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DEVELOPMENT OF AN ITERATIVE METHOD FOR OPTIMIZATION AND ENERGY MANAGEMENT PROBLEM AVOIDANCE IN A SMART BUILDING: CONSIDERING INTEGRATION OF GRID SUPPLY, PV AND BESS

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Abstract

With the emergence of smart grid, which presents the next generation of electrical power systems, residential and commercial buildings have the opportunities to manage their offices energy usage to reduce energy expenditure. This paper presents a differential evolution algorithm to optimize the energy production and consumption systems in a smart office with the integration of renewable

Keywords: Smart grid, Heuristic, Differential Evolution (DE) Algorithm, Micro grid, Battery Energy Storage System (BESS), Optimization, Generic algorithm, PV Panel.

INTRODUCTION

The increasing demand for energy-efficient and sustainable building operations necessitates advanced energy management strategies. (Abushnaf et al., 2023).The integration of photovoltaic (PV) systems and battery storage offers a promising approach to reduce energy costs and enhance energy reliability. (Chen et al., 2022; Pal & Kumar, 2021). However, the intermittent nature of PV generation, coupled with fluctuating electricity prices under Time-of-Use (TOU) tariffs and variable building loads, poses significant challenges in optimizing energy flows (Panda & Pati, 2021). The Building, equipped with PV panels and a battery storage system, requires an effective energy management system (EMS) to minimize operational costs while satisfying electrical demand and adhering to system constraints. (Elkazaz et al., 2020).The primary challenge is to optimally schedule the

energy resources, and battery storage systems. The aim of the study is to optimize energy management in buildings by integrating a photovoltaic (PV) system with a battery storage system, using the Differential Evolution (DE) algorithm to minimize operational costs while ensuring efficient energy utilization and system reliability. To achieve this, energy model using PV, battery, and grid data over 24 hours in 1- hour steps was developed; also, energy cost was minimized by optimizing PV battery and grid usage. Moreover, power balance was kept at equilibrium to meet load demand and enable grid export while battery limits is applied to state of charge (SOC), discharge rate and capacity. In addition, an heuristic differential evolution algorithm was used to solve the energy optimization problem. Three scenarios were evaluated to minimize costs of energy in the offices. Scenario I explored grid supply only, scenario II looked at electricity equilibrium of the micro grid with the PV and grid supply while scenario III considered equilibrium of the micro grid with PV, BESS and grid supply. Moreover, actual time-of-use (TOU) tariffs for electricity prices is evaluated. The simulation results of the devised model are given for different case studies and the effectiveness of the system is demonstrated via a comparative study. As a result, it was found that the operational costs are decreased nearly 92% by integrating only photovoltaic (PV) production according to the case which has no additional sources. Also, a substantial reduction of 90% is achieved by considering both PV and $BESS$. Results find the global optimum solution for the $24-hour$ horizon with important reduction of execution time and by achieving significant energy cost savings of the considered scenarios. To improve modeling and optimization of energy in smart buildings considering the benefits of PV and BESS on the power sector, genetic algorithm is a powerful optimization tool recommended for finding solutions to optimization of energy management decision variables like cost functions, power and so on. It gives the exact solution of micro grid energy management problems which converge as fast as possible as exemplified in this research study.

Power generated by the PV system, the charge/discharge cycles of the battery storage, and the power exchanged with the national grid to achieve cost minimization. The objective is to minimize the total energy cost, which includes the cost of power purchased from the grid, revenue from selling excess power, and battery operational costs (e.g., charging and degradation costs). The system must account for constraints such as power balance, grid import/export limits, PV generation capacity, battery charging/discharging rates, and the prohibition of simultaneous charging and discharging. (Farid et al., 2022). The problem is further complicated by the non-linear and dynamic nature of the energy system, requiring a robust optimization technique capable of handling multiple variables and constraints. To ensure that comprehensive research is achieved, key questions to be addressed are as follows:

1. To what extent does the BESS impact on energy cost savings in COET Building?
2. To what extent do cost function values of the three scenarios used in this research have to differ?
3. To what extent does the stochastic nature of PV affect the power output of the micro-grid

However, this study aims to develop an energy management system for a smart Building using the differential evolution algorithm to optimize the integration of PV and battery storage systems, minimizing energy costs while ensuring reliable operation. It addresses the need for a sustainable energy management solution that can adapt to the real-world constraints and variable conditions, contributing to the efficient operation of the building. Also, the research addresses critical challenges in energy efficiency, environmental sustainability, and smart grid development. Its comprehensive approach offers a scalable, practical framework with far-reaching implications for building operations, policy, and academic research, making it a pivotal contribution to the global transition toward renewable energy systems.

The Differential Evolution (DE) algorithm, a population-based heuristic optimization method, is proposed to address this challenge due to its ability to efficiently handle non-linear, constrained optimization problems and find global optima. Unlike traditional methods like Mixed Integer Linear Programming (MILP), DE can effectively manage the non-linear dynamics of the Building's energy system, including variable TOU tariffs (ranging from 0.017 to 0.572 \$/kWh over 24 hours) and battery state-of-charge constraints involves formulating a single-objective constrained optimization model to minimize the cost function, incorporating terms for grid power over a 24-hour horizon with hourly key steps. (Moghaddam et al., 2020)

$$P_{grid}^{in}(t), P_{grid}^{out}(t), P_b^{ch}(t), P_b^{dch}(t), \forall t\{1,2,\ldots\ldots,24\} \quad (1)$$

Key constraints include maintaining power balance, respecting grid and PV and battery storage capacity limits, and ensuring no simultaneous charging and discharging. (Hasan et al., 2021).

$$P_{grid}^{in}(t) = P_b(t) - P_b^{ch}(t) - P_g^{in}(t) + P_b^{dch}(t) + P_{grid}^{out}(t), \quad (2)$$

$$0 \leq P_{grid}^{in}(t) \leq P_{grid}^{max}(t), \quad (3)$$

$$0 \leq P_g(t) \leq P_g^{max}(t), \quad (4)$$

$$SOC_b^{min}(t) \leq SOC_b(t) \leq 1 \quad (5)$$

$$\forall t \in \{1,2 \ldots .24\} \quad (6)$$

The Differential evolution algorithm will iteratively optimize these variables through initialization, mutation, crossover and selection steps to determine the optimal energy dispatch. (Rahman et al., 2020).

SYSTEM OVERVIEW

THEORECTICAL FRAMEWORK

Battery Storage Systems

Battery Energy Storage Systems (BESS) are cutting-edge technologies that store electrical energy in rechargeable batteries for later use. They cater to a wide range of applications, from small gadgets to large-scale grid systems. Battery Energy Storage Systems (BESS) play a vital role in today's energy landscape. They help us harness renewable energy, boost the reliability of our power grids and support a wide range of applications, no matter the scale (He. G., et al. (2025).

These systems combine various types of batteries sodium – like nickel-metal hydride (NiMH), flow batteries, Sodium sulfur (NaS), lithium-ion, lead acid, nickel-cadmium (NiCD) with advanced battery systems (BMS) to ensure they perform safely and efficiently over time BESS are particularly useful for capturing energy when demand is low or when there's an excess of generation, such as from renewable sources like solar or wind. They can then release this stored energy during peak demand times or when supply is short making them essential for tasks like peak shaving, reducing demand charges, regulating frequency, supporting voltage, and even helping to restore the grid after outages. (He. G., et al. (2025).

Grid Application of Battery Storage

Battery Energy Storage Systems (BESS) play a vital role in today's power grid and commercial activities, especially as we see more renewable energy sources coming into play;

I. **Peak Shaving and Demand Charge Reduction:** In commercial and industrial environments, BESS can store energy during off-peak times and release it during peak demand, helping to lower energy costs This strategy is especially beneficial for businesses like offices and manufacturing plants, where energy rates soar during peak hours. (He. G., et al. (2025).

II. **Grid Services:** BESS are essential for providing key grid services such as frequency regulation, voltage support and black-start capabilities (Zhao et al.,2021). They react swiftly to imbalances in the grid, helping to stabilize frequency and voltage particularly in systems that rely heavily on renewable energy (He. G., et al. (2025). Additionally, BESS assist in restoring the grid after outages by supplying energy needed to restart main generators (Abdolazimi et al., 2022)

III. **Renewable Energy Integration:** BESS help address the unpredictability of renewable energy sources like solar and wind by storing surplus energy and providing it during periods of low generation, which enhances the reliability of the grid.(He. G., et al. (2025)

Energy Management

Energy management is defined as a strategic and systematic process that encompasses the planning, monitoring, control, and optimization of energy use to enhance efficiency, reduce costs, and minimize environmental impact. It involves the deployment of advanced technologies, such as energy management systems (EMS), smart grids, and energy storage systems, to collect and analyze data on energy consumption, temperature, occupancy, and other metrics. This data-driven approach enables informed decision-making to reduce waste, improve infrastructure, and achieve energy savings through strategies like demand response and renewable energy integration. Energy management is driven by the need to address rising energy costs, comply with government regulations, and mitigate climate change, while leveraging innovations like the Internet of Things (IoT), artificial intelligence (AI), and blockchain to promote sustainable energy practices across residential, commercial, and industrial sectors (Zhao., B. 2021).). Energy management is a critical discipline in addressing the global demand for sustainable, efficient, and environmentally responsible energy use.

Advantages and Disadvantages of Energy Management

Key advantages include cost-effectiveness, achieved through reduced energy bills and operational efficiencies, and environmental benefits, such as lower greenhouse gas emissions and reduced resource depletion (Zhao. B., 2021). Technologies like EMS, smart grids, and energy storage systems enable organizations to meet regulatory requirements and contribute to sustainable development. However, challenges include high initial costs for implementation, maintenance, and training, as well as complexities in data management and infrastructure upgrades (Zhao. B., 2021). The environmental impact of manufacturing energy storage systems and the need for sustainable materials are also noted as concerns, requiring further research to address these limitations (Zhao. B., et al. 2021)

Differential evolution Algorithm

Differential evolution is a simple, meta-heuristic, and effective, optimization-based algorithm on population which aims to solve continuous optimization problems. Storn and Price first introduced DE in 1995. DE is famous for its ease of use reliability and effectiveness in solving intricate issues with several optimum points. DE evolves a population of candidate solutions through three main operators: mutation, cross over, and selection. DE has been the focus of intensive research with numerous studies focused on its theoretical foundations It is a branch of evolutionary programming; it was proposed by Rainer Storm and Kenneth Price in 1997 for optimization problems (Hasan. M., et al.2021).

Key Operations in Differential Evolution Algorithms

1. Initialization
2. Mutation
3. Recombination
4. Selection

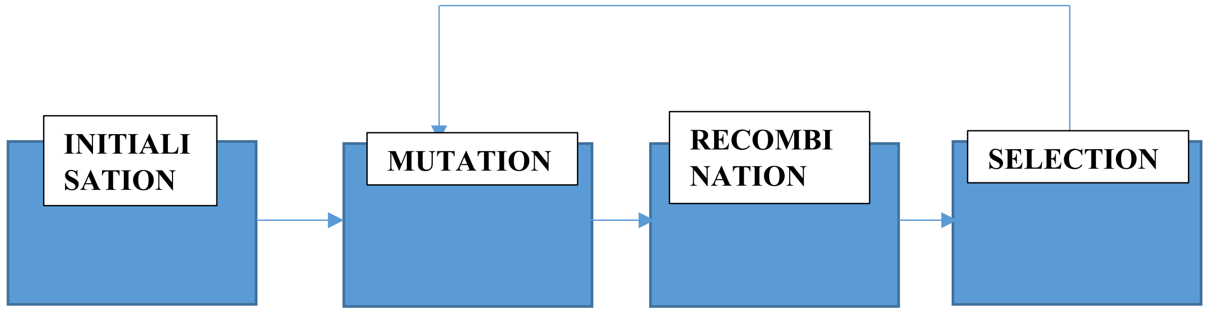

Figure 1: A Block Diagram Showing the Key Operations in Differential Evolution Algorithm

Initialization

The beginning step of the differential evolution algorithm is foundational in setting up the rest of the algorithm. In the initialization phase, we have vectors which are list of numbers corresponding to potential solutions to the problem.

Steps In Initialization

i. Determine a population size: A specific number of starting vectors can be selected each vector is composed of a unique set of numbers that denote possible solutions (e.g.: NP=20).
ii. Limit: Both the upper limit and the lower limit exists. These boundaries are known as search places.
iii. Pick Random Vector: For each of the twenty vectors the algorithm randomly generates values using its random number generator ensuring selections are spread across the designated range
iv. Create Population Size : Upon selecting random values for all twenty vectors you now have a population (a collection of 20 Vectors).

$$X = \{X_{1,}X_{2,} \dots \dots X_{NP,}\}$$

Mutation

In Differential evolution (DE) each individual in the population gets its own unique mutant vector, often referred to as the target vector. This approach set DE apart from traditional evolutionary algorithms which typically rely on small, random tweaks for mutation. Instead, DE's mutation process is driven by the differences between vectors, giving it a distinctive edge when it comes to continuous optimization.

Steps For Mutation

For every target vector $X_{i,\ G}$ in the population at generation G, we create $V_{i,\ G}$ using a mutation strategy. The most widely used strategy, known as DE/rand/1, operates in the folly way;

$V_{i,\ G} = X_{r1,G} + F.(X_{r2,G} - X_{r3,G})$

$X_{r1,\ G}$, $X_{r2,\ G}$, $X_{r3,\ G}$: These are three unique vectors picked at random from the current population ensuring they differ from target vector $X_{ri,G}$.
F: This is the scaling factor (usually$\in$ [0,2] , often around 0.5-1), which helps determine how much perturbation will affect the outcome.
$X_{r2,\ G}– X_{r3,G}$: The represent the difference vector, which illustrates both direction and distance between two random solutions.
$V_{i\ G}$, The mutant vector is formed by adding the scaled difference to the base vector $X_{r1,G}$

Recombination

In the Differential Evolution (de) algorithm, recombination referred to as crossover plays a crucial role after mutation. It's the process where we create a trial vector by blending the mutant vector produced during the mutation phase which is essentially a member of the current population.
Recombination takes element from the mutant vector ($V_{i,\ G}$) and blends them with the target vector
($X_{i,\ G}$) to produce a trial vector ($U_{i,\ G}$) (for each individual in the population during Generation G. This process strikes a balance between the exploration brought on by mutation and retention of beneficial traits from the target vector. C.

Selection

Selection is the crucial final steps in each generation, deciding which candidate solutions get to move onto to the next round. This process comes after mutation and recombination (phases) ensuring that the population is always evolving towards the better solutions. Selections in DE operates like a competitive process where the trial vector ($U_{i,G}$) created through mutation and recombination are compared against the target vector ($X_{i,G}$) from the current population at generation G.

Application of Differential Evolution Algorithms to Optimization and Energy Management

DE, as brought forth by Storn and Price (1997), is particularly well suited for continuous optimization problems, which are common in optimization tasks and energy management. These strengths include the following:

Application to Optimization

i. Non-Linear and Multi-Modal Problems: DE's non-differentiable, multi-modal objective function optimization capability stems from its stochastic search technique exploitation via hit-and-run mutation, crossover, and selection processes. Opara and Arabas (2018) observed that DE is capable of exploring several loci of multiple optima owing to its ability to maintain population diversity with mutation strategy DE/rand/1 or DE/best/1 and thus, tackle problems where traditional methods based on gradients become inoperative.

ii. Global Search Ability: The analyses done in Opara and Arabas (2018) report DE as capable of both exploration and exploitation neutral equilibrium emphasis.
iii. Insensitivity and Multifaceted Nature: DE demands few other constraints than that of differentiability or continuity to the problem being optimized, making DE easier possess fewer tuning factors than problem NP, F, and CR. Even though each task might require different problem simplifications.

Applications in Energy Management

Energy management encompasses the intricacies of optimizing systems like energy distribution, integrating renewable resources, and scheduling with an emphasis on energy efficiency. Most of these systems exhibit non-linear, constrained, and dynamic optimization. It can be said that DE's characteristics are particularly helpful in these domains:

i. Integration of Renewable Energy: DE is widely used for parameter optimization of wind turbines, solar panels, and energy storage systems in renewable energy systems. Dynamic environments characterized by fluctuating renewable energies require nimble adaptation from algorithms. Opara and Arabas (2018) provide theoretical analyses indicating DE mutation strategies like DE/current-to-best/1 to be effective in such scenarios.
ii. Energy-Efficient Scheduling: DE also finds its application in energy management for task scheduling in smart grids or industrial systems with a goal to curb energy consumption.

EMPERICAL REVIEW

Numerous researchers have developed several optimization models to solve the energy management problem in SG specially related to smart home. In, Elham & Shahram, 2015 an automatic and optimal residential energy consumption scheduling technique is proposed as mixed integer NLP that aims to minimize the overall Cost of electricity and natural gas in a building. The scheduling of electrical and thermal appliances has been reached, but it did not consider the wind system generation and V2G, which play an essential role in smart home, because V2G can be used to store the energy and generate it back later when needed. In Chen et al., 2011, a smart energy management system is proposed to coordinate the power production of distributed generation sources and energy storage system for a micro grid, where obtained forecasting model was able to predict hourly power generation, with the missing of integrating of EVs in the model where their charging and discharging process have an important impact and affect the results. In this paper, we present a differential evolution algorithm to optimize the energy production and consumption systems in a smart office with an effective deployment of several DERs, such as the integration of renewable energy production (solar) and battery storage systems as a DG (distributed generation). Different case studies are introduced by varying significant factors through the design of experiments with modulation of the various energy source. After that, a proposed is used to solve the problem of commercial (office) energy management by finding the global optimum solution for different scenario with significant reduction of execution time of the scenarios.

METHODOLOGY

In this section, we present the methodology for the research objectives (a single objective optimization algorithm is applied on a typical smart office to minimize Energy cost. The building considered in this research, comprises of PV panels and Battery energy storage system($BESS$), as shown in Fig.1. It is also connected to the upstream grid for selling/purchasing energy when there is energy excess/shortage respectively. This research considers only one type of demand: electrical demand associated with lighting and other home appliances plus energy prosumer system (Battery storage system). It is also assumed that the building is equipped with smart meter, which provides all the required information. Evaluating the proposed strategy, three scenarios are considered: the smart office flexible and non-flexible loads supplied by the conventional power grid, the smart office electrical loads supplied by conventional power grid plus PV and finally, the smart office incorporating National grid, PV and $BESS$ for its electrical loads. The scheduling horizon is 24 hours with time intervals of 1 hour. Mathematical models of each system component, energy balances and efficiency constraints will be proposed in an optimization framework, as the following. The ultimate goal is to investigate the impact of battery energy in the mentioned hybrid system on cost reduction and energy saving strategies. The mathematical explanations of the utilized units, sources and the optimization problem are shown below.

PROBLEM FORMULATION

The energy management problem is modeled as a Differential Evolutionary algorithm (DE) along the horizon T with t time steps. The time slot is considered$1h$; thus, each day will be 24 slots.

Objective Function

The objective function model of the adopted system is formulated as follows:

$$min\, f\,(cos\, t) = \sum_{t=1}^{24}\left\{(P_{grid}^{im}(t) \times \pi(t) - P_{grid}^{ex}(t) \times C_{sell}(t) + P_{PV}(t) \times C_{PV} + P_{B}^{Disch}(t) \times C_{B}^{Disch}\right\} \tag{7}$$

Where$\pi(t) \equiv TOU(t)$ refers to market $time\text{-}of\text{-}use$ tariff at hour t (₦/KWh), $P_{PV}(t)$ is power generated by the PVunit in period t; C_{PV} is the maintenance generation costs of PV system. $P_{grid}^{im}(t)$represents the purchased electric power from the traditional grid in period$t$, and $P_{grid}^{ex}(\,t)$ is sold electric power to the conventional grid in period t. C_{sell} denotes electricity cost when it is sold to the grid; C_{B}^{Disch}stands for maintenance cost of battery storage, $P_{B}^{Disch}(t)$ is the discharge power of battery storage in time t.

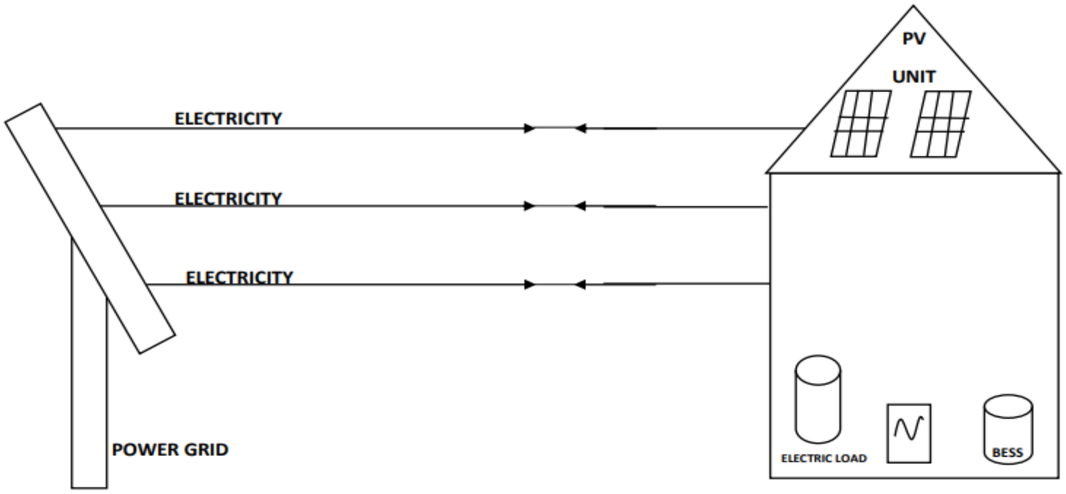

Figure 1: Proposed System Architecture

Power Balance Equality Constraint

In a smart office, ensuring a balance between energy production and consumption is critical. The power balance equality constraint of the smart office is given by eq. (8). The power balance equality constraint ensures that at any given time t, the total power provided by the traditional grid, PV unit , and battery energy storage equals the total power demand by the smart office load (flexible and non-flexible) and any excess power sold back to the traditional grid. This balance is crucial for optimizing (minimizing) the energy management within the smart office and maintaining operational efficiency and reliability of the hybrid energy system.

$$P_{grid}^{im}(t) + P_{PV}(t) + P_{B}^{Disch}(t) = P_{D}^{load}(t) + P_{B}^{Ch}(t) + P_{grid}^{ex}(t) \quad (8)$$

It is noteworthy that the positive values for $P_{grid}^{im}(t)$ are considered as the power purchased from the grid and the negative values as the power sold to the grid. $P_{D}^{load}(t)$ designs the entire smart office load demand in period t. $P_{grid}^{ex}(t)$ denotes the electricity amount sold to the grid in period t, $P_{B}^{Ch}(t)$ represents the charge power by battery energy storage device in period t.

Heat Balance Equality Constraint

The heat balance equality constraint in the smart office for the three scenarios discussed in this paper is non-existent. This is due to the fact that the distributed energy resources examined in this research, along with the upstream grid for energy exchange during surplus or deficit conditions, are unable to produce heat for the smart office. In summary, the single objective constrained optimization problem of interest in the smart office can be summarized as follows:

$$\text{Minimizef(cost)} = \left\{\sum_{t=1}^{24}\left\{\left(P_{grid}^{im}(t)\pi(t) - P_{grid}^{ex}(t)C_{sell}(t)\right) + P_{PV}(t)C_{PV} + P_B^{Disch}(t)C_B^{Disch}\right\}, \pi(t) \equiv TOU(t) \right. \tag{9}$$

Subject to relevant constraints

$$0 \leq P_{grid}(t) \leq P_{grid}^{immax} \tag{10}$$

$$0 \leq P_{grid}^{ex}(t) \leq P_{grid}^{exmax} \tag{11}$$

$$0 \leq P_{pv}(t) \leq P_{pv}^{\max} \tag{12}$$

$$P_B^{disch}(t) \leq P_B^{dischmax(t)} \tag{13}$$

For ease of computation and coding into PYTHON, we introduce the following variables;

$$P_{grid}^{im}(t) = x_{1,t}, P_{grid}^{ex}(t) = x_{2,t} P_{PV}(t) = x_{3,t}, P_B^{Disch}(t) = x_{4,t},\ \ \pi(t) = \pi_t$$
$$C_{PV} = c_1, C_B^{Disch} = c_2,\ \ \ C_{sell} = c_3.$$

The smart office single-objective constrained optimization problem is then equivalent to

$$\text{Minimizef(cost)} = \left\{\sum_{t=1}^{24}\left\{\left(x_{1,t}\pi_t - x_{2,t}c_3\right) + x_{3,t}c_1 + x_{4,t}c_2\right\}\right. \tag{14}$$

In expanded form we have;

$$Minimizef(cos\ t) = \sum_{t=1}^{24}\left\{\left(x_{1,t}\pi_t - x_{2,t}c_3\right) + x_{3,t}c_1 + x_{4,t}c_2\right\} \tag{15}$$

$$\begin{aligned}
&= x_{1,1}\pi_1 + x_{1,2}\pi_2 + x_{1,3}\pi_3 + x_{1,4}\pi_4 + x_{1,5}\pi_5 + x_{1,6}\pi_6 + x_{1,7}\pi_7 + x_{1,8}\pi_8 + x_{1,9}\pi_9 + x_{1,10}\pi_{10} \\
&+ x_{1,11}\pi_{1`} + x_{1,12}\pi_{12} + x_{1,13}\pi_{13} + x_{1,14}\pi_{14} + x_{1,15}\pi_{15} + x_{1,16}\pi_{16} + x_{1,17}\pi_{17} + x_{1,18}\pi_{18} + x_{1,19}\pi_{19} \\
&\qquad + x_{1,20}\pi_{20} \\
&+ x_{1,21}\pi_{21`} + x_{1,22}\pi_{22} + x_{1,23}\pi_{23} + x_{1,24}\pi_{24} \\
&\qquad - \begin{pmatrix} x_{2,1} + x_{2,2} + x_{2,3} + x_{2,4} + x_{2,5} + x_{2,6} + x_{2,7} + x_{2,8} + x_{2,9} + x_{2,10} \\ + x_{2,11} + x_{2,12} + x_{2,13} + x_{2,14} + x_{2,15} + x_{2,16} + x_{2,17} + x_{2,18} + x_{2,19} + x_{2,20} \\ + x_{2,21} + x_{2,22} + x_{2,23} + x_{2,24} \end{pmatrix} c_3 \\
&\qquad + \begin{pmatrix} x_{3,1} + x_{3,2} + x_{3,3} + x_{3,4} + x_{3,5} + x_{3,6} + x_{3,7} + x_{3,8} + x_{3,9} + x_{3,10} \\ + x_{3,11} + x_{3,12} + x_{3,13} + x_{3,14} + x_{3,15} + x_{3,16} + x_{3,17} + x_{3,18} + x_{3,19} + x_{3,20} \\ + x_{3,21} + x_{3,22} + x_{3,23} + x_{3,24} \end{pmatrix} c_1 \\
&+ \begin{pmatrix} x_{4,1} + x_{4,2} + x_{4,3} + x_{4,4} + x_{4,5} + x_{4,6} + x_{4,7} + x_{4,8} + x_{4,9} + x_{4,10} \\ + x_{4,11} + x_{4,12} + x_{4,13} + x_{4,14} + x_{4,15} + x_{4,16} + x_{4,17} + x_{4,18} + x_{4,19} + x_{4,20} \\ + x_{4,21} + x_{4,22} + x_{4,23} + x_{4,24} \end{pmatrix} c_2
\end{aligned} \tag{16}$$

The relevant constraints become;

$$\begin{cases} 0 \leq x_{1,t} \leq P_{grid}^{immax} \\ 0 \leq x_{2,t} \leq P_{grid}^{exmax} \\ 0 \leq x_{3,t} \leq P_{pv}^{max} \\ x_{4,t} \leq P_{BESS}^{Dischmax} \{ \end{cases} \tag{17}$$

The data set for the above optimization problem is as follows;

$$c_1 = 0.05, c_2 = 0.05,\ \ c_3 = 0.80$$

$$P_{grid}^{immax}\ \ {}_{grid}^{exmax}\ \ {}_{pv}^{max}\ \ {}_{B}^{dischmax(t)}$$

in period$\boldsymbol{t}$.

Modeling of Power grid

The electricity power injected from the National grid network during the period$t$is determined by the amount of gas/coal consumed by the National grid$P_{grid}(KW)$and can be expressed as:

$$P_{grid}^{im}(t) = P_{D}^{load}(t) + P_{B}^{ch}(t) \tag{18}$$

The imported electric power from the external grid network $P_{grid}^{im}(t)$ is directly utilized to fulfill the electrical demand of curtailable, flexible and non-flexible loads in the smart office in period$t$.

Power grid constraint:

The quantity of imported electric power from the main grid is constrained by its branch rating or electricity market regulations:

$$0 \le P_{grid}^{im}(t) \le P_{grid}^{immax(t)} \tag{19}$$

Where $P_{grid}^{im}(t)$ designs the imported electric power from the main grid in$t$;$P_{grid}^{immax(t)}$ is designed to meet the maximum imported power from the main gird in$t$. The quantity of electric power sold to the main grid is restricted by its branch rating or regulations within the electricity market:

$$0 \le P_{grid}^{ex}(t) \le P_{grid}^{exmax(t)} \tag{20}$$

Where $P_{grid}^{exmax(t)}$ is the maximum power exported to the main gird in t and $P_{grid}^{ex}(t)$ designs exported electric power to the main grid in t. It is evident that importing/selling electrical energy (E_{imp}/E_{exp}) from / to the upstream main grid at the same time is not achievable. Consequently, the following inequality constraints for the grid must be satisfied:

$$E_{imp}(t) + E(t)_{exp} \tag{21}$$

Modeling of Photovoltaic System:

The limit of the amount of PV generation.

$$0 \le P_{PV}(\mathrm{t}) \le \mathrm{P}_{PV}^{\max}(t). \tag{22}$$

The output power generated from PV system

$$P_{PV}(t) \leq A \times \rho \times SI(t). \tag{23}$$

Where P_{PV}^{max} is the maximum PV power allowed in period$t$, A is the PVsystem area, ρ is the efficiency, and $SI(t)$ is the solar irradiation

Modeling of Battery Storage System

The charging power of the battery storage system is limited by the maximum charging rate of the converter that links the battery storage system to the micro-grid. The boundary for the allowed charging power is:

$$P_B^{ch}(t) \leq P_B^{chmax(t)} \tag{24}$$

The discharge power of the battery energy storage system is constrained by the maximum discharging rate of the converter that connects the battery energy storage system to the micro-grid. The limit for allowable discharging power is:

$$P_B^{disch}(t) \leq P_B^{dischmax(t)} \tag{25}$$

Simultaneous charging and discharging are prohibited.

$$Y(t) + Z(t) \leq 1 \tag{26}$$

Where $Y(t)$ represents the state of the battery at t (= 1 charging; = 0 otherwise); $Z(t)$ represents the state of the battery at t (= 1 discharging; = 0 otherwise).
The electricity stored in the battery is represented as: $t > 1$:

$$Nom_B \times SOC_B(t) = Nom_B \times SOC_B(t-1) + \left(\frac{P_B^{ch}(t) \times dt}{e_c} - e_d \times P_B^{Disch}(t) \times dt\right) \tag{27}$$

The initial state of the battery:

$$Nom_B \times SOC_B(1) = Nom_B^{init\left(\frac{P_B^{ch}(1) \times dt}{e_c} - e_d \times P_B^{Disch}(1) \times dt\right)} \tag{28}$$

The limit of the state of charge of the battery:

$$SOC_B^{min_B} \tag{29}$$

The maximum battery charge limit:

$$\frac{P_B^{ch}(t) \times dt}{e_{c_{B_{B_B}}}} \tag{30}$$

Where $P_B^{ch}(t)$ and $P_B^{Disch}(t)$ denote the charge and discharge power by the battery storage at t.P_B^{Cmax} and P_B^{Dmax}represent the maximum allowable power for charging and discharging the battery, respectively; Nom_Bstands for the battery nominal capacity; $SOC_B(t)$ constitutes the state of charge of the battery; e_c and e_d makes up the charging and discharging coefficient factor; Nom_B^{init}constitutes the initial battery capacity and $SOC_B^{min}$is the minimum state of charge of battery storage.

Modeling of Solving Optimization and Energy Management Problem in Building Considering PV with Integration of Battery Storage System Using the Differential Evolution Algorithm

Power output and of the generating PV units, electric power sold/purchased from the traditional grid, $BESS$ operation which involves three interrelated sets ($P_B^{Disch}(t), P_B^{Ch}(t)$ and SOC_B in the problem, are decision/control variables. Originally, differential evolution algorithm is a simple population-based evolutionary computational algorithm for global optimization. Not only is it considered one of the most accurate, but of course one of the fastest meta-heuristic algorithms introduced in 1995 by Price and Storn (Storn & Price, 1997). This section provides the solution methodology to the energy management problems through differential evolution algorithm (DE).

Parameter Setup

The parameter set up mandates the user topic key parameters that control the differential evolution— population size (L); boundary constraints of optimization variables (NG); mutation factor (f_m), crossover rate (CR); and the stopping criterion of maximum number of iterations (generations) t_{max}. This approach ensures each solution is seen as capable of playing the vector role. Therefore, each solution f should contain these items as follows:$Population\ f = [P_{i,1}, \dots, P_{i,Np}, P_{i,Np+1}, \dots, P_{i,Np+Nb}, H_{i,1}, \dots, H_{i,Nb}, H_{i,Nb+1}, \dots, H_{i,Nb+Nh}]$ (31)

Furthermore, $P_{i,j} = [P_{i,1}, P_{i,2}, \dots, P_{i,Np}]$stands for the position of the j^{th} individual of a population of real valued N_p-dimensional vectors.

Initialization

The initial population encompasses combinations of solely the candidate dispatch solutions, which do not limit themselves to satisfying all the constraints alone, but are feasible solutions of economic dispatch. The element of a parent is the combination of power outputs of the generating units arbitrarily selected by a random number ranging over$\left[P_i^{min_i^{max}}\right]$.

$$P_{ij}^t = P_{ij}^{min(\ )\left(P_i^{max_i^{min}}(i=1,2,\dots,NG, i\neq d, j=1,2,\dots,L)\right)} \quad (32)$$

Where $rand(\quad)$is uniform random number ranging over [0, 1].

$$H_{ij}^{t} = H_{ij}^{min(\quad)\left(H_i^{max_i^{min}}(i=1,2,\ldots,NG,i\neq d,j=1,2,\ldots,L)\right)} \tag{33}$$

Also, the element of a parent is the combination of heat outputs of the generating units chosen arbitrarily by a random number ranging over $\left[H_i^{min_i^{max}}\right]$ (Hasan. M., et al.2021)

Evaluation

Minimizing the operating cost function is the goal here. When penalty factors are calculated, objective function— cost function— is evaluated. After evaluation of objective function, a global best solution is determined ($f_{best,i}$).

Mutation Operation (Differential Operation)

Mutation is an operation that adds a vector differential to a population vector of individuals according to the following equation:

$$A_{ij}^{t} = P_{R_1j}^{t} + f_m\left(P_{R_2j}^{t} - P_{R_3j}^{t}\right)(i = 1,2,\ldots,NG, i \neq d, j = 1,2,\ldots,L) \tag{34}$$

Where T is the time (generation), $P_i^t = \left[P_{i1}^t, P_{i2}^t, \ldots, P_{iNG}^t{}^T\right]$ designs the position of the j^{th}individual of a population of real valued NG-dimensional vectors. $A_i^t = \left[A_{i1}^t, A_{i2}^t, \ldots, A_{iNG}^t{}^T\right]$is the position of the j^{th}individual of a mutant vector. R_1, R_2 and R_3 are mutually different integers that are also different from the running index i;f_m is the mutation factor; and $f_m > 0$ is an actual parameter controlling the amplification of the difference between two individuals with indexes R_2 and $R_3(j)$in a bid to avoid search stagnation. It is usually a constant value taken from the range [0.4,1]. After the heat population is initialized, the mutation operator creates the next population.

$$C_{ij}^{t} = H_{R_1j}^{t} + f_m\left(H_{R_2j}^{t} - H_{R_3j}^{t}\right)(i = 1,2,\ldots,NG, i \neq d, j = 1,2,\ldots,L) \tag{35}$$

$H_i^t = \left[H_{i1}^t, H_{i2}^t, \ldots, H_{iNG}^t{}^T\right]$ stands for the position of the j^{th}individual of a population of real valued NG-dimensional vectors. $C_i^t = \left[C_{i1}^t, C_{i2}^t, \ldots, C_{iNG}^t{}^T\right]$ stands for the position of the j^{th}individual of a mutant vector. $R_1, R_2$and R_3 are mutually different integers (Perez & Maldonado, 2005).

Recombination

Following the mutation operation, recombination is applied to the population to generate a trial vector through replacement certain parameters of the target vector. This is carried out by the corresponding parameters of a randomly generated donor vector. For each vectorA_i^{t+1} and C_i^{t+1}an index $R_5(i)$are randomly chosen using a uniform distribution and a trial vector

$B_i^{t+1} = \left[B_{i1}^{t+1}, B_{i2}^{t+1}, \ldots, B_{iNG}^{t+1\ T} \right]$ and $D_i^{t+1} = \left[D_{i1}^{t+1}, D_{i2}^{t+1}, \ldots, D_{iNG}^{t+1\ T} \right]$ respectively.

$$B_i^{t+1} = \begin{cases} A_{ij}^t & \text{if} \quad (R_4(j) \le CR) \text{ or } (j = R_5(i)) \\ P_{ij}^t & \text{if} \quad (R_4(j) \le CR) \text{ or } (j \ne R_5(i)) \end{cases} (i = 1,2, \ldots, NG, i \ne d, j = 1,2, \ldots, L) \tag{36}$$

$$D_i^{t+1} = \begin{cases} C_{ij}^t & \text{if} \quad (R_4(j) \le CR) \text{ or } (j = R_5(i)) \\ H_{ij}^t & \text{if} \quad (R_4(j) \le CR) \text{ or } (j \ne R_5(i)) \end{cases} (i = 1,2, \ldots, NG, i \ne d, j = 1,2, \ldots, L) \tag{37}$$

Where$R_4(j)$is the j^{th} evaluation of a uniform random number generation with [0,1]. CR is the crossover or recombination rate in the rate in the range [0,1]. Usually the performance of a DE algorithm depends on the three variables; the population size, the mutation factor f_m and the CR (Hasan. M., et al.2021)

Selection Operation

Selection procedure oversees the production of better offspring. To decide the plausibility of vector B_i^{t+1} as a member of the population of the next generation, it is compared with the corresponding vector P_{ij}^t. Thus, f denotes the cost function under minimization, then

$$P_{ij}^{t+1} = \begin{cases} B_{ij}^{t+1}, & (j = 1,2, \ldots, NG);\ f(B_i^{t+1}) < f(P_i^t) \\ P_{ij}^t, & (j = 1,2, \ldots, NG); otherwise \end{cases} (i = 1,2, \ldots, NG) \tag{38}$$

$$H_{ij}^{t+1} = \begin{cases} D_{ij}^{t+1}, & (j = 1,2, \ldots, NG);\ f(D_i^{t+1}) < f(H_i^t) \\ H_{ij}^t, & (j = 1,2, \ldots, NG); otherwise \end{cases} (i = 1,2, \ldots, NG) \tag{39}$$

In the case above, the cost of each of trial vector is compared with that of its parent target vector P_i^t andH_i^t. If the cost f of the target vector P_i^t is lower than that of the trial vector, the target is allowed to advance to the next generation. Otherwise, a trial vector replaces the target vector in the next generation (Chen. H. et al, 2022).

Verification of The Stopping Criterion

Set the generation number for$t = t + 1$. Then repeat mutation, recombination and selection operation until the stop criterion— usually a maximum number of iterations (generations)t_{max}— is met. The stop criterion depends on the type of problem (Elkazaz.M. F, et al, 2020).

Optimization Steps

The CHPED problem is solved by DE algorithm through the seven steps proposed below:
Step 1: initialize solutions randomly;
Step 2: penalize infeasible solutions;
Step 3: evaluate solutions and determine global best solution;

Step 4: create newer solutions;
Step 5: constraint-handle and penalize infeasible solutions;
Step 6: evaluate solutions, select and determine global best solution;
Step 7: if convergence criteria is satisfied, then exit, otherwise go to step 4.

We begin with the Pseudocode for the differential evolution Algorithm

1. **Input**: Fitness function, Lb, Ub, N_p, T, F
2. Evaluate fitness (f) of P

```
for t = 1 to T
for i = 1 to Np
        Generate the donor vector (Vi) using mutation
        Perform crossover to generate offspring (Ui)
end
for i = 1 to Np
Bound Ui
Evaluate fitness (fUi) of Ui
        Perform greedy selection using fUi and fi to update P
end
```

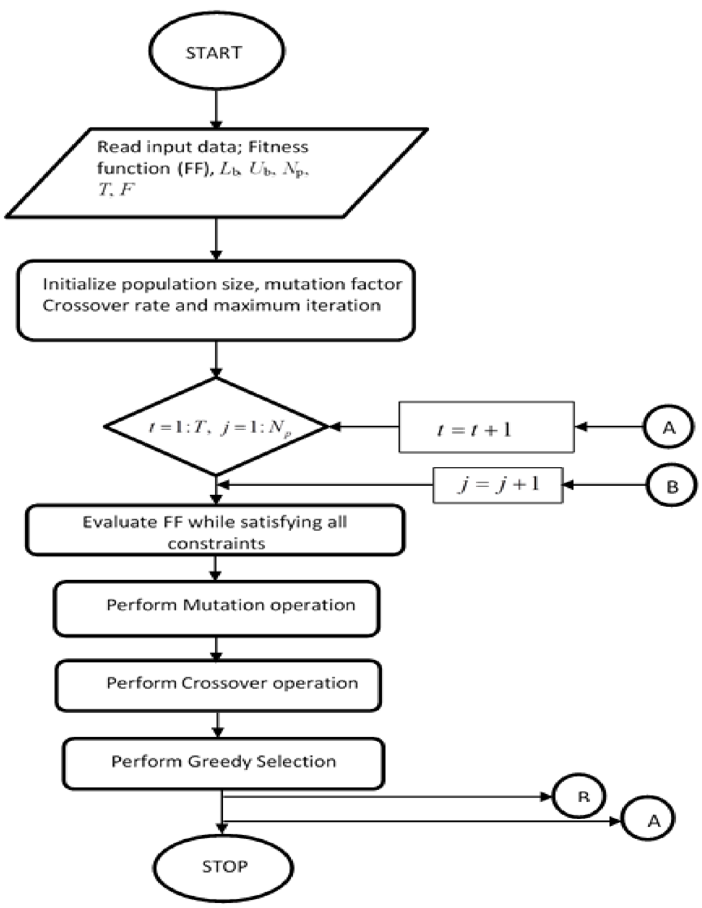

Figure 2: Computational flow of DE.

SIMULATION RESULTS

Based on the flow chart/formulas illustrated above. The sub-routines are found in Appendix A1. The studied smart office can meet its energy consumption (load or/and charging battery storage) from the main power grid or/and the ***PV*** system and the battery storage (discharge mode). If there is a power surplus from all these systems, the exceeding energy can be sold to the grid (this research allows the

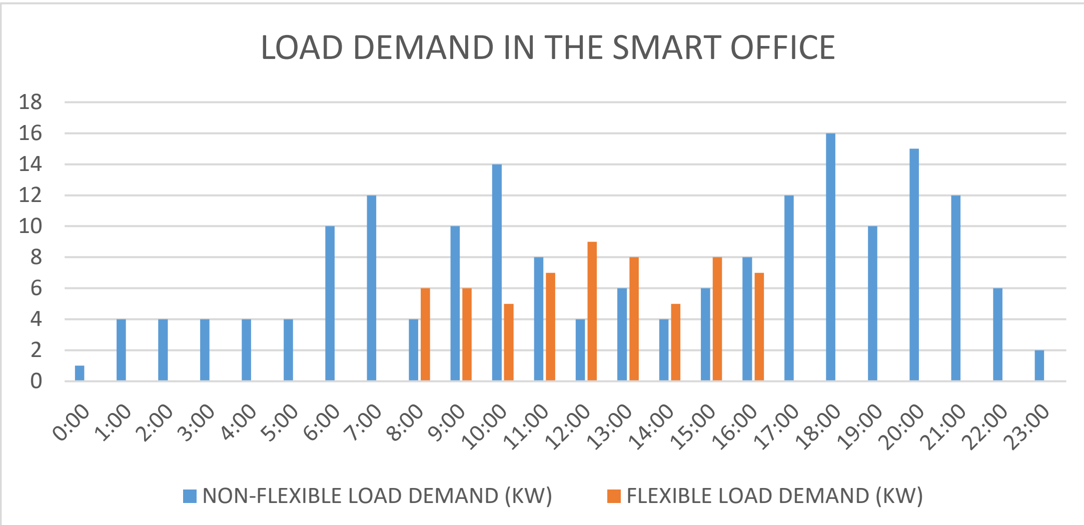

Figure 3: Load Demand in the smart office.

buy/store/sell operation of the electrical power)

The electricity demand data for the smart office is sourced from (Hasan. M., et al.2021).The electricity demand of the smart office is illustrated in Fig. 3. During specific periods, flexible and non-flexible loads (such as TV, sensors, AC, Laptop, cell-phone Illumination, *BESS* etc.) solely draw electricity. However, 24 hours horizon according to the graph profile of Fig.2, both flexible and non-flexible loads, along with the battery energy storage device, draw electricity from the hybrid-energy system.

Table I: Time of use Tariff

t **$/KWh**	**1** **0.033**	**2** **0.027**	**3** **0.020**	**4** **0.017**	**5** **0.017**	**6** **0.029**
t **$/KWh**	7 0.033	8 0.054	9 0.215	10 0.572	11 0.572	12 0.572
t **$/KWh**	13 0.215	14 0.572	15 0.286	16 0.279	17 0.086	18 0.059
t **$ /KWh**	19 0.050	20 0.061	21 0.181	22 0.077	23 0.043	24 0.037

In order to minimize the daily operational cost of the hybrid-energy system along with the consideration of PV energy stochasticity, the hybrid-energy system concept is propounded by using Differential evolution algorithm. The devised hybrid-energy system management model is tested in PYTHON environment to solve for the optimal energy cost of load (flexible and non-flexible) in the office considering the three scenarios. It is important to indicate that power flow equations, loss functions, reactive power flow and losses are beyond the scope of our study. The stochasticity is not considered for the other input data (such as demand) excluding PV unit. From the other perspective, the sizing and investment-based economic analyses of PV unit is not in the scope of our research. Input data considered and related results to different cases will be detailed in the following subsections.

Table II: Parameters Estimates

Parameter	Value	Unit
$P_{grid}^{immax}, P_{grid}^{exmax}$	5,0.6	KW
$C_{PV}(t) = C_B^{Disch}$	0.05	$/KWh
$C_{elec,sell}$	0.80	$ /KWh
$P_B^{Disch}(t), P_B^{ch}(t)$	1	KW
$P_{pv}(t), A, \eta$	3,164,97	KW, m², %
$SOC_{Bmin} SOC_{Bmax}$	0.2,1	pu
$\eta_{ch,} \eta_{dch}, P_B(t)$	97,97,3.8	%, KW
$P_D^{load}(t)$	8	KW

INPUT DATA

In this research, real input data are taken into account for each unit in order to provide more realistic results. A real electricity price considering a ToU tariff is used as energy price. The electricity consumption of a smart office is used for the demand. The stochastic solar energy generation is used to for renewable energy generation. As for renewable energy sources, the 3.0 kW PV installed system has a total area of $164m^2$ and an efficiency of97%. The battery storage device has a capacity of $3.8kWh$, with an initial SOC of $3.0kWh$ and a minimum SOC of$1.5kWh$. It charges and discharges at a rate of$1.0kW$, with an efficiency of 97%. This setup ensures that the battery can store surplus energy from the renewable sources and supply it during periods of high demand or low generation. Finally, the maximum power generated from the grid during period t is chosen to be 5 kW. $C_{PV}(t), and\ C_B^{Disch}(t)$ are set at 0.05 $ /KWh as maintenance cost. The cost of the electricity sold to the national grid is 0.80 $ /KWh and the cost of generated power by the grid is determined in ToU Table I.

NUMERICAL RESULTS

The case study is a typical university lecturer's office. As mentioned before, PV panels along with grid connection is used to supply the building demands. Figure 2 shows the electrical demand of the office and its obtained obtained by means of embedded smart meters in the system. A PV with 3 kW capacity is considered and the battery capacity is 3.8 kW, respectively. The parameters of the office components and the ToU price tariffs are given in table II and I. The state of charge of $BESS$ is 0.2pu. The Differential evolution

algorithm is implemented using PYTHON 3.10 on an H.P Pavilion Laptop, 1.80 GHZ, Intel i7 processor, 16 GB RAM with WINDOWS 10 operating system.
As shown in Fig. 4, in scenario I, the office primarily relies on the conventional grid system to supply energy to the smart office, thereby increasing system efficiency. In other words, greater electricity generation from conventional grid sources promotes sustainability in energy utilization, enhances the resilience of the hybrid, as customers rely on it to power their electrical appliances. However, on this selected da i.e. 0.00 a.m. to 23.00 p.m., the smart home draws electricity from the traditional grid due to lower electricity prices on this selected day due to gas price that is fixed and cheaper. Overall, the significant advantage of conventional grid over photovoltaic system in this scenario is its ability to generate energy at a reduced gas price which is fixed, reliable power supply, grid stability and reduced energy losses compared to PV systems that are stochastic in nature. (Hasan. M., et al.2021)

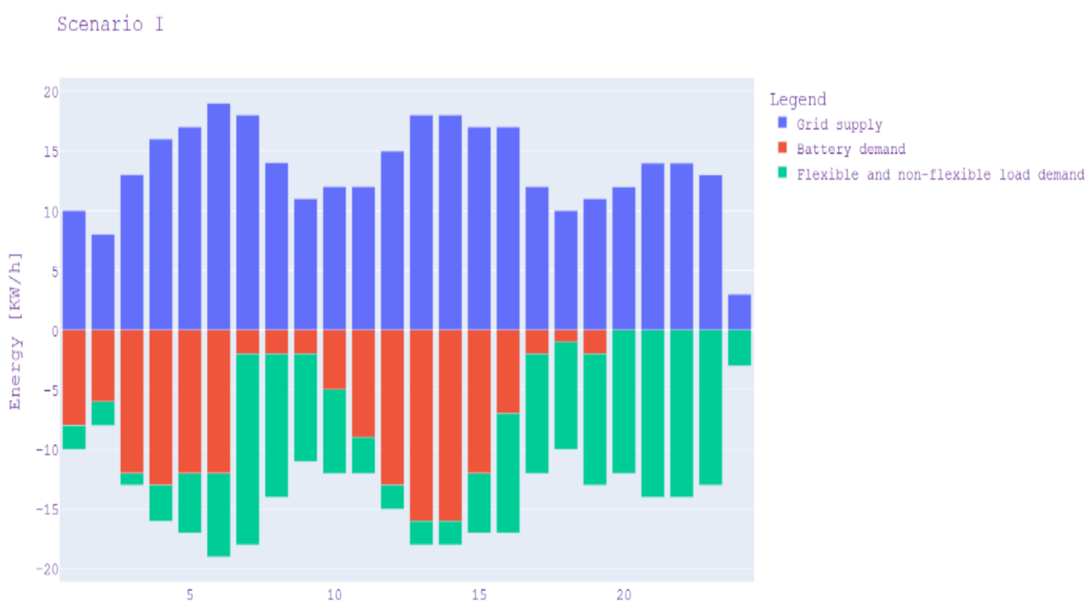

Figure 4: **Electricity equilibrium of the microgrid for scenario I grid supply only**

Figure 5 shows the scattered obtained using the proposed Differential evolution algorithm in scenario$I$. Differential evolution is utilized to tackle the single-objective optimization problem when a conventional grid integrated with a smart office. The population size, maximum number of generations, crossover probability, and mutation probability have been set to 50, 50, 0.9, and 0.2, respectively, for the three scenarios aiming at cost minimization. The results depicted in Figure 5 indicate that scenario$I$ exhibits the highest cost by 92% and 89% in comparison to scenarios IIandIII, respectively, this analysis demonstrates that differential evolution algorithm achieves the maximum cost expenditure by customers when compared with the other scenarios, attributed to its fluctuation. (Hasan. M., et al.2021)

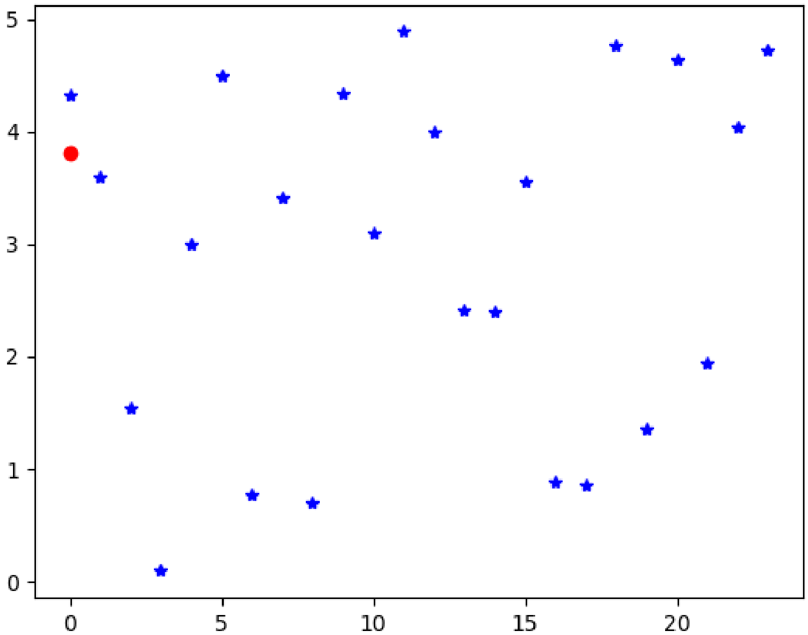

Figure 5: **scattered plot generated by Scenario I**

As depicted in Fig. 6, in scenarioII, the hybrid energy primarily relies on the photovoltaic energy system to supply energy to the smart office, thereby increasing system efficiency. In other words, greater electricity generation from PV energy sources promotes sustainability in energy utilization, enhances the resilience of the hybrid energy system, reduces dependence on the conventional grid, and enables the smart office to sell surplus energy to the upstream grid during peak price hours. However, between 6a.m. to 6p.m., the smart office draws electricity from the traditional grid due to lower electricity prices during this time interval and the stochastic nature of solar energy generation. (Hasan. M., et al.2021). Overall, the significant advantage of the photovoltaic system over the traditional grid in this scenario is its ability to exchange energy with the main grid, resulting inconsiderable revenue.

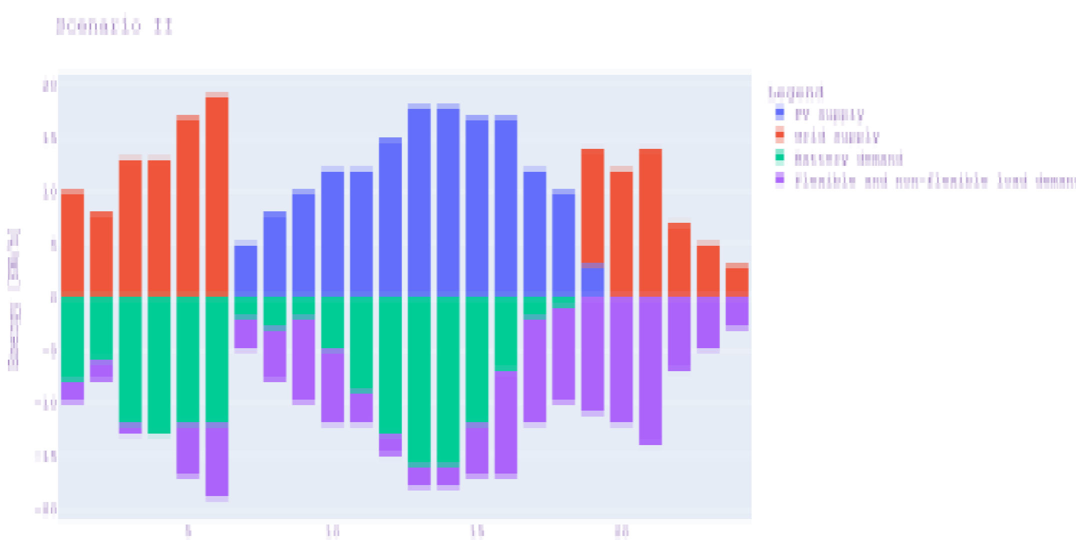

Figure 4: **Electricity equilibrium of the microgrid for scenario II with PV and grid supply.**

Figure 7 depicts the scattered plot of scenario II, showcasing the minimum fuel cost achieved using the proposed algorithm. The performance enhancement of this scenario can be observed in terms of cost, attributed to the integration of a *PV* generation system. The effectiveness of differential evolution algorithm verified using the test system, shows that the algorithm can find better solutions in terms of the objective function value, convergence speed and the number of solutions with lower objective functions compared with other scenarios.

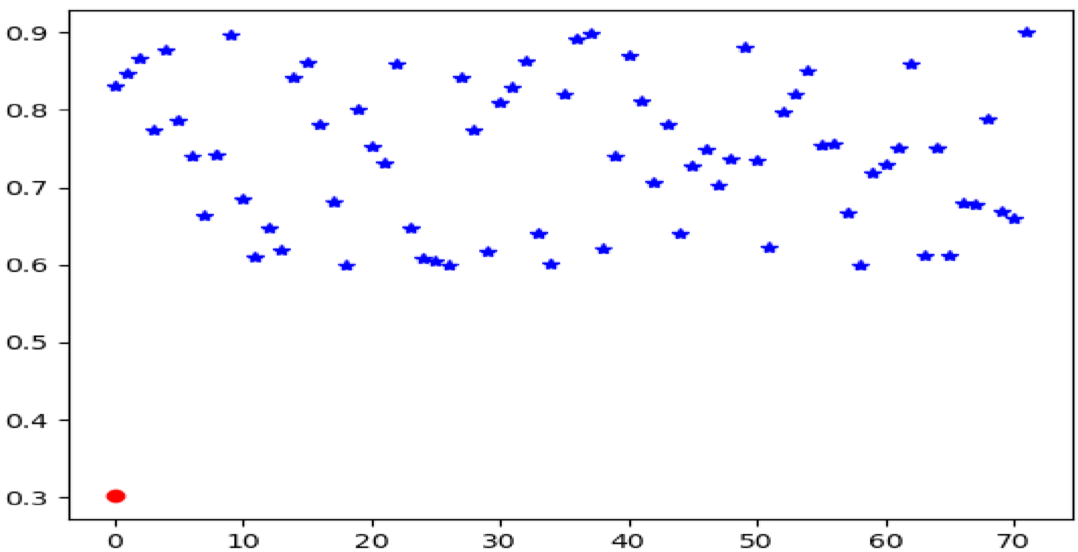

Figure 5: **scattered plot generated by Scenario** *II*

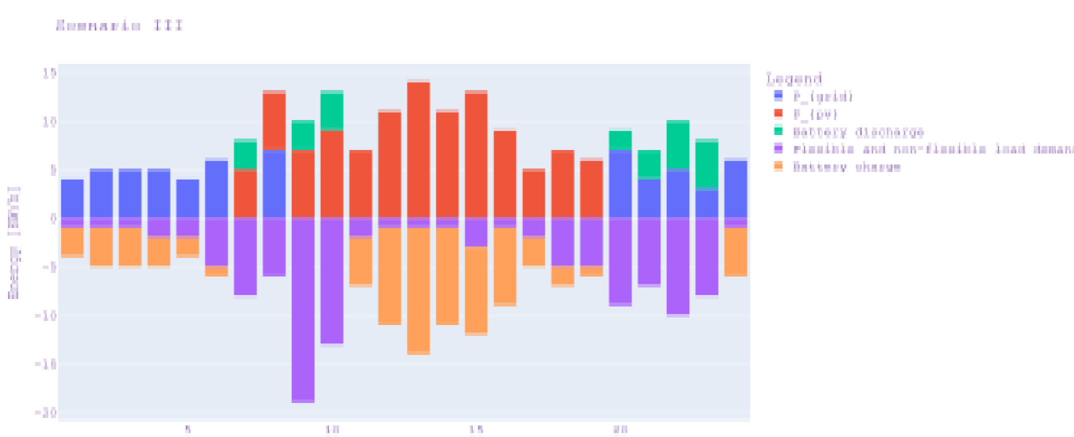

Figure 6: **Electricity equilibrium of the microgrid for scenario** III **with** $PV, BESS$ **and grid supply**

This scenario suggests that the integration of a *PV* generation system yields positive effects when accompanied by appropriate energy management strategies that satisfy various constraints, as indicated by the scenario study. Figure 8 designs the electricity balance of the hybrid energy system with a battery energy storage device integrated into it. It is evident that the PV and battery energy storage device operate at their maximum capacities for most of the hours, providing almost 75% of the total smart home energy consumption. This synergy between the PV and electricity storage device is advantageous, especially considering electricity prices in this scenario. Surplus energy is sold back to the grid during morning hours and late at night, as energy is stored during these off-cpeak periods and then exported to the main grid during peak price periods. (Raman. S.,et al., 2020).

This suggests that during on-peak periods, the smart office can meet its load demands by utilizing the battery energy storage instead of relying on purchases from the traditional grid. To mitigate the additional costs associated with battery degradation, the hybrid energy system endeavors to minimize the duration of discharging mode for the battery. Additionally, it is observed that during the early morning hours, the energy management system opts to purchase power from the upstream grid due to the low-price market conditions and uncertainties arising from the distributed energy resource PV unit. Late in the night (8p.m, 9p.m, 10.p.m, 11.p.m and 12.am) the hybrid system used mixed energy (battery discharge and conventional grid) to supply to the office.

Figure 9 illustrates the scattered plot of the proposed hybrid energy system for scenario III. It is evident that, thanks to the proposed meta-heuristic algorithm, the second-best solution point among all test combinations. This scenario provides a solution very close to the best compromise solution. Furthermore, scenario III highlights that the integration of an energy storage device (BESS) into the electrical grid yields positive effects when accompanied by appropriate energy management strategies that satisfy various constraints outlined in the scenario mathematical model. It is observed that during periods when the battery energy storage device is charging, its state of charge (SOC) is relatively high, and when the electricity price for discharging is lower than that from the upstream grid, the BESS discharges its energy, thereby benefiting from the electrical energy stored during off-peak period. .(Rahman. S.,et al., 2020)

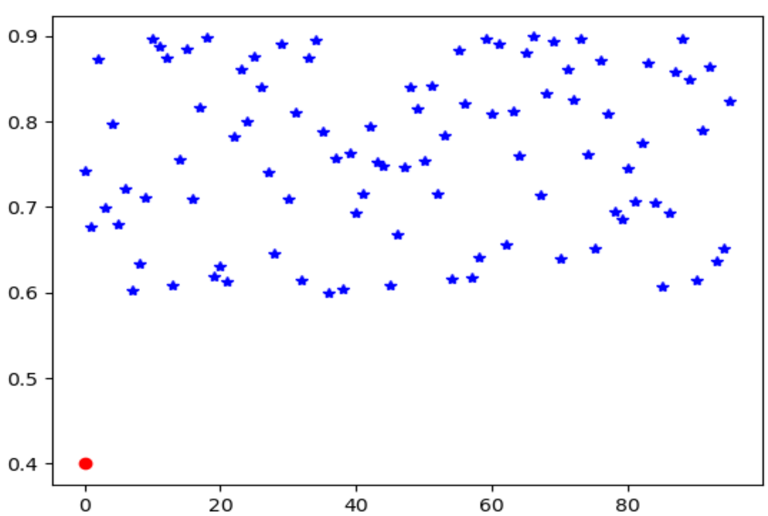

Figure 7: **scattered plot generated by Scenario** III

Table III displays the performances of different scenarios concerning various objective functions. Scenario I represent the baseline scenario with the highest energy costs. This scenario serves as a reference point for comparison. Scenario II exhibits 90% reduction in energy costs compared to Scenario I. This reduction in energy costs in the scenarios indicates that consumers benefit financially from selling excess power to the grid after satisfying their own energy needs. This aspect highlights the economic advantage of integrating renewable energy resources in energy management system. It is evident that scenario III exhibits the second-best performance in terms of cost. However, the integration of BESS leads to higher cost when compare with scenario I. Despite this, the cost and result is reasonable, thus validating the effectiveness of the hybrid energy system management. **(IEEE Transactions on Smart Grid)**

TABLE III. ENERGY COST OF CASE SCENARIOS.

SCENARIOS	ENERGY COST ($ /Day)
$\boldsymbol{I(GRID)}$	3.812
$\boldsymbol{II(GRID\&\ PV)}$	0.301
$\boldsymbol{II(GRID, PV\&BESS)}$	0.400

Since energy cost is of great importance to consumers, daily saving ratio of scenario II in comparison to case I i.e. as the worst case in terms of energy cost can be estimated from TableIII. It is seen that more than 92% reduction in cost can be achieved in scenario II by using energy PV and enabling electricity exchange with the conventional grid. Electrical energy production using PV in scenario IIrevenue is achieved, and this is because of the fact that purchasing this amount of energy from the upstream grid costs much more.(Rahman. S.,et al., 2020)

Also, scenario III show that the incorporation of $BESS$ into electrical grid has positive effects if there is an appropriate energy management with satisfying some constraints according to the case scenario. So we can analyze that in the periods when $BESS$ is operation at smart office with an SOC approximately high and their discharging electricity price is lower than the electricity price buy it from the conventional grid, the $BESS$ discharge their energy by benefiting from the electrical energy previously stored. Therefore, we can deduce that all the demand of the smart office, including flexible and non-flexible appliances load, battery storage charge, are covered with an optimized energy management between the production sources due the implemented models by considering the costs and the several mathematical constraints.

CONCLUSION

A new perspective based on differential evolution algorithm is proposed in this research work for coherent solution of optimal energy management of PV and BESS in a typical university office. Different attributes and constraints such as power demands, capacity limits of units and other operational constraints are taken into consideration in the formulation of energy management problem. The efficacy of the differential evolution algorithm was established using differential evolution algorithm codes. Differential evolution algorithm, it was realized, can proffer better solutions in terms of the objective function value, convergence speed and actual number solutions for the case scenarios. A scenario-based stochastic approach was developed in this sophisticated energy architecture in order to deal with the uncertain nature ofPV, and actual ToU tariffs for electricity prices were evaluated. Various case studies were carried out considering diverse scenarios to validate the effectiveness of the proposed concept.

As a result, it is found that the objective costs get the highest value in the Base Case (using conventional grid to supply the smart office) which has no PV sources and $BESS$. On the other hand, the cost was reduced by nearly 92% with PV integration while 90% reduction was achieved considering both PV and$BESS$. The simulation results show the global optimum solution for many consecutive days with important reduction of execution time and by achieving a significant energy cost savings of the considered scenarios.As a future work, the presented methodology can be extended with taking the advantage of the energy reduction capabilities of curtail able loads by demand side management strategies. Also, different types of energy conversion system assets can be considered. Moreover, the multi-objective system modeling can be adopted existing proposed architecture for analyzing the performance of this optimization algorithm from different aspects.

RECOMENDATIONS

The following recommendations have been suggested for the improvement of modeling and optimization of energy management in smart building, considering $\boldsymbol{PV}$, $\boldsymbol{BESS}$ and its benefits on the energy sector.

- To eliminate rigorous calculations, slower convergence and infeasible result (s) involved, genetic algorithm is a powerful optimization tool for finding solutions of optimization of energy management decision variables (cost functions, power etc.).It gives the exact solution of micro-grid energy management problems which converge as fast as possible as exemplified in this research study. Although, particle swarm optimization, ant bee colony and market exchange algorithms were also applied in some literatures to solve the optimization of energy management problems in smart buildings but the effectiveness of the above named algorithms for larger micro-grids which interact with the conventional grid is not known yet. The reason is that the calculations involved are difficult to manipulate efficiently despite it having the least objective function value. Conversely, chaotic improved harmony search algorithm, biogeography based optimization algorithm, stochastic fractal search algorithm etc. usages are limited to a few problems which make it rather impermissible to use in this kind of research since it falls into local optimum in high-dimensional space, besides, it also have a low convergence rate characteristic in the iterative process. Results obtained by artificial bee colony are often associated with large diversity and in most situations, convergence to either optimal or near optimal solution is rather difficult.
- In addition, the research therefore recommends that not only should this proposed method (differential evolution algorithm) be included in the curriculum

for higher programs, but also be applied when solving modeling and optimization of energy management in smart building problems. Doing this will assist research students in accomplishing desired result (s), eliminate rigorous calculation processes and obtain optimal converging solutions. The financial evaluation should be enhanced by including certain factors such as potential loss of heat during generation in these technologies and reduce maintenance on the operating device.

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