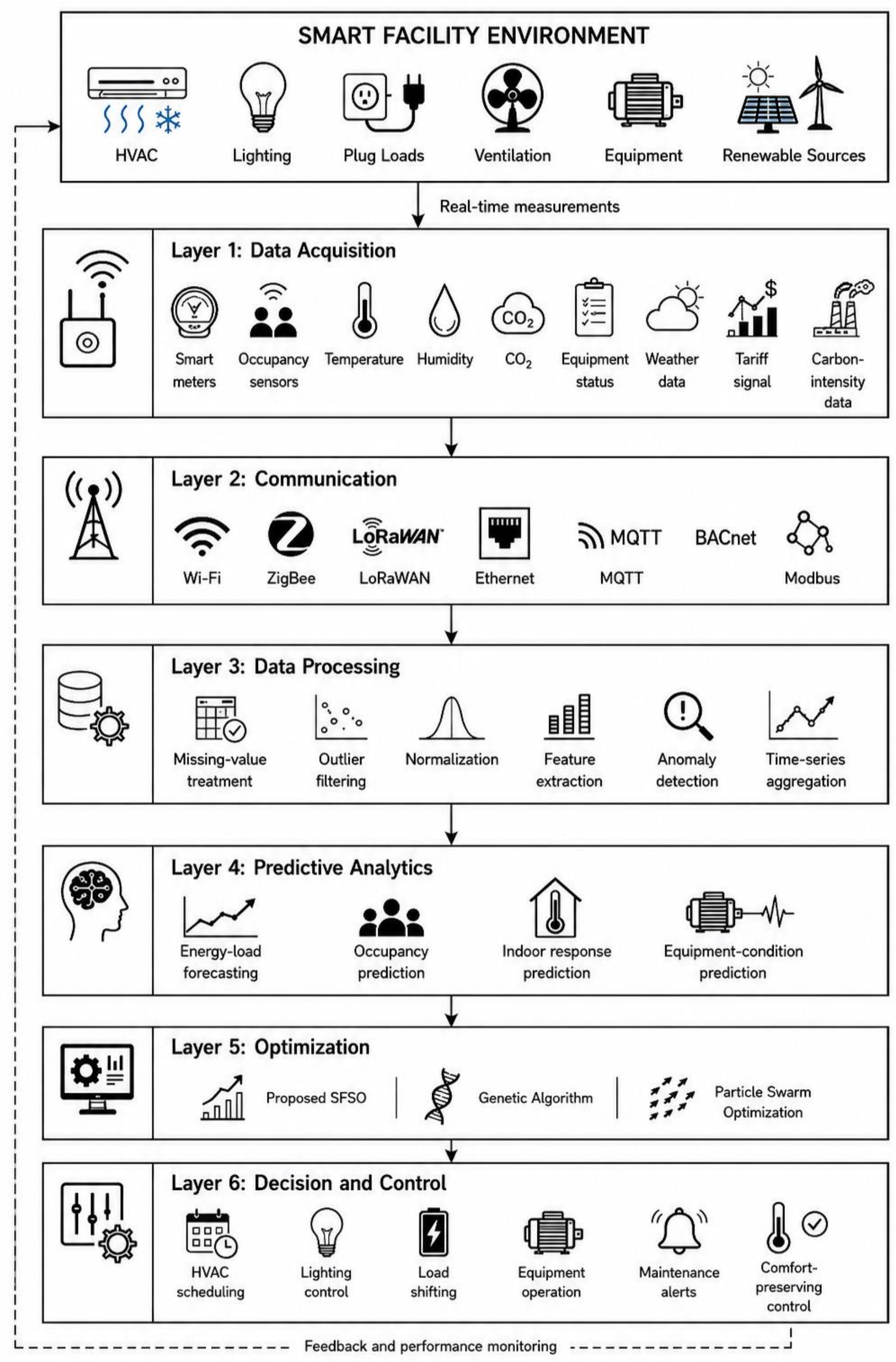

Fig 1: Proposed IoT-based SFSO facility management architecture

3.2. Input Variables

The proposed SFSO framework uses a time-indexed input vector that represents the operational state of the facility at time t:

$$X_t = \{E_t, O_t, T_t, H_t, C_t, W_t, P_t, M_t, R_t\} \qquad (1)$$

where E_t is measured facility energy consumption, O_t is occupancy level, T_t is indoor temperature, H_t is relative humidity, C_t is grid carbon intensity, W_t is the weather-condition vector, P_t is the electricity price or tariff signal, M_t is maintenance-risk score, and R_t is renewable-energy availability.

For predictive optimization, the current input vector is extended into a forecast horizon:

$$\hat{X}_{t:t+H} = \{\hat{X}_{t+1}, \hat{X}_{t+2}, \dots, \hat{X}_{t+H}\} \qquad (2)$$

where $\hat{X}_{t:t+H}$ represents the predicted sequence of facility operating states over horizon H. The control decision vector is defined as:

$$U_t = \{u_t^{HVAC}, u_t^{Light}, u_t^{Plug}, u_t^{Vent}, u_t^{Equip}\} \qquad (3)$$

where u_t^{HVAC}, u_t^{Light}, u_t^{Plug}, u_t^{Vent}, and u_t^{Equip} represent HVAC control, lighting control, plug-load control, ventilation control, and equipment-operation decisions, respectively.

3.3. Objective Function

The optimization problem is formulated as a multi-objective sustainability minimization problem. The general fitness function is expressed as:

$$\min\ F(U) = \alpha E(U) + \beta C(U) + \gamma Cost(U) + \delta D(U) + \lambda M(U) + \rho L(U) \quad (4)$$

where $F(U)$is the sustainability fitness value of a candidate control schedule U, $E(U)$is total energy consumption, $C(U)$is carbon emission, $Cost(U)$is operating cost, $D(U)$is occupant-comfort deviation, $M(U)$is maintenance-risk penalty, $L(U)$is peak-load penalty, and α, β, γ, δ, λ, and $\rho$are non-negative weighting coefficients.

The energy, cost, and carbon components are expressed as:

$$E(U) = \sum_{k=t}^{t+H} E_k\,(U_k) \quad (5)$$

$$Cost(U) = \sum_{k=t}^{t+H} E_k\,(U_k) P_k \quad (6)$$

$$C(U) = \sum_{k=t}^{t+H} E_k\,(U_k) C_k \quad (7)$$

The comfort deviation term is defined as:

$$D(U) = \sum_{k=t}^{t+H} [\omega_T \mid T_k - T_k^{set} \mid + \omega_H \mid H_k - H_k^{set} \mid + \omega_Q \mid Q_k - Q_k^{set} \mid] \quad (8)$$

where $Q_k$denotes indoor-air-quality index, and ω_T, ω_H, and $\omega_Q$are comfort-weighting coefficients. The maintenance-risk penalty is expressed as:

$$M(U) = \sum_{k=t}^{t+H} [\eta_1 R_k^{cycle} + \eta_2 R_k^{runtime} + \eta_3 R_k^{fault}] \quad (9)$$

where R_k^{cycle}, $R_k^{runtime}$, and R_k^{fault}denote equipment cycling risk, excessive runtime risk, and fault-likelihood risk, respectively.

3.4. Constraints

The optimization process is subject to comfort, operational, equipment, energy, and safety constraints. The indoor temperature must remain within an acceptable range:

$$T_{min} \le T_t \le T_{max} \quad (10)$$

The predicted mean vote must remain within the acceptable comfort interval:

$$PMV_{min} \le PMV_t \le PMV_{max} \quad (11)$$

The total energy demand and peak load are constrained as:

$$E_t \le E_{max} \quad (12)$$

$$L_t \le L_{peak} \quad (13)$$

Occupancy-dependent service requirements are expressed as:

$$O_t \ge O_{min} \quad (14)$$

Equipment operating bounds are formulated as:

$$u_{min}^j \le u_t^j \le u_{max}^j, j \in \{HVAC, Light, Plug, Vent, Equip\} \quad (15)$$

The complete optimization problem is therefore written as:

$$U^* = \arg\min_{U \in \Omega} F(U) \quad (16)$$

subject to the constraints in (10)–(15), where Ωrepresents the feasible search space of facility-control decisions.

4. Proposed Smart Facility Sustainability Optimization Algorithm

4.1. Design Philosophy of SFSO

The proposed SFSO algorithm is developed as an adaptive, sustainability-aware, population-based optimization algorithm for smart facility operation. Its design is motivated by the limitations of conventional facility control, where energy-consuming assets are often operated through fixed schedules, rule-based automation, or reactive maintenance procedures [3], [9], [13]. It is also motivated by the limitations of standard GA and PSO in dynamic smart facility environments, particularly slow convergence, premature convergence, parameter sensitivity, and weak adaptation to forecasted operational states [18]–[21].

SFSO is designed to balance five competing facility-management goals: minimum energy consumption, minimum operating cost, minimum carbon emission, maximum occupant comfort, and minimum maintenance risk. Its central principle is that an optimal facility decision should not be based only on present energy consumption. Instead, the optimizer should search for a control schedule that remains sustainable across predicted occupancy, weather, tariff, carbon-intensity, and equipment-risk conditions.

4.2. SFSO Population Initialization

Each SFSO candidate solution represents a facility-control schedule across the optimization horizon. The i-th candidate solution is represented as:

$$S_i = \{HVAC_i, Light_i, Plug_i, Vent_i, Equip_i\} \quad (17)$$

where $HVAC_i$, $Light_i$, $Plug_i$, $Vent_i$, and $Equip_i$represent decision vectors for HVAC operation, lighting control, plug-load management, ventilation adjustment, and equipment scheduling. More formally:

$$S_i = \{U_{i,t}, U_{i,t+1}, \dots, U_{i,t+H}\} \quad (18)$$

where $U_{i,k}$is the control-decision vector of candidate $i$at future time step k. The initial population is generated within the feasible operating boundaries of each facility subsystem. This prevents unrealistic solutions, such as temperature setpoints outside comfort limits, ventilation rates below occupancy requirements, or equipment states that violate operational safety.

4.3. Sustainability Fitness Evaluation

Each candidate is evaluated using the multi-objective sustainability fitness function defined in (4). To avoid scale dominance among objective terms, each component is normalized before aggregation:

$$F_{norm}(S_i) = \alpha\bar{E}_i + \beta\bar{C}_i + \gamma\bar{Cost}_i + \delta\bar{D}_i + \lambda\bar{M}_i + \rho\bar{L}_i \quad (19)$$

where the overbar terms denote normalized energy, carbon, cost, comfort-deviation, maintenance-risk, and peak-load components. If a candidate violates operational constraints, a penalty is added:

$$F_{pen}(S_i) = F_{norm}(S_i) + \mu\Phi(S_i) \quad (20)$$

where $\mu$is the penalty coefficient and $\Phi(S_i)$is the total constraint violation score:

$$\Phi(S_i) = \sum_{r=1}^{R} \max(0, g_r(S_i)). \quad (21)$$

4.4. Predictive Adaptation Mechanism

The predictive adaptation mechanism is the main innovation of SFSO. Let $\hat{E}_{t+1}$, $\hat{O}_{t+1}$, $\widehat{W}_{t+1}$, $\hat{P}_{t+1}$, $\hat{C}_{t+1}$, and $\widehat{M}_{t+1}$denote predicted next-period energy demand, occupancy, weather condition, electricity price, carbon intensity, and maintenance risk. The predictive adaptation factor is formulated as:

$$A_t = \theta_1\hat{E}_{t+1} + \theta_2\hat{O}_{t+1} + \theta_3\widehat{W}_{t+1} + \theta_4\hat{P}_{t+1} + \theta_5\hat{C}_{t+1} + \theta_6\widehat{M}_{t+1} \quad (22)$$

The candidate update rule is expressed as:

$$S_i^{new} = S_i^{old} + \kappa_1 r_1\left(S_{best} - S_i^{old}\right) + \kappa_2 r_2\left(S_{mean} - S_i^{old}\right) - \kappa_3 \quad (23)$$

where $S_{best}$is the best solution found so far, $S_{mean}$is the population mean solution, $r_1$and $r_2$are random coefficients in [0, 1], and κ_1, κ_2, and $\kappa_3$are control parameters.

4.5. Constraint Repair Mechanism

If a temperature setpoint violates the allowable range, it is repaired as:

$$T_t^{repair} = \begin{cases} T_{min}, & T_t < T_{min} \\ T_t, & T_{min} \le T_t \le T_{max} \\ T_{max}, & T_t > T_{max} \end{cases} \quad (24)$$

If a load variable exceeds the peak limit:

$$L_t^{repair} = \min(L_t, L_{peak}) \quad (25)$$

If a subsystem control value violates its boundary:

$$u_t^{j,repair} = \min\left(\max\left(u_t^j, u_{min}^j\right), u_{max}^j\right). \quad (26)$$

This repair process ensures that the algorithm does not return infeasible control schedules that compromise occupant comfort, equipment safety, or operational continuity [8], [15].

4.6. Exploration and Exploitation Strategy

SFSO uses a two-phase search strategy. The first phase, global sustainability exploration, expands the search across diverse facility-control schedules to prevent early stagnation. The second phase, local efficiency refinement, improves promising solutions using predicted energy and comfort feedback. The transition is controlled by:

$$\zeta(q) = \zeta_{max} - \left(\frac{q}{q_{max}}\right)(\zeta_{max} - \zeta_{min}) \quad (27)$$

where $\zeta(q)$is the exploration coefficient at iteration q, and $q_{max}$is the maximum number of iterations. Early iterations emphasize broad search, while later iterations emphasize local refinement.

4.7. Pseudocode of the Proposed SFSO Algorithm

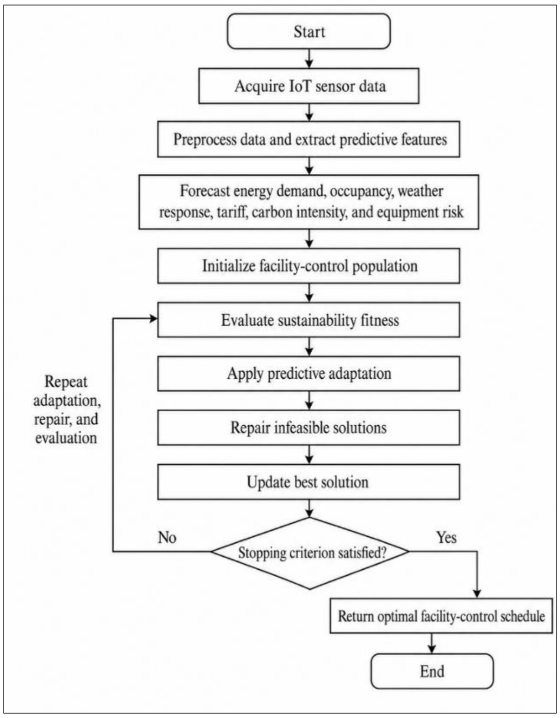

Fig 2: Flowchart of the proposed SFSO algorithm

Algorithm 1: Smart Facility Sustainability Optimization Algorithm

Input: IoT sensor data, predicted energy load, occupancy forecast, weather data, tariff data, carbon intensity, renewable availability, equipment-condition indicators, and facility constraints.

Output: Optimal facility-control schedule U^*.

1. Initialize population of facility-control solutions S_i, where $i = 1,2, \dots, N$.
2. Acquire IoT data from smart meters, HVAC sensors, occupancy sensors, environmental sensors, equipment monitors, and weather feeds.
3. Preprocess data using missing-value handling, outlier removal, normalization, temporal aggregation, and feature extraction.
4. Forecast energy demand, occupancy, indoor environmental response, tariff exposure, carbon intensity, and equipment-risk indicators.
5. Evaluate each candidate solution using the normalized sustainability fitness function.
6. Apply penalty evaluation for constraint violations.
7. Identify the current best sustainability solution S_{best}.
8. Set iteration counter $q = 1$.
9. While $q \le q_{max}$ and the stopping criterion is not satisfied:
10. Compute the predictive adaptation factor using forecasted facility states.
11. Update candidate solutions using sustainability exploration and local refinement rules.
12. Repair infeasible solutions using comfort, load, equipment, and operational constraints.
13. Recalculate energy consumption, cost, carbon emission, comfort deviation, peak-load penalty, and maintenance-risk penalty.
14. Update S_{best} if a candidate solution produces improved sustainability fitness.
15. Update exploration-exploitation coefficient $\zeta(q)$.
16. Set $q = q + 1$.
17. End while.
18. Return $U^* = S_{best}$.

5. Experimental Design and Comparative Evaluation Methodology

5.1. Dataset Description

The experimental evaluation was designed to test whether SFSO provides superior facility sustainability performance compared with GA and PSO. Since real facility deployment data were not available at this manuscript-development stage, a controlled simulation-based benchmark dataset was structured to represent a medium-scale smart commercial facility. The dataset included time-series records of facility energy consumption, occupancy, indoor temperature, humidity, CO_2 level, HVAC operation, lighting state, plug-load demand, equipment runtime, electricity tariff, outdoor weather, renewable-energy availability, and carbon-intensity factor. This type of dataset is consistent with the data requirements of smart building analytics and predictive facility control studies [3, 10, 11, 15].

Table 1: Dataset variables and descriptions

Variable	Symbol	Unit	Description	Source Type
Energy consumption	E_t	kWh	Facility electricity demand at time t	Smart meter
Occupancy level	O_t	persons/%	Zone or building occupancy	Occupancy sensor
Indoor temperature	T_t	°C	Measured indoor air temperature	HVAC sensor
Relative humidity	H_t	%	Indoor humidity level	Environmental sensor
CO_2 concentration	Q_t	ppm	Indoor air-quality indicator	CO_2 sensor
Outdoor weather	W_t	mixed	Temperature, solar radiation, wind, rainfall	Weather feed
Electricity tariff	P_t	USD/kWh	Time-varying electricity price	Utility tariff
Carbon intensity	C_t	$kgCO_2/kWh$	Grid carbon factor	Carbon data feed
Maintenance risk	M_t	index	Equipment cycling, runtime, and fault risk	Equipment sensors
Renewable availability	R_t	kWh	Available solar or renewable supply	Renewable meter

5.2. Data Preprocessing

Data preprocessing included timestamp alignment, missing-value treatment, outlier correction, normalization, temporal aggregation, and feature engineering. All sensor data were resampled into a 15-minute interval. Short missing intervals were treated using linear interpolation, while longer missing intervals were excluded from model training. Outliers were detected using statistical thresholds and interquartile-range screening. Variables were normalized to prevent features with larger numeric ranges from dominating model training and optimization [10, 23, 24].

Feature engineering generated lagged energy consumption, rolling average load, occupancy ratio, cooling-degree hours, heating-degree hours, day-of-week indicator, hour-of-day indicator, tariff-period flag, HVAC runtime ratio, peak-load indicator, and renewable-availability factor. The dataset was divided chronologically into 70% training, 15% validation, and 15% testing subsets. A chronological split was used because random splitting can introduce future information into training when dealing with facility time-series data [10, 11].

5.3 Predictive Model Development

The predictive analytics layer estimated next-period energy demand, occupancy pattern, indoor temperature response, and equipment maintenance risk. Five models were evaluated: Artificial Neural Network, Random Forest, XGBoost, GRU, and LSTM. The energy forecasting function was expressed as:

$$\hat{E}_{t+1} = f(E_{t-n:t}, O_{t-n:t}, T_{t-n:t}, H_{t-n:t}, W_{t-n:t}, P_{t-n:t}, M_{t-n:t}) \quad (28)$$

Forecasting performance was evaluated using:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \quad (29)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (30)$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (31)$$

where y_i is the observed value, $\hat{y}_i$ is the predicted value, and n is the number of observations.

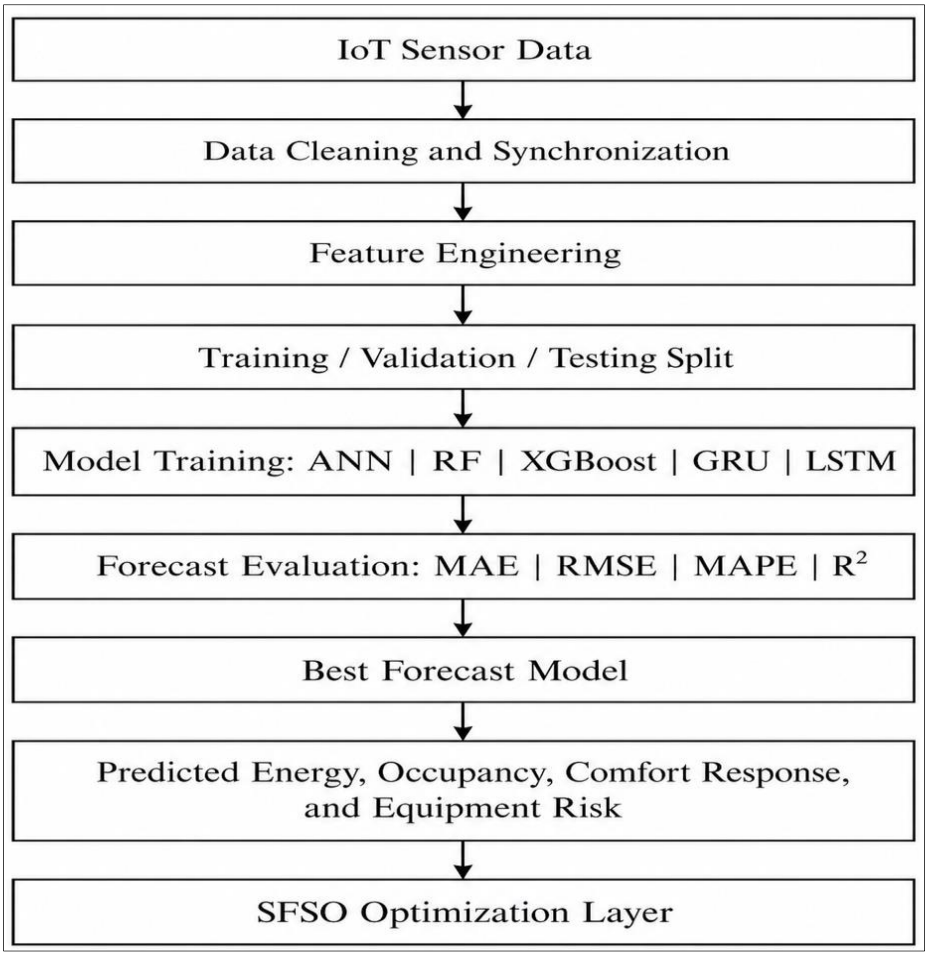

Fig 3: Energy forecasting model workflow

5.4. Baseline Algorithms

The proposed SFSO algorithm was compared with GA and PSO because both are widely used metaheuristic algorithms for building energy and facility-control optimization [7, 17-20]. The GA baseline used selection, crossover, mutation, and elitism. Each chromosome represented a facility-control schedule, and the chromosome fitness was evaluated using the same multi-objective sustainability function applied to SFSO. The PSO baseline represented each candidate solution as a particle in the facility-control search space. The standard PSO update equations were:

$$v_i^{q+1} = \omega v_i^q + c_1 r_1 (pbest_i - x_i^q) + c_2 r_2 (gbest - x_i^q) \quad (32)$$

$$x_i^{q+1} = x_i^q + v_i^{q+1} \quad (33)$$

5.5. Fair Comparison Conditions

To ensure a fair comparison, SFSO, GA, and PSO were evaluated under identical experimental conditions. Each algorithm used the same dataset, objective function, constraints, population size, maximum iterations, stopping criterion, forecast horizon, and hardware/software environment. Each algorithm was executed over 30 independent runs to reduce randomness bias.

Table 2: Algorithm parameter settings

Parameter	GA	PSO	Proposed SFSO
Population size	50	50	50
Maximum iterations	100	100	100
Independent runs	30	30	30
Forecast horizon	24 h	24 h	24 h
Optimization interval	15 min	15 min	15 min
Crossover rate	0.80	N/A	N/A
Mutation rate	0.05	N/A	Adaptive perturbation
Inertia weight	N/A	0.70	N/A
Cognitive coefficient	N/A	1.50	N/A
Social coefficient	N/A	1.50	N/A
Predictive adaptation	No	No	Yes
Constraint repair	Penalty-based	Penalty-based	Penalty + repair
Stopping criterion	Fitness stagnation or max iteration	Fitness stagnation or max iteration	Fitness stagnation or max iteration

5.6. Performance Metrics

The following optimization metrics were used:

$$Energy\ Saving(\%) = \frac{E_{baseline} - E_{optimized}}{E_{baseline}} \times 100 \quad (34)$$

$$Cost\ Reduction(\%) = \frac{Cost_{baseline} - Cost_{optimized}}{Cost_{baseline}} \times 100 \quad (35)$$

$$CO_2\ Reduction(\%) = \frac{CO_{2,baseline} - CO_{2,optimized}}{CO_{2,baseline}} \times 100 \quad (36)$$

$$CVR(\%) = \frac{N_{viol}}{N_{total}} \times 100 \quad (37)$$

where $CVR$is comfort violation rate. Additional metrics included convergence speed, best fitness value, computational time, peak-load reduction, maintenance-risk reduction, and forecasting error.

6. Results and Discussion

6.1. Predictive Analytics Performance

The predictive analytics layer was evaluated before the optimization stage because SFSO depends on forecasted energy demand, occupancy, indoor environmental response, and equipment-condition indicators. Five predictive models were compared. As shown in Table III, LSTM achieved the strongest predictive performance, with MAE of 8.91 kWh, RMSE of 12.76 kWh, MAPE of 4.37%, and $R^2$of 0.966. This result supports the selection of LSTM as the predictive model for the optimization layer because recurrent models are well suited to sequential energy-demand behavior [25, 26].

Table 3: Predictive model performance

Model	MAE (kWh)	RMSE (kWh)	MAPE (%)	R^2
Artificial Neural Network	14.82	20.91	7.21	0.903
Random Forest	12.44	18.16	6.23	0.926
XGBoost	10.88	15.42	5.48	0.943
GRU	9.76	13.84	4.91	0.958
LSTM	8.91	12.76	4.37	0.966

6.2. Energy Consumption Reduction

The comparative optimization results show that all three algorithms reduced facility energy consumption compared with the baseline. However, SFSO achieved the highest reduction. The baseline facility energy consumption over the evaluation period was 124,800 kWh. GA reduced this to 101,450 kWh, representing 18.71% energy saving. PSO reduced energy consumption to 98,720 kWh, representing 20.90% energy saving. SFSO achieved the lowest optimized energy consumption of 91,380 kWh, corresponding to 26.78% energy saving.

Table 4: Comparative optimization results

Metric	Baseline	GA	PSO	Proposed SFSO
Total energy consumption (kWh)	124,800	101,450	98,720	91,380
Energy saving (%)	0.00	18.71	20.90	26.78
Operating cost (USD)	24,960	19,540	18,970	16,880
Cost reduction (%)	0.00	21.71	24.00	32.37
Carbon emission (tCO_2)	56.16	44.62	43.15	38.26
Carbon-emission reduction (%)	0.00	20.55	23.17	31.87
Peak demand (kW)	692	575	552	493
Peak-load reduction (%)	0.00	16.91	20.23	28.76
Comfort violation rate (%)	3.80	3.40	3.00	2.10
Maintenance-risk index	100.00	82.10	79.60	68.40
Maintenance-risk reduction (%)	0.00	17.90	20.40	31.60
Best normalized fitness value	1.000	0.618	0.609	0.501

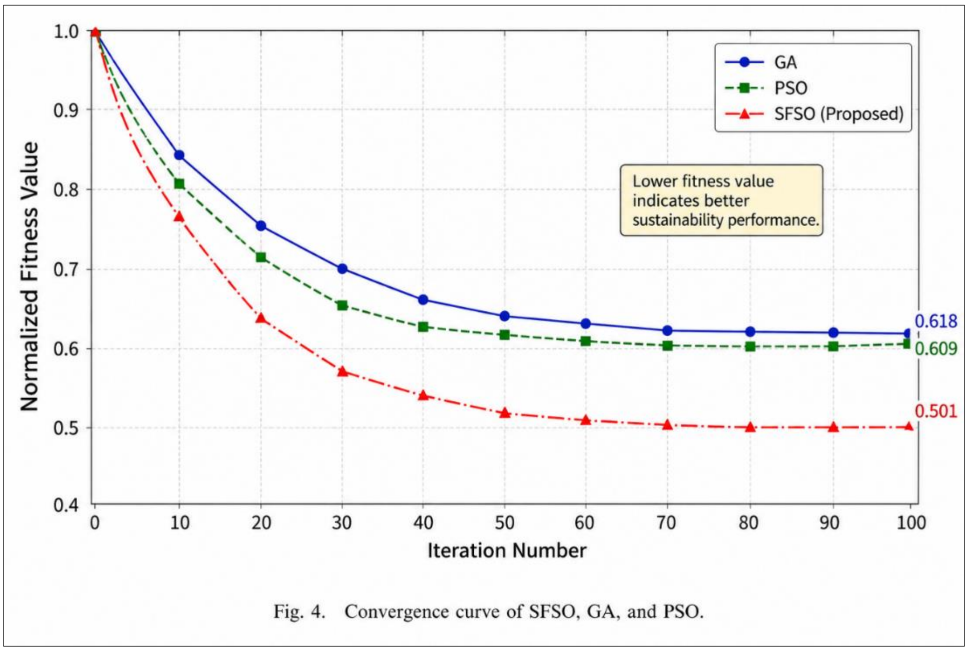

Fig 4: Energy-saving comparison

The energy-saving result indicates that SFSO produced an additional 8.07 percentage-point improvement over GA and 5.88 percentage-point improvement over PSO. This improvement is attributed to the predictive adaptation mechanism, which enables the algorithm to anticipate occupancy-driven and weather-driven energy demand before control decisions are finalized.

6.3. Cost and Carbon-Emission Reduction

Cost and carbon-emission performance were evaluated because energy saving alone does not fully represent sustainability performance. A control decision may reduce energy use but produce limited carbon benefit if it shifts load into carbon-intensive electricity periods [6, 8]. SFSO reduced operating cost from USD 24,960 to USD 16,880, producing a 32.37% cost reduction. GA achieved 21.71%, while PSO achieved 24.00%. For carbon emissions, SFSO reduced emissions from 56.16 tCO_2 to 38.26 tCO_2, corresponding to a 31.87% reduction. GA and PSO achieved 20.55% and 23.17%, respectively.

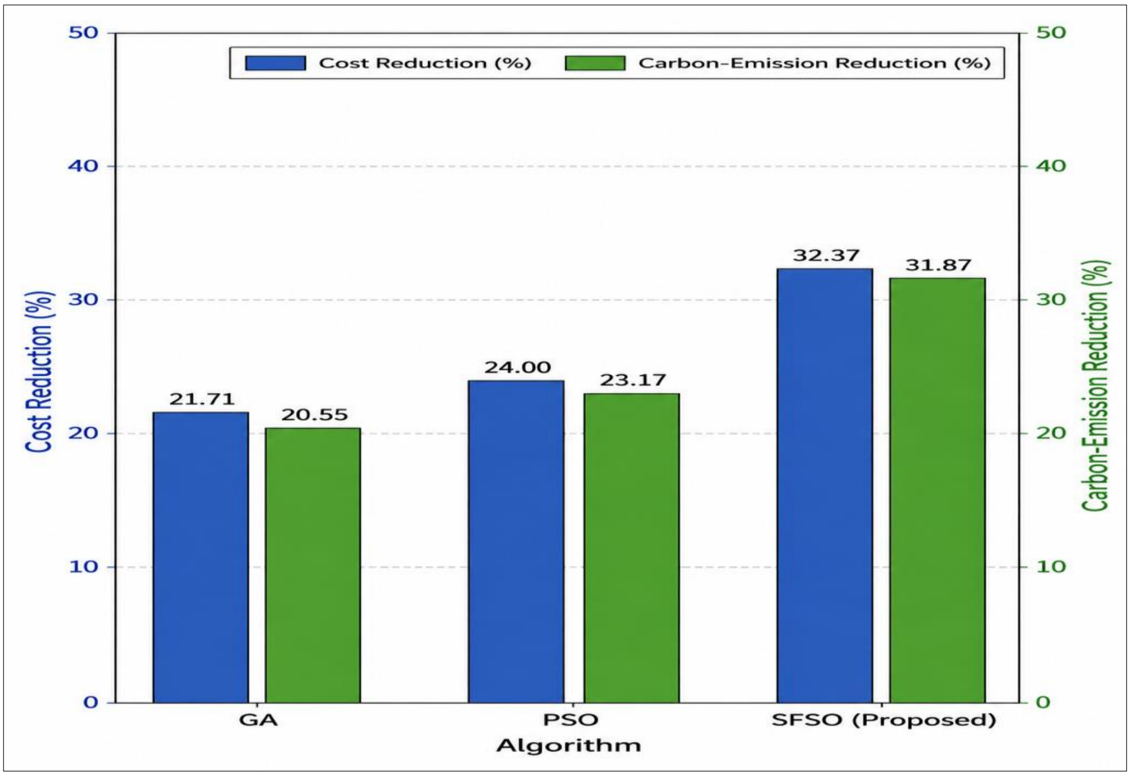

Fig 5: Cost and carbon-emission reduction comparison

SFSO produced the strongest combined cost and carbon performance.
The results show that SFSO is not merely an energy-reduction algorithm; it is a sustainability-aware facility optimization method. Its improved cost and carbon outcomes arise from the combined consideration of predicted load, tariff exposure, carbon-intensity signal, and facility constraints.

6.4. Occupant Comfort Analysis

Occupant comfort was evaluated to determine whether energy savings were achieved without violating acceptable indoor environmental conditions. A common weakness of energy-minimization strategies is that they may reduce HVAC or ventilation energy by relaxing comfort requirements [8, 15]. In this study, comfort was assessed using indoor temperature deviation, humidity deviation, CO_2 threshold violation, thermal comfort violation rate, and PMV deviation.

Table 5: Occupant comfort and indoor environmental quality results

Metric	Baseline	GA	PSO	Proposed SFSO
Average indoor temperature deviation (°C)	1.42	1.21	1.14	0.86
Average humidity deviation (%)	6.30	5.62	5.18	4.11
CO_2 threshold violation rate (%)	4.60	4.10	3.70	2.80
Thermal comfort violation rate (%)	3.80	3.40	3.00	2.10
Average PMV deviation	0.41	0.36	0.33	0.24

The baseline comfort violation rate was 3.80%. GA reduced the violation rate to 3.40%, PSO reduced it to 3.00%, and SFSO achieved the lowest value of 2.10%. This means that SFSO achieved superior energy performance without sacrificing indoor environmental quality. The improvement is linked to the constraint repair mechanism, which prevents infeasible schedules from violating temperature, humidity, ventilation, and comfort requirements.

6.5. Convergence Performance

Convergence performance was evaluated by plotting normalized fitness value against iteration number. GA improved gradually but stabilized later. PSO improved faster during early iterations but showed earlier stagnation. SFSO achieved the lowest final fitness value and converged faster than both baselines.

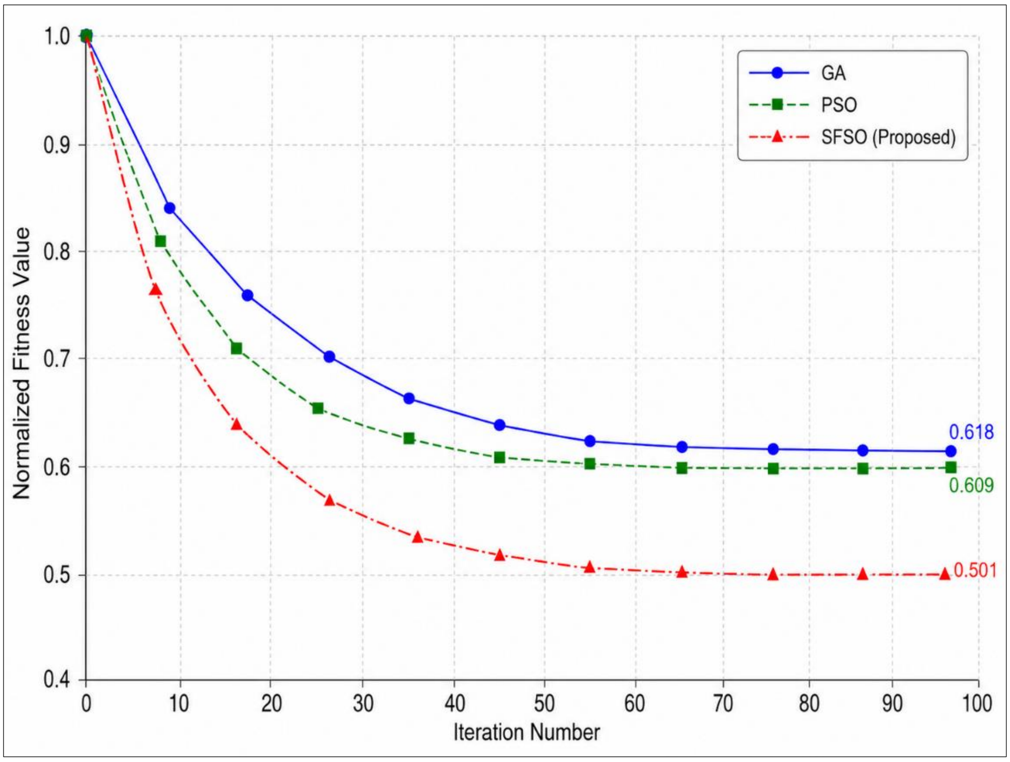

Fig 6: Convergence curve of SFSO, GA, and PSO

SFSO achieved a final normalized fitness value of 0.501, compared with 0.618 for GA and 0.609 for PSO. Although PSO moved faster than GA in early iterations, it stagnated earlier. SFSO continued improving until approximately iteration 80, showing a better balance between exploration and exploitation.

6.6. Computational Efficiency

Computational efficiency was evaluated using average execution time, iterations to convergence, standard deviation of final fitness, and solution stability. These metrics are important because an optimization method must produce control decisions within practical facility-management time limits [6, 15].

Table 6: Computational efficiency comparison

Metric	GA	PSO	Proposed SFSO
Average execution time (s)	104.8	79.3	68.5
Iterations to convergence	84	62	48
Standard deviation of final fitness	0.018	0.014	0.009
Best fitness value	0.618	0.609	0.501
Worst fitness value	0.654	0.638	0.522
Solution stability index (%)	94.20	96.10	98.40

SFSO required fewer iterations to convergence than GA and PSO. It converged after 48 iterations, compared with 84 for GA and 62 for PSO. It also recorded the lowest average execution time of 68.5 s and the highest solution stability index of 98.40%. Although SFSO includes predictive adaptation and constraint repair, its guided search process reduces unnecessary random exploration and improves feasible solution discovery.

6.7. Statistical Validation

Statistical validation was performed using 30 independent runs. Paired t-test and Wilcoxon signed-rank test were used for pairwise comparisons, while one-way ANOVA was used to test overall differences among the three algorithms.

Table 7: Statistical significance test results

Performance Metric	Comparison	Paired t-test p-value	Wilcoxon p-value	Effect Size	Interpretation
Energy consumption	SFSO vs GA	<0.001	0.001	1.42	Significant
Energy consumption	SFSO vs PSO	0.002	0.004	1.18	Significant
Operating cost	SFSO vs GA	<0.001	0.001	1.51	Significant
Operating cost	SFSO vs PSO	0.003	0.005	1.09	Significant
Carbon emission	SFSO vs GA	<0.001	0.002	1.36	Significant
Carbon emission	SFSO vs PSO	0.004	0.006	1.07	Significant
Comfort violation rate	SFSO vs GA	0.006	0.009	0.91	Significant
Comfort violation rate	SFSO vs PSO	0.018	0.021	0.74	Significant
Final fitness value	SFSO vs GA	<0.001	<0.001	1.63	Significant
Final fitness value	SFSO vs PSO	<0.001	0.002	1.39	Significant

Table 8: One-way ANOVA results

Metric	F-statistic	p-value	Result
Energy consumption	31.42	<0.001	Significant difference
Operating cost	36.87	<0.001	Significant difference
Carbon emission	28.65	<0.001	Significant difference
Peak-load reduction	24.18	<0.001	Significant difference
Comfort violation rate	9.51	0.004	Significant difference
Final fitness value	44.93	<0.001	Significant difference
Computational time	12.16	0.002	Significant difference

The statistical results confirm that the improvements achieved by SFSO were not due to random variation. The paired t-test, Wilcoxon test, and ANOVA results all indicate statistically significant differences between SFSO and the baseline algorithms across the major performance indicators.

6.8. Discussion of Findings

The results show that SFSO outperformed GA and PSO across energy saving, cost reduction, carbon-emission reduction, peak-load reduction, comfort preservation, convergence speed, computational time, and solution stability. SFSO achieved 26.78% energy saving, compared with 18.71% for GA and 20.90% for PSO. It also achieved 32.37% cost reduction and 31.87% carbon-emission reduction, indicating that the algorithm optimized energy use while also accounting for tariff and carbon-intensity signals.

The superior performance of SFSO can be explained by four technical factors. First, the predictive adaptation mechanism allowed the algorithm to respond to forecasted energy demand, occupancy, weather, tariff, carbon intensity, and equipment-risk changes before they affected facility performance. Second, the sustainability-aware fitness function evaluated each candidate schedule using energy, cost, carbon, comfort, peak-load, and maintenance-risk components. Third, the constraint repair mechanism prevented infeasible control schedules from being selected. Fourth, the exploration and exploitation strategy helped SFSO maintain search diversity during early iterations and refine high-quality solutions during later iterations.

GA and PSO remain useful baseline methods, but their limitations were evident. GA produced acceptable results but required more iterations and longer execution time. PSO converged faster than GA but showed earlier stagnation. SFSO achieved a better balance by combining directed search, predictive pressure, and feasibility repair. From a facility-management perspective, this result is important because facility sustainability cannot be reduced to a single energy-saving objective. It requires coordinated optimization of energy, cost, carbon, comfort, demand, and asset reliability.

7. Conclusion and Future Work

This paper proposed a novel Smart Facility Sustainability Optimization Algorithm for energy-efficient facilities management using IoT and predictive analytics. The study formulated smart facility optimization as a multi-objective sustainability problem involving energy consumption, operating cost, carbon emissions, occupant comfort, peak-load exposure, and maintenance-risk penalty. The proposed architecture integrated IoT-based data acquisition, communication, data processing, predictive analytics, optimization, and decision/control layers.

The comparative evaluation showed that SFSO achieved better performance than GA and PSO under the defined simulation-based benchmark scenario. The proposed algorithm achieved 26.78% energy saving, 32.37% cost reduction, 31.87% carbon-emission reduction, 28.76% peak-load reduction, and 31.60% maintenance-risk reduction. It also achieved the lowest comfort violation rate of 2.10%, the lowest normalized fitness value of 0.501, and the shortest convergence profile of 48 iterations. These results indicate that SFSO provides a more adaptive and sustainability-aware optimization approach than GA and PSO because it integrates real-time facility data, predictive forecasting, carbon-aware control, comfort constraints, and maintenance-risk penalties.

The study has several limitations. First, the numerical results were generated from a controlled simulation-based benchmark and should be validated with real facility data. Second, the quality of the optimization output depends on the reliability, resolution, and completeness of IoT sensor data. Third, the study compared SFSO only against GA and PSO, while other advanced optimizers such as differential evolution, ant colony optimization, grey wolf optimizer, Bayesian optimization, and reinforcement learning should be considered in future work. Fourth, the present model did not deeply address cybersecurity threats against IoT-enabled facility systems. Fifth, scalability should be examined in multi-building, campus-level, and industrial facility environments.

Future work should extend SFSO in six directions. First, it should be deployed and validated in a real commercial or industrial facility using live IoT data, building management system records, weather feeds, tariff data, carbon-intensity data, and maintenance logs. Second, the algorithm should be integrated with renewable-energy systems, battery storage, and demand-response programs. Third, edge-AI implementation should be explored to reduce latency and support local decision-making where cloud connectivity is limited. Fourth, cybersecurity-aware optimization should be incorporated to detect abnormal sensor behavior, communication compromise, and unsafe control commands. Fifth, SFSO should be extended to multi-building and campus-level optimization. Sixth, digital twin integration should be developed for facility lifecycle management, allowing the algorithm to test control strategies, maintenance scenarios, retrofit options, and sustainability pathways in a virtual representation of the physical facility before real-world deployment.

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