Sustainable Energy, Grids and Networks 39 (2024) 101449

Contents lists available at ScienceDirect

Sustainable Energy, Grids and Networks

journal homepage: www.elsevier.com/locate/segan

Development of an integrated energy management system for off-grid solar applications with advanced solar forecasting, time-of-use tariffs, and direct load control

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ARTICLE INFO

Keywords:
Integrated energy management system
Solar energy forecasting
Supply side management
Demand side management
Time-of-use
Direct load control

ABSTRACT

Effectively managing and maximizing the integration of renewable energy sources is essential for a sustainable power grid due to the stochastic and intermittent nature of renewable energy generation. This study develops a comprehensive Integrated Energy Management System incorporating supply-demand side management in the form of time-of-use credit, direct load control, and generator control to enhance photovoltaic utilization in off-grid applications. A novel three-step solar energy forecasting approach is proposed in this paper, utilizing low-level data fusion and regression models to predict next-day photovoltaic generation with improved accuracy, and a rule-based decision algorithm is developed to correct forecast errors and manage loads dynamically. A techno-economic analysis covering a 20-year duration is carried out for scenarios with and without the integrated energy management system; three configurations are investigated for supplying an off-grid residential home, including diesel generator, diesel generator/photovoltaic system, and diesel generator/photovoltaic system/integrated energy management system. Results reveal that the hybrid configuration with integrated energy management system achieved 44 % and 46 % reductions in costs and carbon dioxide emissions compared to the diesel generator alone, and 8 % and 9 % compared to the diesel generator/photovoltaic setup respectively. The Integrated Energy Management System further enhanced photovoltaic utilisation rate by over 113 % when compared to the diesel generator/photovoltaic system. Further evaluations include customer behaviour impacts, demonstrating that a fully automated system with 100 % compliance significantly outperforms systems with manual customer control, highlighting the detrimental effect of overrides on the efficiency of direct load control. The flexibility of the Integrated Energy Management System framework allows potential adaptation for on-grid applications, showcasing its utility in diverse operational contexts.

1. Introduction

The persistent annual increase in global energy consumption and the rise in greenhouse gas (GHG) emissions have increasingly urged countries to turn to renewable energy sources (RES). These sources are not only abundant and accessible but also exert minimal negative environmental impact, making them a pivotal component in the global energy strategy [1]. Constructing renewable-based generating plants is a critical step toward mitigating carbon emissions. However, this approach alone is not a sustainable and fundamental solution to the above

Abbreviations: ACs, Air Conditioners; BESS, Battery Energy Storage Systems; CB, Customer Behaviour; CBA, Cost-Benefit Analysis; CBR, Cost-Benefit Ratio; CEMS, Corrective Energy Management System; CPI, Consumer Price Index; CPP, Critical Peak Pricing; DF, Discount Factor; DG, Diesel Generator; DLC, Direct Load Control; DR, Demand Response; DSM, Demand Side Management; EMS, Energy Management System; EV, Electric Vehicle; GA, Genetic Algorithm; GC, Generator Control; GHG, Greenhouse Gases; IBDR, Incentive-based Demand Response; IEMS, Integrated Energy Management System; IMF, International Monetary Fund; IoT, Internet-of-Things; IRENA, International Renewable Agency; IRR, Internal Rate of Return; LCCA, Life-Cycle Cost Analysis; LCoE, Levelized Cost of Energy; LLDF, Low-Level Data Fusion; NPV, Net Present Value; NWP, Numerical Weather Predictions; MPC, Model Predictive Control; O&M, Operations and Maintenance; PBDR, Price-based Demand Response; PEMS, Predictive Energy Management System; PP, Payback Period; PV, Photovoltaic; REMS, Real-Time Energy Management System; RES, Renewable Energy Sources; RLA, Regression Learner App; RMSE, Root Mean Square Error; ROI, Returns on Investment; RTP, Real-Time Pricing; SEF, Solar Energy Forecasting; SSM, Supply Side Management; TOU, Time-of-Use.

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https://doi.org/10.1016/j.segan.2024.101449
Received 28 March 2024; Received in revised form 31 May 2024; Accepted 11 June 2024
Available online 13 June 2024

challenges, which emphasises that there must be a focus on efficiently integrating and managing these renewable energy resources to ensure optimal utilisation.

RES, such as wind and solar, are inherently dependent on weather conditions, leading to intermittent energy supply and consequently, grid imbalance [2]. This inherent variability underscores the necessity for sophisticated integrated energy management systems (IEMS) to optimise power and load resource scheduling to maintain grid stability [3]. However, optimising power supply from RES requires resource forecasting and planning [4], while managing load scheduling requires insights into customer behaviour and participation as load operators [5]. Furthermore, RES are increasingly being deployed in hybrid off-grid applications for grid extension [6], presenting additional constraints like higher capital costs and technology requirements. According to a 2021 report by the International Renewable Energy Agency (IRENA), the capacity of off-mini grid installations is over 450,000 MW [14]. With over 900 million people in the world without electricity access [8], hybrid RES applications, particularly photovoltaics (PV) based, are an increasingly viable option. However, off-grid hybrid PV configurations tend to be more expensive than on-grid due to storage and infrastructure requirements and can sometimes be a deterrent to investors because of longer returns on investment (ROI) [7,8]. Reducing wastage and maximizing PV usage in hybrid off-grid applications will be crucial to accelerating solar energy adoption. To address these challenges, the IEMS must combine solar energy forecasting (SEF), and effectively manage both the load and power supply while considering the inputs of customers living in off-grid locations.

The term IEMS is derived from the more popularly referenced energy management system (EMS) and they are sometimes used interchangeably. Since the bulk of the studies refer to an EMS, it is important to differentiate them based on their definitions and functions. An EMS uses a system of methods or strategies to modify, monitor, control, improve and maximise the usage of energy, reducing operating expenses [9] while simultaneously providing flexibility and control to energy resources and the grid [10]. Current EMS frameworks are broadly categorised into Predictive Energy Management Systems (PEMS) and Real-time Energy Management Systems (REMS) [11], with each offering distinct advantages and limitations. PEMS uses historical data to forecast energy demand and supply, optimising resource allocation in advance, but may not adapt swiftly to real-time changes. Conversely, REMS dynamically adjusts to real-time conditions of the load or supply but can lack the predictive foresight to pre-empt issues effectively. In addition, REMS can be replaced with corrective energy management systems (CEMS) if the load/supply data experiences delay and is not in real-time. The escalating complexity of modern energy grids necessitates an evolution toward an IEMS, which amalgamates the strengths of both PEMS and REMS/CEMS to create a more resilient and efficient energy management solution. By evolving EMS into IEMS, we can harness predictive and real-time management strengths, thereby developing a system capable of handling the dynamic and intermittent nature of renewable energy supplies. This evolution is crucial for achieving a sustainable and balanced energy future, especially in off-grid hybrid solar applications where the reliability of PV and diesel generator (DG) systems is paramount. An IEMS is a system that combines predictive and real-time controls by initiating supply and demand responses to balance the grid's power supply and load, utilizing technological and communication advancements to maintain multi-source or multi-energy systems [3]. The typical management mechanisms of IEMS are reviewed as follows.

The effective management of supply or supply side management (SSM) refers to the efforts taken to assure the efficient generation, conversion, transmission, and distribution of energy [4]. Examples include synchronizing back-up power, optimizing supply switching, smart generator control (GC), regulating battery storage and so on. Conversely, demand side management (DSM) and Demand Response (DR) describe programs that influence a customer's electricity usage. DSM refers to methods that modify an electrical grid's load profile in a way that benefits both demand and supply [9]. DR is a subset of DSM and is broadly classified as methods that encourage customers to reduce their short-term energy use in response to a price signal [5]. DR are categorised into incentive-based demand response (IBDR) and price-based demand response (PBDR). Examples of IBDR programs include direct load control (DLC) and demand bidding, while PBDR include time-of use tariffs (TOU), critical peak pricing (CPP), and so on [6].

Customer behaviour (CB) is critical to the success of DR programs and should be considered in evaluating any IEMS. A customer can accept or override a DR command, where overrides cause the customer to lose whatever financial incentive is offered for curtailing consumption. In this study, a 100 % customer compliance rate is classified as a fully automated system. Two events created by DR programs like DLC and TOU are called preconditioning (before DLC event) and rebounding (after DLC event). Preconditioning and rebounding are customer behaviours that result in an increase in the customer's load consumption before and/or after a DLC event or during a TOU peak period to compensate for load curtailment, higher usage costs or threat of penalties [7].

This study employs a multifaceted approach to developing the IEMS and assessing its effectiveness by combining SEF, TOU, GC, and DLC technologies specifically designed for off-grid solar applications. This innovative approach not only enhances the efficiency and reliability of a hybrid PV and DG system but also incorporates comprehensive customer behaviour analysis, thus addressing the deficiencies in existing research (highlighted in Section 2) and providing a robust solution for energy management in off-grid settings. Firstly, we introduce a novel three-step solar energy forecasting model that uses low-level data fusion (LLDF) to combine meteorological variables with selective regression modelling to enhance prediction accuracy. This model integrates data from various meteorological stations to provide more reliable forecasts of solar power generation. Secondly, the IEMS framework incorporates advanced TOU management techniques. The system can optimise load scheduling to align with periods of lower energy costs and higher PV availability by analysing historical energy usage patterns and pricing data. This strategy reduces operational costs and maximises the use of PV. Thirdly, the DLC component of the IEMS is designed to manage energy demand in real-time dynamically. Using smart meters and automated control systems, the IEMS can adjust energy consumption patterns to prevent grid imbalances and ensure a stable energy supply. This includes the ability to initiate load shedding or increase energy supply from DG when necessary. The IEMS is able to achieve this control through the use of rule-based algorithms. A comprehensive techno-economic analysis evaluates the effectiveness of the proposed IEMS. This analysis examines the long-term economic benefits and environmental impacts of implementing the IEMS in off-grid solar applications. By comparing various energy configuration mixes, the study identifies the most cost-effective and environmentally friendly configuration for PV integration. Finally, CB is thoroughly analysed to understand its impact on the performance of the IEMS. By incorporating CB analysis, the study ensures that the IEMS can effectively respond to real-world usage patterns and preferences, further enhancing its reliability and efficiency in managing off-grid solar applications. The contributions are listed as follows:

- The paper proposes a new IEMS that integrates SEF, TOU, GC and DLC technologies specifically designed for off-grid solar applications. This proposed system enhances energy use efficiency and reliability through precise scheduling and intelligent control, optimising the energy use of PV and DG.
- Although solar energy forecasting techniques are widely utilised, the specific three-step solar energy forecasting model introduced in this paper is novel in the context of energy management systems. This model enhances forecast accuracy significantly by integrating data collected from different meteorological stations through LLDF and

selective regression modelling. This innovative approach provides new insights and tools for accurate solar power generation predictions and corresponding load scheduling.

This paper conducts a techno-economic analysis of the IEMS, assessing its economic viability and potential to reduce CO_2 emissions. The study identifies the most suitable configuration for PV integration by analysing various energy configuration mixes, thereby improving energy efficiency, and optimising environmental outcomes.

This paper is organized as follows: The literature review is presented in Section 2. Section 3 discusses the methodology, and Section 4 describes the case study and scenario assumptions, including parameters used in assessing the performance of the IEMS. Section 5 discusses the results, and Section 6 presents the conclusions and future works.

2. Literature review

Falope et al. reviewed that a solar-based IEMS integrates SEF, DSM, and SSM through the use of predictive and real-time controls [12]. This section examines existing literature on these components to provide a foundation for understanding the proposed IEMS. It explores numerical weather predictions (NWP) for SEF, TOU tariffs, DLC for DSM, GC for SSM, and CB modelling. The goal is to understand how various energy management systems function to enhance PV usage and minimize costs for customers or network operators. Each subsection will review current research, highlight key findings, and discuss limitations to establish the context for the proposed IEMS.

2.1. Solar energy forecasting

Improved weather predictions can help decrease uncertainty of solar power generation. In addition, forecasting PV generation is critical to scaling solar energy use in markets dominated by non-predictable energy [13]. The degree to which the predicted value of PV generation is near to the actual (real) value describes the forecast accuracy. There are many SEF methods and approaches, and they are derived from considerations like timescales, data availability and type [14]. There are three types of solar forecasting models: physical, statistical, and hybrid [15]. Physical methods are further classified into sky images, satellite-imaging models, and NWP [16].

This paper will focus on an NWP-based forecasting approach. NWP is one of the most prominent methods used for 24-hour or day-ahead forecasts [17,18]. This method leverages the accuracy and comprehensiveness of meteorological data to provide reliable predictions for solar energy generation. By integrating various atmospheric parameters like relative humidity, solar radiation, atmospheric pressure and so on, NWP models can simulate and forecast weather conditions with high precision, making them indispensable for planning and optimizing solar power systems. The effectiveness of NWP in forecasting PV generation lies in its ability to incorporate real-time weather data, thus continually refining the accuracy of predictions and adapting to changing atmospheric conditions. This dynamic capability ensures that solar power systems can be efficiently managed and utilized, thereby enhancing the overall stability and reliability of energy supply in off-grid applications.

2.2. Demand side management: time-of-use and direct load control

TOU tariffs are a time-dependent pricing structure, charging per kWh based on energy use during peak, average, and off-peak hours [19]. Energy consumption is highest during peak times, whereas other times are charged at lower rates. TOU is one of the simplest forms of DR to implement, with peak-period tariffs sometimes five times higher than off-peak rates. According to Robert et al. [20], TOU is the simplest form of demand response to implement.

In Australia, research by Hall et al. [21], found that approximately 49 % of participants favoured TOU pricing, which performed better than standard pricing schemes. Additionally, in Japan, a study by Malehmirchegini et al. [22] showed a daily peak reduction potential of 10.7 % in using TOU versus 7.3 % for real-time pricing (RTP). Although TOU effectively reduces peak load and manages costs, it requires significant customer education and engagement for optimal effectiveness. Customers must adapt their consumption patterns to benefit from lower tariffs, which can be challenging. Moreover, while TOU addresses peak load issues, it does not provide a comprehensive solution for all aspects of demand flexibility.

DLC is another DSM strategy where utilities offer financial incentives for customers to reduce their electricity consumption during peak periods through smart meters and switches [23]. DLC suits flexible and controllable loads such as washing machines, dishwashers, air conditioners, and water heaters. Customers can accept or override DLC signals, with some programs imposing penalties for non-compliance [24]. Research by Hall et al. [21] demonstrated high receptiveness to DLC technologies among participants, and a study by Fell et al. [25] found DLC had the most favourable outcome, with 37 % of participants expressing willingness to sign up for the program. DLC is effective for managing peak loads and enhancing grid stability but may face issues with customer compliance and override rates. The success of DLC programs heavily depends on customer willingness to participate and their perception of the benefits. This concept is further analysed in this study by evaluating the impact of total and partial compliance in the context of CB. Though these DR responses may require additional infrastructure and continuous monitoring resulting in slightly higher up-front costs, TOU tariffs and DLC have been regarded as important tools for load management [26].

2.3. Supply side management: generator control

SSM can create an energy reservoir to supplement inconsistent energy supply due to intermittency of some RES. There are several SSM techniques include BESS integration [27], optimizing and synchronizing alternative or back-up power [28], dispatch algorithm for multiple energy supply sources [29] and so on. A DG, automatically or manually controlled, may be used to meet peak loads in cases of BESS depletion, rapid changes in load, or RES intermittency [30]. DGs are widely used for off-grid solutions, and therefore offer versatility as they can be used for both off-grid and on-grid applications. In addition, the usage of DG units can also increase the cost effectiveness and dependability of a microgrid system because it may help to reduce the number of battery storage units required [31].

There are several studies [32–36] that include generators as part of a mini-grid configuration. Ekpe and Umoh [36] use backup generators to improve grid reliability integrated with PV. In a study by Khatib et al. [37] in Malaysia, a hybrid PV/DG reduced system cost by 35 % and was more feasible than a stand-alone PV or DG. In a techno-economic analysis by Tsai et al. [38] for the Pratas island in Taiwan, the analysis revealed that the PV/DG hybrid system with a cost of energy (CoE) at 0.3569 $/kWh performed better than stand-alone DG system, stand-alone PV/storage system, and PV/DG/storage hybrid system. In an analysis by Harajli et al. [39] of three countries (Iraq, Lebanon, and Palestine) with grids categorized as “weak”, the authors determined that hybrid-PV-diesel systems perform substantially well in terms of energy, the environment, and the economy than solely diesel and supply from the country’s utility.

The choice between battery energy storage system (BESS) and a generator depends on cost, reliability, and environmental impact. BESS tend to have higher up-front costs than other hybrid alternatives for large installations. They also lose the ability to hold a charge as time goes on. This cost and reliability flaw makes BESS the weakest link in the PV system [40–42]. In an EMS study by Srikranjanapert et al. [43], solar PV integrated with an EMS had the highest benefits when considering net present value, internal rate of return and pay back compared to solar alone, and solar/EMS/BESS. This happened because the cost of the battery outweighed the combined savings from exported PV energy, savings from efficient energy usage via the EMS, and savings from self-consumption. In most cases, the low compensation rate of PV exports in most countries, combined with a lower EMS implementation cost versus BESS cost, is a major contributing factor to using a system without BESS. Additionally, the ability to recycle spent batteries, especially in developing countries, is non-existent. High investment and replacement costs, chemical pollution, short-life spans have led researchers to explore hybrid configurations without storage. In a study by Tsuanyo and Azoumah [44], the authors explore a PV/diesel hybrid configuration without battery storage that relies on optimising supply while managing the load; a formula championed by the proposed IEMS.

2.4. Customer behavioural response to demand signals

Accurately understanding customer consumption patterns and their reactions to price changes and DLC signals is challenging due to the stochastic nature of energy demand [45]. Various methods are used to predict customer response including time-series regressions, neural networks, and transfer learning [46–48]. Time-series regressions analyze historical data to forecast future demand, while neural networks model complex, nonlinear relationships in the data. Transfer learning, which applies knowledge from one domain to another, helps improve prediction accuracy when data is scarce. However, these models often suffer from overfitting with limited data availability, making them less effective in real-world applications. Overfitting occurs when models are too closely tailored to specific datasets, failing to generalize to new data.

Preconditioning and rebounding are common behavioural responses to price and DLC signals and help quantify energy flexibility when predictive controls are used [49]. Preconditioning involves increasing energy use before a DLC event, while rebounding refers to increased consumption afterwards, complicating the prediction process. Behavioural models can significantly enhance demand forecasting accuracy but require extensive and often unavailable customer data. For example, Kumar and Mallipeddi [50] use customer segmentation and clustering models to identify consumption behaviours and patterns by dividing larger customer groups into smaller groups with common behavioural traits. However, these models are less effective when the customer data size is either too small or unavailable. To counter this challenge, current models must aim to capture the nuances of individual and group behaviours in response to various incentives. Effective demand-side management must consider diverse customer behaviours and preferences, which complicates modelling and prediction processes. Different customers may respond differently to price changes and DLC signals, necessitating sophisticated models that account for this variability. Collecting comprehensive data on consumption patterns, appliance usage, and socio-economic factors is essential but challenging. Without such data, models may lack the precision needed for accurate forecasts. Therefore, improving data collection and leveraging advanced analytics are crucial for enhancing the reliability of demand-side management strategies. More effective and responsive energy management systems can be developed by addressing these challenges.

2.5. Energy management system

An EMS combines sophisticated hardware and software to track, manage, and optimize energy use, cutting costs and enhancing grid stability [51]. Its primary task is to optimize objectives like grid failure rate, ramp rate, peak cuts, and electricity cost minimization [52]. To achieve these goals, EMSs employ advanced algorithms and data analytics to monitor and control energy flows in real-time based on forecasted renewable generation and/or load demand [53]. Various studies have explored different EMS architectures, highlighting the importance of integrating predictive and real-time strategies [54–61]. For example, Mohandes et al. [59] develops a new EMS that uses multiplicative weights update to improve an ensemble of deep neural network-based PV forecasts, optimally size a hybrid PV/BESS system, and reduce fluctuation of supply to the grid from RES. For a stand-alone PV power system, Ozden et al. [60] proposes an EMS optimised with dynamic knapsack and multi-agent devices, including a source agent to determine state-of-charge and load agents that measure instantaneous power consumption. The EMS uses a fuzzy logic-based decision maker to effectively schedule load based on the available energy supply, with priority given to critical loads.

Despite these advancements, existing research often lacks the integration of SEF, TOU and DLC technologies, specifically in off-grid applications. Additionally, the impact of CB is frequently insufficiently considered, which is crucial for the successful implementation of any EMS. For instance, George-Williams et al. [62] employed a Monte-Carlo-based framework to model and simulate EV charging while Khizir et al. [63] proposed an EMS for peak-load management that significantly reduced peak load and energy costs. However, both studies did not fully incorporate the complexities of CB in off-grid settings. It is clear to see that more comprehensive EMS frameworks that incorporate advanced forecasting models, DR strategies, and CB analysis are needed. Such integration would enable more accurate predictions of energy supply and demand, better management of energy resources, and enhanced system reliability. Addressing these gaps can lead to more robust and efficient energy management solutions, especially in remote and off-grid locations where traditional grid infrastructure is unavailable.

Finally, the selection of rule-based algorithms to control demand and supply assets is also considered. Rule-based algorithms are renowned for their simplicity, transparency, and ease of implementation [64]. These characteristics make them particularly suitable for real-time applications in off-grid systems where computational resources may be limited and rapid decision-making is crucial. While modern approaches such as model predictive control (MPC) and fuzzy logic theories offer advanced predictive capabilities and adaptive responses, they also come with increased computational complexity and require more extensive parameter tuning and system modelling. For instance, MPC involves solving an optimization problem at each control step, which can be computationally intensive and may not be feasible in all off-grid scenarios, especially in remote areas with limited processing capabilities. Similarly, fuzzy logic controllers require the design of fuzzy rules and membership functions, which can be complex and time-consuming to develop and optimize for specific applications. The Rule-based algorithm was chosen for this study because it strikes a balance between performance and practical applicability. Additionally, rule-based systems can be easily understood and modified by operators, which is advantageous for maintenance and adjustments in the field. A summary of several EMS studies is listed in Table 1.

This study aims to develop a comprehensive IEMS that integrates SEF, TOU, DLC, and GC technologies, to manage supply and demand related uncertainties that may affect the efficiency and reliability of off-grid solar applications. To achieve this, we incorporate a three-step solar energy forecasting model that integrates data from multiple meteorological stations to enhance prediction accuracy. However, to account for the inherent uncertainties in weather predictions, we develop an error correction algorithm to adjust for forecast discrepancies dynamically. The uncertainty and impact of CB on the performance of the IEMS is also analysed considering factors like load override rates, preconditioning, and rebounding behaviours, which can significantly influence the effectiveness of DLC programs. This approach helps us understand how deviations from expected customer responses affect overall system performance. Variations in operational conditions, such as unexpected changes in load demand or generator performance, are also accounted for. The IEMS algorithm includes adaptive mechanisms to dynamically manage load scheduling and generator dispatch based on real-time data inputs. This ensures the system can respond effectively to unforeseen operational challenges, maintaining grid stability and optimizing energy

Table 1
Comparison of Studies on Various EMS Frameworks.

Ref	PV Forecasting	SSM		DSM		Financial Analysis	GHG Emissions	CB
		PV	Generator Dispatch	TOU	DLC			
Srikranjanapert et al. [43]	×	✓	×	✓	×	✓	×	×
Harajli et al. [39]	×	✓	✓	×	×	✓	✓	×
Ali et al. [65]	×	✓	×	✓	✓	×	✓	×
Mahmud et al. [63]	×	✓	×	✓	×	✓	×	×
Kichou et al. [66]	×	✓	×	×	×	✓	×	×
Ozden et al. [60]	×	✓	×	×	✓	×	×	×
Rochd et al. [61]	✓	✓	×	✓	✓	×	×	×
Javed et al. [54]	×	✓	✓	✓	×	✓	✓	×
Candan et al. [55]	✓	✓	×	×	✓	×	×	×
Shreenidhi et al. [56]	×	✓	×	✓	✓	×	×	✓
Anusha et al. [67]	×	✓	✓	×	×	✓	×	×
George-Williams et al. [62]	×	✓	×	×	×	×	×	×
Dinh et al. [68]	×	✓	×	×	✓	×	×	×
Silva et al. [69]	✓	✓	×	✓	✓	×	×	×
Ochoa et al. [70]	×	✓	×	×	×	×	×	×
Sharda et al. [71]	✓	✓	×	✓	×	×	×	×
Tabrizi 2022 [72]	×	✓	✓	✓	×	×	×	×
This Study	✓	✓	✓	✓	✓	✓	✓	✓

usage. The techno-economic analysis conducted in this study will assess the economic viability of the IEMS and its potential to reduce CO_2 emissions. Additionally, various energy configuration mixes will be analysed to identify the most suitable configuration for PV integration, thereby improving energy efficiency and optimizing environmental outcomes. The framework for the proposed IEMS is shown in Fig. 1.

3. Methodology

While Fig. 1 gives an overall view of the proposed IEMS framework, Fig. 2 shows how the IEMS interacts with the power supply and the load. The flow of control starts from obtaining information from the generators and the weather stations. The outputs of this are the PV and generator plants generated power in real-time, and the hourly day-ahead PV generation forecast. The IEMS is then connected to the external power distribution network via smart meters and to the load via smart plugs or sockets. The smart meter enables the TOU tariff or load schedule to be set based on hourly predicted PV generation, while the smart sockets or plugs allow loads to be interrupted or rescheduled based on the dispatch strategy.

3.1. Three-step forecasting architecture

A three-step forecasting approach for forecasting PV generation is proposed. Using data from a local weather station as well as an on-site one, this method selects weather variables with moderate to strong positive correlation to solar radiation, using them to forecast the production of solar energy. The weather data from the two stations are combined by a technique called LLDF, which combines more than one source of raw data to produce new raw data [73]. The data is then normalized and separated into training and testing data samples. The training data sample is used as the input into MATLAB's machine learning toolbox called the Regression Learner App (RLA). The RLA, with a library of over twenty forecasting algorithms, selects the best-performing algorithm based on the lowest Root Mean Square Error (RMSE). This approach has been extensively analysed in [74]. A diagram of the proposed three-step forecasting approach is shown in Fig. 3.

In the first step, data recorded by the on-site weather station at Cranfield University comprising of nine meteorological parameters (inclusive of solar radiation) is combined into a correlation matrix with solar radiation as the independent variable due to its importance in PV generation. In the second step, the same solar radiation recorded by the

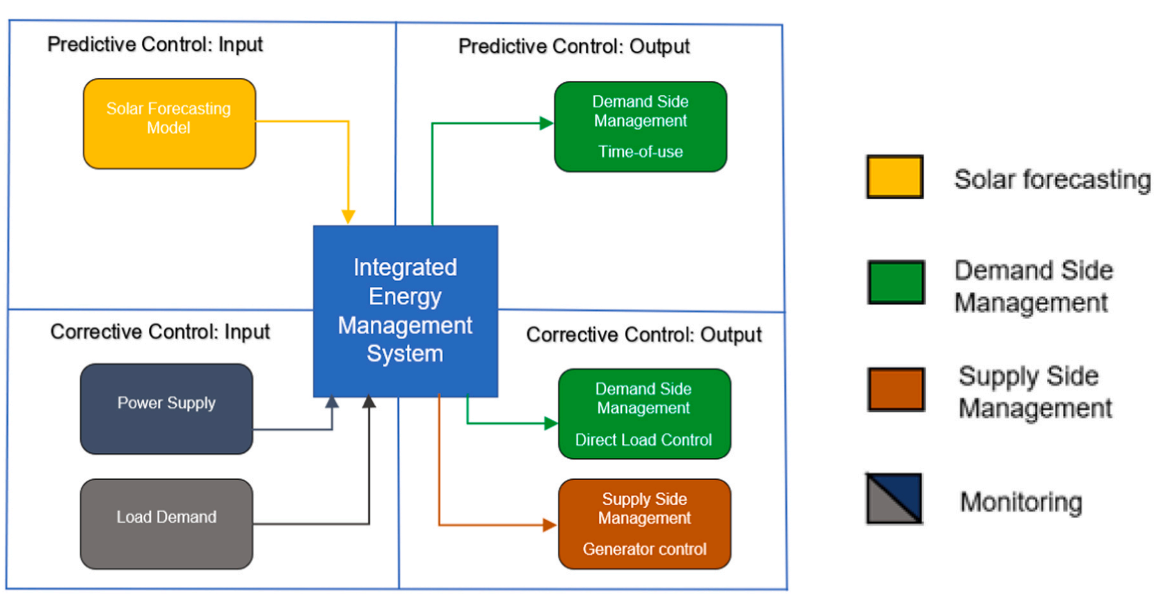

Fig. 1. Proposed integrated energy management system framework.

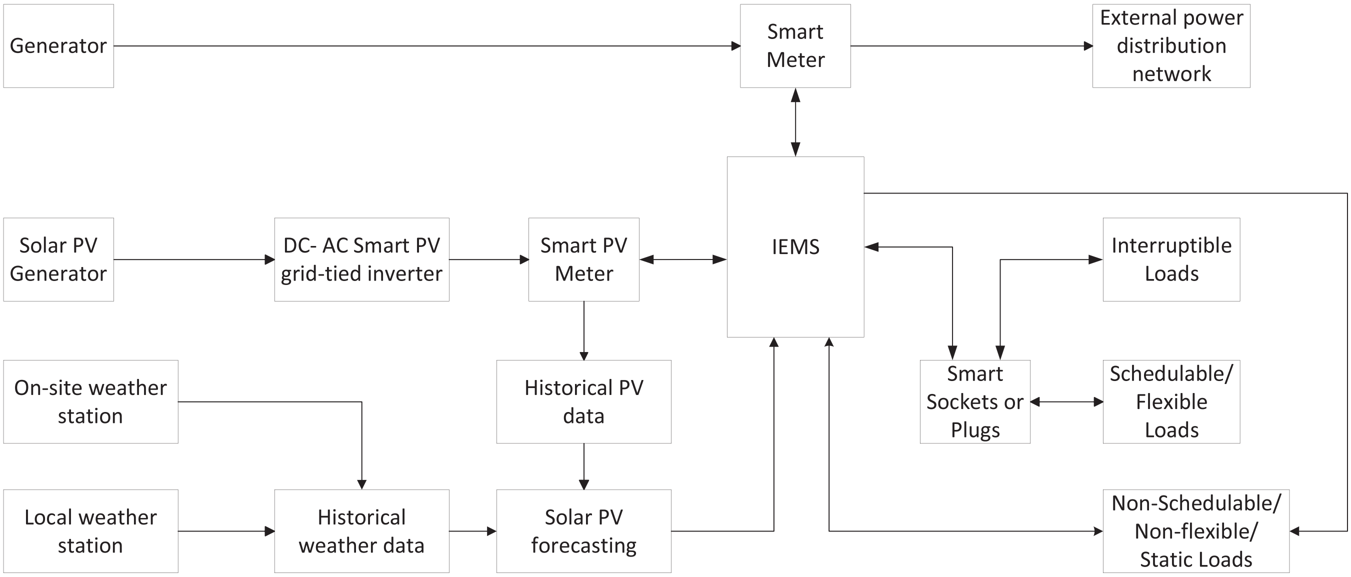

Fig. 2. Block diagram of proposed IEMS.

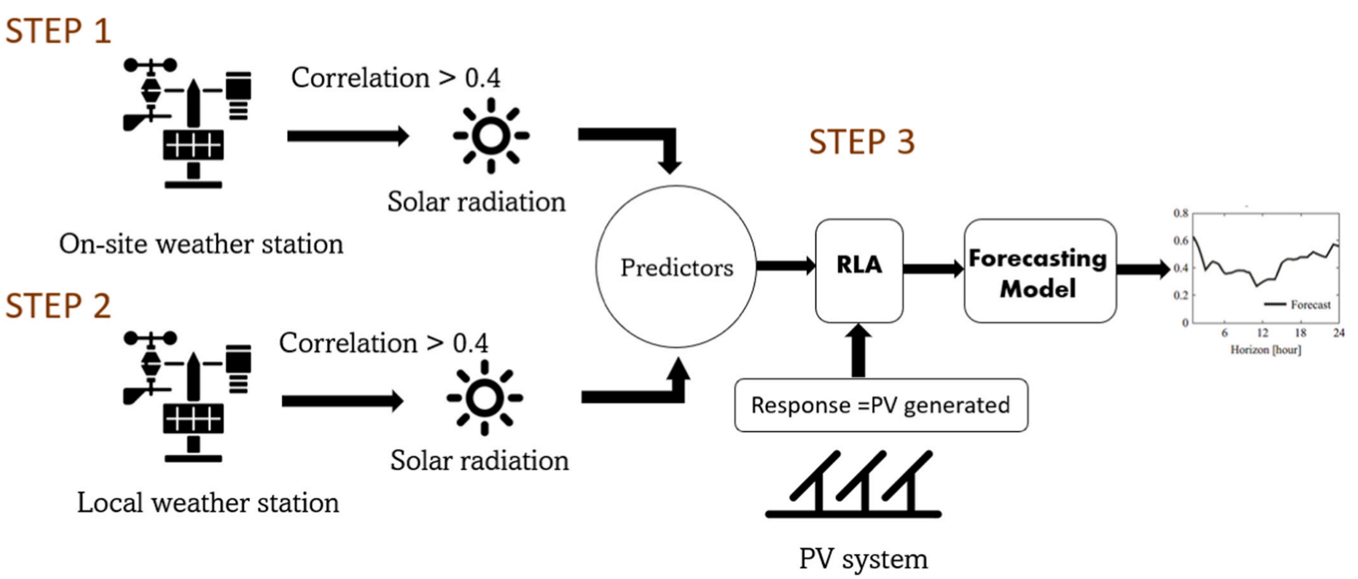

Fig. 3. Proposed three-step forecasting approach.

on-site weather station is selected as the independent variable and combined into a correlation matrix with twelve other meteorological parameters recorded by the Met Office Bedford station. In the final step, the meteorological parameters from both weather stations with moderate to strong correlations (> 0.4) are selected as forecasting model predictors. These weather parameters along with the PV generated become the inputs into the RLA.

3.2. *Financial forecasting tools*

3.2.1. *Discount factor*

The discount factor (DF) is a weighing factor that is multiplied by a future cash flow to express the latter in its present value.

$$DF_n = \frac{1-(1+r)^{-n}}{r} \tag{1}$$

3.2.2. *Net present value*

The total of the present values of all future cash flows is known as the net present value (NPV). NPV is a measure of the value that a project or investment contributes to a developer or business and is used to evaluate a project's profitability [75]. The higher the returns, the higher the NPV.

$$NPV = \sum_{t=0}^{n} \frac{Cf_n}{1+r^n} - C_0 = (I_n \times DF_n) - C_n \tag{2}$$

3.2.3. *Internal rate of return*

Internal rate of return (IRR) is used to compare or assess investment profitability [76]. IRR, or the rate at which NPV equals zero, is the discount rate at which the initial investment is equal to the present value of all future cash flows.

$$IRR \sim NPV = \sum_{t=0}^{n} \frac{Cf_n}{1+r^n} - C_0 = (I_n \times DF_n) - C_n = 0 \tag{3}$$

3.2.4. *Life-cycle cost analysis*

The life-cycle cost analysis (LCCA) considers the present value of all costs related to an investment over the course of its existence [77]. In other words, the overall cost of ownership over a known duration. This covers the acquisition expenses (capital cost, installation costs), the operations and maintenance costs (O&M), the fuel costs, the replacement costs, the conversion and/or the decommissioning costs at the end of the investment's life [78].

$$LCC = \sum_{t=0}^{n} \frac{[(C_n + M_n + F_n - R_n) - I_n}{1 + r^n} = C_n + \{(M_n + F_n) \times DF_n\} - (I_n \times DF_n) \tag{4}$$

3.2.5. Cost-benefit analysis

Prudent developers will perform a cost-benefit ratio (CBA) to assess all potential costs and profits that may be generated if the project is finished prior to building a new facility or taking on a new project. Typically, just the recurrent revenue is considered as the benefit when calculating a cost-benefit ratio (CBR).

$$CBR = \sum_{t=0}^{n} \frac{[(C_n + M_n + F_n - R_n) \div \quad I_n}{1 + r^n} = \frac{C_n + \{(M_n + F_n) \times DF_n\}}{(I_n \times DF_n)} \tag{5}$$

3.2.6. Payback period

The payback period (PP) is the duration required for an investment to generate sufficient income or cash to cover the initial investment's cost.

$$PP = \frac{Capital\ costs}{Annual\ savings} \tag{6}$$

3.2.7. Levelized cost of energy

The levelized cost of energy (LCoE) over the economic lifespan of a system is the proportion of the net present value (NPV) of the total investment (capital costs, fuel expenses, O&M costs) to the net present value (NPV) of the total electricity generated by the system.

$$LCoE = \frac{\sum_{t=1}^{n} \frac{I_t + M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}} = \frac{\{(M_t + F_t) \times DF_n\}}{E_t} \tag{7}$$

Where Cf_n is the future cash flow from period 1 to n, n is the time span, r is the discount factor or interest rate, C_0 is the initial cost of investment at time zero, C_n is the capital cost, M_n is the operations and maintenance cost, F_n is the fuel cost, R_n is the residual cost and I_n is the income. For the time period t, E_t is the electricity generation, I_t is the investment cost, F_t and M_t are the fuel and O&M costs respectively.

For a better understanding of the forecasting tools and their impact on a project, Table 2 has been adapted from definitions summarised in [79].

3.3. Dispatch strategies

The IEMS receives as its input a day-ahead solar forecast of the PV system from the proposed three-step forecasting architecture approach described in Section 2.1. Based on this forecast, it sets the TOU tariffs/ and or load schedule as the first level of control. The IEMS will notify the user through an Internet-of-Things (IoT) enabled environment during load peak periods or periods with low supply. The IEMS with the help of smart meter control, can do a combination of three things: set higher TOU tariffs to reflect periods of low PV supply, notify users about low and peak periods so that they can change/update load priority requests (manually schedule loads), or automatically schedule the load based on PV availability. By doing this, the PEMS function of the IEMS determines the operating schedule of shiftable and interruptible household appliances for the next 24 hours. This is then passed down to the CEMS, which adjusts the schedule due to forecast uncertainty and errors.

Table 2
Financial conditions and definitions.

Condition	Definition	Result
NPV > 0	Investment adds value	Project may be accepted
NPV < 0	Investment subtracts value	Project should be rejected
NPV = 0	Investment neither gains nor loses value	Project will break-even. Other criteria needed for decision
$IRR_2 > IRR_1$	Project 2 has a higher IRR than project 1	Project 2 is more desirable
LCCA > 0	Fails to generate net income	Project may be rejected
LCCA < 0	Generates net income	Project should be accepted
LCCA = 0	Breaks even	Adds no monetary value. Other criteria needed for decision
CBR > 1	Cost exceeds benefit	Project may be rejected
CBR < 1	Benefit exceeds cost	Project should be accepted
CBR = 1	Benefit equals cost	Adds no monetary value. Other criteria needed for decision
$PP_2 > PP_1$	Project 2 has a longer PP than project 1	Project 1 could be more desirable
Cost > LCoE	Electricity cost exceeds LCoE	Greater return on capital
Cost < LCoE	LCoE exceeds electricity cost	Lower return and a possible loss

For the CEMS, the dual monitoring of customer load and power supply levels serves as its input while GC and DLC are the output as shown in Fig. 1. The CEMS regulates the system by checking if the current demand is above the supply level. If this condition is met despite the TOU tariff, the CEMS decisive algorithm will turn-off appliances by using DLC to reduce the load based on customer's demand priority. This is the second level of control. For DLC, the IEMS will use a centralized controller connected to each distributed energy resource in the system via smart plugs or adapters for remote control and access. If this is still not sufficient to curtail the load and balance the supply and demand, then the back-up generator will be called upon to increase the supply. In summary, the IEMS priorities load and energy management before calling up additional supply. Fig. 4 shows the flowchart of the proposed IEMS.

For off-grid applications without storage, there must be a way to deal with excess or unused PV via dummy loads or by exporting to a local islanded network for consumption by other load sources. In this study, excess PV is exported toa local grid as can be seen in Fig. 4.

3.4. IEMS rule-based algorithm

3.4.1. Load dispatch algorithm

As seen in the flowchart in Fig. 4, the IEMS algorithm prioritises and maximises the use of PV before activating the generator. It initiates DSM before SSM. Once PV generation has been detected, the IEMS will compare the load and the PV. If the PV supply is less than the load, the IEMS will reschedule any flexible load. If the load is still greater, the IEMS will initiate DLC and de-activate any interruptible load. If this is still insufficient to reduce the load, then the generator is called as a back-up. The base load is the first to be powered, and along with the schedulable load, must always be powered during any 24-hour period. The interruptible load on the other hand does not always need to be powered. The power to this load is supplied by the DG when there is no PV and will only be powered by the PV if it is sufficient to power the daily total load.

3.4.2. Forecast error algorithm

Apart from generally scheduling the load and supply, the IEMS must account for the errors in the PV forecast prediction by adjusting the load schedule to suitable times of actual PV supply. To achieve this, the IEMS runs a high to low priority-based load schedule. It queues schedulable load from the highest kW to the least and assigns the highest schedulable load to the period of the highest predicted PV supply. It assigns the second highest schedulable load to the second highest hour of predicted

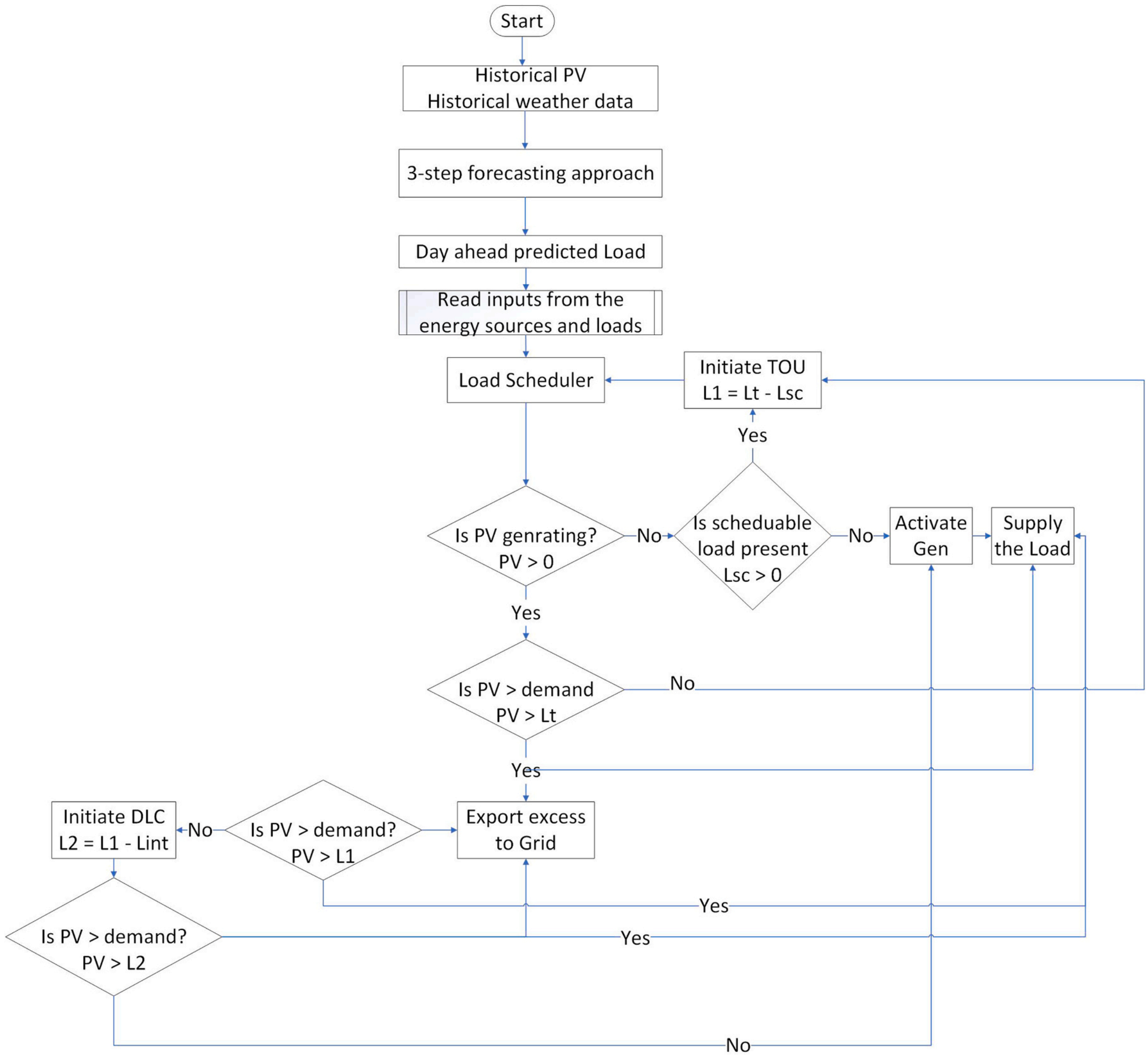

Fig. 4. Flowchart for proposed IEMS.

PV supply and so forth. The IEMS will concurrently look for the earliest time of excess PV and will initiate a schedulable load once the PV supply is sufficient to power both the base load and the schedulable load. In other words, the schedulable load may be powered at any earlier time before its scheduled time if there is enough PV supply to satisfy both the schedulable load and the base load. If there are no periods of excess PV prior to its scheduled time, then the schedulable load will be activated at its original time which is based on the predicted PV. The IEMS looks at the actual PV supply, checks to see if any of the queued loads can be deployed prior to its scheduled time, and will ultimately go back to the default schedule if the actual PV does not exceed the predicted PV. In addition, according to the block diagram in Fig. 2, the system is always collecting historical PV and weather data to improve the forecasting. The forecasting model takes the actual PV, adds it to it's database so the model can be re-trained with new data.

4. Case study

4.1. Data description

To generate the next day PV forecast, one-year historical weather data from both an onsite weather data station located in Cranfield and a local weather station located in Bedford, as well as one-year historical PV generation for a 10-kW PV system are obtained. One-year residential load is obtained through the use of an energy data logger. An energy or power data logger is an electronic device that records/logs or monitors electricity consumption, power quality and other power parameters over time. It is crucial in developing the load profile of a customer. In assessing the technical and economic feasibility of installing a hybrid green system for the school of engineering, University of Nairobi in Kenya, Eze et al. [80] uses a power and energy data logger to determine the building's load profile by monitoring the electrical power demand and consumption. Gerber et al. [81] uses a data logger to aggregate and store voltage and current data in a measurement-informed modelling to quantify and compare energy efficiency and power quality of buildings. The aim of the data logger in this case would be to identify and classify different loads and their time of operations. A data logger was used to obtain the energy consumption for the residential house. An example of the one-day load profile is shown in Fig. 5.

The daily load is categorized into base/non-schedulable load, schedulable/shiftable/TOU load, and interruptible/Curtailable/DLC load. Interruptible loads are loads that can be briefly switched off without causing the user too much discomfort [82]. Schedulable loads are those that can be moved to a more convenient time of operation based on TOU or because of user preference. They are also referred to as flexible or controllable [83]. Non-schedulable or base loads are the highest priority for the customer and cannot be scheduled, interrupted, or delayed. For this study, the plugged loads in Table 3 above, are the

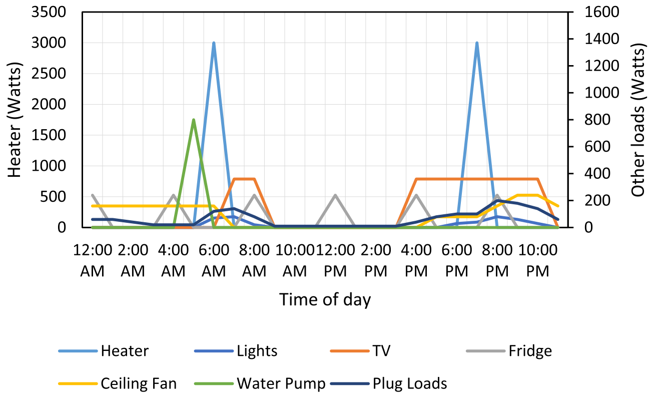

Fig. 5. One-day load profile of residential house.

Table 3
Load demand summary of residential house.

Load Type	Load	Ratings (W)	Quantity	Average operating time (h/day)	Total demand (Wh/day)
Base	Lights	10	8	6	480
	TV	360	1	8	2880
	Fridge	240	1	6	1440
	Ceiling fan	80	3	9	2160
Schedulable	Heater	3000	1	2	6000
	Water Pump	800	1	1	800
Interruptible	Plug Loads	200	Lump	9	1800
	Total	**4690**			**15,560**

interruptible loads, the heater and water pump are schedulable, and all others make up the base load. Table 3 gives the load summary along with the average operating times.

4.2. Financial and economic analysis

For these assumptions, costs will be reflected in 2023 prices based on inflation rates and the federal consumer price index (CPI) supplied by the International Monetary Fund (IMF) [84].

4.2.1. PV system

In this study, an installed 10 kW PV system acts as a back-up to a DG supplying a monthly average residential load of over 500 kWh. With the aid of a supply meter, daily half-hourly meter readings were taken for the entire year in 2019, and the average monthly PV output was determined to be over 432 kWh/month. The analysis will consider 20 years based on the life cycle of PV panels [77,78]. Two key terms that must be considered are the discount rate and discount factor. The discount rate determines the value of future cash flow, and it is affected by a country's present economic state [85]. According to literature, discount rate was found to be between 5 % and 7.25 % [86,87]. In this case study, the unlevered 6 % rate will be considered. According to IRENA, the average installed cost for PV worldwide in 2021 was $867/kW, or the equivalent of £8000 for a 10 kW PV system adjusted by CPI in 2023. A survey of several vendors revealed a range of between £11,000 to £14,000 [88–90] for the 10 kW PV system. For the purposes of this study, the average of £12,500 will be considered. According to a report by the Electric Power Research Institute (EPRI), the overall budget for PV O&M costs is between $10 to $45/kW-year. The report emphasises that for larger utility scale PV systems with a capacity of 1 MW and over, the O&M costs are approximately $10 to $25/kW-year and are cheaper than smaller units due to economies of scale. Ramasamy et al. [91] give the current benchmark of residential O&M costs without storage at $28.97/kW-year. With that in mind, we opt for an amount of $30/kW-year, adjusted with the CPI to £26/kW-year.

4.2.2. Diesel generator

The DG was selected based on the worst-case scenario of simultaneously running all the loads at the same time. From Table 3, this amounts to approximately 5 kW, or 6.25 kVA using the common industry standard power factor of 0.8 [92]. As the primary source of power, the generator is sized using about 80 % of its capacity and should be capable of powering the entire load without back-up. With this design consideration in mind, a 7.5 kVA generator is selected. In terms of cost, several estimations are made based on the DG's capacity. For a 48-kW DG, Das and Zaman [93] list the capital cost as $370/kW, replacement cost as $296/kW and O&M costs as $0.05/h with a lifetime of 15,000 h. In a similar cost and price breakdown, Kumar et al. [94] gives the costs as $665/kW, $535/kW, $0.027/h with a lifetime of 15,000 h. Ghenai and Bettayeb [95], give the capital and replacement costs of a 100 kW generator as $300/kW, O&M costs as $0.01/h, fuel cost as $0.6/litre with a lifetime of 15,000 h. In another study by Ismail et al. [96], the capacity of the DG considered is 7.5 kW and the associated capital cost, fuel cost and fuel inflation rate are $550/kW, $0.6/litre and 5 % respectively. The above is closer to our rated generator sizing and therefore the capital cost is estimated as £400/kW and replacement cost is £300/kW. The fuel consumption loading is derived from Greaves power generator specification sheet [97]. The diesel CO_2 conversion factor for an average biofuel blend usually obtained from a filling station forecourt is obtained from the UK government website [98]. On 23/05/2023, the daily cost price for ultra-low sulphur diesel fuel [99] was obtained, while an average of the half-hourly PV export rates [100] was also obtained.

4.2.3. DLC/TOU programs

DLC and TOU programs use tariff discounts/credits to incentivize customers to remotely shut-off or reschedule their load to an off-peak period. According to a report by the Rocky Mountain Institute [24], DLC programs are typically applied to residential and commercial customers with less than 100 kW demand. Most frequent DLC loads that are controlled are air conditioners (ACs) but may also include water heaters and pool pumps. DLC programme incentive schemes usually consist of a one-time participation payment in addition to fixed monthly payments that are credited to the customer's utility bill. In a study by Kaczmarski et al. [101], the median willingness-to-accept was $9.50 per month through the summer, or approximately $30 per year with a confidence interval of 95 %. This is similar to a DLC program like PNM Power Saver in New Mexico that offers $25 per year. In another study by Xu et al. [102], utility providers in the United States offer $25 to $100 per year, $5 to $20 per month, or 3 cents to $1 per kWh saved. In a survey of 1482 residents, the authors proved that a $30 per year incentive boosted accepted rates into the DLC program. In this case study, a benchmark price of £25 per year will be used for the Plug loads when there are no overrides to the schedule between the periods of 5 am to 5 pm (DLC period). The penalty for non-compliance in overriding the DLC command is at the discretion of the utility operator. For example, during an emergency event, Xcel Energy in Colorado gives a dollar fine of half the annual credit multiplied by the amount of the online load that is in excess of the contractual interruptible load [24]. In our case, we choose to half the yearly credit for overrides above 10 %.

For TOU credits, utilities may offer discount on the normal electricity tariff based on the type of peak period (high, mid or low) or even offer a flat fee based on time of consumption or the consumption profile [103]. For off-peak TOU costs, the Rocky Mountain report cited earlier gives examples of 5 % bill reduction and a $0.10 per kWh for schedulable loads. In a survey of 6 utility providers in the UK, the difference between the peak and off-peak rates for the "Economy 7" electricity tariff for residential customers was 54 %. The significant difference helps to incentivize customers to move their bulk load to off-peak periods. With this in mind, we consider a discount of £0.2 per kWh for any load rescheduled to the off-peak period between 5 am and 5 pm (same as DLC period). The choice of this time-period coincides with PV generation, encouraging customers to operate the bulk of their load (schedulable load) using PV. The total daily schedulable load is 6.8 kWh, which multiplying by £0.2 per kWh equates to a saving of £496 per year.

The Difference between the DG/PV and the DG/PV/IEMS configurations is the IEMS controlled DLC technology for remotely shutting down and rescheduling the load. For our case study, the prices were provided by a leading industry player and include a supervisor (£1100) connected to a gateway hub (£155) that provides the control to the smart sockets. The 200 W plug loads will be spread across 5 smart sockets or 10 outlets (£645). Add an installation cost of £300 and the total cost sums up to £2200.

4.2.4. Customer behaviour factors

In a study of 6389 households across 21 U.S states and a Canadian province [104], the data showed a mean thermostat override rate of 12.9 %. We assume a similar override rate of 14 %. Analysing the use patterns of interruptible and schedulable loads based on our historical profile data, an 80 % preconditioning rate and 20 % rebounding rate were proposed rather than reverse used by Pal et al. [105]. Fig. 6 shows what the DLC/TOU program looks like while Table 4 has a summary of the assumptions broken down into monthly rates for analysis purposes.

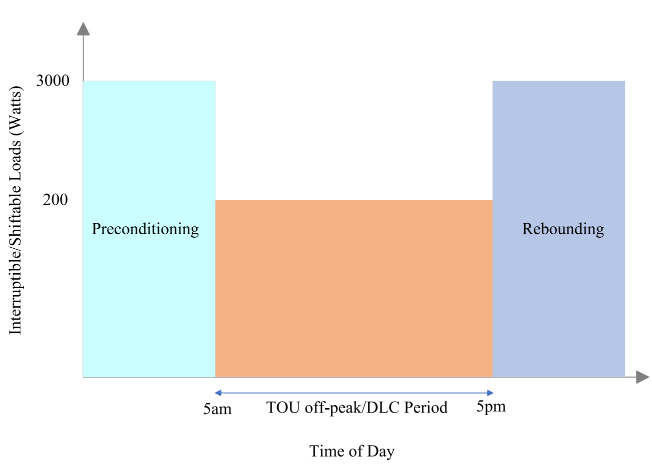

Fig. 6. Demand load control/time-of-use program.

Table 4
Parameter assumptions.

Item	PV	DG
Capacity	10 kW	7.5 kVA
Average monthly output	323 kWh/Month	509 kWh/Month
Capital cost	£12,500.00	£400/kW
DLC equipment	£2200.00	
O & M cost	£2.17/kW-month	£0.14/hour
TOU off-peak discount	£0.2 per kWh	
TOU off-peak/DLC period	5 am – 5 pm	
DLC credit	£2.08/month	
Load override rate	14 %	
Preconditioning rate	80 %	
Rebounding rate	20 %	
Discount rate	0.5 %/month	
Lifespan	240 months	15,000 h
Replacement cost		£300/kW
Fuel cost (diesel)		£1.516/litre
Fuel consumption		100 % load = 2.6 (ltr/hr)
		75 % load = 2.3 (ltr/hr)
		50 % load = 1.8 (ltr/hr)
		25 % load =1.4 (ltr/hr)
Grid export	£63.62/MWh	
CO2 conversion factor	0.0	2.51 kgCO_2e/litre

5. Results and discussion

To evaluate which of the configurations is better, several variables must be determined. Firstly, the monthly load and PV supply for the residential house for the year 2019 is obtained. In the DG/PV configuration, the yearly PV generation is subtracted from the load to determine the share of DG supply. For the DG/PV/IEMS configuration, the IEMS algorithm highlighted in Section 2.4 determines the DG and PV supply outputs. Table 5 provides the results.

5.1. Percent share of DG and PV loads

Table 5 shows that DG/PV has a higher combined load generation output (energy supplied from both DG and PV) than the DG/PV/EMS configuration. This is because the IEMS shuts down some interruptible loads without rescheduling them. In addition, the IEMS reduces the yearly generator output by about 28 %, leading to reduced CO_2 emissions and fuel costs. Even more importantly, the IEMS improves the yearly PV usage of the DG/PV configuration by more than 113 %, thus achieving the overall aim of integrating more PV into the grid system. Fig. 7 gives some further insight into the impact of the IEMS on the system.

The first graph of Fig. 7 displays the PV generation for the selected day with peak periods between 7 am and 12 pm. In the second graph showing the DG/PV configuration, the DG follows the load closely and is mostly supplemented by PV. Even though there is excess available PV generation between 7 am and 12 pm, the major load consumption occurs outside this time frame, between the hours of 4–7 am and 5 pm – 9 pm. This means that the excess PV must be exported. In the final graph, the IEMS shifts the load peaks to better coincide with the maximum PV generation. As a result, there is an increase in load usage as can be seen by the bigger load peaks during 7 am and 12 pm. In addition, these shifted loads are increasingly being powered by PV.

5.2. Forecast accuracy and algorithm error correction

Despite slight differences between the hourly forecast and the actual PV generated, the 3-step forecasting algorithm was able to accurately predict when the highest PV generation occurred and correctly assign the heater and water pump to those times. This means that the loads with the highest consumption were powered by PV. In the future, network operators can incentivize customers to schedule their load this way so that the bulk load is shifted to periods of the highest PV generation, thereby reducing CO_2 emissions. Lastly, the forecast error correction algorithm deployed the schedulable load earlier 40 % of the time, with the 800 W water pump making up the majority. This significant number of times proves that the error correction is effective and useful. Scheduling loads early only occurs when the PV Plant can power the shiftable load more than once a day. In our case, this occurs when the PV plant can generate more than 3000 W or 800 W multiple hours in a day.

5.3. Lifetime expenditure and CO_2 emissions

To determine the fuel costs, the data logger is used to record the hourly load consumption and conversely, the operating hours of the DG can be estimated. The DG loading percentages from Table 4 are applied based on the operating hours, and the amount of fuel used each hour can then be determined. The PV export is simply the share of the PV supply not consumed by the load. As this system does not have any storage, the PV is exported to a local islanded grid. Table 6 provides the results.

Again, Table 6 shows the yearly PV export of the DG/PV/IEMS configuration is about 38 % less than the DG/PV configuration mainly because the IEMS prioritises using PV before exporting it. To further

Table 5
Consumption comparison between DG, DG/PV, and DG/PV/IEMS configurations for a residential house in 2019.

	DG		DG/PV			DG/PV/IEMS		
Month	**DG Load (kWh)**	**DG hrs**	**DG Load (kWh)**	**PV Load (kWh)**	**DG hrs**	**DG Load (kWh)**	**PV Load (kWh)**	**DG hrs**
Jan	734.61	744	674.84	59.78	656	602.99	97.61	629
Feb	590.08	672	513.97	76.11	527	396.08	166.08	506
Mar	487.94	744	434.33	53.61	436	287.34	183.33	418
Apr	446.91	720	372.75	74.17	454	237.87	198.37	467
May	485.81	744	333.74	152.08	434	203.27	275.14	447
Jun	470.14	720	316.15	153.99	399	208.68	268.37	390
Jul	485.81	744	323.49	162.32	403	171.84	312.87	394
Aug	485.81	744	350.24	135.58	434	191.00	290.12	416
Sep	455.85	720	358.82	97.03	450	227.52	219.97	450
Oct	485.81	744	419.83	65.99	434	308.82	162.69	416
Nov	455.85	720	421.45	34.40	420	359.42	79.37	403
Dec	485.81	744	465.28	20.54	434	400.75	63.36	416
Total	6070.44	8760	4984.88	1085.58	5481	3595.59	2317.28	5354
Average	505.87	730	415.41	90.47	457	299.63	193.11	446

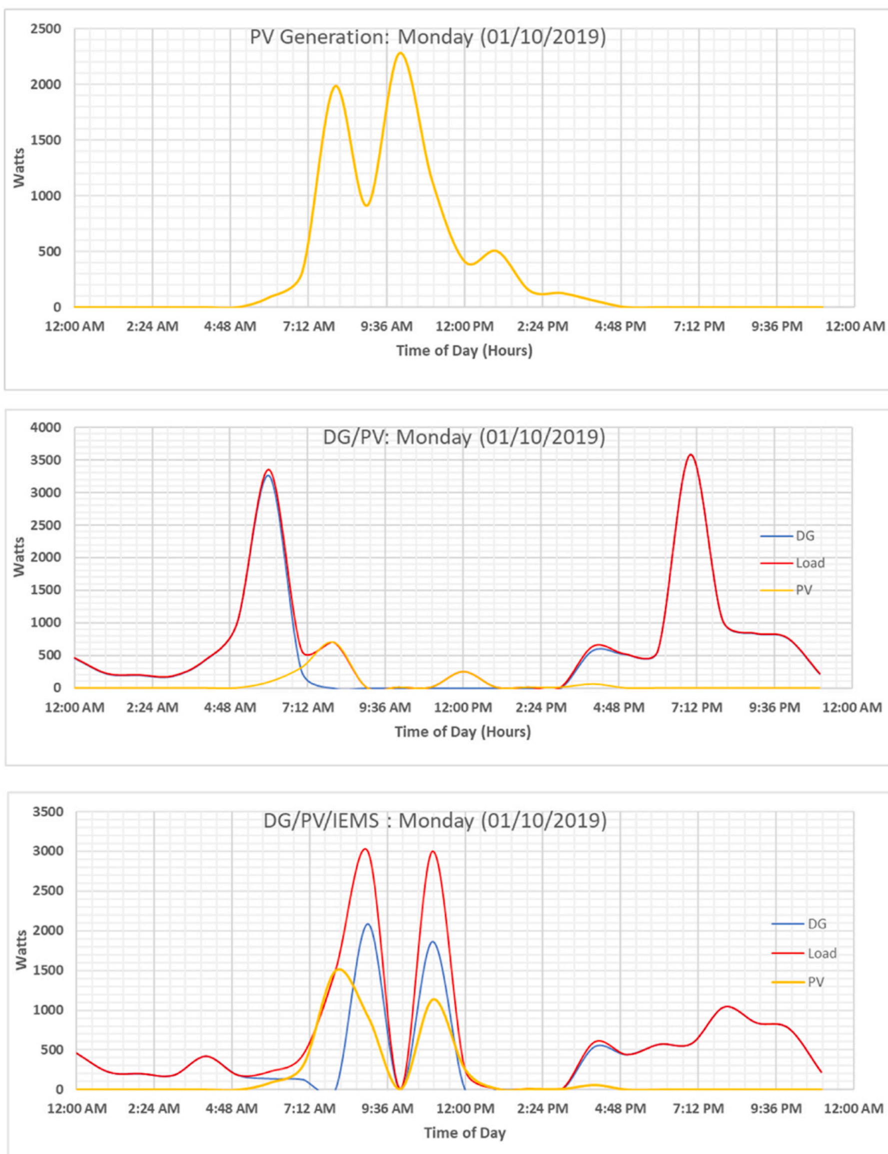

Fig. 7. Comparison of DG/PV and DG/PV/IEMS configurations servicing the load.

Table 6
Fuel comparison between DG, DG/PV, and DG/PV/IEMS configurations.

	Gen	DG/PV		DG/PV/IEMS	
Month	Fuel (L)	Fuel (L)	PV Export (kWh)	Fuel (L)	PV Export (kWh)
Jan	1153.20	689.51	39.13	612.07	1.30
Feb	1014.80	606.76	513.97	538.62	56.25
Mar	1101.39	658.53	277.54	584.57	147.57
Apr	1064.57	690.43	344.75	662.57	219.57
May	1101.39	651.00	498.73	626.20	374.40
Jun	1065.86	602.14	470.56	554.57	353.79
Jul	1101.39	608.04	633.94	551.80	480.90
Aug	1101.39	658.53	514.54	584.57	358.78
Sep	1065.86	683.57	463.17	639.43	339.83
Oct	1101.39	658.53	257.29	584.57	160.59
Nov	1065.86	637.29	153.53	565.71	108.56
Dec	1101.39	658.53	98.28	584.57	55.46
Total	13,038.46	7802.85	4265.44	7089.26	2657.00
Average	1086.54	650.24	355.45	590.77	221.42

evaluate the performance of the IEMS, both configurations are analysed against the base-case scenario. The base-case scenario involves using only a DG to supply the load. The DG is assumed to supply the load 24 hrs a day, throughout the whole year. Since it will be detrimental for the DG to supply uninterrupted power for every hour of the year, two set of DGs are considered; one for night loads and one for day loads. By using the assumptions of Table 4, the capital cost is calculated as £6000. While this is far below the capital costs of the two other configurations, the DG is significantly higher in replacement costs, fuel costs and conversely overall lifetime expenditure. It also gives significantly higher CO_2 emissions over the system lifespan. The Scope 1 emissions, which are direct emissions generated by sources owned by the user, is calculated by multiplying the CO_2 conversion factor by the total litres of fuel in the year, and the system lifespan which is 20 years.

The replacement cost is calculated based on how many times the DG needs to be replaced in 20 years based on a 15,000 h-lifespan. To calculate this cost, the total lifespan of the DG, the replacement cost rate from Table 4 and the total yearly output from Table 5 are needed. Table 7 provides the results.

The fuel costs, replacement and O&M costs sum up to the lifetime expenditure cost of each configuration. However, the PV component of the O&M cost is determined by multiplying the O&M cost rate with the PV capacity and the DF. The DF is calculated by using Eq. 1 and determined to be 139.581. It is important to note that the DF considers the entire lifetime of the system and scales it to a monthly multiplier. Fig. 8 shows a visual representation of the costs.

In Table 7 and Fig. 8, DG/PV/IEMS's performance in comparison to DG/PV and DG shows a reduction of about 8 % and 44 % in lifetime expenditure costs, and a reduction of about 9 % and 46 % in CO_2 emissions respectively. To determine which of the two hybrid configurations should be selected, additional parameters need to be considered. With the data from Table 7 and the assumptions from Table 4, we can begin to evaluate the financial forecasting tools highlighted in Section 2.2.

Table 7
Cost, Output and CO2 emissions comparison between DG, DG/PV, and DG/PV/IEMS configurations.

Costs & CO_2 (System lifetime)	DG	DG/PV	DG/PV/IEMS
Capital costs	£6000.00	£15,500.00	£17,700.00
O&M costs	£24,528.00	£18,376.67	£18,269.19
Replacement costs	£26,280	£16,444.04	£16,061
Fuel costs	£395,326.02	£236,582.49	£214,946.33
CO_2 Emissions	654,531 kg CO_2e	391,703 kg CO_2e	355,881 kg CO_2e

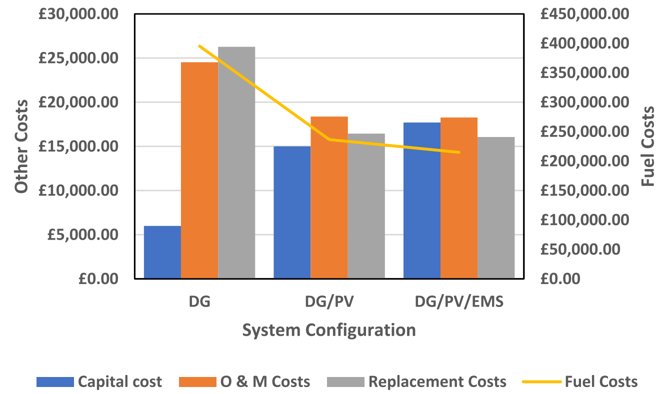

Fig. 8. Cost comparison of DG, DG/PV, and DG/PV/IEMS configurations.

5.4. *Techno-economic analysis*

Two separate analyses are done with and without the impact of CB. In the fully automated scenario, the lifetime net income is calculated by multiplying the income or savings by the DF. The savings/incoming is derived by subtracting the lifetime expenditure of each configuration from the base case. Additional income is generated through energy exported to the grid, the off-peak TLC and DLC rates, and savings from the replacement costs. For instance, in 20 years, the generator in the base case would need to be changed 12 times based on a 15,000-hour lifespan whereas in both hybrid configurations, the generator will be changed 7 times. The difference between the replacements costs is considered a savings. The sum of the average monthly PV output supplied to the load and the monthly PV export, multiplied by DF, makes up the lifetime PV generation. This is then added to the DG lifetime output to make up the lifetime net electricity generation.

To investigate the impact of CB, we run the same analysis mentioned above but include assumptions made in Section 3.2.4. A 14 % override is applied to the automated TOU schedules (heater and water pump). Out of the 14 %, we ensure that 80 % of the load occurs from 12 am to 5 am (precondition) and the other 20 % occurs from 5 pm to midnight (rebound). We also do the same for the DLC plug loads. By using Eqs. (2) to (7), Table 8 provides the comparison outcome using the financial forecasting tools.

According to Table 8, the DG/PV/EMS without CB outperforms DG/PV and DG/PV/IEMS with CB in seven out of the nine categories. Although the DG/PV/EMS with CB outperforms DG/PV in six out of nine categories, it is outperformed by DG/PV/EMS without CB confirming that overrides can reduce the value and objectives of the DLC program [106]. Comparing these results to Table 2, three indicators highlighted in red show unfavourable results. The LCCA, CBR, and LCoE all suggest that both configurations should be rejected. The LCCA should be less than zero, the CBR should be less than 1 and the LCoE should be close to or comparable with the average residential electricity rate. Currently, the annual cap of household energy prices in the UK is £2500, or the equivalent of 34.0p/kWh [107]. This is way less than the calculated prices of £1.68/kWh and £1.92/kWh. An explanation is that as Fig. 8 suggests, DGs used as the primary supply source are always associated with high maintenance and fuel costs. In the end, the DG/PV/EMS without CB is the most favourable investment to make, earning the most income and savings with the least expenditure and CO_2 emissions over the project's entire lifetime.

Despite some cost limitations, the proposed IEMS holds significant policy relevance across broader themes of energy, sustainability, security, and social welfare. By achieving high utilization levels of PV, the IEMS reduces GHG emissions while supporting the transition to a cleaner grid. As energy security and independency becomes an urgent agenda for many world governments, solutions like the IEMS will be crucial in diversifying energy sources and enhancing grid resilience

Table 8
Techno-economic analysis of DG/PG and DG/PV/IEMS configurations.

				Performance		
	DG/PV	DG/PV/IEMS Without CB	DG/PV/IEMS with CB	DG/PV	DG/PV/IEMS without CB	DG/PV/IEMS with CB
Lifetime expenditure	£271,403.21	£249,276.55	£252,537.35		✓	
Lifetime net income	£177,886.29	£204,887.85	£200,782.84		✓	
Lifetime net electricity generation	161,939 kWh	129,771 kWh	137,834 kWh	✓		
PP	1.74 years	1.73 years	1.76 years		✓	
NPV	£162,386.29	£187,187.85	£183,082.84		✓	
LCCA	£109,016.92	£62,088.69	£69,454.52		✓	
CBR	1.61	1.30	1.35		✓	
LCoE	£1.68/kWh	£1.92/kWh	£1.83/kWh	✓		
CO2 Emissions	391,703 kg CO2e	355,881 kg CO2e	361,130 kg CO2e		✓	

against natural disasters, cyber-attacks, and other disruptions. Additionally, by augmenting DSM, the IEMS creates transparency and accountability for energy users by increasing customer participation and ownership. Policy makers can experiment with different DSM packages to ensure energy access is extended to underserved areas while promoting energy equity for all. Ultimately, the attractive preposition of grid stability, reliability, and energy efficiency, will lead to lower energy costs, which makes IEMS attractive for policy makers and energy regulators.

6. Conclusion

This paper proposes an innovative integrated energy management system engineered explicitly for off-grid solar applications, amalgamating advanced solar energy forecasting, time-of-use tariffs, generator control, and direct load control. This comprehensive framework addresses the critical necessity for enhanced efficiency and dependability in energy management within regions isolated from traditional grid systems. By innovatively implementing a three-step solar forecasting model that capitalises on low-level data fusion and selective regression analysis from diverse meteorological stations, the study significantly bolsters the predictability and reliability of solar energy supplies, which is paramount for productive power management. The utilization of rule-based algorithms to control both supply and demand assets effectively balances the power system without computational complexities. The contributions of this research not only refine the methodologies associated with solar energy forecasting but also broaden the practical applications of integrated energy management system in optimising the utilisation of photovoltaics and diesel generators to meet energy demands sustainably.

The findings from this exploration underscore the efficacy of the integrated energy management system in diminishing operational costs and carbon dioxide emissions, as evidenced by a meticulous techno-economic evaluation. The optimised hybrid configuration of diesel generator/Photovoltaics/Integrated energy management system exhibited substantial reductions in lifetime expenditure costs and CO_2 emissions compared to conventional setups, underscoring the dual advantages of integrating cutting-edge forecasting and management technologies in energy systems: economic feasibility and enhanced environmental sustainability. Specifically, the diesel generator/photovoltaics/integrated energy management system configuration showed a 44 % reduction in lifetime expenditure costs, a 46 % reduction in CO_2 emissions compared to diesel generator alone, and an 8 % and 9 % reduction compared to diesel generator/photovoltaics respectively. Furthermore, the integrated energy management system showed a higher annual PV usage of 2317 kWh compared to 1086 kWh from the diesel generator/photovoltaics configuration, achieving the goal of maximising and increasing PV penetration. The techno-economic analysis revealed that the lifetime net income for the diesel generator/photovoltaics/integrated energy management system configuration without customer behaviour considerations was £204,887.85, compared to £177,886.29 for diesel generator/photovoltaics alone. Additionally, the diesel generator/photovoltaics/integrated energy management system configuration without customer behaviour resulted in a Net Present value of £187,188, compared to £162,286 for diesel generator/photovoltaics, suggesting the former adds more value to the owner.

However, some limitations remain of the proposed Integrated Energy Management System. The current Integrated Energy Management System model predominantly focuses on specific meteorological conditions and may not universally apply to all geographic locations or unforeseen atmospheric variations, potentially curtailing its broader applicability. Future endeavours could focus on adapting the forecasting model to encompass various environmental scenarios and testing the system's resilience against unpredictable climatic conditions. Moreover, augmenting the system's capacity to integrate real-time data inputs would allow for more dynamic and responsive energy management. Additional renewable resources, such as wind or hydropower, could provide a more complete approach to sustainable energy solutions in off-grid systems. These advancements would amplify the system's operational effectiveness and extend its applicability to a myriad of off-grid energy challenges across the globe.

Funding

This research was supported by the Petroleum Technology Development Fund (PTDF) [PTDF/ED/OSS/PHD/TOF/1945/20].

CRediT authorship contribution statement

Tolulope Falope: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Liyun Lao:** Writing – review & editing, Supervision. **Da Huo:** Writing – review & editing, Supervision. **Boyu Kuang:** Writing – review & editing.

Declaration of Competing Interest

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

Data Availability

Data will be made available on request.

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2024-09-01

Falope TO, Lao L, Huo D, Kuang B. (2024) Development of an integrated energy management system for off-grid solar applications with advanced solar forecasting, time-of-use tariffs, and direct load control. Sustainable Energy, Grids and Networks, Volume 39, September 2024, Article number 101449
https://doi.org/10.1016/j.segan.2024.101449