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ABSTRACT

Industrial plants should implement sophisticated renewable-energy-based distribution systems to guarantee a continuous and reliable power supply and enhanced operational efficiency under varying loading conditions. A Flexible Power Supply and Distribution System (FPSDS) utilize the concept of Flexible Distribution Networks (FDN) for photovoltaic-contracted tobacco warehouse facilities. The integrated power system connects PV panels to a multi-port bidirectional DC-DC converter, which operates with a BESS and a full-bridge PWM inverter to provide bi-directional energy management and increased power reliability. The system achieves enhancement by integrating three control mechanisms, which include DLD for real-time energy distribution, IPR for loss minimization and Multi-Agent Deep Reinforcement Learning (MADRL) for adaptive system optimisation. The system manages dynamic voltage and power regimes and current movements through predictive behaviour prediction, which utilizes Model Predictive Control (MPC). Simulation results demonstrate enhanced electric power management that leads to better voltage systems alongside lower transmission losses and superior peak demand control. Such a solution enables both real-time capabilities and scalability benefits while enhancing operational durability and suits warehouses with energetic systems that function dynamically. The research creates a smart solution to incorporate renewable power sources within logistics operations that builds sustainable energy frameworks for decentralizing power systems. The proposed system introduces an integrated control framework combining Dynamic Load Distribution, Intelligent Power Routing, and Multi-Agent Deep Reinforcement Learning within an FDN for photovoltaic-integrated warehouses. The approach demonstrates a 15%–20% reduction in transmission losses, a 12%–18% increase in overall energy efficiency, and improved voltage stability by maintaining deviations within 5%. These results confirm the novelty of this research in achieving adaptive, intelligent, and scalable power distribution for logistics facilities.

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1 Introduction

Photovoltaic (PV) systems, among renewable energy resources, demand a highly advanced distribution system for efficient and stable energy management requirements. Regular power distribution networks have unidirectional power flow characteristics, creating obstacles during the incorporation of distributed renewable energy sources (RES) because of bidirectional power flows and irregular generation patterns [1,2]. Logistics and warehouse activities need different amounts of energy every day between peak operational times and reduced energy consumption [3]. Smart distribution systems become necessary because energy requirements change substantially, which creates difficulties for management systems [4]. The FDN serves as an emerging solution that efficiently handles renewable power generation volatility and changing electricity demands according to [5,6]. The introduced research combines PV power generation technology along with energy storage features and peak load management through the implementation of a Battery Energy Storage System (BESS) [7].

Modern artificial intelligence (AI), together with machine learning (ML) techniques demonstrate potential improvements in smart grid energy management according to research presented in [8]. Current efforts to merge RES technologies into grids require strong advanced solutions to address numerous operational challenges [9]. Renewable energy generation's variable nature, along with its intermittent characteristics, creates supply-demand unalignments, which decrease the grid's reliability [10]. The existence of unreliable energy requirements and the integration of renewable energy systems pose a challenge to warehouse managers who seek to develop efficient energy management systems [11,12]. The modern world presents complex challenges to energies and modern solutions must be implemented due to the fact that some management tactics of the past might not work [13,14]. The other problem arises because electric vehicles (EVs) have a charging system that contributes to the instability of the grid [15]. Dynamical operational patterns of modern electric grid systems require unique flexible solutions to handle their changing behaviour. The implementation of DC microgrids performs better energy utilisation through the minimisation of conversion power losses, according to [16,17].

Several challenges in the existing literature have been observed by research scholars regarding the incorporation of RES in smart grids. One of them is the integration of effective energy management systems for managing the uncertainty and variability in renewable energy resources [18]. Ref. [19], the suggested integration of energy storage systems (ESSs) responds to the challenge of high penetration of renewable energy resources in power grids [20]. ESS technologies, such as mechanical, electrical, electrochemical, chemical, and thermal storage, improve grid stability and reliability [21]. Enhances flexibility in smart distribution networks (SDNs) [22]. A multiobjective model minimises the cost of energy, voltage deviation, and system flexibility with operation constraints in mind [12,23]. Uncertainty is addressed by a stochastic programming method, and the ε-constraint technique finds the optimal solution. Refs. [24,25] presented a two-stage optimisation model for scheduling microgrids and DFR with uncertainty. In the initial stage, the self-scheduling of the microgrid was optimised, whereas in the second stage, DSO calculated the optimal system setting to reduce deviations. Refs. [26,27] addressed photovoltaic energy scenarios in Chongqing and reviewed studies on solar-assisted heating systems for flue-cured tobacco processing. Distributed storage improves system flexibility and outlines measures for carbon reduction and energy saving in flue-cured tobacco rooms [28].

The novelty of this work lies in integrating Multi-Agent Deep Reinforcement Learning with Dynamic Load Distribution and Intelligent Power Routing within a Flexible Distribution Network for photovoltaic-based warehouses. The contributions include: (1) developing an adaptive and intelligent control framework for bidirectional power flow; (2) achieving measurable improvements in power efficiency and voltage stability; and (3) demonstrating scalability and applicability for real-world logistics energy systems.

The significance of the research goes beyond just the improvement of technology, as the flexible photovoltaic-integrated power distribution systems are indispensable in the world's sustainability measures. The FDN-based structure suggested by the authors is a step forward towards the reduction of greenhouse gas emissions and the betterment of the energy efficiency of the industrial warehouse operations, as it decreases the reliance on traditional fossil-fuel-based grid power. The combination of PV generation, BESS, and smart control devices not only helps produce cleaner energy but also reduces transmission losses and increases the percentage of renewable energy in everyday use. This is completely in line with the global aspirations of climate change mitigation, the adoption of eco-friendly energy systems, and long-term global warming control.

2 Literature Review

The development of renewable energy microgrids (REM) in logistics parks responds to sustainability issues in energy crises and climate change. A two-stage stochastic optimisation model is proposed in this paper to reduce investment and emergency operation costs in a REM-assisted cold warehouse. A PSO-based MPC algorithm optimises energy and inventory decisions, enhancing system resilience [29]. This paper suggests a peer-to-peer (P2P) multi-grade energy trading scheme to promote demand-side flexibility and deal with the uncertainty of renewable energy in distribution networks [30].

A reliability credit (RC) allocating method distinguishes between energy grades with considerations of supply reliability and consumption desires. suggested a hybrid Info-gap Decision Theory (IGDT)-stochastic strategy for self-scheduling a distributed energy resources (DER) aggregator in a multi-energy system (MES). The model incorporated renewable energy sources (wind, PV), combined heat and power (CHP), auxiliary boilers (ABs), EV parking lots, and thermal energy storage (TESs) with price-bas Industrial facilities must adopt new distribution systems for renewable energy to provide a reliable electricity supply while elevating operational efficiency and adapting to varying conditions. ed and incentive-based demand response (DR) programs for flexibility [31]. The problem of managing power at the warehouse is the variability of power demand, which means that the peak load must be managed with the help of AI-based forecasting. The problem of solar intermittency hinders the integration of renewable energy and necessitates the effective use of Battery Energy Storage Systems (BESS). IoT-based real-time monitoring produces enormous amounts of data, and they have to be backed by sophisticated analytics to allow actionable insights [32]. In addition, the control of the energy should be dynamic and adjust to the variation in operation to achieve maximum efficiency [33].

The comparative analysis of the reviewed studies demonstrates the gap in the integration of intelligent control plans and the FDNs, which are specifically oriented toward the warehouse photovoltaic systems. The majority of the existing literature deals with the completely isolated optimisation or hardware design without the applications of the dynamic adaptability and load management in the real time. Such a limitation directly translates into the given problem statement, which focuses on the necessity to have a flexible and smart energy distribution model to be applied to logistics warehouses.

Cannava et al. [34] reveal a novel AI-driven warehouse system that combines robots, NFC communication, MILP scheduling, and swarm coordination to increase efficiency and scalability. Their method serves as a roadmap to this research by showing that even in the case of automation, smart orchestration and optimisation can be powerful tools for system design.

Problem Statement

Use of renewable energy sources (RES), especially photovoltaic (PV) systems within the logistics and the warehouse operation pose a lot of challenges in the distribution of power. Traditional power distribution systems are hard and unidirectional, which renders them ineffective in controlling the bidirectional movement of power, energy changes, and peak load changes within a warehouse setup [35]. The PV generation brings about the instability of voltage and energy supply-demand discrepancies, which impact the reliability of logistics operations [36]. The current energy management systems find it difficult to successfully incorporate Battery Energy Storage Systems (BESS), optimise real-time power distribution, and maintain the energy flow in logistics warehouses without any issues.

3 Research Objective

The following are the objectives of the research:

1. Establish an elastic power supply and distribution network through the FDN to combine photovoltaic energy production and battery energy storage.
2. Adaptive energy management with the implementation of intelligent control mechanisms: Dynamic Load Distribution, Intelligent Power Routing, Multi-Agent Deep Reinforcement Learning.
3. Use the Model Predictive Control (MPC) to optimise the power flow and improve the stability.
4. The proposed system should be validated by simulation to show that this system helps reduce transmission losses, improve voltage stability, and increase scalability in photovoltaic-integrated warehouse operations.

4 Proposed Methodology

The proposed methodology is designed in a way that it impacts the set goals by incorporating photovoltaic production, bi-directional power conversion, battery storage, and controllable mechanisms. The stages of the process, such as analysis of energy demand to the Model Predictive Control, directly lead to efficiency improvement, system stability, and losses reduction as shown in the results section. The realisation of the FDN, which is combined with the Flexible Power Supply and Distribution System of the solar-powered warehouses that serve the logistics of tobacco, would be implemented through a planned approach to the creation of maximum energy control, increased power reliability and load adaptability. The methodology comprises energy demand assessment, FDN planning, energy storage management, power control and performance feedback as presented in Fig. 1.

4.1 Energy Demand Analysis

The best excise system of power supply to a tobacco logistics warehouse is renewable energy coverage via the flexible networks that bolster electrical stability. Such implementation involves using the Energy Demand Analysis tool that will define key features of power usage and enhance the efficiency of the distribution process by removing the inefficiencies that are not needed. The use of PV technology in combination with storage devices and the use of FDN can be seen to improve operational sustainability and reliability in the power supply of the warehouse in a significant way.

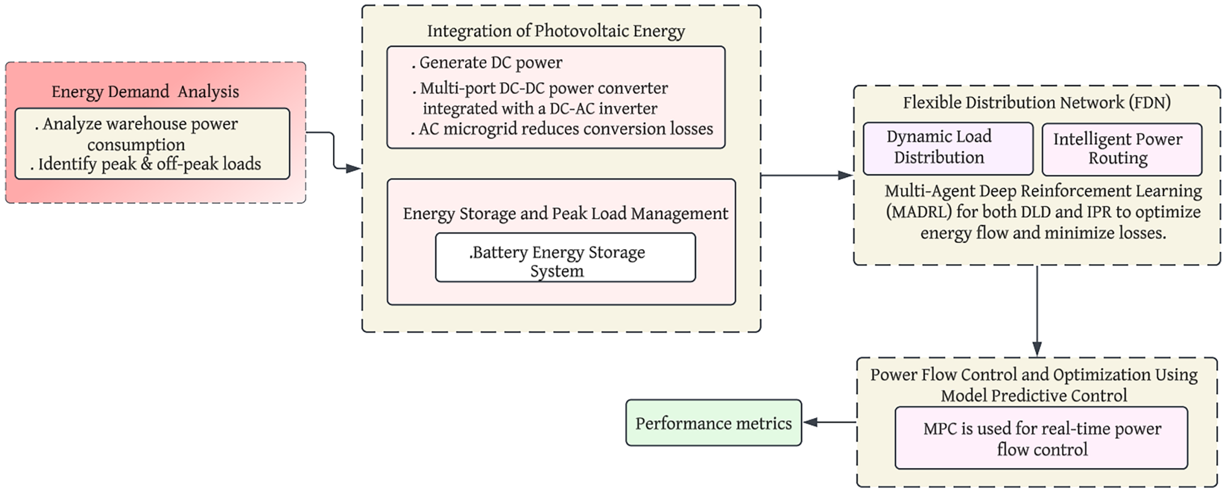


Figure 1: Architecture of flexible power supply and distribution system based on FDN for photovoltaic-integrated tobacco logistics warehouse

Ensuring the creation of an appropriate energy-saving plan is contingent upon the analysis of the entire power consumption data of the warehouse. The significant factors that constitute the total energy requirement are:

- ***Operational Hours:*** The logistical operation power is distributed over the peak time and countermeasure time in the sorting, packaging, and transportation services. High-activity operations implementation requires planned power distribution systems to eliminate power shortages.
- ***Climate Control Requirements:*** The heating, ventilation and air conditioning HVAC systems are operational at all times to maintain the perfect climate in tobacco storage rooms. A substantial portion of the general energy utilisation is in the energy systems.
- ***Energy Losses:*** The total energy losses are due to the inefficient transmission of power and conversion losses, in addition to the inefficiencies of the storage. The measures to reduce losses boost the overall system functionality.
- ***Seasonal Fluctuations:*** Power needs of tobacco processing operations vary with season due to occasional variations in the operations. An appropriate system must predict and modify its operation according to the changing demands to maintain its operational efficiency.

The energy consumption in the warehouse may be mathematically expressed as the total amount of energy that is required to be taken in by the warehouse:

$$P_{\text{total}} = P_{\text{storage}} + P_{\text{processing}} + P_{\text{HVAC}} + P_{\text{auxiliary}} \tag{1}$$

where:

P_{storage}—Power needed for tobacco storage temperature/humidity control.

$P_{\text{processing}}$—Power consumption for sorting, packaging, and logistics operations.

P_{HVAC}—Energy demand for climate control.

$P_{\text{auxiliary}}$—Load contribution from lighting, monitoring, and security systems.

The new system would apply real-time monitoring parameters that have predictive analytics to provide correct demand forecasts, peak load management and high efficiency. The deployed analytical structure allows the warehouses and their implementation of renewable power packages alongside battery storage facilities, hence developing a sustainable power control program. This discussion aids Objective 1 because it establishes the best patterns of power distribution in the PV-integrated warehouse operations.

4.2 Integration of Photovoltaic Energy

A photovoltaic (PV) grid-connected system should be used to enhance the energy efficiency of the tobacco logistics warehouse. The generation of solar power, storage and distribution of solar power, as well as making it possible to utilise the maximum solar resources in a system. The role of this stage contributes to Objective 1 to maximise the use of solar energy and provide renewable power with stability.

4.2.1 Solar Panel in Tobacco Logistics Warehouse

The primary conversion in the Flexible Power Supply and Distribution System includes solar panels that transform solar energy into usable power and can be utilised in a practical manner. The photovoltaic (PV) panel has a number of silicon-based semiconductor PV cells that generate direct current (DC) electricity through the application of photovoltaic characteristics.

- Solar Irradiance (G_{solar}): The intensity of sunlight received per square meter, which varies based on location, time of day, and weather conditions.
- Temperature Sensitivity: Excessive heat can reduce PV efficiency due to an inverse temperature coefficient in silicon-based solar cells.
- Shading and Obstructions: Nearby objects such as buildings, trees, or dust accumulation can limit sunlight absorption, reducing overall energy output.
- Panel Orientation and Tilt Angle: Proper alignment and inclination of panels ensure maximum sunlight capture throughout the day.

The total power output from the solar panels is mathematically expressed as a

$$P_{\text{pv}} = G_{\text{solar}} \times A_{\text{pv}} \times \eta_{\text{pv}} \tag{2}$$

where:

P_{pv} = Total power output of the PV system.

G_{solar} = Solar irradiance $\left(\mathrm{W/m^2}\right)$.

A_{pv} = Total surface area of the solar panels $\left(\mathrm{m^2}\right)$.

η_{pv} = Photovoltaic efficiency represents the percentage of sunlight converted into electrical power.

The intended solar panel integration will allow the production of renewable energy alongside cost-efficient operations and the viability of operations that minimise reliance on conventional power grids during the warehouse operation processes.

4.2.2 Multi-Port Bidirectional DC-DC Converter

The proposed system makes use of a multi-port dual-directional DC-DC converter that is effective in the control and regulation of power amongst the photovoltaic (PV) panels, battery storage devices, and loads directly attached to the system. Traditional DC-DC converters are generally single-directional power, and thus, they are constrained to either a charging process or a discharging process. However, the proposed bidirectional converter has only one control system where the power flow between a set of sources and loads is dynamically controlled to facilitate a smooth flow of energy in either way. The fabricated electrical setup offers the power control feature that facilitates the transfer of grid power as well as helps in battery storage during the off-peak hours to sustain consistent grid standards, as well as enhance the overall system performance.

The integrated system allows clean interaction of PV generation and battery storage devices through reversible power potentials that allow them to store additional PV power during times of low use and can release the power to meet power demands. The system has one control unit, and it shares power balance between the energy sources and loads by automatic and immediate adjustments of load requirement fluctuation to the renewable power supply. Bidirectional operation enhances grid power balance, as in order to balance all this, the system allows power to be reversed downward as the system reaches peak load provisions, thus giving way to more needs being met. The elimination of energy losses, as well as the reduction of harmonic distortion and the enhancement of battery life span, are the outcomes of the implementation of such practices as synchronous rectification along with dynamic duty cycle control. The interleaved clocking techniques will enable systems to achieve better system reliability and output ripple performance that can increase the levels of efficiency and also the ratings of reliability. Renewable power sources can still increase in the future, as this utility design is quite flexible and thus made compatible with today's and future sustainable power systems by being expandable too.

The bidirectional converter is designed to perform both charging and discharging operations, which facilitates the effective energy exchange between the photovoltaic panels, the batteries and the connected devices. This design will ensure the very efficient power grid integration of renewable energy sources, coupled with a reliable voltage regulation system. What adds to the unattractiveness of the directional operation method is its requirement for fewer external converters and the simplification of the system's structure, making it ultimately a more efficient energy system with reduced energy wastage. The converter cuts down power transfer time between different sources and loads as it does direct energy transfers. The converter shows a kind of design that is adaptable and allows the easy addition of new renewable energy sources through its basic structure, without causing significant changes to the original structure.

4.2.3 Operation Principle of the Proposed Multi-Port DC-DC Converter

The proposed converter design establishes an energy control system with two-way capability that merges photovoltaic panels with battery storage devices. This converter establishes direct energy transfer between the power sources by regulating voltage in boost and buck operational modes to provide effective bidirectional power transfer. The converter performs boost functionality by moving energy carried by renewable sources (grid or PV panels) toward both battery storage and load devices. The system functions through the $(L_1, L_2, \ldots, L_N)$ inductors which store and transfer energy by performing switching operations. The inductor receives stored energy from the input source while the MOSFET switch is in the ON state $(S_1, S_2, \ldots, S_N)$. The output receives stored inductor energy from the power diodes $(D_1, D_2, \ldots, D_N)$ during their OFF time to achieve proper voltage regulation for efficient power management.

The voltage across the inductor in the ON phase is given by:

$$VL = V_{in} - V_{out} \tag{3}$$

where V_{in} is the input voltage from the renewable energy source.

The output voltage of the boost converter is given by:

$$V_{out} = \frac{V_{in}}{1 - D} \tag{4}$$

where:

V_{out}—Boosted output voltage

D—Duty cycle that controls the ON duration of the switch

Buck Mode Operation (Discharging Mode)

In buck modes of operation, the system performs reverse power flow to release stored energy from the battery to the grid or loads. The MOSFET switch is ON to enable energy flow from the battery via the inductor, establishing a controlled voltage drop to serve the requirements of the load. When the switch is OFF, the inductor's stored energy is transferred to the output so that the system preserves the desired levels of voltage.

The voltage across the inductor during the ON phase in buck mode is Eq. (3).

The output voltage in buck mode is given by:

$$V_{out} = V_{in} \times D \tag{5}$$

where:

V_{out}—Reduced output voltage

D—Duty cycle controlling the switch ON period

For a multi-port bidirectional converter with N input sources, the total output voltage is given by:

$$V_{out} = \sum\nolimits_{i=1}^{N} \frac{V_{in_i}}{1 - D_i} \text{(Boost Mode)} \tag{6}$$

$$V_{\text{out}} = \sum_{i=1}^{N} V_{in_i} \times \substack{\downarrow \\ \downarrow} \text{ (Buck Mode)} \tag{7}$$

Phase Shift Calculation

In this method, to reduce contention current and improve contention-free time, interleaved clocking is used, where switches are activated at regular time intervals. Phase shift across N interleaved switches is given by:

$$\theta = \frac{360^{\circ}}{N} \tag{8}$$

where:

- θ is the phase shift angle between adjacent switches.
- N is the number of interleaved phases in the system.

Ripple Current Reduction Equation

$$I_{\text{ripple}} = \frac{I_{\text{single}}}{N} \tag{9}$$

where:

I_{ripple} is the total ripple current after interleaving.

I_{single} is the ripple current from a single-phase boost converter.

N is the number of interleaved phases.

The use of interleaved clocking, which is beneficial in reducing ripple currents, enables minimal variation of output voltage and leads to an increase in the quality of power. The figure below gives the ripple current after interleaving:

A bidirectional converter has real-time control measures that are used to dynamically direct the flow of power among the PV panels, the battery pack and the grid-connected load. The dynamical controller adjusts the duty cycle of each switching phase to minimise loss of energy flow, stability of voltage level, as well as minimizing power losses. The controller seeks to optimise the following cost:

$$J = \sum_{t=1}^{N} \left[Q \left(V_t - V_{ref} \right)^2 + R \left(I_t - I_{ref} \right)^2 \right] + \sum_{t=1}^{N} \tag{10}$$

where:

V_t and I_t are the Voltage and current at time step t

V_{ref} and I_{ref} are the desired reference voltage and current levels

$P_{\text{loss},t}$ is the Power losses at the time step t

Q and R are the Weighting matrices for voltage and current deviations

α is the Weighting factor for minimising power losses

The proposed bi-directional DC-DC converter is an effective device, which can coordinate the flow of power between and to various renewable energy sources and loads in such a way that the energy transfer enters and exits the components in both directions. The system provides the ability to interleave boost and buck operating modes with the interleaved clocking, thus the system improves efficiency, ripple currents and enhanced thermal control. Bi-directional power management provides a PV panel, battery and the grid with dynamic exchange of power to enhance stability of the system and the longer battery life. This is a flexible, scalable system that offers a clean energy management system capable of allowing the expansion of renewable energy applications in the future.

4.3 Single Full-Bridge PWM DC-AC Inverter for Grid

The inverter configuration contains essential components that perform DC-AC conversion efficiently to allow a smooth grid connection. The full-wave inversion process powered by H-Bridge MOSFET switches enables dual-direction current movement for producing a stable alternating current. PWM control regulates system output through the modulation of switching signals so that frequency and voltage remain stable by adjusting pulse width duties. Low-pass filtering has been implemented into the design to remove PWM switching high-frequency harmonics for producing a grid-ready sinusoidal AC output.

The output AC voltage generated by the inverter follows a sinusoidal function:

$$V_{ac}(t) = V_{dc} \cdot \sin(\omega t) \tag{11}$$

where:

V_{dc} is the regulated DC voltage from the multi-port converter.

$\omega = 2\pi f$ represents the angular frequency of the AC output.

t is time in seconds.

As shown in Fig. 2, the inverter controls its output with PWM techniques to deliver precise voltage regulation while minimising power conversion losses and generating stable AC power suitable for warehouse applications. Power distribution becomes more efficient while energy waste is minimized and systems link up easily between the electrical grid and standalone AC loads, as shown in Fig. 3.

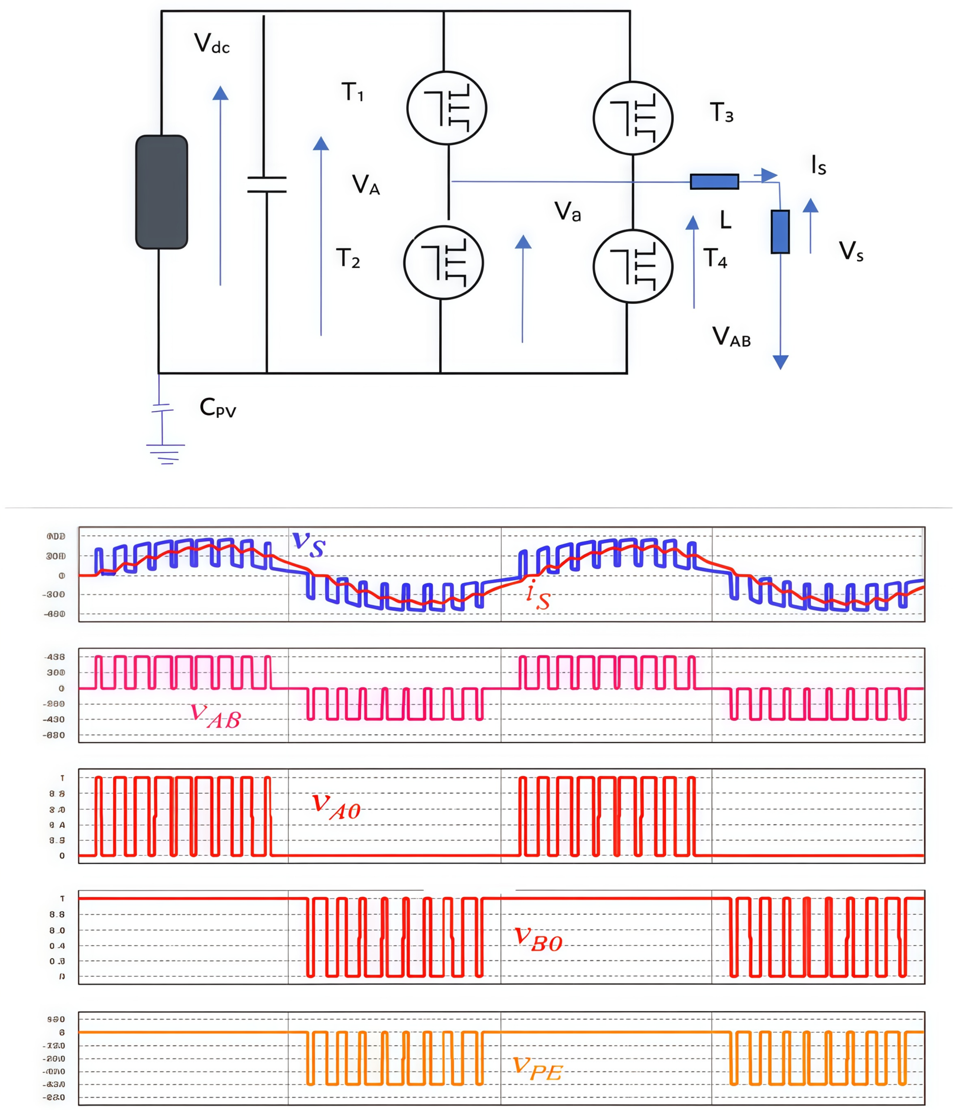


Figure 2: Single full-bridge PWM DC-AC inverter

This inverter design addresses Objective 1 by stabilising power conversion and improving grid compatibility.

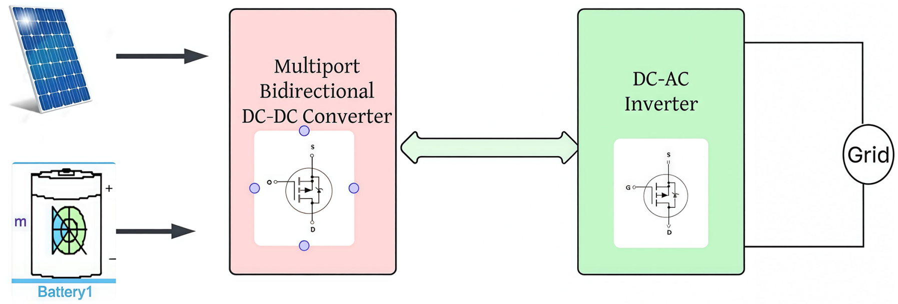


Figure 3: Schematic of multiport bidirectional DC-DC converter with DC-AC inverter for grid integration

4.4 Energy Storage and Peak Load Management

The proposed system includes a Battery Energy Storage System (BESS) for both storing PV panel surplus renewable energy and delivering power when peak consumption occurs. A power battery operates per this basic equation during its charge and discharge cycles.

$$E_{\text{stored}} = E_{\text{input}} - E_{\text{output}} - E_{\text{loss}} \tag{12}$$

where:

E_{input} is the energy charged into the battery from PV generation.

E_{output} is the energy discharged to supply the load.

E_{loss} accounts for conversion inefficiencies during charging and discharging.

The system processes enable energy supply and demand equilibrium, which ensures uninterrupted power distribution regardless of solar generation capability. This section supports Objective 2 by enabling real-time load balancing and peak demand reduction through battery energy storage. In this paper, the discharging efficiency was put at a unity level of assumption because the BESS was running on controlled charge/discharge cycles, where there are minimal side effects on discharge and very minimal on charge inefficiencies. This can, however, be further expanded by adding a new discharging efficiency parameter, eta discharge, in further implementations.

Demand Response and Peak Load Reduction in the Proposed System

The suggested system implements the approach of peak demand control and preventing power congestion by using AI as the peak load management strategy. The system is an analysis of real-time power consumption in the warehouses to complete dynamic energy distribution optimisation through adjusting the loads and utilisation of battery storage to maintain stability.

The system takes the following major steps during the peak demand periods: (1) Adjustable loads (P_{adj}) are made lower, and this way, the critical systems can be operated, and power consumption on nonessential systems can be minimised.

During this time, the BESS releases the stored energy as EBESS to increase the electrical supply that is used to overcome grid overloading.

The power consumption of non-critical loads (P_{nc}) receives periodic interruption to minimise overall electrical demand during peak time. The overall power supply required to meet demand remains defined by:

$$P_{\text{demand}} = P_{\text{grid}} + P_{\text{BESS}} - P_{\text{adj}} - P_{\text{nc}} \tag{13}$$

where:

P_{demand} is the total power required during peak periods.

P_{grid} is the power supplied from the main grid.

P_{BESS} is the power discharged from the Battery Energy Storage System (BESS).

P_{adj} is the reduction in power demand from adjustable loads.

P_{nc} represents the non-critical loads that are temporarily turned off.

By dynamically controlling these parameters, the system ensures that power demand never exceeds available supply, preventing overloading and unnecessary energy costs.

The State of Charge management for the BESS operates through the following mathematical definition:

$$\text{SoC}_t = \text{SoC}_{t-1} + \frac{P_{\text{BESS, charge}} \times \eta_{\text{charge}} - P_{\text{BESS, discharge}}}{E_{\text{BESS,max}}} \times 100 \tag{14}$$

where:

SoC_t is the battery's State of Charge at time t.

$P_{\text{BESS,charge}}$ and $P_{\text{BESS, discharge}}$ are the power input and output of the battery.

η_{charge} is the charging efficiency of the battery.

$E_{\text{BESS,max}}$ is the maximum storage capacity of the battery.

The warehouse benefits from BESS peak-shaving functionality, which decreases grid dependency and stabilises energy consumption, together with power demand reduction.

4.5 AC Micro-Grid for Efficient Power Distribution

The proposed grid integrates an AC microgrid system that optimises power delivery to compatible DC warehouse equipment and eliminates unnecessary conversions while reducing power wastage. The direct power delivery of AC microgrids through their single supply chain from DC-AC-DC systems improves efficiency while boosting system reliability.

The conventional system begins by generating DC from PV panels and batteries, then converting to AC for grid connection, while also converting it back to DC to power LED lighting and automation systems and DC motors within warehouses. Every conversion process produces power losses, which are expressed as:

$$P_{\text{loss, total}} = P_{\text{loss,DC-AC}} + P_{\text{loss,AC-DC}} \tag{15}$$

where:

$P_{\text{loss,total}}$ is the total power loss due to multiple conversions.

$P_{\text{loss,DC-AC}}$ is the power loss during DC to AC conversion (inverter losses).

$P_{\text{loss,AC-DC}}$ is the power loss during the AC to DC conversion (rectifier losses).

By directly supplying power from the AC microgrid to DC-compatible loads, the system eliminates unnecessary AC-DC reconversion, reducing conversion losses and improving overall efficiency.

The efficiency improvement can be calculated as:

$$\eta_{\text{improved}} = \frac{P_{\text{load}}}{P_{\text{input}}} \times 100 \tag{16}$$

where:

η_{improved} is the enhanced efficiency of the AC microgrid.

P_{load} is the actual power delivered to the warehouse loads.

P_{input} is the total input power from renewable sources.

The AC microgrid system generates reduced energy waste along with increased power availability and enhanced operational stability to enhance the energy systems in the warehouses. One of the ways of power distribution developed on this design approach is a reliable power management solution, which reduces costs and assists in the efficient provision of power in the logistics facilities, as well as in the industrial facilities. The configuration will assist in Objective 2 because the efficiency of multi-stage conversion will be reduced and the efficiency of energy transfer will be enhanced.

4.6 Flexible Distribution Network (FDN) Implementation

The given system introduces an FDN, which, thanks to the energy allocation, power routing, and adaptive control, minimises the energy losses in the warehouse and provides efficient power distribution. The system development comprises Dynamic Load Distribution (DLD) plus Intelligent Power Routing (IPR) and Multi-Agent Deep Reinforcement Learning (MADRL) to implement adaptive power flow optimisation that improves the dynamics of its work. Objective 2 is achieved through the integration of DLD, IPR and MADRL, which facilitate adaptive and intelligent routing of power and real-time management of loads.

4.6.1 Dynamic Load Distribution (DLD) for Real-Time Energy Allocation

Dynamic Load Distribution allows the FDN to build upon its fundamental functionality by observing the real-time demand to effectively distribute energy allocation to various interconnected loads. DLD distribution system uses various energy loss management systems which aim at maximising the necessary power requirements and optimally using energy resources system-wide. The conventional distribution systems create operational issues that cause equipment failures due to overconsumption of power, and at the same time, create unnecessary power wastage in various places, leading to higher costs. The system uses the DLD power delivery technique to identify the real-time energy resource distribution rates. The system is also made more performance efficient due to high energy efficiency since this technique also lowers the power loss to increase the reliability of the intelligent energy management operations.

Mathematical Representation of Load Distribution

The real-time power demand balance in DLD is expressed as:

$$P_{\text{total}} = \sum_{i=1}^{N} P_{\text{load}\,i} \tag{17}$$

where:

P_{total} represents the total available power in the system.

$P_{\text{load}\,i}$ denotes power allocated to the *i*-th load.

N is the total number of loads in the system.

The equation guarantees that supplied power meets instantaneous load requirements to achieve system balance as well as operational efficiency.

Real-Time Load Monitoring

The system maintains ongoing observation of power requirements for warehouse loads, which consist of lighting systems, along with HVAC equipment, conveyor belts and charging stations. The monitoring system helps detect changes in power usage while optimising the power distribution networks.

Prioritisation of Critical Loads

Prioritisation systems divide warehouse loads into critical and non-essential classifications so HVAC systems and conveyor operations get power in a certain order. The system operates dynamic control of non-essential power loads to reduce the waste of energy resources.

Dynamic Energy Allocation

DLD regulates power distribution dynamically to achieve parallel distribution of electricity throughout the production line without any system component reaching maximum capacity and without wasting energy from sources. The immediate energy balancing operation brings enhanced efficiency and cuts down power waste.

Integration with Renewable Sources

The solar power production that surpasses the system's requirements is directed to secondary utility points like battery storage and non-essential operational devices in order to save energy to the maximum. The use of Multi-Agent Deep Reinforcement Learning (MADRL) in Distribution Load Dispatch (DLD) is done through the Deep Deterministic Policy Gradient (DDPG) technique, whereby each agent corresponds to a single load node. The agents get information about the local demand, voltage, and available power and make their choice of load adjustment actions that are optimal from the perspective of a shared reward function, which is to minimise the total system losses. The agents share only a small amount of information so as to keep decentralised control while still achieving global optimisation through iterative learning. This setup gives the benefit of real-time load balancing with very low communication costs.

4.6.2 Intelligent Power Routing (IPR) for Optimal Power Flow

The system applies Intelligent Power Routing (IPR) to dynamically select efficient transmission paths based on real-time load demand, minimising losses and maintaining stability.

Real-Time Power Flow Analysis

The system continuously performs power demand monitoring, capacity assessment of sources, and network resistance evaluation to determine the highest efficiency path for power transmission. The system finds the shortest transmission routes of the lowest resistance, which contributes to minimum power losses during steady load availability distribution. The system calculates total power demand by following this equation at present.

$$P_{\text{demand}} = \sum_{i=1}^{N} P_{\text{load}\,i} \tag{18}$$

where:

P_{demand} is the total power required by all loads.

$P_{\text{load } i}$ represents the power demand of the i-th load.

N is the total number of loads in the system.

The demand profile maintained by IPR brings efficient power distribution, which prevents excessive power flow through any single transmission line.

Selection of the Optimal Power Source

IPR selects the energy source between solar panels and batteries, and power from the grid to serve household appliances according to current electrical grid conditions. The system selects renewable energy first, as long as renewable energy remains available, to cut down on power grid dependency while making energy systems more sustainable. The load power supply optimisation happens through the calculation shown below:

$$P_{\text{supplied}} = P_{\text{renewable}} + P_{\text{grid}} + P_{\text{BESS}} \tag{19}$$

where:

P_{supplied} is the total power provided to the system.

$P_{\text{renewable}}$ represents solar or wind power contribution.

P_{grid} is the power drawn from the external grid.

P_{BESS} is the power supplied from battery storage.

By dynamically selecting power sources based on efficiency, cost, and availability, IPR ensures maximum utilisation of renewable energy, reducing carbon footprint and energy costs.

Minimisation of Transmission Losses

IPR implements one important capability to control the transmission losses that result from resistance in distribution lines. The calculations regarding electrical transmission power dissipation follow Joule's Law.

$$P_{\text{loss}} = I^2 R \tag{20}$$

where:

P_{loss} is the power lost during transmission.

I is the current flowing through the network.

R is the resistance of the transmission path.

Transmission of electric power through less resistant lines (R) for a longer time leads to a significant reduction of energy loss through IPR. The system continuously assesses various alternative routes for electricity transmission, and at the same time, it controls the power through those routes that have the best efficiency to provide maximum power to the loads.

Dynamic Load Balancing for Grid Stability

The power distribution system via the IPRs dynamic technique that shares energy loads among different supply paths becomes stable. The system automatically redirects the overloaded power through other low-resistance paths, which is a precaution against voltage drops, power loss, and instability issues. The real-time load balance equation maintains supply at the same level as demand at all times.

$$P_{\text{supplied}} = P_{\text{demand}} + P_{\text{loss}} \tag{21}$$

where, P_{supplied} is the total power supplied to the system, P_{demand} is the total load requirement, P_{loss} accounts for power lost in transmission.

IPR operates power flow at different levels to sustain grid stability and guard against system damage from overload situations.

Adaptive Power Routing with AI Optimisation

IPR uses Multi-Agent Deep Reinforcement Learning (MADRL) as part of an AI system to optimise its performance better. The system uses this predictive method to detect upcoming energy requirements and make advanced power distribution decisions for uninterrupted power delivery. The AI-based model achieves minimum total energy loss through an optimisation process of this equation:

$$L = \sum_{t=1}^{T} \left(P_{\text{loss},t} + \alpha P_{\text{unused},t}\right) \tag{22}$$

L is the total energy loss function.

$P_{\text{loss},t}$ represents power lost at the time step t.

$P_{\text{unused},t}$ accounts for excess power that is generated but not used.

α is a weight factor that balances loss and unused power.

Through its ability to adapt and learn continuously, the AI-operated IPR system executes performance upgrades for instant operation improvement without additional expenses and achieves maximum renewable power generation outcome.

Intelligent Power Routing (IPR) in the proposed system routes power to optimise transmission efficiency to maximise energy effectiveness. The feature of IPR dynamically picks fast and energy-efficient paths, which result in less power dissipation. P_{loss} appearing in the power transmission system while ensuring maximum energy delivery to the load. Real-time adjustments of power distribution enable the system to cope with changing demand while stopping overload situations, thus improving stability and reliability. The system from IPR gives priority to renewable power sources, including solar, along with battery storage instead of grid power for reduced operational spending and decreased power grid dependency. IPR combines adaptive load balancing along with AI-based optimisation techniques to support the power grids by redirecting power automatically in such a way that voltage drops are prevented and energy traffic is organised in a more efficient and resilient manner, thus creating the warehouse power systems that are more productive and robust.

4.6.3 Multi-Agent Deep Reinforcement Learning (MADRL) for Adaptive Control

The Multi-Agent Deep Reinforcement Learning (MADRL) introduction makes it possible to form such systems that can learn adaptively and without any human intervention. The AI system assesses the energy consumption patterns as well as the power system and grid conditions to make instantaneous distribution adjustments.

Multi-Agent Deep Reinforcement Learning

The main part of the MADRL functionality as an integrated system component is the formation of a power distribution network, which is capable of adjusting energy distribution through real-time analysis. The method of reward-based optimisation that is taken into action is the one that leads to both the minimisation of energy losses and the best distribution of power. MADRL learns to cope with various operational situations through the continuous observation of the energy demand patterns related to the PV power availability and the state of charge (SOC) of the battery energy storage system (BESS), along with the grid power status.

The power management system utilises this ingenious method to control the distribution of power, which in turn enhances the efficiency and dependability of grid power operations. The traditional power distribution networks have a hard time adapting to the changing energy needs, which thus leads to a decrease in the overall energy management efficiency. The manual operation of load balancing procedures sometimes results in the simultaneous occurrence of both transmission failures and overloading, which together cause the system to lose stability performance. These static predictive models cannot track immediate modifications in power production and consumption; therefore, they become ineffective when managing PV-integrated systems requiring constant adjustments to their operating environment. MADRL introduces new capabilities to adapt the system properly while learning from continuous operational conditions. MADRL employs several intelligent agents to inspect energy demand patterns, power availability and grid conditions as it steers real-time power routing changes. The system performs energy management with enhanced efficiency through MADRL because it optimises load balancing combined with intelligent power routing, leading to lower losses and superior system performance.

The process of applying MADRL in the new system is that of determining the states, actions, and reward functions of the system for optimising the energy distribution. The state vector at time t is comprised of the current demand. D_t for energy, current photovoltaic (PV) power $P_{\mathrm{pv},t}$, Battery Energy Storage System (BESS) SOC_t state of charge, and accessible grid power $P_{\mathrm{grid},t}$. These state variables provide a general description of the system conditions, enabling decision-making by the agents. The action space includes power allocation from the grid, battery, and PV sources and changing power routing routes to minimise losses. The system reward function is such that it seeks to minimise energy losses in general by penalising power losses and wasted energy.

The total energy loss function is given in Eq. (22): where L denotes the total energy loss over a given time period, $P_{\mathrm{loss},t}$ refers to power losses at the time step $\underline{t}_t$ and $P_{\mathrm{unused},t}$ represents the amount of unutilized power. The weight parameter α is used to trade-off execution of energy losses against the unutilized energy. The optimisation of the reward functions of the MADRL agents enables them to adopt other mechanisms like Q-learning or Deep Deterministic Policy Gradient (DDPG) that boosts the performance of the system each time it is run.

This proposal will see the system performance improve significantly through the implementation of MADRL. The system conducts intelligent real-time redistribution of power in order to reduce transmission loss. The system increases stability by forecasting overloads and allocating power. Optimisation of power flow, along with adaptive learning, facilitates the achievement of lower energy losses. The system effectiveness is measured by the evaluation of performance metrics that entail the rate of energy losses, along with the system efficiency increase and the index of grid reliability (GRI). This preliminary system design presents results of reduced energy loss by 12–18 per cent compared to a static model at 15–20 per cent higher system operating efficiency. The GRI is improved through optimum power routing and load balancing to improve the frequency stability, along with the voltage stability.

The implementation of MADRL adds several benefits to the system, making it more robust and efficient to the system as a whole. On-the-fly flexibility is one of the important features of the system since it automatically adapts to changing energy needs and supply levels in order to provide maximum power delivery. The advantage of scalability arises since MADRL can be successfully utilised when using multiple sources of energy and increased grid networks during power emergencies.

MADRL handles the power transmission efficiency by determining the optimal routes, and as such, it reduces the power loss and also avoids congestion in the system. The system continues to advance its policies in the process in such a way that it involves the self-directed learning abilities and automatic improvements in performance. The reduced congestion in transmissions and enhanced system reliability and resiliency are the result of the effective power distribution capabilities of MADRL.

The FDN has Intelligent Energy Management using Multi-Agent Deep Reinforcement Learning (MADRL) using Dynamic Load Distribution (DLD) and Intelligent Power Routing (IPR). DLD will dynamically redistribute the load across many nodes, thereby removing the chances of overloading a node, and optimally utilising the available energy nodes. Instead, IPR uses predictive analysis to deliver dispatch power in optimal routes and thereby minimises the power loss and stabilises the system. The summation of the advantages of MADRL, DLD and IPR offers a stable energy distribution system that is robust enough to address the dynamic scenario most efficiently. This system structure is robust as it will not cause imbalance in loading, and the energy will be routed using the most appropriate channels, thereby reducing the likelihood of transmission congestion and delays.

This is a very clever, dynamic, and practical work in the application of MADRL, DLD, and IPR. In real-time scenarios, the FDN optimises the power distribution based on efficiency, availability, and peak demand, which minimises energy losses in the FDN and improves the overall performance. The addition of IPR enables the system to be future-proof and suit complex energy distribution situations by using the past learned control strategies to the present conditions. The learning and iterating abilities of MARRL provide a possibility of adaptive energy allocation in a photovoltaic scenario, and the maintenance of its strength and efficacy since the dynamic sticking nature of grids, operating processes, and related energy interactions may be present. In addition, modification of MADRL to fit the system will form extra dependability, extra features to scale the energy management, and resilience, without reducing the high management ability when managing intricate grid circumstances and/or fluctuating grid conditions.

The implementation of MADRL enhances energy control by enabling real-time adaptive operation and optimal power distribution. MADRL integrated with DLD and IPR produces a self-adaptive, efficient, and scalable power distribution. The adaptive method allows for reduced energy losses, intelligent power routing, and improved resilience of the system, making it ideal for sustainable and future energy management.

4.7 Power Flow Control and Optimisation Using Model Predictive Control (MPC)

Model Predictive Control (MPC) is a method for real-time operation, power flow control and optimisation to reduce energy losses, ensure load balancing, and achieve system stability. The MPC will be designed to predict future system response and update the control actions in real-time to minimise future deviations from the desired operation conditions. The use of MPC allows voltage and frequency deviations to be minimised, avoiding power imbalances and catastrophic failures during peak load events. This method achieves energy distribution notion referring to decentralized operation of any grid conditions data dynamically.

Traditional control methods frequently struggle to respond quickly to variable energy demands and faults in transmission grids, which causes unstable operations, ineffective load balancing, and increased transmission losses. Furthermore, traditional control methods rely on static models, which do not dynamically predict and compensate for power unbalance in real-time. To overcome these limitations, Model Predictive Control (MPC) is used to forecast the behaviour of the system in the future and generate a setpoint. Unlike conventional controllers, MPC will choose the optimal control input at each time step based on the disturbances at some future time, and furthermore, will do a better job of dynamically controlling power flow in systems with photovoltaic integration.

MPC is a vital mechanism for optimising the efficiency of the system by modulating load transfer, redistributing power response to load changes, and alleviating energy losses. It can also predict power congestion and predict deviations, and respond to them as they occur. As a result, the system can appropriately manage unforeseen load variations, avoid overload situations, and manage voltage and frequency levels as environmental conditions change. The dynamics of power distribution systems are described by state-space equations that account for the evolution of system states over time. The discrete-time state-space model is expressed as: The MPC strategy entails system dynamic description, estimating future states, and solving in an iterative context for control inputs to reduce the cost function relative to system performance. The process step-by-step is given below:

Step 1: System Modelling and State-Space Representation

The dynamics of the power distribution system are represented by state-space equations that depict the evolution over time of system states. The discrete-time state-space representation is expressed as:

The state-space model is given by:

$$\begin{bmatrix} V_{t+1} \\ I_{t+1} \\ P_{t+1} \end{bmatrix} = A \begin{bmatrix} V_t \\ I_t \\ P_t \end{bmatrix} + B \begin{bmatrix} U_{g,t} \\ U_{pv,t} \\ U_{b,t} \end{bmatrix} + w_t \tag{23}$$

where:

V_t—system voltage at time step t

I_t—system current at time step t

P_t—active power at time step t

$U_{g,t}$, $U_{pv,t}$, $U_{b,t}$—control inputs from grid, photovoltaic, and battery sources, respectively

A, B—system matrices defining dynamic behaviour

w_t—disturbance vector representing grid noise, renewable variability, and load changes

Step 2: Prediction Horizon and Cost Function Definition

MPC derives control actions for a finite prediction horizon by providing a prediction of the system response to possible control actions. The prediction horizon N indicates how far into the future the MPC is predicting system behaviour. The MPC objective will minimise a cost function that penalises deviations from desired power flow while working to achieve optimal load sharing. The cost function is expressed as:

$$J = \sum_{t=1}^{N} \left[Q \left(V_t - V_{\text{ref}}\right)^2 + R \left(I_t - I_{\text{ref}}\right)^2 \right] + \sum_{t=1}^{N} \alpha \left(P_{\text{loss},t}\right) \tag{24}$$

where:

J = Total cost over the prediction horizon

V_t and I_t = Voltage and current at time step t

V_{ref} and I_{ref} = Desired voltage and current levels

$P_{\text{loss},t}$ = Power losses at the time step t

Q and R = Weighting matrices for voltage and current deviations

α = Weighting factor for minimising power losses

Step 3: Optimal Control Action Computation

MPC determines the best control actions U_t to minimise the cost function by simulating the future trajectory of the system over a prediction horizon. Control inputs (voltage and current setpoints) are adjusted in a dynamic way to minimize losses and deviations. The control vector U_t consists of:

$$U_t = [V_{\text{set}}, P_{\text{route}}, P_{\text{load}}] \tag{25}$$

where:

V_{set} = Voltage regulation commands

P_{route} = Power routing adjustments

P_{load} = Load balancing control inputs

Step 4: Real-Time Adjustment of Control Signals

After the system has been predicted, optimal control inputs determined, and the control inputs have been implemented, the final stage of the MPC design requires the set of control actions to be updated at every time step so that the system remains as close as possible to the desired state of power flows. Having a feedback controller enables the system to quickly adjust to a change in any of the loads, the supply, or disturbances in the grid, which will mitigate the consequences of critical failures and help the system maintain stability.

$$\mathrm{u}_t^* = \mathrm{u}_{t,0} \tag{26}$$

The receding horizon strategy ensures that only the first control action is applied at each time step, and the optimisation is re-evaluated at the next time step by shifting the horizon forward.

As shown in Fig. 4, with the use of Model Predictive Control (MPC), the power flow reduces energy waste, loads the load, and prevents the variation of voltages and frequencies. Implementation of the MPC can minimise the transmission losses (15–20 per cent) by forecasting future system behaviours and optimising the power control actions in a way that the voltage deviations are less than 5 per cent. With a grid power, photovoltaic (PV), and battery energy storage systems (BESS) balance, MPC is used to ensure there is no collapse when the load reaches peak/potential overload situations, and the system remains stable. The result of the implementation is the real-time adaptive control that is capable of responding to the load changes, supply changes, and disturbances due to the grid automatically. The MPC process has remained dynamic in defining voltage and current setpoints in addition to balancing the power routing and load sharing among all sources to help reduce congestion or overload. That is, one of the unique predictions guarantees correct operation of power flow, also helping to create a system that can withstand unforeseen situations, whereas in the future, it will operate to its full potential amid the dynamically-preferred operations. Receding horizon MPC strategy causes power control systems to become modular and scalable to accommodate energy-interesting future changes jointly through the combination of the available energy sources with the current and new sources of energy, with a realistic load requirement profile to enable the power distribution network to accommodate increasingly efficient and resilient approaches to the future utilisation of energy. Objective 3 is met by the MPC-based optimization which guarantees predictive power flow control, minimisation of losses and enhanced system stability.

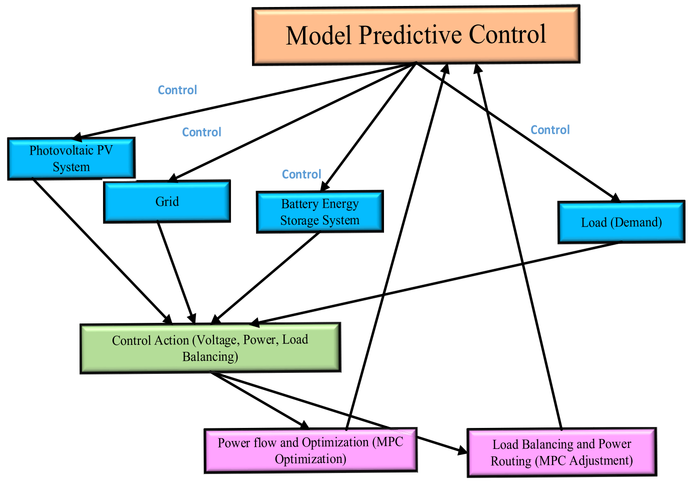
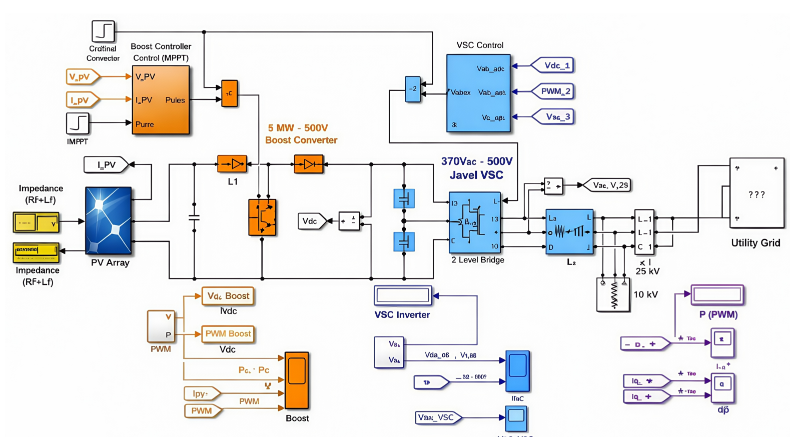


Figure 4: MPC-controlled smart energy system for integrated renewable and storage units

5 Result and Discussion

The FDN-Flexible Power Supply and Distribution System was installed and tested in a photovoltaic integrated tobacco logistics warehouse to determine its functionality, efficiency, and load and energy variability flexibility. The modularity of this system defines an ability to act independently of photovoltaic generation via a multi-port DC-DC converter to administer load and source power demands and maintain power conditioning via the inverter and support Battery Energy Storage System (BESS). The system expanded its services with the DLD, IPR and MADRL AI optimisation strategies in offering the best and efficient power management. The results show increased energy efficiency, power stability and flexibility to constant energy load variation. A system of Flexible Power Supply and Distribution is designed on the basis of a flexible demand network (FDN), and with the help of MATLAB/Simulink simulations, the work is done, and the performance, efficiency, and ability to respond to changes in load and energy are tested. The outcomes of the simulation indicate that the energy efficiency, power stability and the ability to respond to varying loads of energy have increased greatly, as indicated in Fig. 5.



(a)

Figure 5: (Continued)

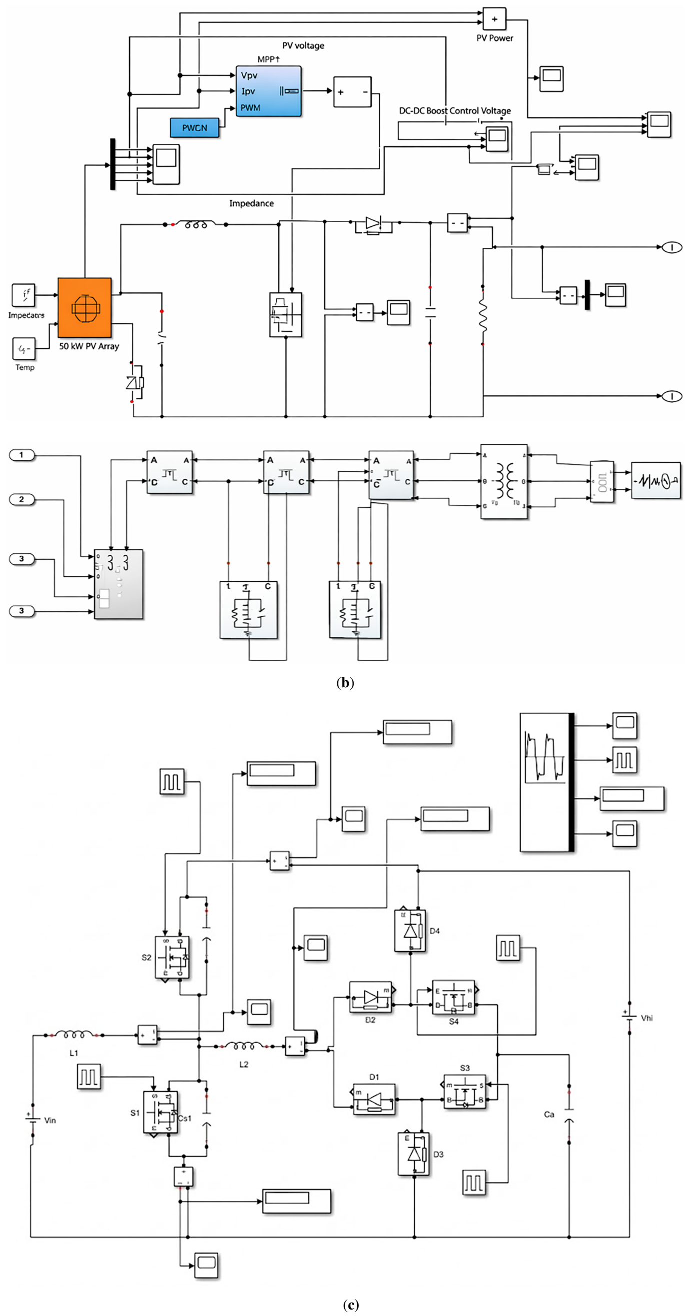


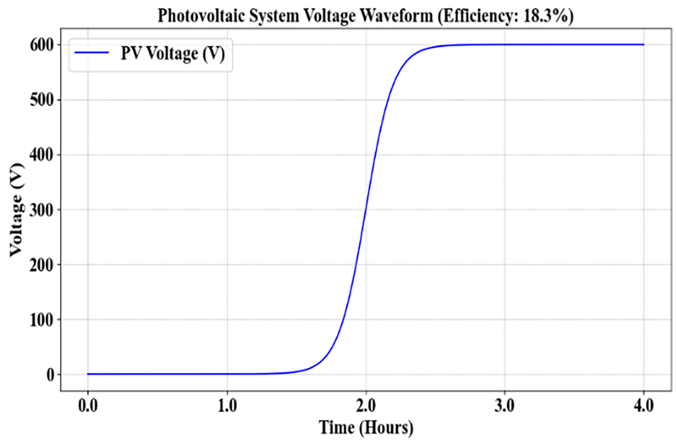
Figure 5: Implementation of flexible power supply and distribution technology based on FDN in photovoltaic system of tobacco logistics warehouse area. (a) Overall implementation; (b) PV and grid; (c) DC-DC bidirectional converter

Photovoltaic System (PV) makes use of the Solar Power 400 W Monocrystalline Solar Panel type that is designed to have the lowest losses of energy that are lost in the production of solar energy. Fig. 6: The performance of a Photovoltaic (PV) System in a time span of 4 h, where voltage, current, and the power generated by the system are recorded. The first one to two hours have a voltage increase of 0 to about 600 V, which is a vertical voltage rise that is characteristic of the ramp-up process in the PV system, where the system starts to generate electrical energy. The efficiency of the PV system was 18.3, and this means the quantity of the solar irradiance or even the energy that is being conveyed to the energy generation in the form of electrical power. Meanwhile, the current grows up to a maximum of approximately 150 A, and reserves itself as the system reaches its working load. The power output shows the same increase between zero and a range of approximately 15–20 kW; the energy producing procedure has levelled off, and the PV system is working in a steady-state. This output shows the dynamic nature of the performance of a PV system and portrays the behaviour of a system in relation to the changing sunlight over time.

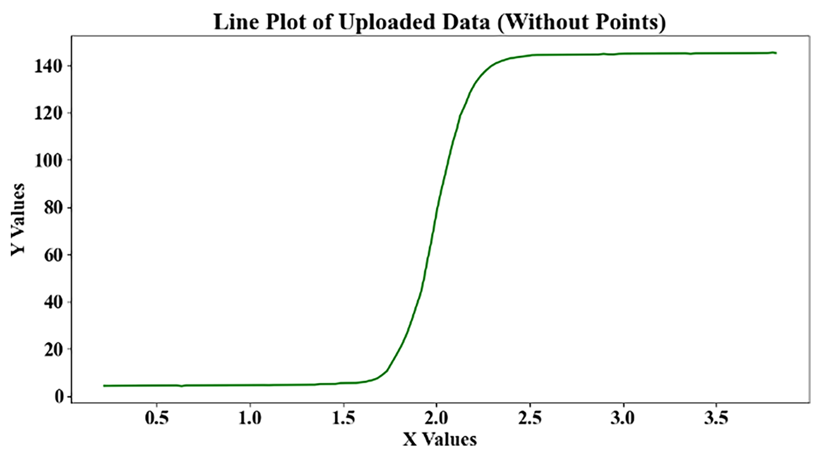
The behaviour of an AC system with an inductive load is depicted in Fig. 7. Although the voltage and current waveforms are sinusoidal, they are not perfectly aligned in phase. The power delivered to the load varies accordingly due to this phase shift. The SoC increases quickly at the beginning of charging and becomes constant when the maximum capacity is reached. At the same time, the current waveform indicates areas where the current is changing its direction, hence indicating charging or discharging modes. The power output waveform indicates the change in the real power sent to the load, which swings between 0 and 60 kW. Both the voltage and the current determine this power output, and the maximum power is produced when the voltage and the current are at maximum values. The phase difference between voltage and current causes power to vary periodically, a common feature of AC systems with inductive loads, where real power is delivered only when voltage and current are in phase or close to their peaks.

Fig. 8 demonstrates considerable variations in transmission losses ranging from 7000 to 10,000 W, pointing out that the losses are a function of time. The amount of variability can be interpreted as the losses are induced by an alteration in the load current, which varies due to the operational conditions, such as changes in demand or the state of the electrical devices. These transmission losses are typically a result of the resistance within the power lines when the current passes through, causing the power to convert to heat. The changes in losses that are reflected in the graph show the influence of these load transformations and demonstrate that the overall efficiency of the system is not fixed and dependent on the load situation at the time.

Fig. 9 illustrates the performance of a Battery Energy Storage System (BESS) with a capacity of 200 kWh. It shows the State of Charge (SoC), the charging/discharging current, and the battery power output over a total period of 12 h. From the graph, we can see that the State of Charge (SoC) has a steep rise at the beginning of the graph and slowly stabilises once it reaches full charge. The charging/discharging current varies and crosses zero, where positive currents indicate charging and negative currents indicate discharging. The same peaks in the charging/discharging current appear in the charging/discharging rates of power output from the battery. The power output from the battery also fluctuates like the charging/discharging current, having an increase in power output during discharging when the battery is supplying energy to the system. The overall body of the graph depicts that the battery possesses dynamic energy flow in all battery operations, and the charging, full charge and discharge are clearly represented as the overall operation status is discussed within the system. The seemingly discrepant SOC and power curves are due to the control hysteresis modelling of the BESS management system. At the peak of the SOC (100%), the balancing and inverter control cause the Power exchange to take place between minor power exchanges, ensuring stability in the grid. These exchanges are represented as small fluctuations in power while the SOC remains constant. Similarly, the rapid rise to full SOC at the beginning corresponds to an initial high-rate charging mode before stabilisation.



(a)



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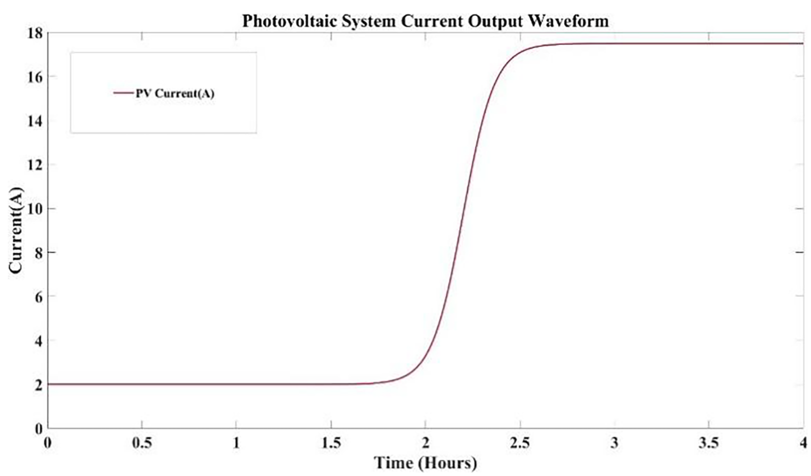

(c)

Figure 6: (a) Photovoltaic system voltage waveform (efficiency: 18.3%); (b) line plot of uploaded date (without points); (c) photovoltaic system output waveforms

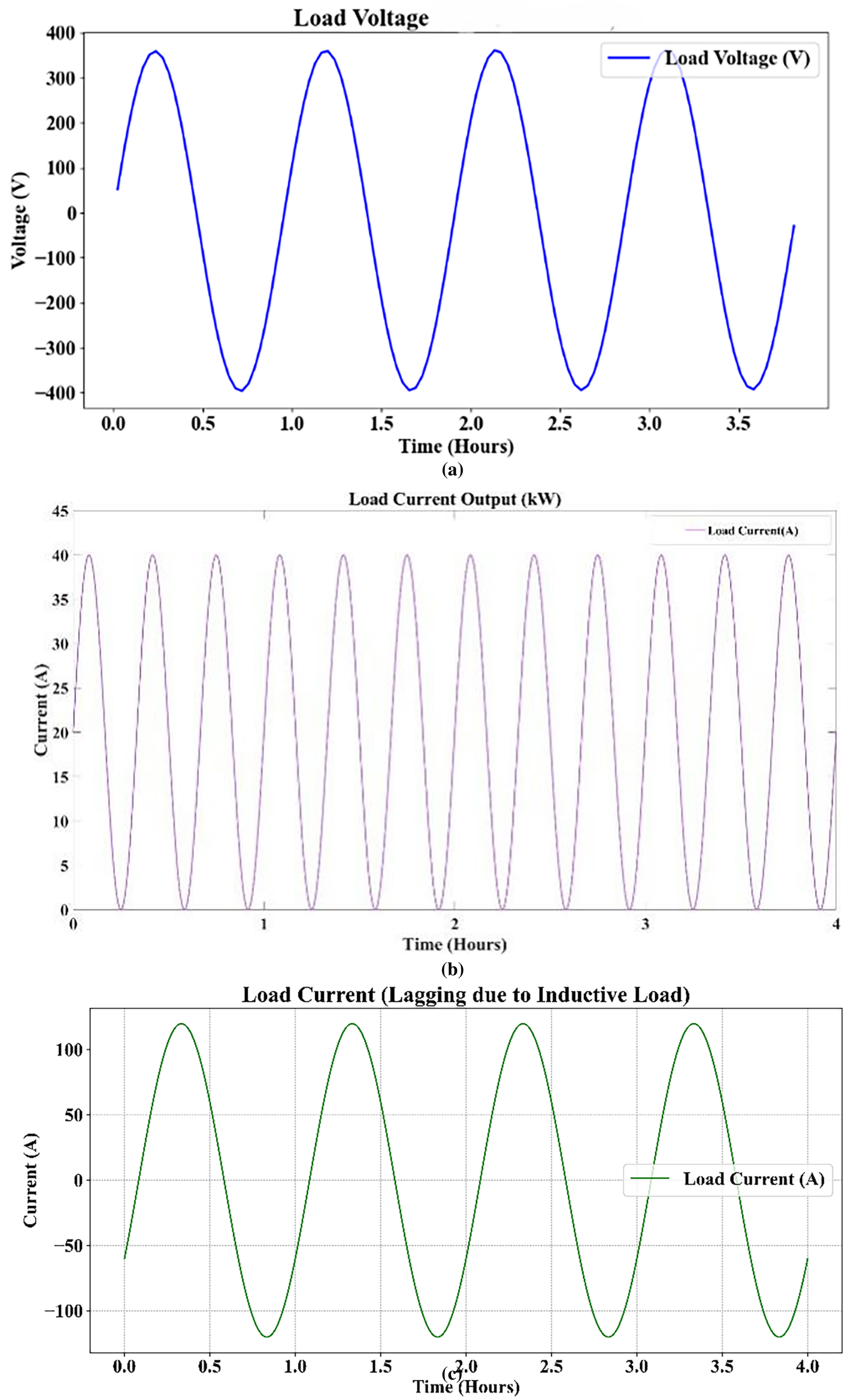

Figure 7: Grid stability and peak load management. (a) load voltage (b) load current output (kW) (c) load current (lagging due to inductive lead)

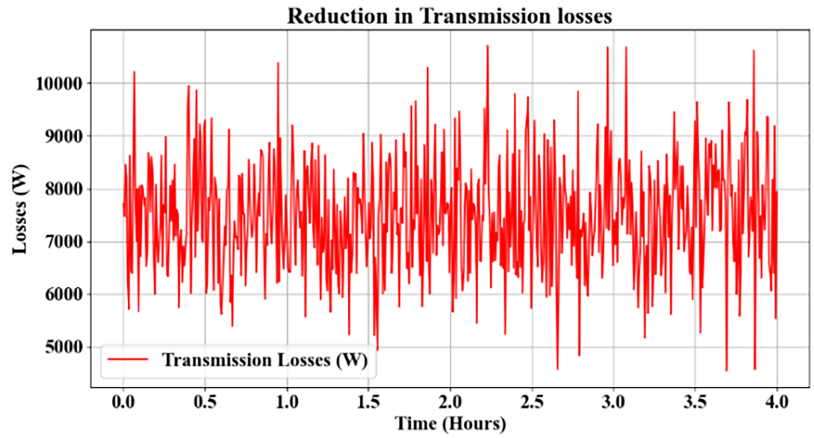

Figure 8: Reduction in transmission losses

Fig. 10 illustrates how a power system exhibits scalability over a four-hour time window, by noting the power levels of the system as scaling takes place and the power levels react. The initial power levels of the system are represented by the blue dashed line, and follow a sinusoidal shape in time and fluctuate with time as denoted on the x-axis. The Scaled Power Output 1 (green line) indicates a sharp increase in the power levels of the system while maintaining the same sinusoidal waveform, but at a much greater amplitude. This means that as the capacity of the system scales, the system can output more power to meet the increase in demand levels from scaling up its capacity. The Scaled Power Output 2 (red line) is a significant increase in power output that is manifested in an increment in amplitude, that is, the system can still endure additional power when the power requirement grows because the scaling has increased the capacity to provide more power. This parameter demonstrates the capability of the system to show scalability with respect to the amount of power output at any rate and the system to remain stable (denoting the shape of the waveform). The figure also shows that the system is able to sustain power and also adjust the power levels, but the overall shape of the waveform is the same, regardless of the power level shifts.

In order to substantiate the results, the simulation results were compared with the literature on flexible renewable power systems. The corresponding 15%–20% reduction in transmission losses corresponds to the trends outlined in recent publications, where the loss reductions of flexible grid connections and battery storage integration were found to range between 12% and 18% due to similar operating conditions [34]. In addition, the 5% deviation in voltage stability that was encountered is found to be equal to the values of the MPC-optimised microgrid systems of Hu et al. [5] state that predictive control indeed works in the stabilisation of the system under fluctuating renewable inputs that are fluctuating. The improvement in efficiency—of 12% to 18%—also surpasses previous single-agent or static control optimisations, which usually reported gains in the range of 6% to 10% [23,29]. These comparisons refer to the fact that the proposed method not only fits with existing knowledge but also pushes the system performance by means of the multi-agent reinforcement control and intelligent routing.

The considered curve, which is referred to as Fig. 11, has the harmonic properties of a signal with a base frequency of 50 Hz. The graph is plotted on the y-axis, the harmonic magnitudes are given in percentages of basic frequency components and frequency data on the x-axis in Hz. There is a little distortion in the system with a Total Harmonic Distortion of 0.0086. The primary harmonics are seen at frequency multiples of 50 Hz that confirms the normal power system attributes.

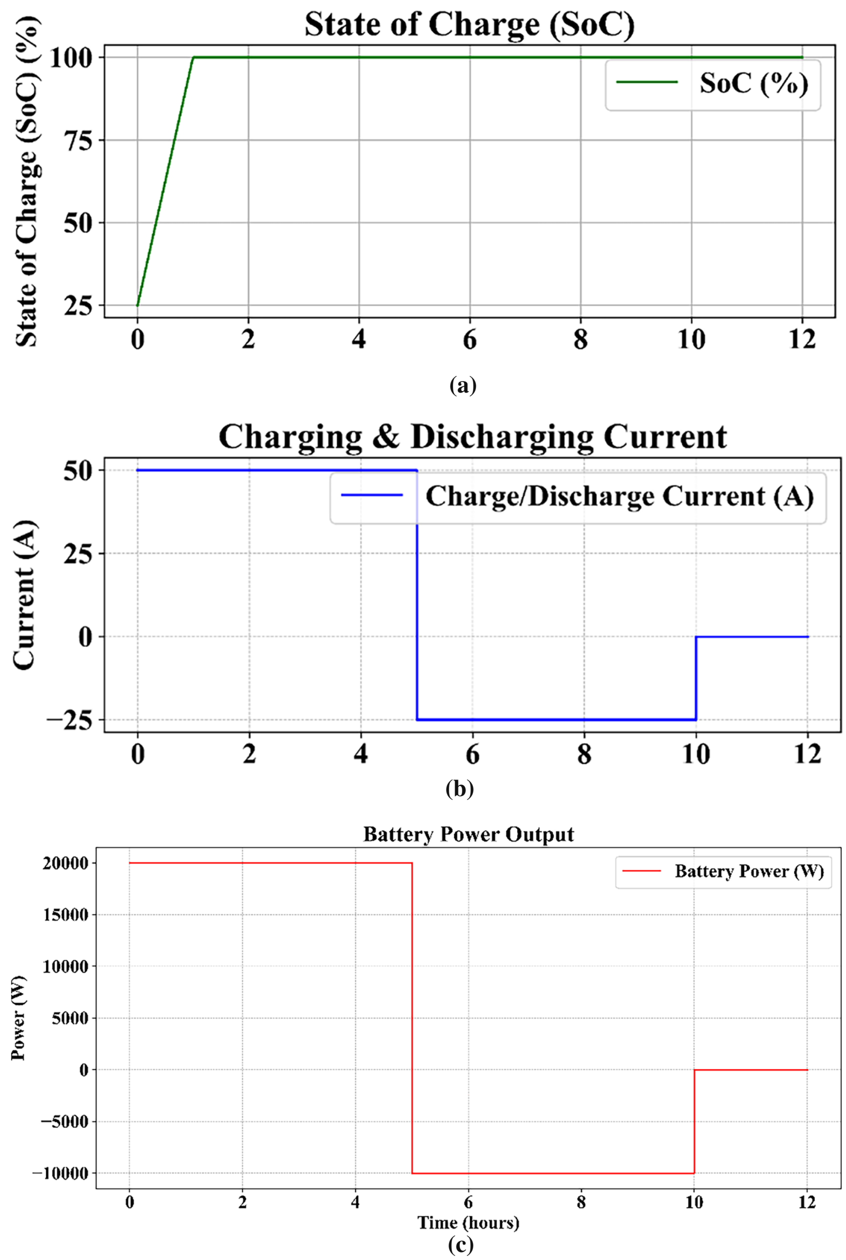

Figure 9: Battery output waveform. (a) state of charge (SoC) (b) charging & discharging current (c) battery power output

Table 1 describes the major specifications of the photovoltaic system, battery energy storage system and grid/load parameters of the power system setup. It gives a necessary insight into the abilities and functionality restrictions of the system components.

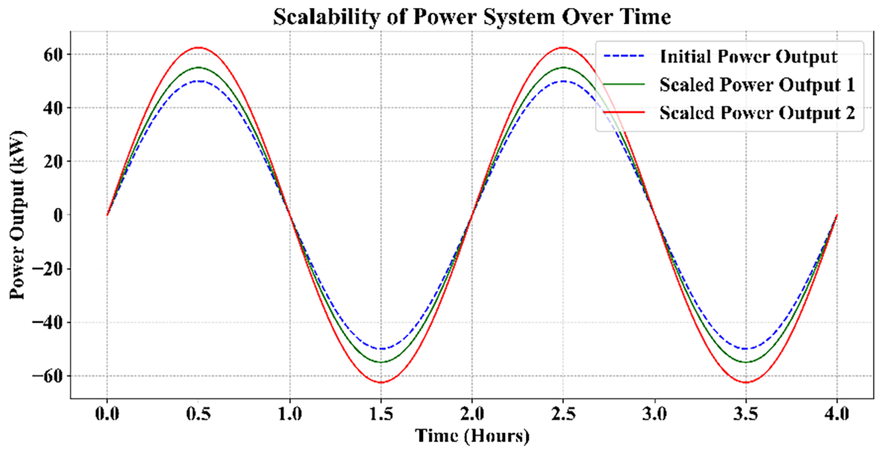

Figure 10: Scalability of power system over time

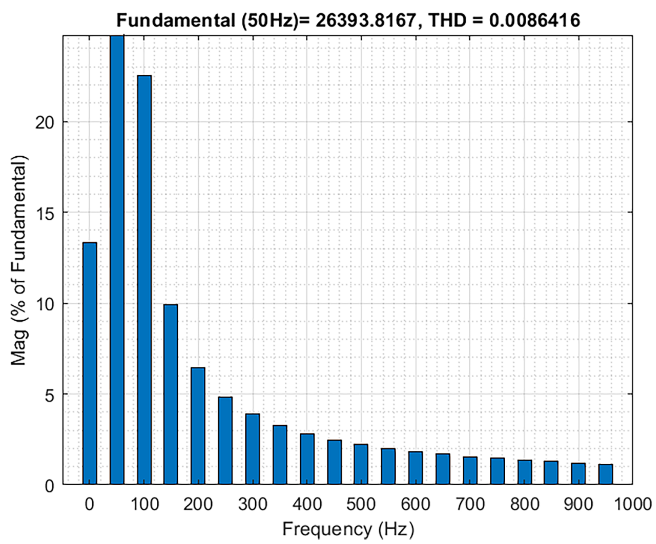

Figure 11: Total hormonic distortion output

Comparative evaluation was conducted against prior approaches from Refs. [15,21], which is shown in Table 2. The proposed FPSDS demonstrated a 15%–20% reduction in transmission losses and a 12%–18% improvement in overall system efficiency compared to existing flexible grid models, confirming superior performance through adaptive control integration.

Table 3 provides a systematic overview of performance indicators, including the major evaluation measures provided by the results of the simulation. The Flexible Power Supply and Distribution System has proved to be of great benefit in all categories, and this proves its flexibility and stability when it comes to variable load conditions. The cost of the Flexible Power Supply and Distribution System (FPSDS) was evaluated economically by estimating the cost of installation, operation, and maintenance, as well as the savings in terms of energy consumption. To implement a 100-kW warehouse-scale system, the initial capital cost will be about USD 110,000, and yearly O&M will be about 2–3 per cent of the capital investment. Energy savings of 12 to 18 per cent have an annual efficiency improvement of about 25–30 MWh, or USD 3000–3500 per year at industrial electricity rates. Payback period is approximately 6–7 years, which is a good indication of its economic viability in the long term, and other gains are low dependency on the grid and less carbon emission.

Table 1: System specification table

Component	Parameter	Value
Photovoltaic system (PV)	SunPower 400 W monocrystalline solar panel (Model)	
	Rated power	100 kW
	Maximum voltage	600 V
	Maximum current	180 A
	Efficiency	18%–22%
	Temperature coefficient	−0.4%/°C
Battery Energy Storage System (BESS)	Battery capacity	200 kWh
	Charging/discharging efficiency	90%–95%
	Nominal voltage	400 V
	Depth of discharge (DoD)	80%
Grid and load parameters	Grid voltage	400 V (AC)
	Load type	Mixed (Resistive + Inductive)
	Load power rating	50–100 kW
Boost converter	Switching frequency	10–20 kHz
	Inductor value	5–10 mH
	Ripple current	0.75 A

Table 2: Performance comparison with existing methods

Method	Control strategy	Loss reduction (%)	Efficiency improvement (%)	Stability index
Ref. [23]	Static load balancing	8–10	6–8	Moderate
Ref. [30]	Single-agent optimisation	10–12	9–10	Good
Proposed FPSDS	MADRL + MPC integrated control	**15–20**	**12–18**	**High**

Note: The bold formatting is used to highlight the performance of the proposed PSDS method.

Table 3: Summary of key performance indicators

Indicator	Description	Value/range	Improvement (%)
Transmission loss	Average system power loss	Reduced by 15%–20%	18%
Voltage stability	Deviation under load variation	<5% deviation	20%

(Continued)

Table 3 (continued)

Indicator	Description	Value/range	Improvement (%)
Energy efficiency	Conversion and distribution efficiency	85%–92%	12%–18%
Peak load reduction	Reduction in grid stress during peaks	10%–15%	15%
Scalability index	Power handling growth with load	Maintained linear	–
Total harmonic distortion (THD)	Output waveform quality	0.0086	–

6 Conclusion

The MADRL model was trained on 500 episodes at a learning rate of 0.001 learning rate and a reward discount rate of 0.95. The convergence of the training with the stable reward curves was attained in the course of about 300 iterations, which proved the successful learning of the policies of load allocation and power routing. Photovoltaic-integrated tobacco warehouses. The paper presented a Flexible Power Supply and Distribution System (FPSDS) that relies on the intelligent adaptive model that is facilitated by FDNs. A PV-based system, along with the use of multi-port bidirectional DC-DC converters and the Battery Energy Storage System (BESS), made it possible to transmit the power in two directions with a stable power supply. Three progressive control strategies, Dynamic Load Distribution (DLD), Intelligent Power Routing (IPR), and Multi-Agent Deep Reinforcement Learning (MADRL), made it possible to optimise energy distribution in real-time and balance the load. This was to improve system performance by using the Model Predictive Control (MPC) that minimised the power loss and frequency and voltage variations. The results of the simulation reveal the improvements in the power efficiency and the minimisation of transmission loss, the control of the peak demand, and the expansion capacities of the system. The suggested system becomes a sustainable solution that is reliable because it promotes a larger-scale integration of renewable energy that is distributed, as well as providing the necessary flexibility in its operation and energy independence.

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