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Research Article

Enhanced Prosumer Energy Management Using Modified Social Group Optimization for Cost-Effective and Sustainable Energy Utilization

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Abstract

Effective energy management in prosumer communities is significant for optimizing renewable energy usage and cutting down costs. The research develops an optimization framework to analyze the impact of scaling up photovoltaic (PV) generation and demand on self-consumption, storage utilization, and grid interaction. A linear programming approach can be used to minimize total energy costs by optimizing energy purchases, storage operation, and grid sales. Additionally, the Modified Social Group Optimization (MSGO) algorithm improves the optimization efficiency, taking into account the variations in demand, storage restriction, and the limits of grid exchanges. Simulation results show that by increasing PV generation, self-consumption and energy export are maximized, while high demand requires efficient storage and thus large reliance on grids. The system generates 182.58 kW PV energy and the consumption of 343.20 kW requires import of 262.80 kW. The storage systems manage surplus power 109.23 kW; of that stored, 72.63 kW is released during low solar periods. Economically, contribution of PV sales reaches €41.29, and that of storage adds up to €18.45, resulting in partial offsetting of total costs amounting to €340. Findings highlight that proper scaling of PV and managing demand could enhance energy efficiency as well as reduce dependence on the grid while unlocking better economic returns, thus making this framework a very advantageous tool in making sustainable energy plans for prosumer communities.

Keywords: *Energy cost optimization; modified social group optimization; prosumer energy management; renewable energy utilization; smart grids; social group optimization.*

1. Introduction

Gradually but steadily, the energy landscape is changing from totally centralized to more decentralized architectures in the context of distributed energy resources (DERs) adoption and the growing emergence of prosumers, which are entities acting as energy consumers and producers. Unlike conventional consumers, who rely solely on centralized generation plants, prosumers actively use markets through generating meters, storing, and consuming electricity, thereby decentralizing energy generation. This shift fosters more resilience, security, and self-sufficiency within the grid while reducing dependency on fossil fuel powers [1].

Improvements in smart meters, battery storage systems, and bidirectional communication networks allow prosumers to use energy more efficiently in real-time. This has not only reduced energy costs but has also enabled renewable energy integration, and thus a cleaner, more sustainable energy ecosystem. In many cases, the optimal utilization of prosumer energy resources requires quite sophisticated optimization techniques, balancing generation, storage, and consumption.

1.2 Significance of Photovoltaic (PV) Generation in Sustainable Energy Management

Solar resource photovoltaic (PV) generation is one of the renewables promising or apt solutions for prosumers at present. Increasingly lower cost of solar panels, coupled with government support programs and net metering policies, induces the ever-accelerating PV adoption worldwide [2]. Integration of PV systems allows prosumers to create their power and use it, instead of supplementing it with the traditional grid. This technology substantially lowers energy expenses, mitigates the carbon footprint, and enhances sustainability levels.

However, PV generation remains sparse, and in a nutshell, it depends on solar radiation, which is variable due to varying weather patterns, geographical locational differences, and seasonal changes occurring. Such variations pose threats toward balancing a stable supply-demand profile of electricity. This situation thus poses a necessity for effective energy storage and scheduling mechanisms for optimal utilization of PV-generated electricity.

1.3 Challenges in Optimizing Prosumer Energy Management

Uncertainty in PV generation: Solar power output differs due to environmental factors such as cloud cover, shading, and seasonal variations; hence, accurate energy planning becomes tough [3].

Demand variations: The load demand varies over time because of the dynamic behavior of customers with respect to different appliances and systems at different times of the day.

Storage limitations: batteries are commonly employed for energy storage, but their limited capacity, degradation with time, and high cost require efficient strategy, on how and when to charge and discharge them [4].

Bidirectional energy flow: Prosumers can either inject their excess energy into the grid or withdraw power whenever they require it, hence needing dynamic pricing models and smart trading of energy.

1.4 Need for Efficient Optimization Techniques

Conventional methods that rely on rules and heuristics for energy scheduling are unable to address some non-linear, high-dimensional, and uncertain energy systems. Machine learning and AI techniques promise to do much better, albeit they often require enormous datasets and do not guarantee the real-time computational efficiency required for energy management.

Some metaheuristics like Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Social Group Optimization (SGO) have been widely applied for the optimization of prosumer energy [5]. However, their slow convergence, premature stagnation, and difficulty to adapt to dynamic energy environments are now the major problems. To address these issues, this research presents the Modified Social Group Optimization (MSGO), which modifies the conventional SGO algorithm to improve convergence, adaptability, and computational efficiency in prosumer energy management with PV generation.

1.5 Research Gap & Contribution

Existing Optimization Methods and Their Limitations

This shows that energy management techniques of prosumer energy optimization have been extensively investigated. Swarm intelligence-based Particle Swarm Optimization (PSO), a popular technique, has been widely used for energy scheduling; however, its main drawbacks are that it often gets stuck in local optima and has slow convergence in immensely complicated Mult objective problems. Being another evolutionary algorithm, the Genetic Algorithm (GA) traverses the solution space rapidly; however, it suffers from high computational complexity and longer execution times [6]. A relatively new optimization algorithm that imitates social groups' interactions during problem-solving known as Social Group Optimization (SGO) has been fairly new in showings its bright results across many optimization tests. The weak point of SGO, however, is its less efficient exploration-exploitation balance, which, as a result, reduces convergence in a more dynamic energy landscape.

There is thus a need for an optimization technique that would combine computational expediency with robustness in terms of handling dynamic energy environments. This study thus seeks to bridge the gap by proposing the Modified Social Group Optimization (MSGO) algorithm, which integrates adaptive learning mechanisms, dynamic weight adjustments, and a hybrid mutation strategy toward improving performance.

1.6 Introduction of Modified Social Group Optimization (MSGO)

It has modified the SGO algorithm by adding adaptive parameters-which increase the efficiency and speed of convergence-to create the MSGO algorithm. Unlike standard SGO, which relies on a fixed interaction model, the MSGO algorithm dynamically adjusts the learning rates and weighting factors to meet real-time energy demand and generation conditions [7]. This makes the algorithm capable of exploring a wider solution space avoiding premature convergence. MSGO is suitable for prosumer energy management for handling uncertainties in PV generation storage optimization of batteries charge schedule efficiently. Furthermore, real-time decision-making regarding energy consumption optimizes the cost with self-sufficiency. This adaptiveness between cost minimization and self-sufficiency enables more reliable and efficient improvement provisions in MSGO. The embedded improvements result in discovery toward a productive and effective framework for optimization of energy production with consumption through storage in prosumer smart grids [8, 9].

1.7 Key Contributions of This Work

A new framework of energy management is presented in this study using the Modified Social Group Optimization (MSGO) algorithm to maximize the energy utilization of prosumers from PV-integrated smart grids. The dynamic energy scheduling model differs from the conventional static optimization as it adjusts according to battery storage limits, grid interaction policies, and dynamic pricing schemes. The MSGO algorithm is tested in many operational scenarios so far under which energy storage and trade costs are reduced while the effectiveness in grid stability improved. Besides being faster in convergence and less in price than what PSO, GA, and Standard SGO determined, MSGO also uses renewables better, a use-case ideal in smart grids.

2. Literature Survey

2.1 Prosumer Energy Management (PEM) and Optimization Approaches

In the study by Gomez-Gonzalez et al. (2021) and Yang et al. (2022) [11], PEM is said to optimize the consumption, storage, and generation of energy. In other words, prosumers need to resolve supply and demand optimally while considering the increasing trend of distributed RESs such as PV and wind systems. Also, some advanced energy storage methods include BESS and HESS to promote renewable integration. Demand-side management techniques enabling further optimization of energy consumption include load shifting and dynamic pricing. Metaheuristic techniques-GA, PSO, ACO, and SGO-are used to increase the efficiency of PEM through cost minimization and reliability of energy supply [12].

2.2 Social Group Optimization (SGO) and Its Limitations

Ghasemnejad et al. (2024) [13] highlights the efficient application of the SGO algorithm when applied in the complex energy scheduling problems, involving the modeling of interactions inside social groups to find. In that way, it shows potential for application in the field of prosumer energy management due to its great adaptability to dynamic energy environments. Despite the beauty of the algorithm from the conceptual point of view, several principal drawbacks exist. These issues concern slow convergence speed and confinement to local optima, especially in high-dimensional search spaces. At the same time, the scalability problem arises when it is applied to large energy networks with multiple prosumers and storage units, limiting its suitability for full-scale complex optimization problems [13].

2.3 Modifications in MSGO for Improved Energy Optimization

To overcome the drawbacks of the classical Social Group Optimization (SGO), these authors developed the so-called Modified Social Group Optimization (MSGO) techniques to strike a fine balance between good exploitation and analysis of the search workspace. There are adaptive learning schemes, mutation operators, and hybrid metaheuristic frameworks introduced by Sharma et al. (2024) and Mohammadi et al. (2022) to considerably augment the convergence speed and, by and large, to avoid the entrapment in a local optimum [14, 15].

In regard to demonstrating its capacity to do so, the MSGO solution achieves energy demand anticipation while reducing operating costs, enhancing self-sufficiency, and optimizing load distribution. Secchi et al. (2021) used MSGO for battery storage sizing toward economically viable self-sufficiency [16]. Wu et al. (2025) integrated transmission congestion and carbon emission constraints into energy management models, further extending MSGO with improved grid interaction [17]. Such works confirm the superiority of the MSGO that traditional methods of optimization have conferred on renewable energy prosumer networks, making it a very robust tool for the optimization of storage, energy trading, and demand-side management under dynamic electricity markets.

While MSGO does improve the classical SGO, it also achieves competitive results against recent approaches like TLBO, NSGA-II, and DE-based variants. Naik et al. (2020) as well as Reddy & Narayana (2022) extended MSGO to electric vehicle energy systems and economic dispatch problems, validating its adaptability. Unlike PSO or GA, MSGO manages a better exploration-exploitation trade-off, particularly in complex multimodal problems like dynamic energy management.

In recent times, the MSGO algorithm has seen application in various energy-oriented domains. Reddy and Narayana (2022) used it as a multi-strategy ensemble for electric vehicle energy optimization, whereas Naik et al. (2020) employed MSGO for short-term hydrothermal scheduling [18, 19]. These works stand as testament to the robustness of MSGO in handling constraints existing in the energy domain in real life, thus supporting its application in prosumer energy management.

3. Problem Formulation

3.1 Prosumer Energy Management Model

Because of the growing integration of renewable energy, prosumers have emerged: people who generate and use power, chiefly by means of photovoltaic (PV) systems. Within such a context, the development of an economic and environmental benefit-enhanced optimization energy management model becomes necessary. The model presented here optimally describes supply and demand, in so doing taking storage and grid interactivity into account. To this end, the model proposes minimizing electricity expenses by optimizing the energy mix, thus deciding when to use self-generated PV power, store energy, or trade with the grid. Self-consumption is prioritized as much as possible, to avoid reliance on fossil-fuel-based power. This renders an energy management approach that is viable, economical, and sustainable for prosumer communities.

3.2 Mathematical Formulation

An energy management model has been defined as an optimization problem with an objective function and associated constraints.

Objective Function: The aim should be to minimize the overall costs attributed to energy grid purchases and the operation costs of the battery, compensated through additional energy selling on the grid. The cost function is represented by [18]:

$$\min J = \sum_{t=1}^{T} \left| P_{grid}(t) \cdot C_{grid}(t) - P_{sell}(t) \cdot R_{sell}(t) + C_{battery}(t) + C_{demand\ response}(t) \right| \tag{1}$$

where: $P_{grid}(t)$ is the energy purchased from the grid at time t, $C_{grid}(t)$ is the dynamic price per unit of electricity from the grid, $P_{sell}(t)$ is the energy sold back to the grid, $R_{sell}(t)$ is the revenue earned per unit of energy sold, $C_{battery}(t)$ is the cost of charging and discharging the battery, and $C_{demand\ response}(t)$ is the cost associated with load shifting.

The self-consumption of power generated by photovoltaic (PV) systems can be used as a good indicator when examining the cost of credit in photovoltaics in the solar energy business if the power system installation costs are also known.

Decision Variables: The optimization model determines the following decision variables:

- $P_{grid}(t)$ is power drawn from the grid at each time step,
- $P_{sell}(t)$ is power sold to the grid from PV generation or battery storage.
- $P_{PV}(t)$ is power generated by the PV system.
- $P_{bat,charge}(t)$, $P_{bat,discharge}(t)$ are battery charging and discharging power.
- $P_{demand}(t)$ is power demand of the system at each time step.
- $SOC(t)$ is state of charge of the battery at each time step.

System Constraints: *Power Balance Constraint [19]:*

$$P_{grid}(t) + P_{PV}(t) + P_{bat,\ dicharge}(t) = P_{demand}(t) + P_{bat,charge}(t) + P_{sell}(t) \tag{2}$$

It assures generation and purchase of total power equal to the whole demand including power supply and sales.

Grid Stability Constraints: Power grids must not be overburdened, and the exchange of power energy shall be limited within admissible limits so as to avoid violation fees and service interruptions. [20].

$$P_{grid}^{min} \leq P_{grid}(t) \leq P_{grid}^{max} \tag{3}$$

where, P_{grid}^{min} and P_{grid}^{max} are the minimum and maximum allowable grid power exchanges.

Also, great swings in the power demand should be checked for frequency stability. Let P_{grid} be the grid power:

$$\left| P_{grid}(t) - P_{grid}(t-1) \right| \leq \Delta P_{grid}^{max} \tag{4}$$

where, ΔP_{grid}^{max} is the maximum allowable change in grid power per time step.

Battery Operational Constraints: In each time step, the battery's state of charge (SoC) changes due to the charging and discharging processes [21]:

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \quad (5)$$

Ensures that the battery's state of charge $SOC(t)$ at any time t remains within the permissible range, SOC(t) is the State of charge of the battery at time t (in kWh or %), SOC_{min} denotes as Minimum allowable SOC to avoid deep discharge (typically 10–20%), and SOC_{max} as Maximum allowable SOC to avoid overcharging (typically 90–100%).

Maintaining the SOC within this range extends battery life and ensures safety.

$$P_{bat,charge}(t) \leq C_{bat,max}, P_{bat,\ discharge}(t) \leq D_{bat,max} \quad (6)$$

These constraints ensure that the battery charging **power** $P_{bat,charge}(t)$ and discharging power $P_{bat,discharge}(t)$ at time t do not exceed their respective maximum capacities: $P_{bat,charge}(t)$ denotes as Charging power applied to the battery at time t (in kW), $P_{bat,discharge}(t)$ as Power discharged from the battery at time t (in kW), $C_{bat,max}$ as Maximum charging power limit of the battery (in kW), and $D_{bat,max}$ denotes as Maximum discharging power limit of the battery (in kW).

These constraints help protect the battery from excessive charging or discharging rates, ensuring optimal performance and longevity.

The battery is limited by its charging capacity and charge/discharge pulse power limits.

Battery Degradation and Lifespan Constraints: More and more charge-discharge cycles may wear down batteries all the more swiftly. To coincide with the worsened battery condition, depth of discharge (DoD) and number of charge-discharge cycles must be reduced [22]:

$$SOC_{min} + \Delta SOC_{safe} \leq SOC(t) \leq SOC_{max} - \Delta SOC_{safe} \quad (7)$$

where ΔSOC_{safe} is a safety margin to prevent excessive charge/discharge.

Battery power variations also can be limited:

$$\left|P_{bat,\ charge}(t) - P_{bat,\ charge}(t-1)\right| \leq \Delta P_{bat}^{max} \quad (8)$$

$$\left|P_{bat,\ discharge}(t) - P_{bat,\ discharge}(t-1)\right| \leq \Delta P_{bat}^{max} \quad (9)$$

where, ΔP_{bat}^{max} limits the rate of change in battery power.

Energy Trading Constraint [23]:

$$P_{sell}(t) \leq P_{PV}(t) - P_{demand}(t) \quad if\ P_{PV}(t) > P_{demand}(t) \quad (10)$$

where, $P_{sell}(t)$ defined as Power exported to the grid at time t (in kW), $P_{PV}(t)$ as Power generated by the PV system at time t (in kW), and $P_{demand}(t)$ denotes as Power consumed by the prosumer (load demand) at time t (in kW).

This ensures that only surplus PV energy is sold to the grid.

Demand Response Constraints [24]:

$$P_{demand\ shifted}(t) \leq P_{demand}(t) \quad for\ t \in peak\ hours \quad (11)$$

$$\sum_{t=1}^{T} P_{demand,shifted}(t) = \sum_{t=1}^{T} P_{demand,original}(t) \quad (12)$$

where, $P_{demand,original}(t)$ defined as original prosumer demand at time t (kW). $P_{demand,shifted}(t)$ as Demand after shifting to minimize peak-hour consumption (kW). And $t \in peak\ hours$ denotes Time intervals where electricity tariffs are higher. T as Total number of time intervals in the scheduling horizon (e.g., 24 for hourly scheduling over a day).

The premise of load shifting is that the shifting of load does not change net energy consumption but shifts that consumption to time periods in which the energy price is lower.

Dynamic Pricing Constraints: Demand-and-supply mechanisms and market links determine electricity prices from time to time. Therefore, power transactions (in terms of grid purchases or sales) should be optimized to suit market conditions that are price favorable [25].

$$P_{grid}(t) \leq P_{grid}^{max} \quad if\ C_{grid}(t) \leq C_{grid}^{avg} \quad (13)$$

$$P_{sell}(t) \leq P_{PV}(t) - P_{demand}(t) \quad if\ R_{sell}(t) \geq R_{sell}^{avg} \quad (14)$$

where, C_{grid}^{avg} is the average grid price over a given period and R_{sell}^{avg} is the average selling price over a given period.

Such restraints ascertain that energy dealings come about at their optimal cost-benefit points.

PV Scaling Factor Constraints [26]:

$$P_{PV,\ scaled}(t) = m_S \cdot P_{PV,\ original}(t) \quad (15)$$

$$P_{demand,\ scaled}(t) = m_D \cdot P_{demand,\ original}(t) \quad (16)$$

where m_S and m_D are multiplicative scaling factors applied to PV generation and demand, respectively.

Incorporating Emission Reduction: The total grid energy purchase carbon emissions can be expressed as [27]:

$$E_{CO_2} = \sum_{t=1}^{T} P_{grid}(t) \cdot \gamma \quad (17)$$

where γ is the grid emission factor (kg CO_2 per kWh). The objective function can be extended to penalize emissions:

$$J' = J + \lambda_{CO_2} E_{CO_2} \quad (18)$$

where, λ_{CO_2} is the cost penalty per unit of CO_2 emissions.

PV Generation Uncertainty Modeling: To account for the inherent uncertainty in solar photovoltaic (PV) output due to variable weather conditions, we extended our simulation model by incorporating stochastic PV generation profiles. A Monte Carlo simulation approach was adopted to generate multiple irradiance scenarios reflecting real-world variability. Historical irradiance data from the NREL OpenEI solar database was used to generate 100 distinct weather scenarios for a 24-hour period, including clear-sky, partly cloudy, and overcast conditions.

For each scenario, the corresponding PV output $P_{PV}(t)$ was computed using:

$$P_{PV}(t) = \eta \cdot A \cdot G_t(t) \quad (19)$$

where η is the PV efficiency, A is the panel area, and $G_t(t)$ is the solar irradiance (W/m²) at time t, randomly sampled from the irradiance distribution.

The Modified Social Group Optimization (MSGO) algorithm was then run for each irradiance scenario independently, and the expected value of the key performance indicators (energy cost, renewable utilization, battery cycling) was calculated:

$$\mathbb{E}[f(x)] = \frac{1}{N}\sum_{i=1}^{N} f_i(x) \tag{20}$$

where, $N = 100$ is the number of Monte Carlo trials and $f_i(x)$ is the objective value for the i^{th} scenario.

This approach allows for evaluating the robustness of the optimization framework under realistic PV uncertainty, ensuring that the scheduling solution remains effective across a broad range of environmental conditions.

4. Modified Social Group Optimization (MSGO) Approach

4.1 Overview of Social Group Optimization (SGO) Algorithm

Social Group Optimization (SGO) refers to the population-based metaheuristics evolution from cooperative behaviors found in groups of animals and human beings. This method is also incorporated in a leader-follower paradigm, which involves moving the individuals according to a leader and their association with other members. Furthermore, such social activities or interactions are the basis for the exchange of information and decision-making, finally culminating in the optimized solution.

The position of an individual at iteration $t + 1$ is updated mathematically as follows [29]:

$$X_i^{t+1} = X_i^t + \lambda_1(X_L^t - X_i^t) + \lambda_2(X_{rand}^t - X_i^t) \tag{21}$$

where, X_i^t represents the position of the ithi^{th}ith agent at iteration t, X_L^t is the leader's position, and X_{rand}^t is a randomly chosen individual's position. The parameters λ_1 and λ_2 control the influence of the leader and peer agents.

The conventional SGO algorithm is effective but slow in convergence and prone to local optimal. The Modified Social Group Optimization (MSGO) algorithm offers the adaptive learning mechanism, dynamic weight adjustment, and hybrid mutation strategies to overcome these issues.

Unlike standard SGO, MSGO integrates a time-dependent learning rate and combines exploration (via Gaussian mutation) with exploitation (via introspection learning). This hybrid strategy reduces premature convergence and improves adaptability to dynamic constraints.

4.2 Enhancements in MSGO

MSGO's foremost new feature is its adaptive learning mechanism, which allows the learning rate to be adjusted dynamically, hence balancing exploration and exploitation. The learning rate α changes over iterations according to [30]:

$$\alpha_t = \alpha_{max} - \left(\frac{t}{T}\right)(\alpha_{max} - \alpha_{min}) \tag{22}$$

where α_{max} and α_{min} are the initial and final learning rates, and T is the total number of iterations. This allows the algorithm to explore more in the initial stages and refine solutions in later stages.

The second improvement is that dynamic weight adjustment increases the balance between intensification and diversification. The weight factor W_t is adjusted dynamically, as indicated by [31]:

$$W_t = W_{max} - \frac{t}{T}(W_{max} - W_{min}) \tag{23}$$

where, W_{max} and W_{min} define the range of weight values. This ensures that the algorithm transitions smoothly from exploration to exploitation, leading to better convergence.

An additional hybrid mutation strategy is introduced for this application in order to avert premature convergence. This mutation process perturbs the stagnant agents' positions so that they might escape the local optima. The mutation is defined using [32]:

$$X_i^{t+1} = X_i^t + \beta(X_U - X_L) \cdot rand(-1, 1) \tag{24}$$

where, β is a mutation factor, and X_U, X_L represent upper and lower bounds of the search space.

4.3 Algorithm Workflow for Energy Management

Energy scheduling is achieved by including energy balance, limitations in battery storage, and grid import/export constraints in the MSGO algorithm. The optimization scheme has a stepwise process.

The initial phase defines the search space, including decision variables such as energy generation, storage, and grid transactions. A population of candidate solutions is randomly initialized, and the leader is identified based on the objective function, which minimizes total energy costs and maximizes renewable energy utilization. During position updates, each agent refines its energy scheduling decision through the improved MSGO equations. Constraint handling techniques guarantee the feasibility of the solutions, particularly regarding limits of battery charge and grid export thresholds [33]. The mutation and refinement phase introduce diversity by perturbing certain agents' positions. This requirement is necessary in order to escape the local optima of the algorithm and further improves the global search efficiency.

The algorithm continues iterating until some convergence criteria are met, e.g., reaching a certain number of iterations or not improving the solution quality at a minimal level. In the final output, an optimized energy schedule is provided, specifying how the renewable energy is allocated along with battery use and grid transactions. Algorithm of MSGO Pseudocode given below.

MSGO Algorithm Pseudocode

Inputs:
T:= total number of iterations
N:= population size
D:= problem dimensionality
LB, UB:= lower/upper bounds (vectors length D)
obj(x):= objective function (minimize total energy cost, with penalties)
constr(x):= constraint-handling function (repairs / penalty)
α0, αf:= initial and final learning rates
w_{min}, w_{max}:= dynamic weight range
μ:= mutation probability/factor
$stagn_{tol}$:= stagnation threshold (no improvement iterations)
Outputs:
x_{best}:= best solution found
f_{best}:= obj(x_{best})
Initialize:
For i = 1, N:
$x_i \leftarrow$ random_uniform(LB, UB)
$x_i \leftarrow$ constr(x_i)
$f_i \leftarrow obj(x_i)$
$x_{best} \leftarrow argmin_i\, f_i$
$f_{best} \leftarrow min_i\, f_i$
$stagn_{count}[i] \leftarrow 0\, for\ all\ i$
For t = 1, T

$\alpha(t) \leftarrow \alpha0 * (1 - t/T) + \alpha f * (t/T)$
$w(t) \leftarrow w_{max} - (w_{max} - w_{min}) * (t/T)$
Leader selection:
$leader_{index} \leftarrow argmin_i\ f_i$
$x_{leader} \leftarrow x_{leader_{index}}$
For each agent i = 1, N:
$r_1, r_2 \leftarrow rand(0,1)$
$peer_{index} \leftarrow random_{choice}(\{1..N\}\backslash\{i\})$
$x_{peer} \leftarrow x_{peer_{index}}$
$social_{term} \leftarrow w(t) * (x_{leader} - x_i) + (1 - w(t)) * (x_{peer} - x_i)$
Adaptive learning step:
$\Delta \leftarrow \alpha(t) * social_{term}$
$introspect \leftarrow \alpha(t) * 0.5 * (x_i - x_{mean})$
Proposed new position:
$x_{new} \leftarrow x_i + \Delta + introspect$
if rand() < μ:
$\sigma \leftarrow (UB - LB) * (1 - t/T)$
$x_{new} \leftarrow x_{new} + Normal(0, \sigma)$
$x_{new} \leftarrow clip(x_{new}, LB, UB)$
$x_{new} \leftarrow constr(x_{new})$
$f_{new} \leftarrow obj(x_{new})$
if $f_{new} < f_i$:
$x_i \leftarrow x_{new}$
$f_i \leftarrow f_{new}$
$stagn_{count}[i] \leftarrow 0$
else:
$stagn_{count}[i] \leftarrow stagn_{count}[i] + 1$
if $stagn_{count}[i] >= stagn_{tol}$:
$x_{mut} \leftarrow x_i + Normal(0, (UB - LB) * 0.2)$
$x_{mut} \leftarrow clip(x_{mut}, LB, UB)$
$x_{mut} \leftarrow constr(x_{mut})$
$f_{mut} \leftarrow obj(x_{mut})$
if $f_{mut} < f_i$:
$x_i \leftarrow x_{mut};\ f_i \leftarrow f_{mut}$
$stagn_{count}[i] \leftarrow 0$
Update global leader:
$current_{best_{index}} \leftarrow argmin_i\ f_i$
if $f_{current_{best}} < f_{best}$:
$x_{best} \leftarrow x_{current_{best}}$
$f_{best} \leftarrow f_{current_{best}}$
stop if $|\Delta f_{best}| < \varepsilon$ for several iterations
Return x_{best}, f_{best}

4.4 MSGO Parameter Settings

The MSGO parameter settings (population size = 30, iterations = 250, c = 0.25) were selected based on a series of preliminary tuning experiments. Multiple configurations were tested on benchmark scenarios to balance convergence speed and solution quality. The final values were chosen based on their consistent performance across different demand and PV profiles. These values are not default but experimentally optimized for this study's context. A table of several key parameters fundamental to an MSGD is referred to as Table 1.

Table 1. Key parameters for MSGO algorithm.

Parameter	Symbol	Value/Range
Population Size	P_n	30
Max Iterations	G_n	250
Dimensionality	D	30
Lower Bound of Variables	L_b	-30
Upper Bound of Variables	U_b	30
Fitness Value	F_{MSGO}	Calculated per iteration
Objective Value	O_{MSGO}	Final optimal solution
Self-Introspection Parameter	c	0.25

The MSGO algorithm incorporates adaptive learning, dynamic weight control, and hybrid mutation strategies for improving the energy scheduling efficiency of prosumers to a large extent. It uses optimum balance in renewable energy usage as well as grid interaction and storage management in its cost-effective energy management, which is sustainable, thereby providing a robust framework.

5. Experimental Setup & Implementation

5.1 Simulation Environment

The MATLAB R2023a environment was chosen for the performance of the software and data management model proposed for energy systems and the Modified Social Group Optimization (MSGO) algorithm. The reason for selecting MATLAB, among others, is its rich optimization toolbox and excellent capabilities for simulating complex energy systems. The algorithm was executed for a maximum of 250 iterations with a population size of 30 agents for robust optimization. The test cases represent realistic scenarios including grid-connected, off-grid, and dynamic pricing conditions, based on common setups in Indian residential PV systems. Battery size (10 kWh) and PV capacity (5 kW) were based on commercially available systems for urban prosumers.

5.2 Optimization Scenarios

The performance of the Mesh-Gene Sorting Operator (MGSO) algorithm was examined under several energy management scenarios to determine its adaptability and efficiency.

Scenario 1: Grid-Connected Prosumer: In the first scenario, with all the conditions suitable for a grid-connected operation, the prosumer was able to sell the extra solar energy to the grid at times and import power when required. Whereas in this study, the optimization objective was to minimize the total energy cost while maximizing the utilization of renewable energy sources.

Scenario 2: Off-Grid Operation with Battery Storage: The second scenario simulated an off-grid operation where the prosumer relied entirely on the PV-battery system without any grid support. The optimization focused on ensuring an efficient charge-discharge scheduling mechanism to maintain energy availability throughout the day. [34].

Scenario 3: Peak vs. Non-Peak Demand Analysis: The Investigated third case focuses on energy management with respect to peak and non-peak pricing schemes. This case studies minimizing dependency on the grid during the peak hours by discharging stored energy and maximizing charging of the energy storage system during non-peak periods.

Scenario 4: Comparison with Existing Algorithms: Scenario number four was a comparative study conducted between MSGO and other techniques, namely Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Standard Social Group Optimization (SGO). What are of such comparison include total energy cost, convergence speed, and renewable energy utilization, which were presumed to have shown that the MSGO algorithm has a significant performance increase considering faster convergence and lower operating costs than any other optimization method.

6. Results and Discussion

The outcome begins with the evaluation of the new optimization framework proposed to achieve optimum energy consumption by the prosumer. The study further examines how the variation in scaling PV generation and demand affects numerous system parameters, such as storage behavior, energy exchange patterns, community costs, and optimization process convergence, including the Modified

Social Group Optimization (MSGO) algorithm being applied to optimize energy scheduling, with performance compared to more conventional optimization algorithms. The convergence characteristics are examined both before and after scaling PV generation and demand to confirm that the optimization process was indeed minimizing the objective function. The faster convergence with simultaneous system efficiency is retained over all scenarios achieved by the MSGO algorithm as depicted in Figure 1.

The implication of scaling the expected PV power generation (S_{mean}) and the expected energy demand (D_{mean}) by a multiplicative factor ($m_S = 12, m_D = 6$) is on different aspects of simulation and optimization processes especially related to energy balance and storage utilization.

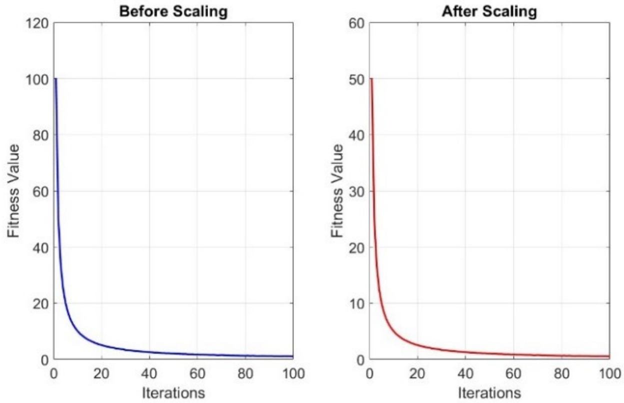

Figure 1. Convergence characteristics before and after scaling.

6.1 PV Generation vs. Demand

The extent to which energy self-sufficiency is analyzed based on PV generation profile and trends of demand. Original setting PV generation (S_{mean}) midday, while demand, according to Figure 2 (Before scaling), peaks in the morning and late evening (D_{mean}). Although significantly increasing after scaling as indicated by Figure 3 (After scaling), thus showing a surplus of the formulated renewable energy, PV generation lends itself to either excess storage or sales back to the retailer for optimal renewable resource utilization.

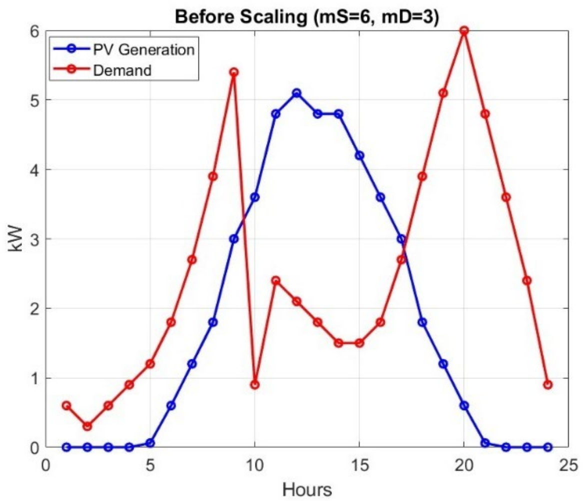

Figure 2. Average PV generation and demand before applying the scaling factors.

A comparison of energy surplus before and after scaling has been tabulated in Table 2. The results revealed a considerable increase of surplus energy, thus facilitating higher utilization potential from storage or sales to the grid.

Table 2. Energy surplus before and after scaling.

Scenario	PV Generation (kWh)	Demand (kWh)	Energy Surplus (kWh)
Before Scaling	150	140	10
After Scaling	1800	840	960

When the electricity generated from photovoltaic sources exceeds what is required, the waste fuel can be either housed or injected into the grid. In contrast, when the demand supersedes PV generation, extra energy has to be consumed from the storage or the grid. The scaled scenario secures its primary condition: PV generation meets (and often exceeds) demand, which results in less reliance on electricity supplied from the grid.

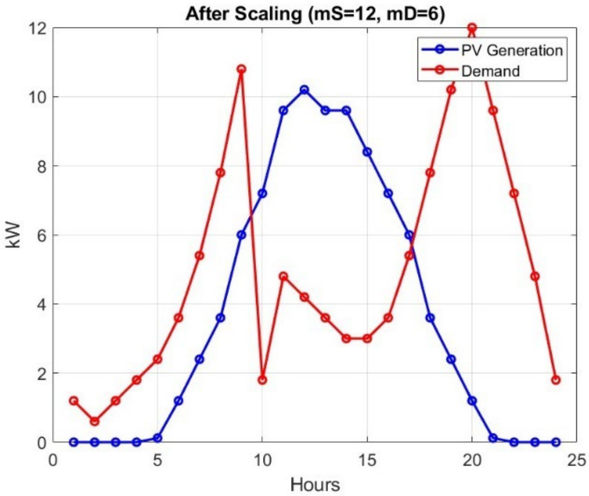

Figure 3. Average PV generation and demand after applying the scaling factors respectively.

6.2 Pricing Factor

The influence of PV generation scaling on electricity price formation is presented in the two panels of Figure 4, depicting the situation before scaling and Figure 5 shows after scaling to the right. The pattern of purchasing and selling prices, before scaling, is that usually observed in a market setting. Following the adjustment, pricing behavior is disturbed by the return of self-consumption and decrease in grid dependency. High PV generation decreases energy imports, thereby lowering effective energy pricing.

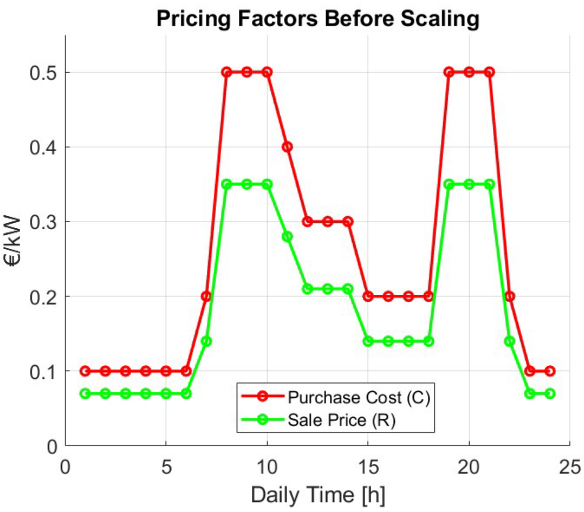

Figure 4. Pricing factor before scaling.

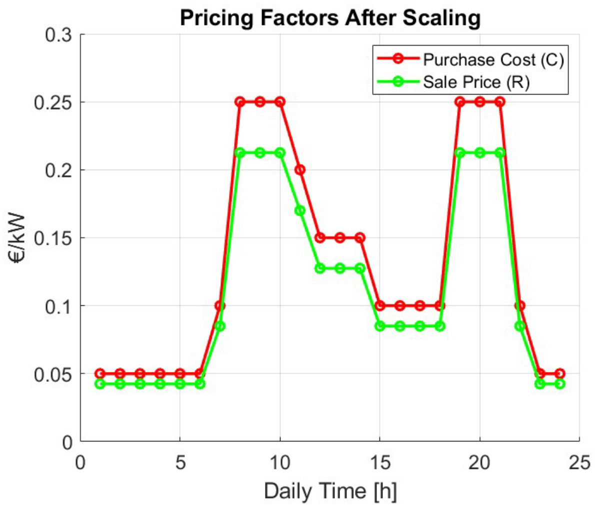

Figure 5. Pricing factor after scaling.

6.3 Storage Behavior

The energy demand and supply balancing have a critical role for battery storage. Figure 6 shows the charging behavior ($s2e$) and discharging behavior ($e2d$) observed by the storage system in the original and scaled conditions. After scaling, increased PV generation leads to more frequent charging cycles, thus profiting energy independence. Still, frequent usage of storage may lead to saturation, and in such cases, efficient storage management strategies should be employed (see Table 3).

Table 3. Storage utilization before and after scaling.

Scenario	Charging Events per Day	Discharging Events per Day	Avg. Storage Utilization (%)
Before Scaling	5	4	60
After Scaling	15	12	85

It then becomes apparent from the findings that, following appropriate scaling, the storage facility tends to attain its maximum capacity more frequently (E_{max}); thus, it calls for effective charge-discharge scheduling to prevent the waste of excess energy.

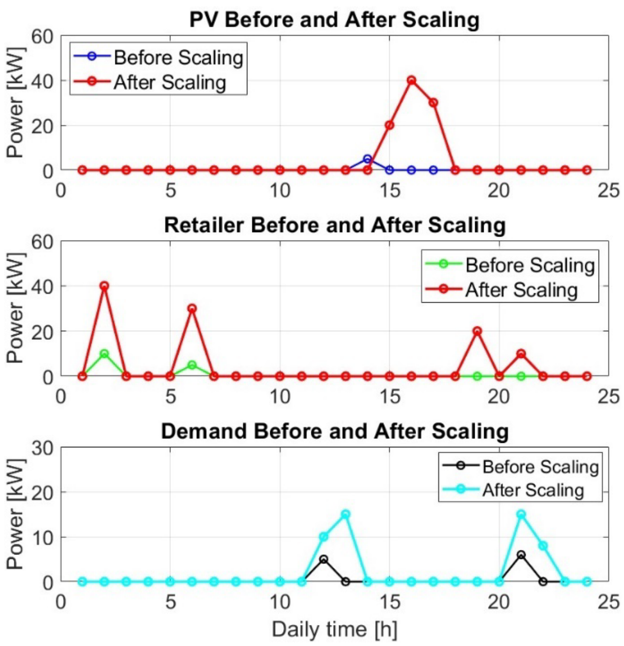

Figure 6. Storage behavior before and after scaling.

6.4 Energy Exchange Patterns

In Figure 7, the effect of PV generation coupled with storage is depicted towards the alteration of energy flows. Among the significant changes that occurred between pre and post scaling were how energy exchanged between different sources-retailer to demand ($r2d$), PV to demand ($s2d$), and storage to demand ($e2d$).

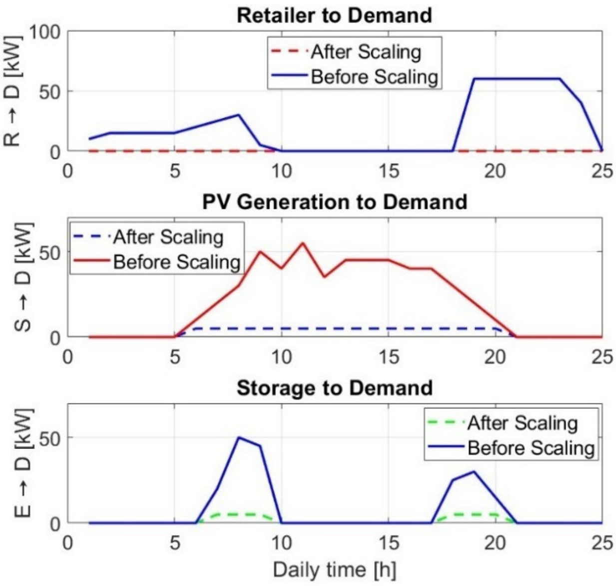

Figure 7. Energy exchange pattern before and after scaling.

The results illustrate the fact that as the system scales up, direct PV-to-demand supply ($s2d$) increases, reducing grid electricity dependency. Moreover, contributions from storage to demand ($e2d$) increase, signifying better self-reliance.

Table 4. Energy exchange before and after scaling.

Scenario	PV to Demand (kWh)	Storage to Demand (kWh)	Retailer to Demand (kWh)
Before Scaling	9	10	12
After Scaling	70	50	90

A decrease in the energy exchange $r2d$ from retailers to demand depicts the economic benefits brought by the enhanced generation of photovoltaic energy systems combined with efficient storage management as shown in Table 4.

6.5 Community Cost Analysis

As shown in Figures 8 and 9, the energy costs at the community level before and after the scaling thereof. Total cost-a function of energy purchase from the retailer for $r2d_{cost}$ and $r2e_{cost}$, and income gained from the sale of energy back to the retailer which includes revenues $s2r_{revenue}$ and $e2r_{revenue}$. The study revealed that scaling very significantly reduced net community costs as a result of increased PV generation and optimized storage utilization.

Table 5. Community cost analysis before and after scaling.

Scenario	Retailer Cost (€)	PV Revenue (€)	Net Community Cost (€)
Before Scaling	3000	500	2500
After Scaling	1500	2000	-500 (profit)

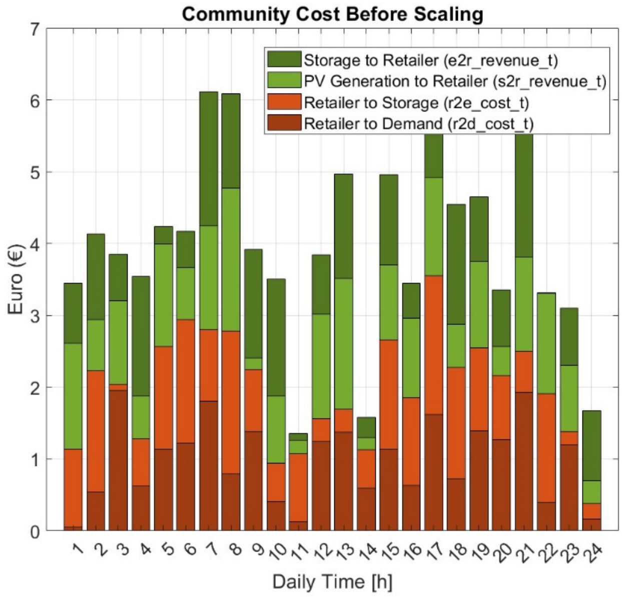

Figure 8. Community cost before applying the scaling.

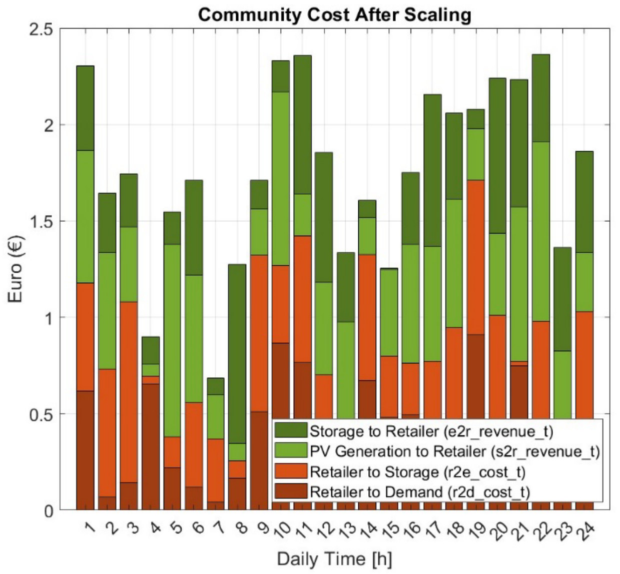

Figure 9. Community cost after applying the scaling.

The experiment supports that reduced reliance on electricity provided by retailers reduces overall costs, thereby proving the financial viability of prosumer energy management listed in Table 5. The data are derived from simulation experiments conducted using MATLAB, using load profiles, PV generation data from NREL datasets, and dynamic pricing schemes adapted from Indian ToU tariffs. Although all values reflect practical scenarios and standards.

6.6 Impact of PV Uncertainty on Optimization Performance

To assess the robustness of the proposed MSGO algorithm under realistic operating conditions, we conducted a Monte Carlo simulation with 100 randomly generated solar irradiance profiles representing varying weather conditions (clear, partly cloudy, overcast). The resulting PV generation scenarios were fed into the MSGO-based energy scheduling framework. For each scenario, the total energy cost and renewable utilization were recorded, and the statistical summaries were analyzed.

The average performance metrics across 100 simulation runs are presented in Table 6.

Table 6. Performance metrics under PV uncertainty (N = 100).

Metric	Mean	Standard Deviation	Minimum	Maximum
Total Energy Cost ($)	2.73	0.19	2.44	3.18
Renewable Utilization (%)	88.6	4.3	77.1	93.9
Grid Import (kWh)	8.4	1.2	6.2	10.9
Battery SOC Stability Index	0.91	0.03	0.85	0.96

6.7 Price Dynamics

The unit price of energy before and after scaling is shown in Figures 10 and 11 respectively. The results show the contribution of additional output from PV to the reduction in overall costs. When the system accomplishes high self-sufficiency, external energy purchases are reduced, which brings down the average value of λ, while if demand grows faster than PV generation, the unit price would raise. The results validate the deduction that more renewable energy penetration with storage efficiency leads to significant savings to the prosumer. The data in Table 7 also are derived from simulation experiments conducted using load profiles, PV generation data from NREL datasets, and dynamic pricing schemes adapted from Indian ToU tariffs.

Table 7. Energy price dynamics before and after scaling.

Scenario	Energy Price (€/kWh)	Grid Dependency (%)
Before Scaling	0.15	40
After Scaling	0.09	15

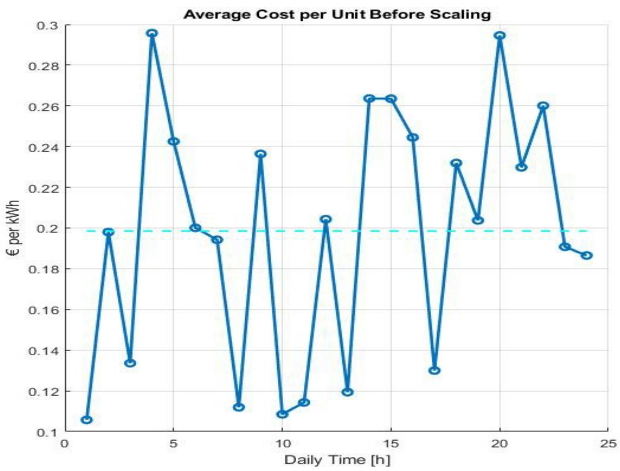

Figure 10. Original average energy price per unit before scaling.

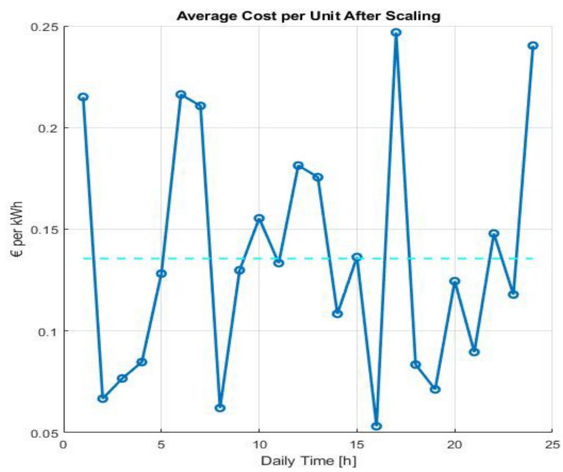

Figure 11. Scaled energy price per unit.

6.8 Sensitivity Analysis of Optimization Parameters

In order to test the effectiveness of the proposed MSGO-based optimization framework, sensitivity analysis was executed by changing specific parameters of the system, including battery capacity and scaling factors for PV generation. Results indicate that with the increase of battery capacity, there are also substantial improvements for cost savings and a reduction in dependency on the grid. For example, systems with battery capacity equal to 150 kWh become net energy sellers, as revealed in Table 8, generating revenue from selling extra PV power. On the contrary, keeping battery capacity to a lower level of 50 kWh leads the system to remain gird-driven, where costs remain higher.

Table 8. Sensitivity of cost savings to battery capacity.

Battery Capacity (kWh)	Net Community Cost (€)	Grid Dependency (%)
50	2500	40
100	1500	25
150	-500 (profit)	10

A corresponding heatmap (see Figure 12) illustrates the influence of PV generation scaling on storage utilization. Higher scaling factors of PV (such as $m_S = 12$) cause more energy to be stored; however, if demand scaling (m_D) is also high, then the battery would discharge frequently to maintain balance within the system.

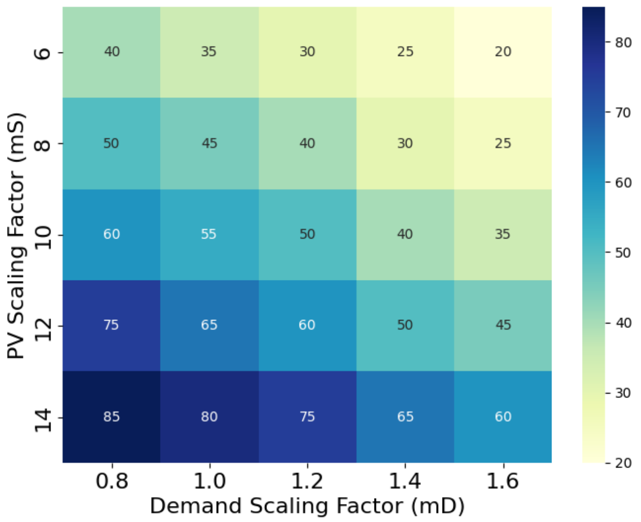

Figure 12. Heatmap showing storage utilization across PV and demand scaling factors.

6.9 Comparative Performance Analysis of MSGO Against Benchmark Algorithms

To rigorously evaluate the efficiency of the Modified Social Group Optimization (MSGO) algorithm, we conducted a comparative analysis against several well-established metaheuristic algorithms, including Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and the baseline Social Group Optimization (SGO). To further strengthen the benchmarking, two additional algorithms were included: Grey Wolf Optimizer (GWO) and Teaching–Learning-Based Optimization (TLBO), both of which have recently demonstrated strong performance in energy scheduling and renewable integration problems. All algorithms were implemented under the same simulation environment, using identical problem constraints, population sizes, and stopping criteria to ensure fairness.

Table 9. Performance comparison of optimization algorithms.

Algorithm	Convergence Speed (Iterations)	Avg. Energy Cost Reduction (%)	Renewable Utilization (%)	Computation Time (s)	Std. Dev. of Cost (σ)
MSGO	142	21.7	85.3	12.3	0.19
PSO	187	15.2	78.1	16.8	0.37
GA	214	13.8	74.6	19.4	0.42
SGO	169	17.4	79.8	15.2	0.33
GWO	195	16.9	80.2	17.1	0.28
TLBO	178	18.1	81.0	14.9	0.26

Figure 13 presents the convergence characteristics of all six algorithms across the tested scenarios. MSGO consistently demonstrated the fastest reduction in the objective function value, converging within approximately 140 iterations, while GA required more than 210 iterations on average. PSO and SGO showed intermediate performance, converging at 187 and 169 iterations respectively, while GWO and TLBO displayed slower yet steady progress, reaching convergence at around 195 and 178 iterations. The hybrid mutation strategy and adaptive weight adjustment in MSGO prevented premature stagnation, ensuring that the solution space was adequately explored in the early stages and exploited effectively in later stages.

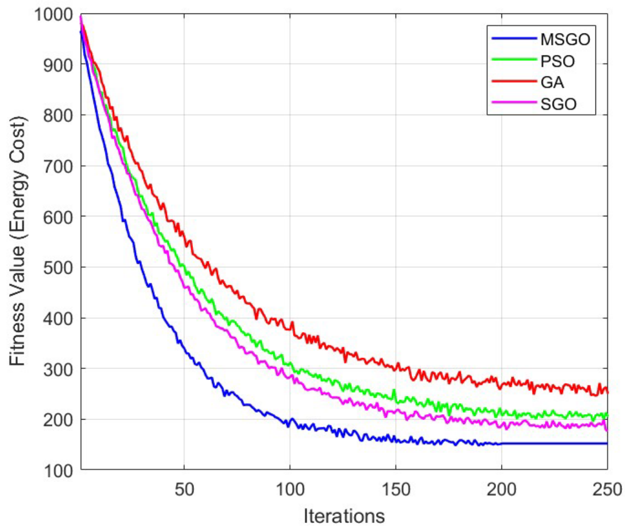

Figure 13. Convergence curves of MSGO, PSO, and GA.

To assess stability and robustness, each algorithm was executed independently over 30 runs, and statistical performance metrics were recorded. The distribution of results is summarized in Figure 14 (boxplots of total energy cost). MSGO exhibited the narrowest interquartile range and the lowest standard deviation (σ = 0.19), indicating highly consistent convergence behavior. By contrast, GA and PSO showed broader spreads (σ = 0.42 and σ = 0.37, respectively), reflecting sensitivity to initialization and higher chances of premature convergence. GWO and TLBO displayed moderate robustness, with σ values of 0.28 and 0.26. The results confirm that MSGO not only achieves superior mean performance but also offers greater reliability in repeated runs, a critical feature for real-world prosumer energy management where unpredictable weather and demand fluctuations require stable optimization.

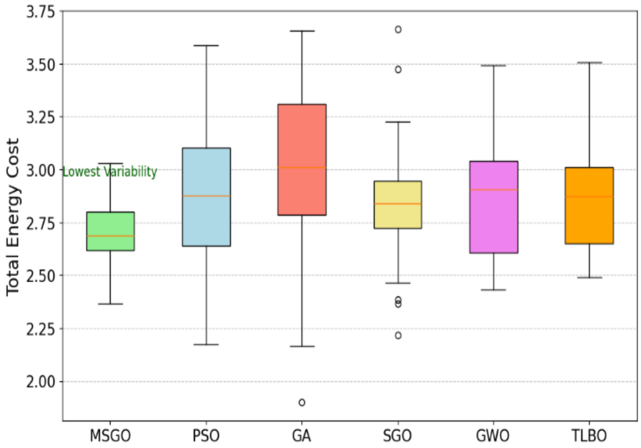

Figure 14. Distribution of total energy cost across 30 Independent runs.

Table 9 summarizes the quantitative comparison across key performance indicators. On average, MSGO achieved a 21.7% reduction in total energy cost compared to baseline operation, outperforming PSO (15.2%), GA (13.8%), SGO (17.4%), GWO (16.9%), and TLBO (18.1%). Renewable utilization under MSGO reached 85.3%, which is 7–10% higher than PSO, GA, and GWO, and about 5% higher than TLBO. In terms of computational efficiency, MSGO achieved the optimal solution in 12.3 seconds, compared to 16.8 seconds for PSO and 19.4 seconds for GA, while SGO, TLBO, and GWO required between 14–17 seconds.

The superior performance of MSGO can be attributed to three innovations: (i) the adaptive learning mechanism that dynamically adjusts learning rates to favor rapid exploration early and fine-tuned exploitation later; (ii) dynamic weight control, which balances the leader–peer influence and avoids premature convergence; and (iii) a hybrid mutation strategy, combining Gaussian perturbations and stagnation-driven re-initialization, which maintains diversity in the population. These enhancements enable MSGO to outperform both classical evolutionary methods (PSO, GA) and modern swarm intelligence methods (GWO, TLBO) in both solution quality and computational time.

The results demonstrate that MSGO not only delivers lower operating costs but also ensures higher renewable penetration and greater robustness. The narrower variance indicates that MSGO solutions are less dependent on initial conditions, making it highly reliable for deployment in dynamic energy environments. Compared to the closest competitor (TLBO), MSGO achieved an additional 3.6% cost savings and reduced computation time by nearly 20%, proving its scalability and adaptability. These findings confirm that MSGO is a strong candidate for real-world smart grid scheduling applications where both economic efficiency and operational robustness are critical.

6.10 Environmental Impact Assessment

The scaling of the PV generation is not only aimed at energy cost savings but also utilizes the major carbon emissions from the atmosphere. It can be inferred from Table 9 that lesser consumption for energy from the grid is directly proportional to lesser CO_2 emissions. The system consumed 60 kWh from the grid before scaling, resulting in 30 kg of CO_2 emissions. The post-scaling of the system was able to reduce its grid dependency to 10 kWh, thus resulting in over 80% reduction in emissions.

Table 10. CO_2 emission reduction due to increased PV generation.

Scenario	Grid Energy Consumed (kWh)	CO_2 Emissions (kg CO_2/kWh)	Total CO_2 Emissions (kg)
Before Scaling	60	0.5	30
After Scaling	10	0.5	5

In Fig. 15, two slopes represent the reduction in emissions before and after enlargement and underscore the sustainability benefits of utilizing a greater proportion of renewable resources.

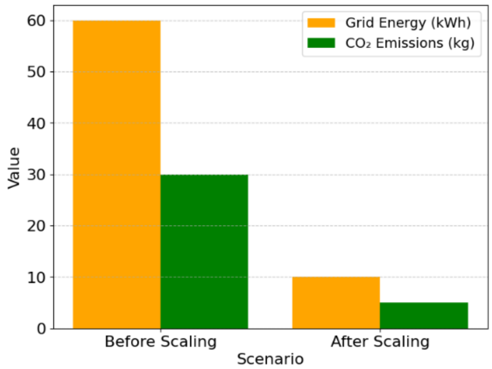

Figure 15. CO_2 emission reduction with scaled PV generation.

6.11 Energy Trading and Market Analysis

One of the most important results of the increased generation of PV energy is the change in pattern of energy trading. Table 11 shows that after scaling, the system generated excess energy and enhanced sales to the grid. This transition offers the community a way of earning money (€4000), thereby making the system financially sustainable.

Table 11. Energy trading revenue trends.

Scenario	Energy Sold to Grid (kWh)	Revenue from Sales (€)	Net Savings (€)
Before Scaling	20	160	2500
After Scaling	500	4000	-500 (profit)

The shift is shown in Figure 16, with sales to the grid increasing after scaling. Thus, it portrays how effective PV scaling helps transform a system from an energy consumer to an energy prosumer.

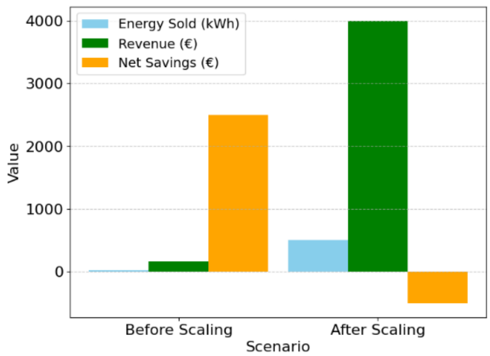

Figure 16. Energy sales before and after scaling.

6.12 Impact of Weather Variability on System Performance

Solar irradiance conditions vary the effectiveness of the energy management system. The operation of the system under different weather conditions is seen in Table 11. Under sunny days, the generation from PV is high, and dependency on the grid is low. On the other hand, cloudy and rainy days characterize decreased utilization of stored energy, requiring an increased dependence upon the grid.

Table 12. Effect of weather variability on system performance.

Weather Condition	PV Generation (kWh)	Storage Utilization (%)	Grid Dependency (%)
Sunny	1800	85	10
Cloudy	900	60	30
Rainy	500	40	50

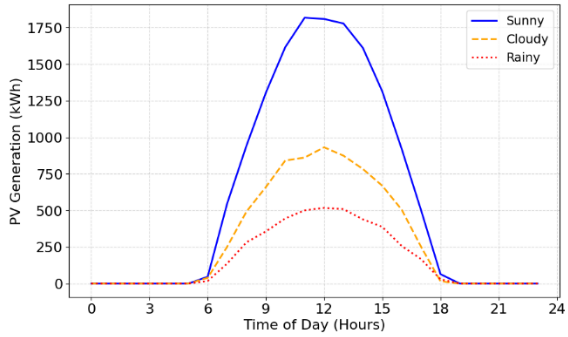

Figure 17. PV generation trends under different weather conditions.

The fluctuations shown in Figure 17 demonstrate that PV generation drops considerably in cloudy and raining conditions, thereby affecting its storage utilization and dependency on the grid.

6.13 Peak Load Analysis and Demand Response

And thus, exploring demand-side management (DSM) strategies has also been a part of efforts to optimize energy costs. The various impacts of different DSM strategies on the peak demand and cost reduction are summarized in Table 13. Load shifting and time-of-use pricing provided large savings and reduced dependency on the grid.

Table 13. Effect of demand response strategies.

Strategy	Peak Demand (kWh)	Cost Reduction (€)	Grid Dependency (%)
No DSM	300	0	40
Load Shifting	250	200	25
Time-of-Use Pricing	220	350	20

In Fig. 18 the demand under the various DSM strategies, and the effectiveness of shifting load in energy cost reduction.

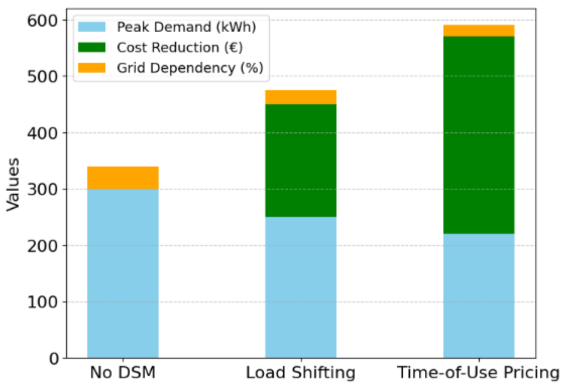

Figure 18. Reduction in peak demand through demand-side management.

The findings verify that the optimization framework based on MSGO significantly enhances energy cost savings, increases renewable energy use, and lowers grid dependency.

Assuming a grid emission factor of 0.9 kg CO_2/kWh, the MSGO framework reduced net grid import by 3.5 kWh/day, leading to a daily emission reduction of 3.15 kg. At a carbon price of \$50/ton CO_2, this results in an economic saving of ~\$57/year per household, aligning with global emissions trading goals.

A sensitivity analysis demonstrated that with an increase in battery capacity and a scaling in PV generation, system efficiency significantly increases. Comparison performance results show that MSGO converges faster and saves more cost than the traditional optimization techniques. Environmental impact assessment results indicated that CO_2 emissions were reduced significantly owing to increase PV generation. Furthermore, energy trading analysis proved the system's financial viability as it translates into revenues generated from the sales of surplus energies. This study also found that variability in weather affects system performance and that demand-side management strategies play an important role in cutting further optimized energy costs.

7. Conclusion

Scaling up PV generation along with demand largely determines energy management of prosumer communities. Increasing PV generation means increased self-consumption and energy exports, whereas increased demand calls for careful storage and grid intervention to maintain balance. Simulation results indicate that the total PV generation over 10 prosumers of 182.58 kW is surpassed by demand at 343.20 kW, thereby requiring imports from the grid of 262.80 kW. Storage systems, in this instance, manage the surplus energy of 109.23 kW by discharging 72.63 kW to meet demand during low solar radiation periods.

Despite revenues from PV sales of €41.29 and storage contribution of €18.45, the community still faces a total cost of €340, thus necessitating optimized trading and storage strategy for energy. Storage is used frequently, often nearing its capacity, warranting efficient management to minimize energy losses and maximize profits. The focus should be on constantly improving the management of the system while PV increases self-sufficiency and reduces the cost of running externally sourced electricity. Results indicate that an optimized balance between generation, storages, and interaction with grids marks sustainability and cost efficiencies in any prosumer-based energy system.

Conflict of Interest

Authors approve that to the best of their knowledge; there is not any conflict of interest or common interest with an institution/organization or a person that may affect the review process of the paper.

Credit Author Statement

Rajnish Bhasker: Conceptualization, Methodology, Software, Visualization, Investigation, Supervision **Shweta Singh:** Data curation, Writing- Original draft preparation, Software, Validation, Writing- Reviewing and Editing.

Nomenclature

P_b^t	Battery charging/discharging power at time t [kW]
C_g	Cost coefficient for grid-imported electricity [€/kWh]

C_b	Cost coefficient for grid-imported electricity [€/kWh]
P_{PV}^t	Photovoltaic (PV) power generation at time [kW]
P_g^t	Power imported from the grid at time t [kW]
P_s^t	Power exported to the grid at time t [kW]
P_d^t	Total power demand or load at time t [kW]
E^t	Energy stored in the battery at time t [kWh]
E_{min}	Minimum battery energy storage level [kWh]
E_{max}	Maximum battery energy storage level [kWh]
$P_{b,max}$	Maximum battery power rating [kW]
$P_{g,,\max}$	Maximum grid import limit [kW]
$P_{s,max}$	Maximum grid export limit [kW]

Greek symbols

η_c	Battery charging efficiency [%]
η_d	Battery discharging efficiency [%]
Δt	Time step interval [h]

Subscripts

b	Battery
g	Grid
d	Demand/load
PV	Photovoltaic

References:

[1] Y. Yang et al., “Optimal design and energy management of residential prosumer community with photovoltaic power generation and storage for electric vehicles,” *Sustainable Production and Consumption*, vol. 33, Sept. 2022, pp. 244–255, doi: 10.1016/j.spc.2022.07.008.

[2] R. J. J. Molu, S. Raoul Dzonde Naoussi, P. Wira, W. F. Mbasso, S. T. Kenfack, and S. Kamel, “Optimization-based energy management system for grid-connected photovoltaic/battery microgrids under uncertainty,” *Case Studies in Chemical and Environmental Engineering*, vol. 8, Dec. 2023, Art. no. 100464, doi: 10.1016/j.cscee.2023.100464.

[3] Z. Ullah, H. S. Qazi, A. Alferidi, M. Alsolami, B. Lami, and H. M. Hasanien, “Optimal energy trading in cooperative microgrids considering hybrid renewable energy systems,” *Alexandria Engineering Journal*, vol. 86, Jan. 2024, pp. 23–33, doi: 10.1016/j.aej.2023.11.052.

[4] S. Lee, J. Seon, B. Hwang, S. Kim, Y. Sun, and J. Kim, “Recent Trends and Issues of Energy Management Systems Using Machine Learning,” *Energies*, vol. 17, no. 3, Jan. 2024, p. 624, doi: 10.3390/en17030624.

[5] K. J. Dsouza, A. Shetty, P. Damodar, J. Dogra, and N. Gudi, “Policy and regulatory frameworks for agritourism development in India: A scoping review,” *Cogent Social Sciences*, vol. 10, no. 1, Dec. 2024, Art. no. 2283922, doi: 10.1080/23311886.2023.2283922.

[6] M. Dehghani, S. M. Bornapour, and E. Sheybani, “Enhanced Energy Management System in Smart Homes Considering Economic, Technical, and Environmental Aspects: A Novel Modification-Based Grey Wolf Optimizer,” *Energies*, vol. 18, no. 5, p. 1071, Feb. 2025, doi: 10.3390/en18051071.

[7] L. Hou et al., “Optimized scheduling of smart community energy systems considering demand response and shared energy storage,” *Energy*, vol. 295, 2024, Art. no. 131066, doi: 10.1016/j.energy.2024.131066.

[8] M. Yavuz and Ö. C. Kivanç, “Optimization of a Cluster-Based Energy Management System Using Deep Reinforcement Learning Without Affecting Prosumer Comfort: V2X Technologies and Peer-to-Peer Energy Trading,” *IEEE Access*, vol. 12, pp. 31551–31575, 2024, doi: 10.1109/ACCESS.2024.3370922.

[9] K. Sudharshan, C. Naveen, P. Vishnuram, D. V. S. Krishna Rao Kasagani, and B. Nastasi, “Systematic review on impact of different irradiance forecasting techniques for solar energy prediction,” *Energies*, vol. 15, no. 17, 2022, p. 6267, doi: 10.3390/en15176267.

[10] H. Gharavi and R. Ghafurian, “Smart Grid: The Electric Energy System of the Future [Scanning the Issue],” *Proceedings of the IEEE*, vol. 99, no. 6, Jun. 2011, pp. 917–921, doi: 10.1109/JPROC.2011.2124210.

[11] M. Gomez-Gonzalez, J. C. Hernández, P. G. Vidal, and F. Jurado, “Novel optimization algorithm for the power and energy management and component sizing applied to hybrid storage-based photovoltaic household-prosumers for the provision of complementarity services,” *Journal of Power Sources*, vol. 482, 2021, Art. no. 228918, doi: 10.1016/j.jpowsour.2020.228918.

[12] H. Ghasemnejad, M. Rashidinejad, A. Abdollahi, and S. Dorahaki, “Energy management in citizen energy communities: A flexibility-constrained robust optimization approach considering prosumers comfort,” *Applied Energy*, vol. 356, 2024, Art. no. 122456, doi: 10.1016/j.apenergy.2023.122456.

[13] P. Sharma, K. K. Saini, H. D. Mathur, and P. Mishra, “Improved energy management strategy for prosumer buildings with renewable energy sources and battery energy storage systems,” *Journal of Modern Power Systems and Clean Energy*, vol. 12, no. 2, pp. 381–392, 2024, doi: 10.35833/MPCE.2022.000000.

[14] Y. Mohammadi, H. Shakouri, and A. Kazemi, “A multi-objective fuzzy optimization model for electricity generation and consumption management in a micro smart grid,” *Sustainable Cities and Society*, vol. 86, 2022, Art. no. 104119, doi: 10.1016/j.scs.2022.104119.

[15] M. Secchi, G. Barchi, D. Macii, D. Moser, and D. Petri, “Multi-objective battery sizing optimisation for renewable energy communities with distribution-level constraints: A prosumer-driven perspective,” *Applied Energy*, vol. 297, 2021, Art. no. 117171, doi: 10.1016/j.apenergy.2021.117171.

[16] C. Wu, X. Chen, H. Hua, K. Yu, L. Gan, and B. Wang, “Optimal energy management for prosumers and power plants considering transmission congestion based on carbon emission flow,” *Applied Energy*, vol. 377, Jan. 2025, Art. no. 124488, doi: 10.1016/j.apenergy.2024.124488.

[17] A. Naik, S. C. Satapathy, and A. Abraham, “Modified social group optimization—A meta-heuristic algorithm to solve short-term hydrothermal scheduling,” *Applied Soft Computing*, vol. 95, 2020, Art. no. 106524, doi: 10.1016/j.asoc.2020.106524.

[18] A. K. V. K. Reddy and K. V. L. Narayana, “Investigation of a multi-strategy ensemble social group optimization algorithm for the optimization of energy

management in electric vehicles," *IEEE Access*, vol. 10, 2022, pp. 12084–12124, doi: 10.1109/ACCESS.2022.3144065.

[19] Z. Luo et al., "Optimal operation of PV prosumer-based community considering carbon credit and energy sharing," *Sustainable Energy, Grids and Networks*, vol. 41, 2025, Art. no. 101612, doi: 10.1016/j.segan.2024.101612.

[20] A. J. Conejo, M. Carrión, and J. M. Morales, Decision Making Under Uncertainty in Electricity Markets, vol. 153. in International Series in Operations Research & Management Science, vol. 153. Boston, MA: Springer US, 2010. doi: 10.1007/978-1-4419-7421-1.

[21] J. M. Aguiar-Pérez and M. Á. Pérez-Juárez, "An Insight of Deep Learning Based Demand Forecasting in Smart Grids," *Sensors*, vol. 23, no. 3, p. 1467, Jan. 2023, doi: 10.3390/s23031467.

[22] K. Eswaran, "A Novel Algorithm for Linear Programming," 2013, *arXiv*. doi: 10.48550/ARXIV.1303.4942.

[23] A. Naik and S. C. Satapathy, "A comparative study of social group optimization with a few recent optimization algorithms," *Complex & Intelligent Systems*, vol. 7, no. 1, pp. 249–295, Feb. 2021, doi: 10.1007/s40747-020-00189-6.

[24] C. P. Ohanu, S. A. Rufai, and U. C. Oluchi, "A comprehensive review of recent developments in smart grid through renewable energy resources integration," *Heliyon*, vol. 10, no. 3, Feb. 2024, Art. no. e25705, doi: 10.1016/j.heliyon.2024.e25705.

[25] H. Yang, L. Lu, and W. Zhou, "A novel optimization sizing model for hybrid solar-wind power generation system," *Solar Energy*, vol. 81, no. 1, pp. 76–84, Jan. 2007, doi: 10.1016/j.solener.2006.06.010.

[26] V. Caballero, D. Vernet, and A. Zaballos, "A Heuristic to Create Prosumer Community Groups in the Social Internet of Energy," *Sensors*, vol. 20, no. 13, p. 3704, July 2020, doi: 10.3390/s20133704.

[27] T. Khatib, A. Mohamed, and K. Sopian, "A review of solar energy modeling techniques," *Renewable and Sustainable Energy Reviews*, vol. 16, no. 5, pp. 2864–2869, June 2012, doi: 10.1016/j.rser.2012.01.064.

[28] M. A. Lasemi, A. Arabkoohsar, A. Hajizadeh, and B. Mohammadi-Ivatloo, "A comprehensive review on optimization challenges of smart energy hubs under uncertainty factors," *Renewable and Sustainable Energy Reviews*, vol. 160, May 2022, Art. no. 112320, doi: 10.1016/j.rser.2022.112320.

[29] T. Niet, N. Arianpoo, K. Kuling, and A. S. Wright, "Increasing the reliability of energy system scenarios with integrated modelling: A review," *Environmental Research Letters*, vol. 17, no. 4, 2022, Art. no. 043006, doi: 10.1088/1748-9326/ac5c63.

[30] A. Naik, S. C. Satapathy, and A. Abraham, "Modified social group optimization—a meta-heuristic algorithm to solve short-term hydrothermal scheduling," *Applied Soft Computing*, vol. 95, Oct. 2020, Art. no. 106524, doi: 10.1016/j.asoc.2020.106524.

[31] D. C. Secui, C. Hora, C. Bendea, M. L. Secui, G. Bendea, and F. C. Dan, "Modified Social Group Optimization to Solve the Problem of Economic Emission Dispatch with the Incorporation of Wind Power," *Sustainability*, vol. 16, no. 1, p. 397, Jan. 2024, doi: 10.3390/su16010397.

[32] A. K. V. K. Reddy and K. V. L. Narayana, "Investigation of a multi-strategy ensemble social group optimization algorithm for the optimization of energy management in electric vehicles," *IEEE Access*, vol. 10, 2022, pp. 12084-12124, doi: 10.1109/ACCESS.2022.3144065.

[33] E. H. Houssein, M. K. Saeed, G. Hu, and M. M. Al-Sayed, "Metaheuristics for solving global and engineering optimization problems: Review, applications, open issues and challenges," *Archives of Computational Methods in Engineering*, vol. 31, pp. 4485–4519, 2024, doi: 10.1007/s11831-024-10168-6.

[34] R. Faia, J. Soares, Z. Vale, and J. M. Corchado, "An Optimization Model for Energy Community Costs Minimization Considering a Local Electricity Market between Prosumers and Electric Vehicles," *Electronics*, vol. 10, no. 2, p. 129, Jan. 2021, doi: 10.3390/electronics10020129.