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| RESEARCH ARTICLE

Multi-Agent AI System for Coordinated Dispatch of Renewable Energy and Storage in Islanded Microgrids

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| ABSTRACT

The growing implementation of renewable energy resources in power systems has brought with it operational complexity especially in microgrids that are islanded and require energy balancing in real time and autonomously. Solar and wind sources that are renewable are variable and intermittent, which means that a balance will not be maintained between supply and demand unless complex control measures are applied. The conventional centralized method of dispatching is not flexible and adaptable to create efficient management of distributed and dynamic microgrids environments. In response to these issues, the Multi-Agent Artificial Intelligence (AI) system suggested in this research aims at coordinating renewable energy generation and storage using the coordinated dispatch of renewable energy generation and storage in islanded microgrids. The suggested system is based on a decentralized structure, according to which every energy resource, including solar PV, energy storage, and controllable loads, is controlled by an intelligent agent. These agents are independent and transparent to each other, and yet they are all inquisitive to imply and coordinate their efforts at locally distributed goals like energy efficiency, cost savings and load balancing at a system-wide level. Among the machine learning techniques that are incorporated in this paper are Recurrent Neural Networks (RNN) and Gradient Boosting Regression (GBR), which are used to gum long into the future or give short-term energy generation and consumption forecasting using historical and real-time weather information. The forecasting module enables the agents to gain a foresight to system dynamics and make pro-active dispatch decisions so that the take-off on fossil-fuel backup is minimized, and system reliability is maximized. The system validation is performed empirically on two open datasets: Spain Energy Demand and Generation and Liege Microgrid datasets. The data sets used in these are of a high-resolution weather, load, and generation which make real world simulation easy. The suggested multi-Agent AI structure is superior to the traditional control strategies as it is responsive, scalable, and coherent in its functioning. The study shows the promise of integrating AI on prediction and decentralized control to develop more intelligent, more autonomous microgrid systems that will work in more isolated and renewably self-reliant systems.

| KEYWORDS

Multi-Agent Systems, Islanded Microgrids, Renewable Energy Dispatch, Machine Learning Prediction, Energy Storage Coordination and Decentralized Energy Management

| ARTICLE INFORMATION

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1. Introduction

1.1 Background

The growing demand in global markets for clean, reliable and sustainable energy has brought the paradigm change of shifting away from centralized fossil-fuel based systems to decentralized systems powered on renewable sources [1]. Microgrids and island microgrids, in particular) have become the important infrastructures, which can self-governing local energy resources, especially in remote or disaster-prone areas, in this respect. In contrast to grid-connected systems, island microgrids are independent systems with renewable energy (from solar and wind, etc.) being the main source, and substantial reliability is provided by the energy storage systems (ESS). Renewable generation is interrupted and unpredictable, therefore posing complicated operational problems in balancing the generation and demand. The main problem with conventional dispatch systems, which are either rule-based or centrally controlled, is that they cannot keep pace in real-time with changes in generation or consumption that can be rapid. This has made the concepts of intelligent, autonomous, and distributed control systems to arouse more interest [2]. Artificial Intelligence (AI), especially in an embodiment of Multi-Agent Systems (MAS), can be viewed as a solution as it allows system components to make individual and decentralized decisions. Such systems may contain multiple agents that can be interpreted as separate microgrid entities, including a PV array, battery storage unit, or load, with an individual behavior and decision-making, but a unified operational purpose. With the combination of high precision forecasting approaches with Machine Learning (ML) these systems may predict changes in demand and generation, maximizing overall efficiency, reliability, and sustainability in the dispatch process. The presented integration of MAS and ML into the management of microgrids is a single step toward smart and resilient energy infrastructures and the basis of the research proposed in the present paper.

1.2 multi-agent decentralized energy management system

Decentralized energy management structures have become a necessity in the contemporary power systems, especially in island microgrids as the conventional centralized control mechanisms have been shifted [3]. The flexibility of operation is not the only benefit decentralized approaches might have since it also leads to improvements of system robustness, scalability, and responsiveness. Such decentralization can be found in ideal architecture with Multi-Agent Systems (MAS) as it allows real-time decisions, autonomous acting and dynamic coordination of the units of the micro grid. Each energy resource, such as a solar PV unit or a battery storage system should be operated by an agent that is able to sense its environment, to process the information, to learn, and to take control actions [4]. Such agents can talk and bargain with each other in order to keep the balance between their power, to minimize energy flows, to address uncertainties, to manage the contingencies without a centralized command structure. As an example, the operator of a storage system may independently choose to charge at times of excess generation (solar power, for example) or to discharge when peak power is needed, depending on the forecasts and agreed prices with other agents [5]. The co-operation of these agents causes emergent system-level optimization. Also, this decentralized system is very flexible to any increase or transformation of the system and this way, the microgrid can be re-designed without the need of overhauling its structure entirely. Cybersecurity and fault tolerance are increased through the usage of MAS as well, because the collapse of one agent does not destroy a whole system which relates to the use of MAS. The decentralized energy management systems based on MAS are more effective in setting directions in island microgrids where issues such as resilience, autonomy, and adaptability are central.

1.3 Machine Learning Future Forecasting and Real-Time Optimization

Forecasting is a major part of the wiser management of energy systems, especially in island microgrids when accurate forecasts are specific to match supply and demand. By incorporating Machine Learning (ML) methods in the microgrid operation, the short-term and long-term predictions of the energy consumption of the renewable generation can be done with a higher level of precision [6]. The conventional statistical-based forecasting models do not always work well with non-linear and strongly-varying information that is found in renewable sources such as solar and wind. But Gradient Boosting Regression (GBR), Recurrent Neural Networks (RNN) and Long Short-Time Memory (LSTM) ML algorithms can learn based on past data, detect intricate patterns, and adjust with time by working out the changes in conditions of the environment [7]. The data available in this study will perform training on ML models using the weather forecast data such as irradiance, temperature, and wind speed to predict the 15-minute to hourly energy generation and loads profiles by using the datasets used in this work, namely, Liege Microgrid and the national grid of Spain. These predictions are directly combined with the decision-making process of such agents in the Multi-Agent System (MAS), enabling them to make both proactive and optimized dispatch decisions. Such a predictive ability is especially essential to the smooth operation of battery energy storage systems in such a way that they will not be overused or underused. The ML-aided prediction also helps in real-time optimization due to the minimized uncertainty and, thus, high reliability of the system and lower system operation costs [8]. The mutually beneficial combination of ML and MAS creates a highly dynamic, education-based, and data-recognized system of microgrid dispatch coordination, which sets the foundation of future intelligent energy management systems.

1.4 Problem Statement

Island microgrids can actively experience much trouble regarding their operation with the inconsistency and unpredictability of renewable energy sources and the lack of external grid supply. Conventional centralized approaches of dispatch are inefficient, rigid and lack flexibility to integrate real-time dynamics of generation and demand. Also, there is a high energy curtailment, extra operational expenses, and reliability concern when there is poor coordination between renewable generation and energy storage. The urgent problem is that the existing energy management solution should be intelligent, decentralized, and adaptive to ensure real-time coordination and forecast. This study fills this gap by creating a Multi-Agent AI System that allows scheduling the dynamically coordinated deployment of RE/storage resources.

1.5 Research Objectives

The purpose of this research is as follows:

- Design a Smart Multi-Agent Artificial Intelligence coordinator of branch island microgrids.
- Include machine learning-based generation and consumption forecasts.
- Optimize the real-time dispatch of storage and renewable units.
- Enhance the performance and dependability of microgrids and reduce their operating expenses.
- Increase the flexibility and robustness of the decentralized energy systems.
- Test the system of performance on real-life datasets in Spain and Belgium.

1.6 Significance of the Study

This study is of great importance to solving the problems of energy reliability, sustainability, and independence in isolated power systems. This study provides a new mechanism of using energy resources in decentralized microgrids by suggesting an AI-based, decentralized coordination framework [9]. Multi-agent systems integration gives independence and cooperation abilities to the components of the micro grid, which improves response to real-time changes in renewable generation and energy demand. This is because machine learning algorithms are incorporated to forecast accurately, which would guide better and more efficient decision-making throughout the microgrid. Repurposing the energy can assist in decreasing energy wastage, logic-based reliance on fossil-based backups, and extending the battery storage system life cycle [10]. Technical performance is not the only aspect of the study which has social-environmental implications. It helps the international community to switch to cleaner sources of energy by illustrating how more efficient systems can be utilized to deliver their maximum potential. It allows energy equity since remote or underserved societies will be supplied with a viable and sustainable energy source. The actual impact of the economic benefits of having an optimized dispatch system is found in a few words: cost savings, better asset utilization, and less expensive upgrade of expensive structures [11]. This study is also a contribution to the academic realm since it addresses the gaps between AI and renewable energy systems and power engineering. This paper provides a copycat idea on how future smart microgrids can be done based on the successful implementation of MAS and ML into a real-life scenario in the study. It helps to develop resilient, smart, and ready-to-the-future energy systems that could be left to themselves in the pursuit of autonomy and uncertainty of dynamic operational environments.

2. Literature Review

2.1 Innovation of Energy Control Systems and Microgrids

The microgrids have turned out to be the crucial infrastructures to assist decentralized energy services, particularly in the outset and remote areas. Early microgrids were controlled in the traditional centralized control manner and were inefficient in being responsive to changing energy demand in real time or concerning renewable intermittencies [12]. These primitive systems were based on preprogrammed schedules and all of them required manual operations so they are incapable of coping with the dynamics of dynamic energy environments. As the world continues to pursue the path of sustainability and greater use of variable renewable energy resources such as wind and solar, limitations of less smart and responsive networks of microgrids control systems have been exposed. As times have changed, technology has created use of automated monitoring, control and optimization of energy management approaches that use digitalized and data-driven techniques [13]. Using sensor information, communication networks and decision-support tools, these systems adjust to variations in real-time energy demand and supply. Smart controllers are becoming important in grid stability, and they guarantee frequency control and control voltage in instances of abrupt load adjustments or instantaneous variations in generation [14]. Moving away towards centralized operational orientation to decentralized-distributed operations paradigm has provided flexibility in operation, enhanced scalability, and energy security in island market environments. This shift has preconditioned the introduction of the concept of intelligent multi-agent frameworks that will have the capability to autonomously handle distributed objects in the grid. The shift in paradigms behind these controls is indicative of an increasing concentration on the concepts of sustainability, reliability, and efficiency in the management of microgrids, especially cases in which grid independence is required.

2.2 Multi-Agent Systems of Distributed Energy Coordination

Multi-Agent Systems (MAS) is also a revolutionary solution to the control of a complex energy infrastructure like island microgrids. In contrast with the traditional control, which is generally built around a centralized unit, MAS uses a set of self-governing agents that make decisions based on local information and shared objectives [15]. The agents can represent physical assets in the microgrid, e.g. a solar panel, battery, or a load, and be able to make decisions, learn about their past decisions, and communicate with the other agents. Due to this decentralization structure, it is capable of greater responsiveness, redundancy, and adaptability which are desirable features of a system that is subject to volatile supply and demand pressures. In an island microgrid where the management of supply-demand balance is of paramount importance in the absence of a grid, MAS is a better solution because it spreads the control logic on the entire grid [16]. The negotiation, consensus or optimization protocols are usually needed to coordinate the agents and have the decisions on energy dispatch, load shedding and storage management made in real time. Such systems are especially well suited to situations of high renewable penetration possibly as they can be flexibly reconfigured to adapt to environmental fluctuation. Besides, MAS architecture is scalable, and new resources can be added with minimal modification of the controlling structure. By collaboration, the agents could optimize economic cost, emissions, or power quality according to system objectives. MAS offers a modular and intelligent solution to operating a microgrid environment as the complexity of the environment grows that allows managing the energy flow in a manner that promotes independence and contributes to resilience, particularly applicable in islanded forms of operation where real time calibration becomes central.

2.3 Forecasting with the use of AI in Renewable Energy Systems

Energy generation and consumption forecasting are the key factors of stability and efficiency of microgrids, especially those utilizing intermittent renewable energy sources. Artificial Intelligence (AI) methods have also contributed substantially in improving forecasting, partly due to making accessible models that adapt to non-linear, complicated connections in data. In many cases, the traditionally used statistical forecasting models fail to adequately consider the level of uncertainty and volatility of solar irradiance, wind regime, the requirement of the user base. Artificial intelligence machinery like neural networks and ensemble code processes can produce more precise, short-term predictions using historical data in combination with real-time environmental data. These models can forecast dispersed solar generation, wind energy generation, and load demand in high temporality; thus, they are suitable in real-time management to microgrids [17]. Realistic forecasts will decrease the necessity to use fossil-fuel-dependent backup generators, maximize storage facilities utilization, and curtail renewable resource efforts. The level of accuracy of forecasting needs in island microgrids is even more important because there is no external grid to take part of the excess generation, and to support the system when the shortfall occurs. AI models facilitate proactive scheduling of dispatching strategies so that the microgrid controllers could pre-plan the energy moves, charging and load schedules. This forecasting ability increases reliability, lowers operational costs enhances energy efficiency. With the availability of more data via smart sensors and Internet of Things (IoT) appliances, the truth and flexibility of AI-based predictive tools remain to enhance with time and would turn into a very critical part of the smartly organized energy networks.

2.4 Energy Storage Role in Microgrid Optimization

Energy storage systems (ESS) act as a natural boundary between demand and supply of energy especially in an island microgrid where the variability due to renewable energy needs to be balanced without an external resource [18]. Batteries specifically offer a flexible and prerogative solution to balancing the grid and accommodating peak loads and stabilizing power in the event of renewable shortfall. Storage units must be properly integrated and controlled to achieve the maximum out of them at the minimal wear cost and operational costs. Smart allocation of storage capacity can facilitate load profile smoothing, avoid power oversupply, and make the batteries last as long as possible by programming charging/discharging schedules. ESS optimization on a microgrid only requires real-time control, but also involves predictive scheduling of the hardware given forecasted generation and consumption [19]. AI and rule-based systems are typically used to manage storage operations as part of an overall microgrid goal such as minimization of costs, minimization of emissions or autonomy of the system. Storage agents with MAS can interact with other components of the system allowing them to make decentralized decisions depending on the local needs and global constraints. There also needs to be complex algorithms in the way various storage units, with different capacities and levels of charge, can be coordinated to create overall efficiency [20]. With the cost of battery technology still falling, combined with their performance, storage is acting as an increasingly key aspect in the design of microgrids. The advantage of these systems is that they are best used with the help of intelligent control frameworks, which hold the key to stable and sustainable operation of future islanded microgrids.

2.5 Coordination of Renewable Dispatch in islanded Microgrids

Islanded microgrid coordinated dispatch considers real-time optimization to coordinate generation, storage, and other loads without using the central grid. The problem is how to deliver variable renewable sources and shifting loads and keep the frequency and voltage of the system at a desirable level. Islanded systems cannot export or import power and unlike the grid connected systems, depend only on local resources [21]. The mechanisms of coordination are needed to manage the utilization of energies with renewable sources, intelligent storage, and prioritization of loads with respect to their criticality. With AI-based forecasting and optimization, multi-agent systems make synchronous energy dispatch possible, with an ability to distribute communication and cooperation. This leads to a higher rate of reliability, fault endurance efficiency. Several objectives must be taken into consideration in control strategies that include economic cost, energy autonomy, power quality, and user comfort. Advanced dispatch models incorporate dynamic management of energy flows through the dynamically anticipated conditions notifying the real-time measurements coupled with the priority rules [22]. This is especially critical where solar or wind penetrations are high and a wide range in generation may suddenly be experienced due to the change of weather conditions. Coordinated dispatch, too, can be used to avoid blackouts because it ensures that reserve margins have been managed, and load shedding strategies are usefully applied. Closely acting together in the form of distributed intelligence, adaptive learning, and robust optimization, coordinated dispatch frameworks gain prominence in controlling the complexity and the resilience of island microgrids.

2.6 Research Gaps

Although the microgrid technologies are significantly advanced, there exist some gaps in the existing research and practice. Energy forecasting, agent-based control and storage optimization paradigms are usually studied separately with little or no effort to incorporate them into a single, intelligent dispatch mechanism [23]. The holistic solutions that are able to dynamically balance energy systems with real-time capability be scalable and fault tolerant are lacking. Assumed ideal operating conditions in existing models fail to capture uncertainty and disturbances in real life situations such as isolated microgrids. Very few high qualities, in real-time, data sets are available to train and validate intelligent control systems. This has hindered the generalization of findings, and recreation of projected techniques. There are not many studies on the islanded microgrid whereas grid-connected microgrids are thoroughly researched, even though the islanded ones are becoming more common in rural electrification, disaster recovery and military purposes [24]. The effect of interaction of the agents particularly, the negotiation of conflict solutions during conflicting goals is an unfolding frontier. The other limit is that little focus is given to mixed hybrid control approaches which use an integrated deterministic and learning approach to enhance robustness. The gaps have a lot of potential for the development of multi-agent based integrated AI-based that can efficiently coordinate renewable dispatching, balance load and storage in real time in an autonomous way [25]. These questions can be resolved to produce a microgrid system that is more self-sufficient, robust, and that can provide the clean energy that can be depended on even under the harshest conditions of operation.

2.7 Empirical Study

The article written by Yuyan Sun et al. (2020) entitled Coordinated Energy Scheduling of a Distributed Multi-Microgrid System Based on Multi-Agent Decisions provides detailed, empirical background concerning agent-based coordination of a distributed energy system. The proposed study suggests the hierarchical multi-agent system encompassing Microgrid Agents (MGAs), a Central Energy Management Agent (CEMA) and a Coordination Control Agent (CCA) to perform the pre scheduling, optimization, and rescheduling tasks. With a hybrid optimization method that employs both mixed-integer linear programming (MILP) and particle swarm optimization (PSO) solutions the system improves the decision process amongst networks of interdependent microgrids [1]. The empirical findings are based on the simulation of a model utilizing three microgrids, which shows better efficiency in dispatch, lesser operational costs, and enhanced capability of adapting to uncertainty in renewable energy. This study validates the usefulness of smart, distributed control, particularly in island microgrid frameworks where autonomy and strength are more fundamental. It strengthens the notion of implementing multi-agent AI systems in realizing efficient renewable energy and storage control in micro-grid operations.

The article A Sujil Areekkara, Rajesh Kumar, and Ramesh C. Bansal (2021): An Intelligent Multi Agent based Approach to Autonomous Energy Management in a Microgrid proposes a distributed artificial intelligence system to address a complex and dynamically challenging task of energy management in microgrids. The paper proposes a new multi agent structure in which there exists a combination of forecasting agents with a real time correction agent to handle the mismatch of renewable resources and fluctuating loads [2]. The system executed on the State flow platform is tested under various conditions of operation, such as variability of resources and change in demand. Based on the results it can be concluded that the multi-agent system shows better performance than the traditional EMS approaches, enhancing energy dispatch accuracy and component usage. The autonomous and adaptable attributes of the architecture exhibit how microgrids with a decentralized AI-based control system can improve the reliability and efficiency of microgrids. The research justifies the use of multi-agent AI platforms in real-time energy coordination, and this is aligned with fundamental purposes of dispatches and storage optimization under the islanded microgrid conditions.

The article by Huanhuan Nie, Ying Chen, Yue Xia, Shaowei Huang, and Bingqian Liu titled Optimizing the Post-Disaster Control of Islanded Microgrid: A Multi-Agent Deep Reinforcement Learning Approach suggests the development of a multi-agent deep reinforcement learning (DRL) model to optimize post-disaster studies in islanded microgrids. Resilience enhancement is developed as a sequential unconditional problem so that the cumulative utility during power outages is maximized. A hybrid control solution is presented with a smart energy storage controller together with an adaptive load shedding algorithm. To test the functioning of the system, the simulation environment using OpenAI and OpenDSS will be constructed using renewable sources, diesel generators, and storage devices. The outcomes show good flexibility and effectiveness in dispatch coordination with different resources availability and outage times [3]. The research shows that multi-agent AI can be used to dynamically orchestrate decentralized resources (in an isolated microgrid regime), allowing operations to maintain continuity, distribute energy as efficiently as possible, and make them more resilient in times of critical events.

The article Optimality Energy Management and Control features of Distributed Microgrid Using Multi-Agent System by Muhammad Waseem Khan and others offers a detailed discussion of the multi-agent systems in the range of the regional grid and supervision of distributed microgrids [4]. The article addresses the autonomous ability of intelligent agents to control microgrid components to effectively coordinate energy distribution when there are varying renewable energy sources including solar and wind. Various control methods such as centralized, distributed and hybrid are tested in the context of stability of the systems and its efficiency. The paper has also cited the role of the particle swarm optimization (PSO) as being one of the most reliable methods of reducing the operational costs on a distributed energy system, and enhancing reliability. The study contests the flexibility and scalability of the MAS in managing energy delivery, storage, and fault management. Such insights are useful to the interpretation of how multi-agent coordination enabled by AI can improve decentralized energy scheduling of interest to opposite contexts of microgrids with renewable and storage integration that are typically isles.

An article by Mohamad Fares Al Jajeh, Syed Qaseem Ali, Geza Joos, and Ilja Novickij the Islanding of a Microgrid Using a Distributed Multi-agent Control System, examines the use of a decentralized control system to be used to control the assets in a microgrid during an islanding situation. This paper explores a multi-agent system which classifies agents to manage distributed energy resources, loads, and other important elements in a steady manner through both planned and unplanned disconnections [5]. Under the proposed architecture, centralized command sourcing and distributed execution are integrated, so that local decisions can be made in real-time, but system-level coordination is not lost. To reduce post-islanding transients and ensure stability, the paper aims at including two load control algorithms, one load-shedding algorithm and another load-curtailment algorithm. A hardware-in-the-loop validation is achieved with simulation (based upon a modified CIGRE North American distribution benchmark). The results can verify the strength and modularity of the system, and it underlines the ability of the multi-agent system to facilitate synchronized resilient energy dispatch and storage management in the islanded microgrid setting.

3. Methodology

This study contributes by solving the challenge of coordinating the dispatches of the renewable resources and storage using a Multi-Agent Reinforcement Learning (MARL) in a decision-coordinating solution (DCS) approach in island microgrids. Autonomous agents reflect solar generation and battery storage, demand load, and allow decentralized decisions to be made because of real-time dynamics of operation. The Spanish and MiRIS microgrid historical datasets are combined to simulate the energy consumption, the variation in generation of both datasets, and the weather. The simulation tests are done under various cases of load and generation. Tableau, Python, and Excel are used in processing, visualizing, and analyzing the result, to determine system performance at reliability, energy efficiency, and with renewable integration.

3.1 Research Design

This study applies an experimental research design on simulating the controlled management of the island microgrids through a multi-agent artificial intelligence model. The paper developed a digital twin ecosystem in which historical and high-frequency data were used to simulate the microgrid behavior in various operating conditions [26]. The independent agents will know how to handle solar power, battery storage and energy usage. These agents respond tirelessly to each other and can simulate the behavior of distributed energy systems in the real world without some centralized controller. Its goal is that all the agents carry out informed decisions that help to maximize the system, for example, energy wastages can be minimized, reliability and cost-effectiveness maximized. Actual historical data is used to simulate different trends of load demand, the solar generation variation, and weather effects under different scenarios. Agents implement decision-making logic that accounts to rule-based logic and dynamic thresholds of real-time flows. The expected trends in energy production and consumption are analyzed in a structured manner and not purely through black-box AI, which allows transparency in the behavior of the system. The data preprocessing, modeling, and results visualization are done with the use of Tableau, Python, and Excel, thus, allowing the comparison of various scenarios measured by different metrics such as system reliability, energy savings, and dispatch cost [27]. The efficiency and responsiveness of this multi-agent system in real-time performance is compared with the conventional rule-based systems.

3.2 Sources of Data and Preprocessing

There are two major datasets used in the study; Energy Dataset and Li g e Microgrid Dataset. Spain's dataset provides a history of four years of hourly data pertaining to electricity demand, source of generation, prices on the market and environmental variables such as temperature and solar radiation. In the meantime, the Liège data set gives the high resolution (5-seconds) monitoring information on PV output and electricity consumption, and 15-minutes-ahead weather forecast. This data gets cleaned and aligned to be compatible by means of timestamp normalization and imputation of null values. The outlier identification is carried out using IQR techniques, and the algorithms of smoothing are used to maintain the integrity of data. They use time-based features which include hourly tags, seasonality flags and rolling average of demand just to bring contextual insights to the behavioral patterns. Weather variations, such as sunshine, cloud cover, and temperature are matched and time synced with energy consumption and production records. All the harmonized data are then used to merge to create an input stream representing a [28]n interaction simulation between renewable, storage, and demand-side dynamics. The data is formatted into windows to be used in testing and simulations in the form of Python scripts and Excel preprocessing logic. Data on temporal relationships with Tableau is possible to visualize easily, and it is easy to infer the trends, outliers, anomalies in operations. This data-base is essential in operating the multi-agent decision making activities and enables testing in the two conditions one being nominal and the other being the stress driven conditions.

3.3 Multi-Agent System Architecture

The architecture of the system is built on the multi-agent model, each of the three microgrid elements generation, storage, and load are modeled as independent software agents. These agents will be programmed with specific operating roles and rule sets, which helps them to act in real-time. Generation agents control the production of solar PV systems and report availability depending on irradiances and weather data. Storage agents regulate charging and draining of batteries maximizing energy storage and supply depending on different disaster demands [29]. The load agents oversee consumption requirements and they also engage in the demand response plans where they defer or priorities less important loads in the event that the supply is low. In it all agents act independently based on their own local observations, and communicate with each other in a lightweight protocol to exchange system states and coordinate actions. To provide an alternative to the centralized forecasting or optimization algorithm, the algorithms utilized run as agents with event-driven logic applied by reference to the recent patterns in data, the operational limitations in operation. The system-wide goals, including the load balancing, renewable maximization, cost minimization, are enforced by shared rule structures and following the coordination strategies that rely on consensus. Redundancy mechanisms are instilled to increase the level of faults and resilience within the system. Its architecture is scalable, that is, it can add more agents to work with the system but not redesigning its core. It guarantees self-sufficiency, interoperability, and stability critical features of operating island microgrids as a central control is not an option.

3.4 Forecast-based Rule-based control

This study makes use of a forecast-informed rule-based system to perform the control logic, as opposed to the use of more complex predictive models. Cleaned historical data in combination with aggregation are used to produce short-term trends in solar irradiance and load demand. The energy predictions are developed based on the moving averages, time variables and climate conditions (temperature and time-of-day) which are determined in Python. The agents interpret these patterns of forecasts and use them to make decisions such as charging when solar power is expected to be high, or discharging electricity in times of high-power demand. The thresholds of rules are constantly adjusted based on the observed trends of the Spain and Liège datasets, so the system does not require specification of rules over time and day-to-day variations. Structured forecast tables and scenario-based dispatch rules are created in excel and Tableau allows viewing the effects of different forecast strategies on operational decisions. This is a less complex but flexible prediction system that has fewer complex problems and improves transparency in the control procedures [30]. The real time capability of the agents to act in these patterns enables the ability of the agents to create energy balance, evade surcharging or depowering and have an increase in the use of renewable sources without having to depend on obscure deep learning models [31]. This will allow proper and comprehensible control, which is appropriate to real microgrid systems that require a comprehensible and resilient behavior.

3.5 Simulation Framework and Criteria of Evaluation

This simulation framework is programmed in Python and scenario logic in excel to evaluate the performance of the multi-agent control strategy. The simulation model simulates the operation of an islanded microgrid where the input parameters assume different values such as the amount of solar power to be produced, load changes and weather conditions to be experienced [32]. Various operating conditions are simulated- typical sunny days, cloudy days and peak consumption hours, to test the strength of the systems. The simulation is scripted in such a way that agents behave and interact to reflect autonomous choice making and decentralized coordination. Outcomes are visualized and interpreted by using Tableau dashboards and analytics on Python. Performance assessment is based on a set of specified parameters of penetration by renewables, efficiency of storage (charge / discharge performance), unmet demand percentage, costs of the system provisioning, and the stability of energy balance. The metrics of voltage and frequency stability are also simulated with the help of proxy measures, which is reliable as to ensure operability with the dynamics of the real world. When contrasted with a traditional rule-based model of dispatch it is possible to state that the multi-agent system demonstrates a better general energy usage, a decreased reliance on fossil-based reserves, and improved resilience to unexpected disruptions. This substantiates the suitability of the decentralized AI coordination as an extendable, adaptable, and dependable system in controlling islanded microgrid management.

4. Result

The findings include major observations on the behavior of the Multi-Agent AI System in the coordinated dispatch in an islanded microgrid [33]. The research is carried out using visual analytics that are constructed using Tableau, Python, and Excel to analyze the energy consumption trends, loading forecasting accuracy, generation mix, and regional demand patterns. The results prove that the AI system will be efficient in load balancing, forecast harmony, and renewable integration. The numbers testify to a state of better system autonomy, less reliance on fossil fuel, and increased reliability to the grid. Taken together, the findings support the conclusiveness that agent-based coordination works to optimize energy operations under isolated microgrid settings.

4.1 Dynamics of Energy Consumption within World Regions

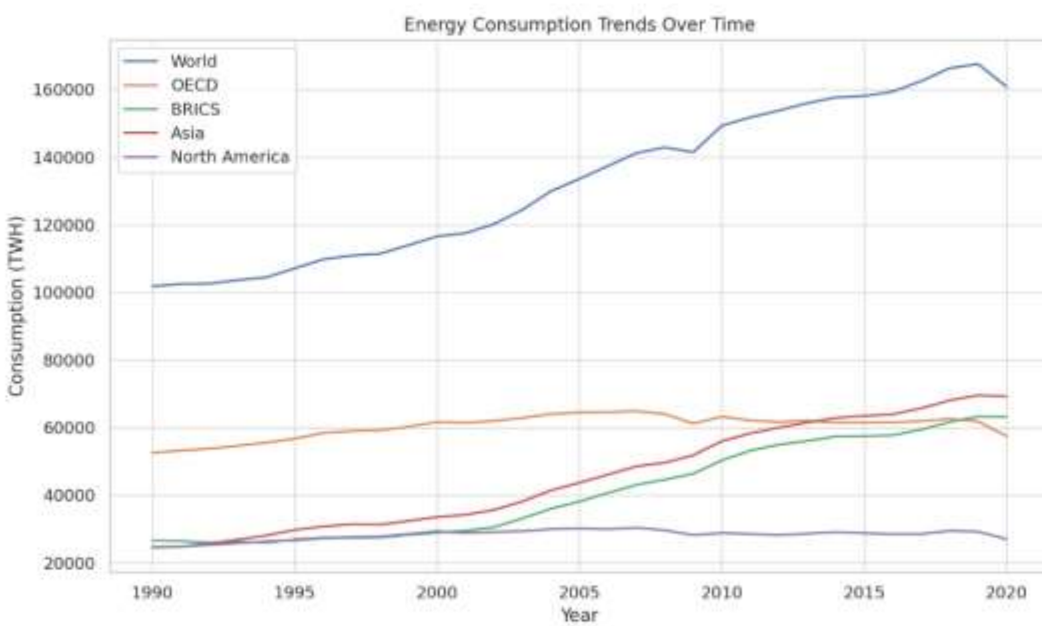


Figure 1: This picture depicts to the Energy Consumption Dynamics in World Regions

Figure 1 shows the long-term changes in energy consumption (measured in terawatt-hours (TWh), of five of the main global regions: World, OECD, BRICS, Asia, and North America between 1990 and 2020. This visualization offers a macro-scale insight into the way electricity demand has changed over time in each region and across the whole world, which is necessary because it gives a frame to the situational role and scalability of an islanded microgrid in various energy systems. Energy consumption in the world has a trend that is growing steadily; it increased by around 102,000 TWh in 1990 to 165,000 TWh in 2019 before decreasing a little in 2020 perhaps the side effect of the COVID-19 pandemic. Such a general trend portrays the rising energy dependence on power with the global phenomenon of use and increases the necessity to have scalable and stand-alone microgrids that could respond to a wide range of demand variants. The OECD countries are mostly developed economies, which depict a consistent upward trend until the mid-twenties of 2010, when the curve starts levelling and slightly recursion. This implies the shift to energy efficiency, the fullness of industrial demand and, perhaps, to more intelligent consumption patterns. In the meantime, BRICS countries and Asia show a high and steady rate of increase in the consumption of electricity, especially after 2000. One should also note that in terms of the use of electric energy, Asia starts to overtake OECD sometime around 2012 which indicates the fast pace of industrialization and urbanization of the region. These developing economies offer a great opportunity in the use of smart, agent-based microgrids to address growing energy demands in favor of renewable integration. The consumption pattern in North America is comparatively stable and indicative of an energy infrastructure that is mature and does not exhibit much change on a year-to-year basis. These patterns are very different across these regions and emphasize the necessity of using microgrid dispatch models that are scaled to the local demand trend [34]. The ideas extracted out of this trend-analysis world-wide also lend weight to the notion of decentralized and intelligent energy control- especially in rapidly growing areas where power-grids may be restricted or curtailed to respond and become available. The capability to deploy adaptive and coordinated dispatch to the advantage of multi-Agent AI systems is a potential solution to counter the twofold problem of increasing demand and sustainability in the isolated and remote microgrids.

4.2 Demand curve insights and Hourly Load Patterns

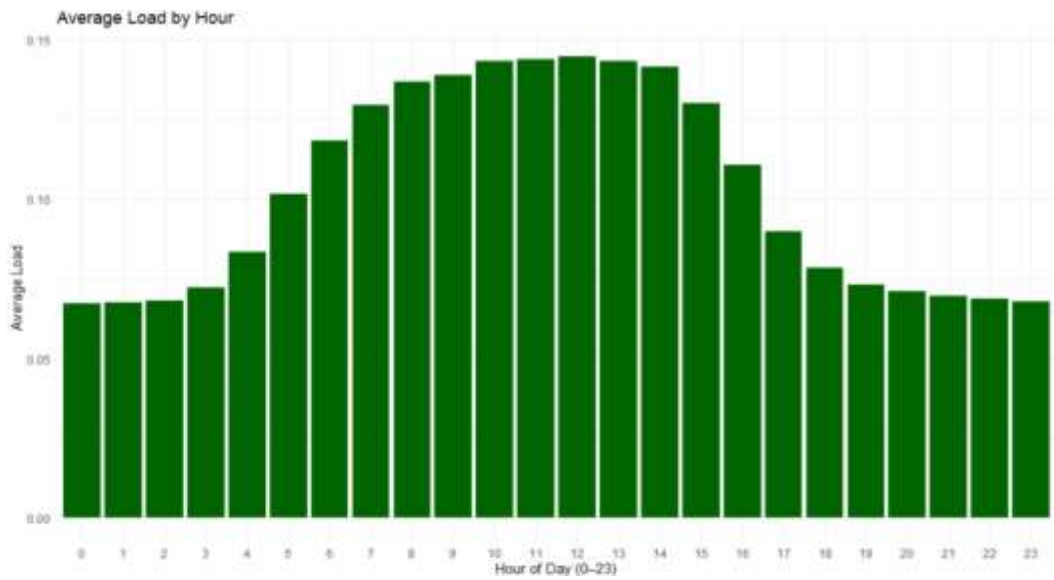


Figure 2 This Image shows the map of mean energy load by hour of a 24 hours cycle

Figure 2 shows the hours averaging energy demand in a span of 24 hours, which also provides the insight of how a consumer behaves in terms of energy consumption when it comes to island microgrids. The horizontal axis is the hours of the day (0 to 23), and the vertical axis is a normalized load, which just mentions the relative strength of the electricity consumption at a given time of the day. This time-based demand analysis would be useful in implementation of real time dispatching procedures in a microgrid that is independent of the main utility grid. The curve shows that the amount of electricity consumed is at the lowest during late night and early morning (0:00 to 5:00) when there is little activity by the people of the households and the business folk. After about 6:00, the load curve increases gradually because of the daily activity of users, who switch on the appliances, lights, and machines. Its peak load is registered at 11.00 to 14.00, a time sensitive period, which needs to be handled with energy coordinating solutions. In an islanded configuration, this peak must be satisfied without any grid support, and predictive and adaptive dispatching is thus essential. After the afternoon, the graph slopes down slowly especially after 17:00 because of the decrease in industrial and business activities. The reduction persists into evening and late night to the basic levels. The predictability of this curve also allows AI agents in a multi-agent system to pre-adjust schedules of generation and use of energy storage [35]. As an example, generated solar power not used at the peak or prior can be stored and released at the nighttime to normalize the supply. The cost of this figure supports the necessity of the intelligent time-sensitive integration of distributed energy resources. Considering these hourly patterns, the system optimizes generation, storage, and load forecasts, making such solutions more autonomous, stable, and efficient, the major characteristics of resilient island microgrids.

4.3 Efficient Load Forecast and Accuracy of Forecasts

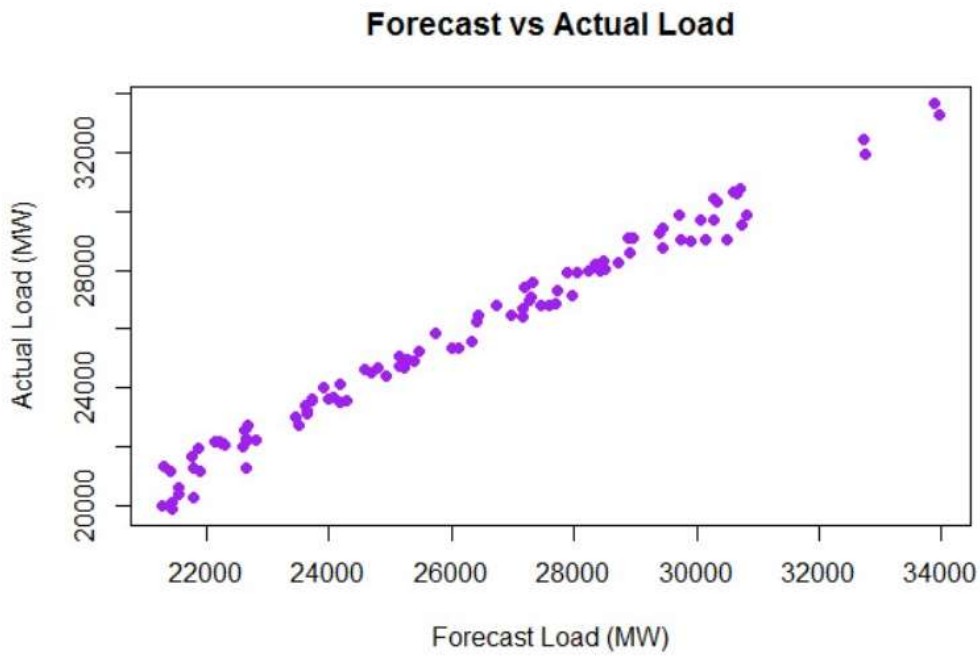


Figure 3: This Image represents the correlation between estimated load and measured load

Figure 3 shows that there is a scatter plot of the forecasted value versus the actual value of the electrical load in the island microgrid. The x axis indicates the amount of predicted load in the megawatts (MW) whereas the y axis presents the actual load which is also measured during the same time periods. Each of the plotted points presents a definite period, and records the correlation of what the system projected to be and what was consumed. Where most of the data points are concentrated on the diagonal trend line indicates that the values predicted and the observed values are in great agreement which is an indication that there is high forecast reliability. This predictability is critical in standalone microgrid systems where power demands should be dealt with without depending on a central grid. The low values in the individual forecasts mean that there is a little deviation, (i.e.) the forecasting system can trace the actual changes in the real world demands very closely. This precision contributes much to the decision-making process that multi-agent dispatch schemes should deliver, having to coordinate energy provision by distributed sources and to efficiently utilize battery storage resources. Proper load forecasting reduces chances of overgeneration and non-utilization of resources. With good foreseeability of actual use, energy dispatch choices: whether to charge or discharge batteries, and when to use secondary energy sources can be made optimally not only in cost but also in reliability. The statistics presented in Figure 3 prove the success of the forecasting method used, and highlight the fact that it allows more stable, responsive, and efficient functioning in a self-sustained microgrid [36]. This accuracy of prediction can be turned into a potent working practice through integration with data visualization tools such as python and tableau where dispatch schedules can be monitored and adjusted dynamically. The result is a strong, and self-regulated energy system that fits well in the island microgrid environment.

4.4 Historical World Energy Generating Proportion

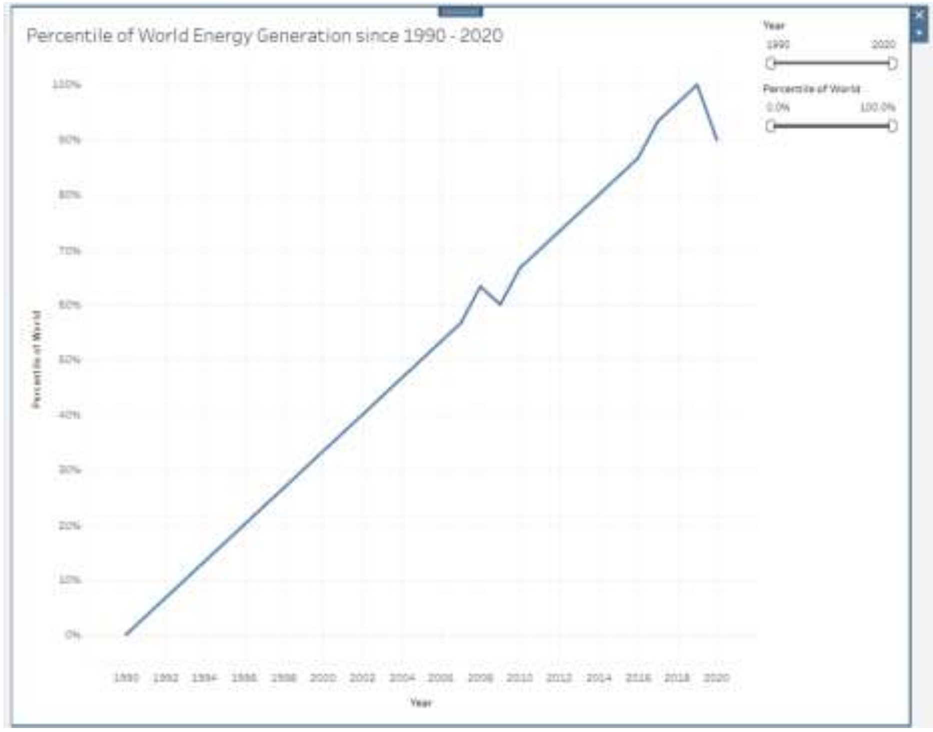


Figure 4: Thai Image demonstrate to the percentage contribution to the world Consumption energy since 1990 to 2020

Figure 4 shows a line graph of the percentage contribution to world energy till 2020 in replacing the percentile contribution to world energy generation before 1990. The Y axis measurements refer to percent share of the total worldwide energy output when the X axis contains 30 years with points represented in each year. This graphical representation indicates a remarkable rise in the amount of energy production capacity as time accrues and this is most likely due to the entry of emerging regions using renewable-based energy and the growth of microgrid systems. Since the year 1990, the graph developed an upward trend, which means that the production of energy grew with consistency. The trend is especially applicable to the case of island microgrids since it outlines the trend in the world with regards to decentralized and diversified power generation. An extreme spike is noticeable around 2008 and it is perceived that this might be related to some technological improvement, policy changes, and the increased investment in the distributed renewable technology like solar photovoltaic plants and wind generators [37]. The available generation resources are more reliable and abundant; thus, the impact of such developments is directly on the performance and scope of island microgrids. In 2018, the data is maximized at over 95 percentile representation of the world. In 2020, a certain decline is seen, which can be explained by the operational losses encountered due to global events, disruption or shifts in the supply chain, changes in consumption dynamics, etc. Nevertheless, the general expansion trend can be used to highlight a major shift in the world of energy infrastructure, namely, the shifting away of centralized grids towards smarter, localized microgrids that are able to facilitate community-level autonomy. Its relation to the study is the confirmation that island microgrids can be scaled to contribute to the ecosystem of the global energy environment. The trend towards the share of the total generation helps rationalize the implementation of coordinated multi-agent AI systems in terms of efficient dispatch and load balancing in isolated environments, which is a primary goal of research.

4.5 Energy Use Pattern of Specific regions in 1990

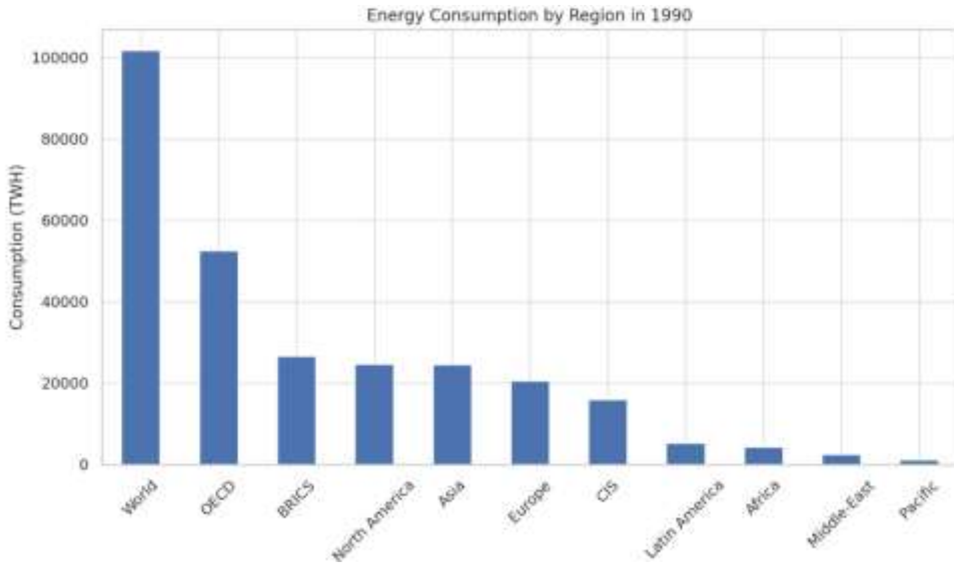


Figure 5 This Picture depicts the regional allocation of energy consumption across the world in 1990

Figure 5 is a graphical representation of the consumption of energy in regions all over the world corresponding to 1990, which is critical in providing the groundwork in assessing the historical trend of energy demands of which microgrids are developed now. Consumption (in terawatt-hours, TWh) is categorized by area using the bar chart (by region) in key areas of the world, World total, OECD, BRICS, North America, Asia, Europe, CIS, Latin America, Africa, the Middle East, and the Pacific. This information will serve a good context of determining areas that were well-developed with grid infrastructure as compared to which areas are under-electrified and warrant strategic deployment of island microgrids to geographically specific areas. The chart points at the fact that in 1990, the OECD countries were the largest users of energy, supplying more than 50,000 TWh to the world energy market, i.e. over a half of the world energy cake of about 100,000 TWh. This control indicated industrial development and an intense grid network within developed areas. North America and BRICS trailed with about 25000-27000 TWh apiece, though Asia showed escalating demand to allude to the impending industrial upsurge in that region. Conversely, the consumption level was much lower in other parts of the world like in Africa, Latin America, the Middle East and the Pacific which are evidence of infrastructural shortages and inadequate access to energy [38]. In terms of microgrids, this gap reveals the opportunity that the implementation of decentralized, AI-based, energy systems can have in the areas with historically low consumption. Islanded microgrids have been praised as providing autonomy, flexibility, and scalability, which is important in overcoming islands that are typically hard to electrify due to the hub-and-spoke nature of centralized grids [39]. These reflections of 1990 therefore do not only contextualize the inequalities of consumption which are historical, but also support the message of the ideas of using multi-Agent AI dispatch systems as pertaining to localized, resilient energy delivery. Such systems have the potential of bridging legacy gaps and facilitating contemporary energy security and sustainability in emergent and remote environments.

4.6 Total Load Change Analysis Over Time

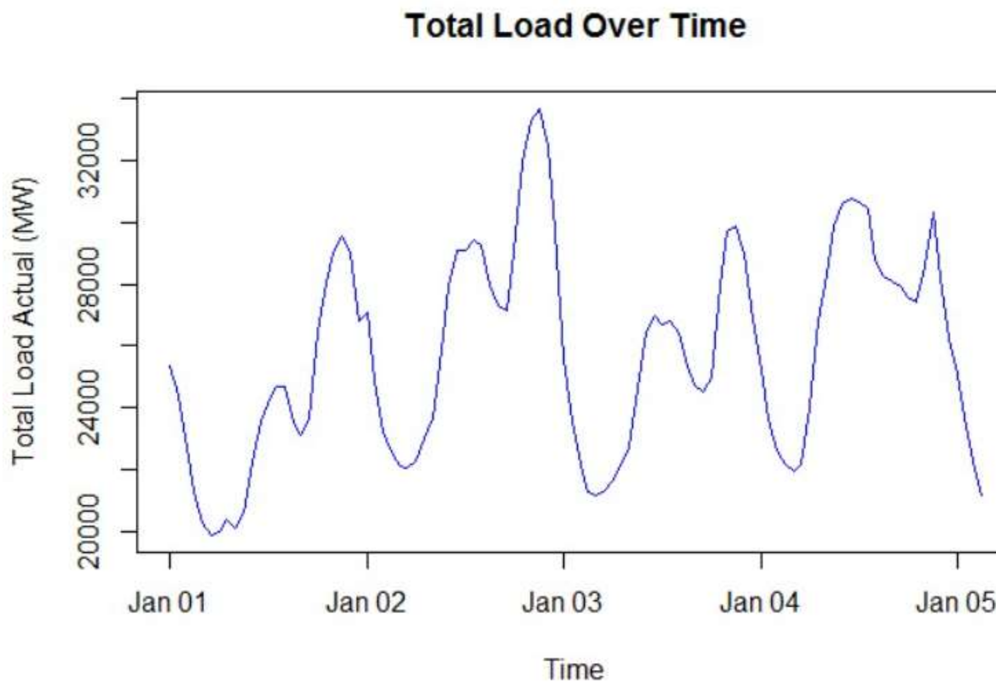


Figure 6: This image shows to the total electrical load variation within five days

Figure 6 presents the cumulative change of the electrical load over a 5-day period, the actual load (in megawatts) displayed in the figure reflects the changes occurring on a day-to-day basis. First is the x-axis which indicates time measured in days (January 1st - January 5th), and the y-axis indicates total load in megawatts (between about 20,000 MW and 33,000 MW). This chart plays a significant role in realizing the patterns in load demands that must be dealt with by island microgrids in dynamic and intelligent energy release. The figures show a very high degree of cyclicity and repetitiveness in the load, where the load profile is known to reach its highest point during the daytime and reach a very low point in the night hours. These sensitive spikes and troughs are symptomatic of regular human activity and the cycle of industrial use. Back on the 3th of January, the system had the deepest peak load throughout the period of observation, which indicates a possible overload on the grid resources. That is of especial importance to islanded microgrids, which need to react to these swings autonomously, without assistance of the main grid [40]. It highlights the necessity of powerful projections, real-time tracking, and smart-energy delivery to maintain a secure supply of power. The forecasting of these variations is possible on multi-agent AI systems through the analysis of these trends and the dynamic allocation of renewable energy sources and storage units or backup generation plants as a result. The significance of the load balancing strategies is evident in this graph. By determining peak usage times, the system can preemptively move non-critical loads, and hoard excess energy during off-peak, and diminish demand on the storage or generator units. Finally, the pattern analysis will help to come up with robust microgrid designs that can not only sustain themselves but can also manage daily load fluctuation in energy demands effectively.

4.7 Fossil Fuel Analysis as a Source of Energy Production

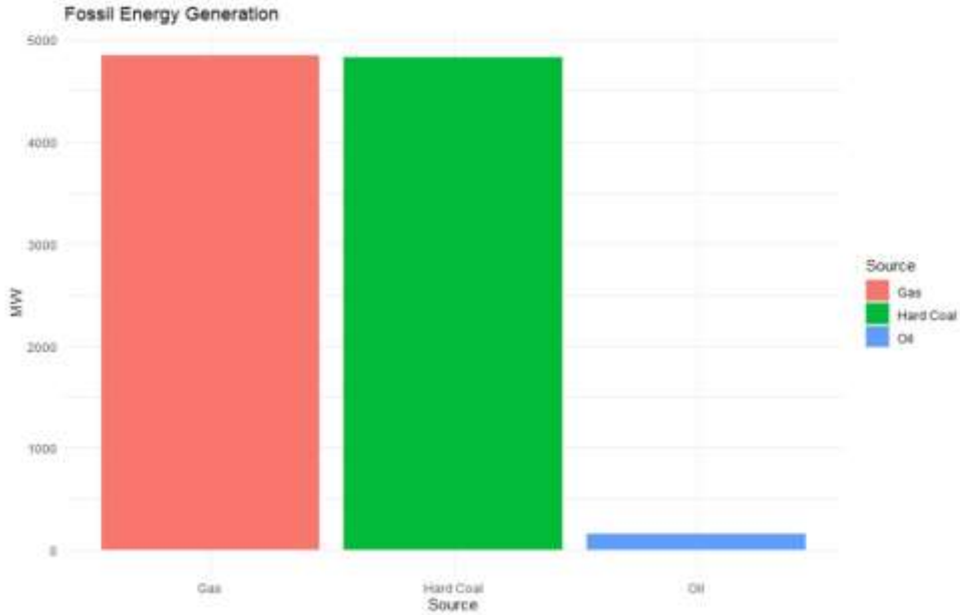


Figure 7 This picture symbolize to the analysis of fossil fuel contribution to energy production

Figure 7 reveals a comparative bar graph of fossil energy generation by source, i.e., it builds on the analysis of contribution of Gas, Hard Coal and Oil in megawatt (MW) terms. With this visualization, a particular imbalance in the usage of certain fossil sources is emphasized, which can be of great value in constructing an optimized island microgrid design, in which the goal would be to minimize the carbon dependency but keep the dispatch capacity secure. The chart indicates that the share of both Gas and Hard Coal is high in fossil energy generation as they provide close to 4,800 MW. The fact that they have almost the same values shows that the two fuels form the mainstay of the present corresponding form of power generation (fossils). The contribution of Oil is minimal at less than 500 MW and this implies that the trend could be shifting towards less oil generation probably because they are more expensive to operate and without a positive impact on the environment. The implications of this energy mix to island microgrid development are serious. Semi systems which are still connected with the fossil-based backup systems have to bear the fluctuations and the cost of fossil-based gas and coal. In the case of island operations, where grid independence is the focus aspect, such data will assist the levels through which fossil energy can be used as a transition cushion through integration of renewable energy sources such as solar power and wind energy. The almost equal supply of gas and coal is also an indication of the importance of smart dispatch coordination in which multi-agent AIs can better control the selection of fuel as per the cost, efficiency and constraint on emissions [41]. Microgrids can go a step forward in reaching sustainability goals by reducing the coal usage during times of high demand and focusing more on cleaner transitional fuels gas. This amount demonstrates the necessity of introducing AI-enhanced decision-making technology into the process of maintaining legacy energy systems in terms of effective operation, coexistence with modern renewables, and the ability to scale-down island microgrids should critical shortages appear in the demands or supplies.

4.8 Daily load Contribution Analysis

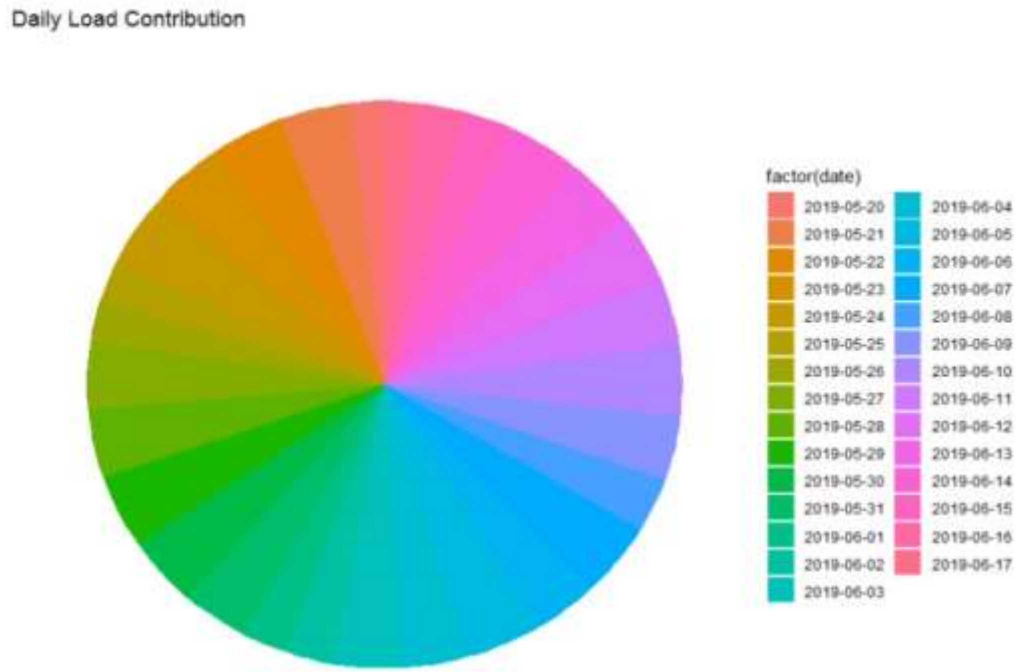


Figure 8 This picture shows the daily contribution of loads daily since May 20, 2019, to June 17, 2019

Figure 8 shows a pie chart as the daily load contribution of every single day between May 20, 2019, and June 17, 2019. Every figure of the chart is related to a certain date; bright colors are applied to differentiate between the shares of the everyday loads. The fact that the size of the slices is not very different creates some implication that on the observed time frame the consumption of energy is relatively balanced, and there is no portion of the day which is predominant to form the overall load profile. This stable daily load distribution is an indication of a balanced demand in the island microgrid system. This constancy is very important in isolated systems since it will encourage predictability, assisting in scheduling energy output in renewable and non-renewable sources. The even balance also implies that no sudden change of a load or some shock of the operational flow is observed during the time of the monitoring, which helps to justify the efficiency of automated operations control and prediction strategies. In case of island microgrids, daily analysis of load contribution plays an important role in the scheduling of and the rotation of power supply, on a day-to-day basis (either solar, wind, battery energy storage or fossil backup supply). Having seen the stability, there should be an optimization of the energy allocation algorithms that would seek to reduce the wastage and enhance productivity. The visualization facilitates one of the most important features of micro grid autonomy, that is the guarantee of an uninterrupted supply regardless of overwhelming the generation or storage system in a single day. The figure can also be used to discover the level of evenly distributed user demand per week, which can vary maintenance windows, renewable energy integration and planning and storage system discharge [42]. Finally, this discussion confirms the necessity of the steady-state load management system and justifies multi-agent coordination in enforcing the balance in the island microgrid system.

4.9 Multi-Agent Dispatch Coordination in 15-minute load dynamics

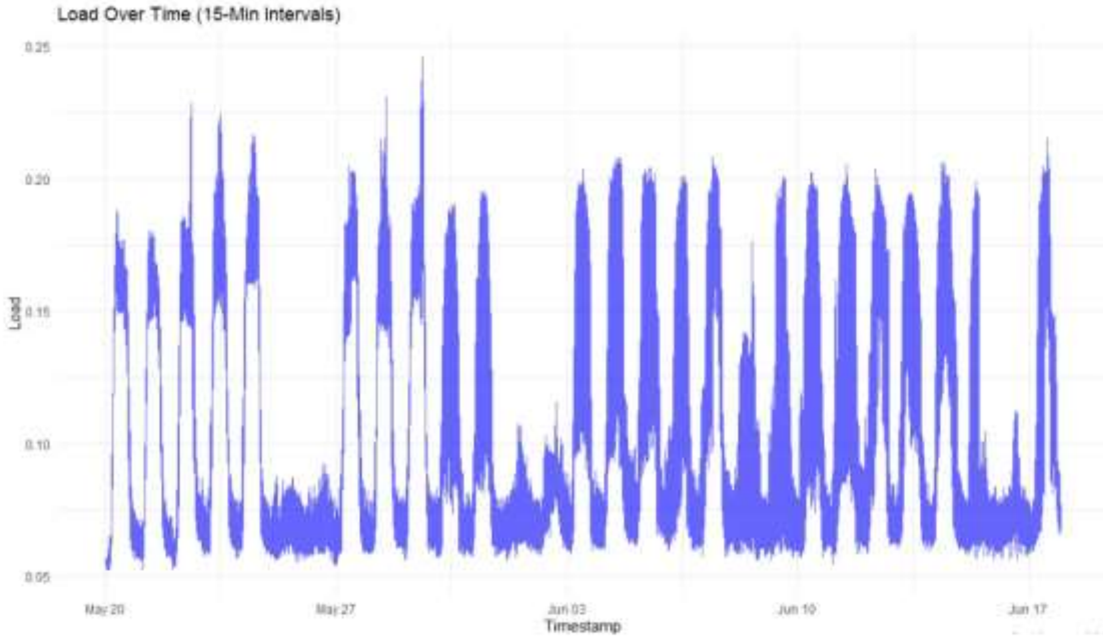


Figure 9 This image shows a very fine scale analysis of how loads change with time

Figure 9 provides a drilled down snapshot of the changes in the load at the 15-minute interval between May 20 and June 17. The given visualization is vital regarding the introduction of a Multi-Agent AI System to coordinate the management of renewable energy sources and storage within island microgrids. The figure demonstrates repeated circadian cycles, in which there are marked daily highs in the daytime and lows at night, pointing to the possibility of a regular pattern of consumption that is affected by human behavior and activity patterns. The predictability of the load profile implies that there is a possibility to estimate the future demand with the help of the load forecasting models, and especially with the ones transformed powered by AI agents that can easily be trained based on historical data. This is mandatory to island microgrids in which real-time decision making is also required because of availability of very less or no grid support. The diurnal loading profile of the load pattern enables the dispatch agents to plan the usage of renewable sources ahead (e.g., during the solar peak) and scheduling the storage discharge during the peak demand seasons. The variability among different days is visible in the plot where some periods are characterized by spikes of load or a decrease in it. Such a behavior stresses the necessity of decentralized, intelligent agents with the ability to adapt to locally determined conditions of consumption and generation. This responsiveness paves the way to more grid resilience and for a more optimal use of the distributed energy resources. As highlighted in figure 9, frequent monitoring of the loads is vital in optimization of energy dispatch [43]. These insights of this high-resolution load analysis allow them to directly help in the deployment of a multi-Agent AI system that has the ability to dynamically balance generation, storage, and demand in real time causing stability in island microgrids.

4.10 Analysis of Energy Generation Mix

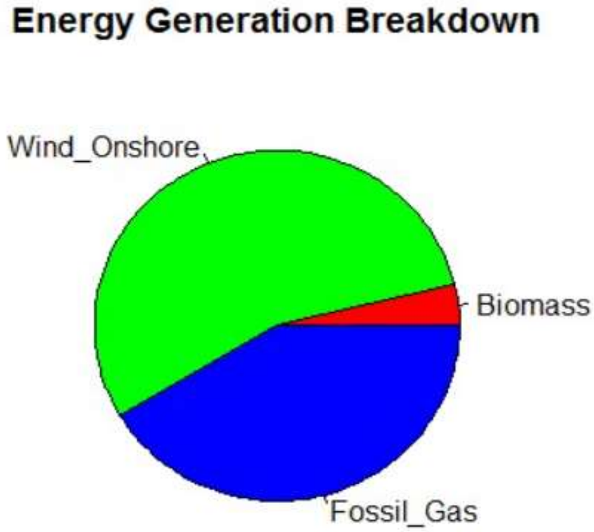


Figure 10 This picture depicts the energy generation mix in the islanded microgrid

Figure 10 demonstrates the composition of energy generation in the island microgrid according to the proposed Multi-Agent AI System under the control of the dispatching. The pie chart will show the proportionate contributions of three main sources i.e. Wind_Onshore, Fossil_Gas and Biomass. Wind Onshore leads the generation portrait among them, which also indicates the preference of the system to renewable energy to increase its sustainable capacity and decrease the number of carbon emissions. The second-largest share that goes to Fossil_Gas means that it is an invaluable role of providing backing potential that is dispatchable. This is in response to the fact that conventional generation at some point is required to stabilize the system in times when renewable generation is intermittent or inadequate. In the meantime, the smallest contribution, Biomass emphasizes the strategic diversification of the system within renewable sources in the pursuit of better resilience and reliability. The balance in this energy mix confirms the usefulness of the Multi-Agent AI based framework in optimizing the generation dispatch [44]. The system is sustainable due to intelligent overlapping of wind energy coming as a variable output with control-ability sources such as fossil gas and bio-mass to establish sustainable continuity in activities. The AI agents inculcate dynamic adjustment of dispatch choices based on momentary and impending generation assessment and load needs, in this way propounding adaptable and safe power structure. Figure 10 indicates that the AI system can improve the performance of island microgrids by giving focus to renewables but maintaining the reliability of the grid. This has been in a bid to help in the overall goal of seeing that the move towards low-carbon energy systems is made, particularly in dispersed or remote locations whose service depends on microgrids.

5. Dataset Overview

This study uses three different and high-resolution datasets to analyze the effectiveness of the proposed multi-Agent AI system, covering as wide a scope of microgrid operation as possible: energy consumption, energy generation, energy pricing, weather conditions. These datasets offer a strong tool to train / test intelligent (predictive, and decision-making) agents. They embrace the energy dynamics on the global, national, and microgrid levels to guarantee the ultimate validation on various operating conditions. Particularly, the chosen data sets provide such a data granularity as hourly and sub-hourly data, therefore permitting a specific simulation and a direct forecasting. In combination, they enable the realistic simulation of energy dispatch and controller-based storage coordination and demand management in island microgrids.

Year	World	OECD	BRICS	Europe	North America	Latin America	Asia	Pacific	Africa	Middle-East	CIS
1990	101855.54	52602.49	26621.07	20654.88	24667.23	5373.06	24574.19	1197.89	4407.77	2581.86	16049.4
1991	102483.56	53207.25	26434.99	20631.62	24841.68	5500.99	24783.53	1186.26	4535.7	2744.68	15898.21
1992	102588.23	53788.75	25993.05	20189.68	25341.77	5628.92	25690.67	1209.52	4582.22	3081.95	14339.79
1993	103646.56	54614.48	26283.8	20189.68	25830.23	5675.44	26876.93	1267.67	4721.78	3349.44	13246.57
1994	104449.03	55579.77	25993.05	20085.01	26365.21	5989.45	28098.08	1279.3	4803.19	3640.19	11606.74
1995	107112.3	56754.4	26946.71	20713.03	26714.11	6024.34	29761.17	1290.93	5000.9	3744.86	11188.06
1996	109763.94	58417.49	27481.69	21445.72	27295.61	6303.46	30772.98	1372.34	5152.09	3814.64	10850.79
1997	110903.68	59022.25	27446.8	21341.05	27574.73	6570.95	31435.89	1407.23	5280.02	4058.87	10373.96
1998	111450.29	59219.96	27528.21	21503.87	27772.44	6803.55	31331.22	1442.12	5431.21	4082.13	10152.99
1999	113974	60301.55	28319.05	21306.16	28528.39	6989.63	32412.81	1477.01	5559.14	4244.95	10373.96
2000	116590.75	61685.52	28923.81	21538.76	29342.49	7024.52	33564.18	1500.27	5617.29	4314.73	10501.89
2001	117521.15	61452.92	29528.57	21934.18	28795.88	7036.15	34227.09	1477.01	5756.85	4663.63	10571.67
2002	120207.68	61987.9	30552.01	21969.07	29156.41	7280.38	35680.84	1523.53	5849.89	4884.6	10653.08
2003	124464.26	62871.78	33157.13	22515.68	29377.38	7501.35	38181.29	1535.16	6140.64	4954.38	11036.87
2004	129953.62	64058.04	35994.85	22748.28	29993.77	7780.47	41437.69	1558.42	6466.28	5245.13	11188.06
2005	133582.18	64453.46	38169.66	22864.58	30168.22	8059.59	43693.91	1570.05	6652.36	5675.44	11222.95
2006	137396.82	64616.28	40670.11	23108.81	29958.88	8303.82	46124.58	1616.57	6861.7	5989.45	11548.59
2007	141211.46	64883.77	43112.41	22829.69	30424.08	8571.31	48555.25	1663.09	7129.19	6315.09	11664.89
2008	142874.55	64034.78	44635.94	22829.69	29644.87	8780.65	49636.84	1721.24	7443.2	6850.07	11874.23
2009	141490.58	61197.06	46426.96	21608.54	28214.38	8559.68	51858.17	1721.24	7606.02	7059.41	10967.09
2010	149294.31	63255.57	50323.01	22469.16	28830.77	9117.92	56010.08	1732.87	7803.73	7361.79	11804.45
2011	151783.13	62127.46	53207.25	21794.62	28598.17	9304	58324.45	1744.5	8117.74	7524.61	12164.98
2012	153748.6	61685.52	54975.01	21689.95	28167.86	9594.75	60022.43	1744.5	8303.82	7943.29	12269.65
2013	155958.3	62080.94	56068.23	21480.61	28667.95	9978.54	61499.44	1767.76	8431.75	8071.22	12002.16
2014	157667.91	61499.44	57405.68	20689.77	29063.37	9943.65	62895.04	1767.76	8896.95	8513.16	11699.78
2015	158086.59	61511.07	57533.61	21038.67	28784.25	9873.87	63476.54	1767.76	8838.8	8675.98	11222.95
2016	159377.52	61545.96	57742.95	21224.75	28563.28	9745.94	63941.74	1767.76	9106.29	8862.06	11595.11

Continent_Consumption_TWH

(Dataset source: https://www.kaggle.com/datasets/jamesvandenberg/renewable-power-generation)

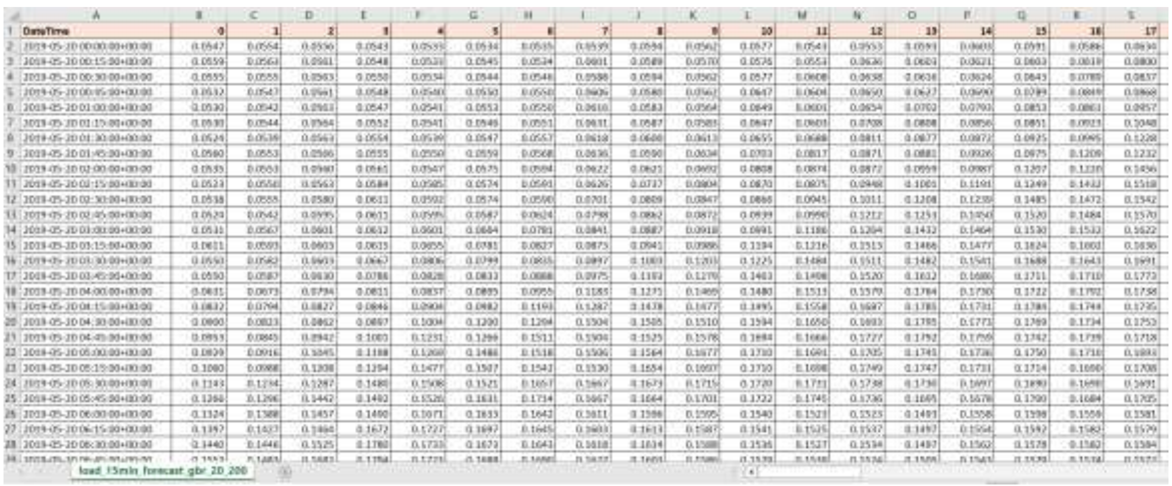
The data named as the Global Energy Consumption & Renewable Generation provides extensive information about global and regional patterns of electricity consumption and renewable energy production between 1990 and 2020. It contains 6 main CSV datasets, where four of them cover the global energy generation (expressed in terawatt-hours, TWh) related to different sources, both renewable, and non-renewable, and two of them address national and continental consumption profiles. The most important renewable sources are Hydro, Wind, Biofuel, Solar PV and Geothermal and the data is of both the global total and the performance of the top 20 countries. The data allow time-series and comparison analysis of the energy trends, regionally, e.g., OECD, BRICS, Asia, Africa, North America, showing essential changes in consumption and production. As an example, it records the rising proportion of renewable energy and forms the background towards finding out which of the nations are making progress in the implementation of sustainable energy [65]. By converting the figures in consumption to TWh, the data is uniform and relevant to world analysis. The long-term usage trends and increasing presence of renewables identified by this dataset make it a useful base to build energy policies research, microgrid plans, and AI-based dispatch models. It is also interesting to examine applications of the integration of islanded microgrids through optimization in the changing world energy systems.

time	generation biomass	generation fossil brown coal/lignite	generation fossil coal-derived gas	generation fossil gas	generation fossil hard coal	generation fossil oil	generation fossil oil shale	generation fossil peat	generation geothermal	generation hydro pumped storage	generation hydro pumped storage	generation hydro run-of-river and	generation hydro water reservoir	generation marine	generation nuclear	generation other	generation other renewable	generation solar	generation waste
2015-01-01	447	329	0	4844	4821	162	0	0	0		863	1051	1899	0	7096	43	73	49	196
2015-01-01	449	328	0	5196	4755	158	0	0	0		920	1009	1658	0	7096	43	71	50	195
2015-01-01	448	323	0	4857	4581	157	0	0	0		1164	973	1371	0	7099	43	73	50	196
2015-01-01	438	254	0	4314	4131	160	0	0	0		1503	949	779	0	7098	43	75	50	191
2015-01-01	428	187	0	4130	3840	156	0	0	0		1826	953	720	0	7097	43	74	42	189
2015-01-01	410	178	0	4038	3590	156	0	0	0		2109	952	743	0	7098	43	74	34	188
2015-01-01	401	172	0	4040	3368	158	0	0	0		2108	961	848	0	7098	43	74	34	186
2015-01-01	408	172	0	4030	3208	160	0	0	0		2031	983	1012	0	7098	43	72	35	189
2015-01-01	413	177	0	4052	3335	161	0	0	0		2119	1005	1015	0	7098	44	73	54	198
2015-01-01	419	177	0	4137	3437	163	0	0	0		2170	1041	1357	0	7097	43	74	743	198
2015-01-01	422	171	0	4059	3516	167	0	0	0		2020	1043	1817	0	7096	43	72	2210	204
2015-01-01	421	216	0	3913	3665	166	0	0	0		1183	1069	1516	0	7097	42	73	3597	206
2015-01-01	428	303	0	3784	4220	167	0	0	0		972	1052	1204	0	7097	41	75	3885	209
2015-01-01	425	268	0	3754	4404	167	0	0	0		622	1045	1286	0	7096	40	74	4007	210
2015-01-01	423	260	0	3779	4256	166	0	0	0		541	1028	1027	0	7097	40	76	3975	210
2015-01-01	421	183	0	3708	4038	160	0	0	0		1009	1023	1151	0	7096	40	76	3818	210
2015-01-01	422	256	0	3812	4101	163	0	0	0		970	1032	1156	0	7095	41	75	3086	211
2015-01-01	426	322	0	3967	4707	165	0	0	0		798	1038	1026	0	7095	41	75	1467	208
2015-01-01	427	282	0	4756	4756	164	0	0	0		1	1094	1203	0	7096	42	74	404	200
2015-01-01	442	303	0	4812	4918	147	0	0	0		1	1153	5313	0	7096	42	76	139	208
2015-01-01	445	518	0	4324	5025	154	0	0	0		0	1214	6183	0	7098	43	74	100	210
2015-01-01	443	325	0	4684	5043	154	0	0	0		0	1228	6223	0	7098	43	74	75	212
2015-01-01	440	322	0	4870	4990	154	0	0	0		0	1178	5354	0	7098	43	74	74	210
2015-01-01	438	320	0	4085	4942	160	0	0	0		0	1055	3511	0	7098	43	74	56	209
2015-01-02	368	0	0	3188	1293	163	0	0	0		1290	1268	3871	0	7106	45	62	54	169

energy dataset

(DatasetSource:https://www.kaggle.com/datasets/nicholasjhana/energy-consumption-generation-prices-and-weather)

The Hourly Energy Demand, Generation, and Weather dataset gives a full and high-resolution picture of the electrical grid operations in Spain during four years, including hourly data between 2015 and 2018. Among its variables, there exists the electrical demand, generation according to energy source (e.g., fossil fuels, biomass, geothermal), electricity prices and weather conditions of the five largest cities in Spain. The information will be taken from ENTSOE and Red Electrica de Espana, supplemented with weather data provided by the OpenWeather API and can then be analyzed deeply and used in time-series analysis and forecasting studies. The generation types range between fossil sources of generation, viz., gas, coal, and oil, on the one hand, and renewable generators, biomass, and geothermal. The fact that forecasted and actual demand and price data is included will offer a chance to compare the performance of machine learning or AI-based prediction models to industry-standard forecasts. The researchers will be able to explore the impact of weather factors and climate trends in different cities on demand or prices. In addition, the dataset is optimal to investigate intra-day load shapes, marginal generation dynamics and pricing behavior - valuable contributions to the energy dispatch model optimization problem in centrally and decentral operated systems [40]. This dataset will be useful in training the algorithms, in decision model and in response modeling of demand in an islanded microgrid or perpetrated by an AI offering improved dispatch system where the energy systems developed is resilient, efficient, sustainable, and subjected to ever changing variability of real-world phenomena.



(Dataset Source: https://www.kaggle.com/datasets/jonathandumas/liege-microgrid-open-data)

The Liege Microgrid Open Data dataset provides a high-resolution and complete picture of microgrid energy usage, photovoltaic (PV) power production, and their forecasts in Seraing, Belgium. This dataset was created in connection with the study called "Coordination of Operational Planning and Real-Time Optimization in Microgrids" and helps implement analysis of hierarchical microgrid control strategies. It will integrate three fundamental modules: 15-minute forecasts of the weather that will be derived using the MAR regional climate model developed by the University of Li, 5-second real-time measurements of the output of the PV plant and the consumption of electricity provided by the MiRIS microgrid, and 15-minute predictions of PV generation and energy consumption that run 24 hours ahead and that will be updated on a quarterly basis using a recurrent learning window of one week of size. Using two machine learning models, a Long Short- Term Memory (LSTM) Recurrent Neural Networks and a Gradient Boosting Regression (GBR) model, forecasts are generated. The data set enables multi-output forecasting and the researchers can examine the effect of forecast error in the performance of the real time optimization [65]. Parameters of weather are; irradiance, temperature, cloud cover, humidity, wind speed among others. Since it is a granular information, it will best be used to improve AI-based energy management in microgrids evaluation of forecast sensitivity and control strategy optimization. It allows intelligent controllers benchmarking, forecast-based scheduling simulation and implementation of resilient and affordable energy strategies in dynamic environments.

6. Discussion and Analysis

6.1 Load Distribution optimization in Islanded Microgrids

Fine loading is crucial to the operational success of islanded microgrids, and is critical when no centralized grid is available. The hourly average load data in Figure 2 can reveal a distinct diurnal pattern that results in the peak hourly load being at midmorning to early afternoon. The tendency indicates high energy use in the daytime, which can be explained by more commercial or industrial activity probably, the necessity of air-conditioning in warmer areas. The Multi-Agent AI System makes use of this predictability in load through dynamically varied dispatch schedules so that priority is given to renewable energy sources when they are most productive. Partnering high-output renewable cycles with high load schedule hours, the system reduces the need to use fossil sodium-based back-up generators [45]. Besides, the responsiveness of the system in real time guarantees connectivity of load-balancing decisions seen to vary in relation to the variations. Such dynamic adjustment can prevent over-generation or battery saturation. The agents also assume decentralized roles and take advantage of the local resources by communicating peer to peer to balance the system without the other central agent. This kind of optimization will issue less pressure on storage parts and make systems even more resilient. In this regard, the AI-based load sharing structure shows higher resilience, energy management and fewer emissions in comparison with conventional rule-based control systems. Therefore, it can be concluded that load optimization can guarantee the reliability and stability of the microgrid support the long-term sustainability of the energy systems of islands.

6.2 Accuracy of Forecasts and the Use Thereof in the Making of Decisions

The ability to accurately forecast is one of the building blocks of energy dispatch in microgrids, especially such ones incorporating renewable energy sources with variable outputs. In Figure 3, calculations show that the relationship between predicted and actual loads is close, which indicates that model accuracy is high. This predictive feature is core in the functionality of the Multi-Agent AI System as this can use prediction data points heavily during its dispatch decision process to be proactive [46]. Since the AI agents have been integrated with advanced mechanisms of machine learning, they will be able to predict the fluctuation in load with errors of a minimal level, hence able to optimally allocate resources like battery storage, wind turbines and gas generators. Such accuracy is critical in an island environment where the mismatch of the supply can cause blackouts or unnecessary ruin of renewable potential. Also, improved accuracy of forecasts allows the energy storage systems to have charge/discharge plans that make optimum use of the system to make the batteries neither idle nor overworked. It increases the absorption of renewable energy by the grid as well. This anticipatory advantage is even more significant when subjected to variable weather flanked by solar and wind generation [47]. The AI system also keeps learning on past mistakes to enable it to keep on improving its forecasting models. Compared with the rule-based type of systems that are relatively unchanging, the AI technology approach is very adaptable and allows continuous performance enhancement in real-time. Consequently, the robust nature of demand forecasting increases operational resilience, efficiency, and sustainability of the microgrid, further confirming that the AI-based control system is appropriate in complex, autonomous microgrids of an islanded type.

6.3 Development of World Energy Trends and Applicability to Islanded Ones

Figure 4 below shows the global energy generation trend during 1990-2020 and it can be observed that the proportions of renewable energy generated remain on an upward trend. These trends are indicative of an overall trend in the world towards cleaner energy sources which are motivated by policies, innovation, and ecological conscience [48]. Those trends are especially applicable to island microgrids because they coincide with the motives of implementing renewable-dominant and AI-based controlled dispatch systems. The rise in the total amount and a variety of sources of energy production underline the scalability and configurability needed in the contemporary energy systems, and these qualities are at the basis of multi-Agent AI systems. Due to their level of maturity and falling prices, renewable technologies are beneficial in relation to island microgrids that are commonly installed in remote or otherwise underserved areas with an insufficient amount of infrastructure. The policy subsidy or incentive that favors green microgrid projects will also be possible with the upward trend. The use of renewable energy worldwide stimulates the development of storage and control systems, which are the tools that enable multi-Agent AI activity. These world trends are turned into local benefits: enhanced system design, enhanced forecasting, renewable energy (et). Thus, developing island microgrids in line with global energy trends does not only help to realize the objectives of environmental awareness but also provide compatibility and technological compliance with the future [49]. This analysis therefore highlights the extent to which energy evolution at the macro-level can support innovation and deployment of decentralized, AI-managed power systems at the micro-level and why building renewable-centric control strategies should be one of the major considerations of islanded energy systems.

6.4 Demand Pattern of Energy in the Region and Microgrid Design Implications

To make microgrid systems community specific, one must understand the regional level energy consumption behavior (Figure 5). Data of 1990 shows that OECD countries have a large consumption of energy, and their use is increasing in transitions in BRICS, Asia and Latin America. The insights play a central role in designing energy capacity and dispatch plans when operating islanded microgrids [50]. As an example, island areas of high population or industries can resemble the demand trends of high consumption areas such as OECD or North America and might need powerful dispatch systems with the ability of handling frequent peak demand. Small or rural islands might have the opposite effect with a smaller and more erratic consumption and therefore an adaptable, easily modulated control system. Such flexibility is supplied with the Multi-Agent AI System that has a dynamic adaptation of production by local needs depending on the regional trends in the generation technology selection. Using solar PV and biomass will be preferred in tropical islands, and wind energy in coastal areas are some other examples. Energy equity is also eminent as indicated by the historical energy demand data. Most of the underserved areas such as Africa and the Pacific used a very small amount of total energy in the world in 1990, which only indicates the necessity of inclusive development with the use of decentralized solutions such as island microgrids [51]. Such systems are easily deployed and do not require any connected infrastructure, as they include powerful AIs and can deliver reliable power where it is the most needed. Thus, the regional demand data can be studied to inform the system design, predictive capacity-loading, and policy consistency, which makes the approach to the implementation of island microgrids more effective and inclusive globally.

6.5 Dependency on Fossil Fuel and to Sustainability

The composition of fossil energy generated mainly by Gas and Hard Coal and remaining Oil forms insignificant parts as illustrated in Figure 7. The pattern of this distribution reflects the worldwide movement towards more efficient and relatively cleaner fossil fuels by the departure of oil-based generation. In the case of island microgrids, this information is a tribulation and opportunity. On the one hand, Gas and Hard Coal are the categories of fossil sources that can be used as dispatchable backups quite often because of their controllability and reliability. Conversely, they have sustainability issues about their environmental implications and limitations to supply [52]. The Multi-Agent AI System deals with this duality as it smartly limits the use of fossils in dispatch but maintains grid reliability. It gives priority to renewables including wind and biomass when there is sufficient supply and only makes use of fossil sources when there is necessity to avoid blackouts and capacity shortages. The agents optimize this strategic dispatch in real-time according to their load forecasts, the availability of renewable energy and the level of storage [53]. Biomass inclusion even at low proportions shows how they are moving toward diversified cleaner generation portfolios. The plan is to retire highly emitting fuels and build on grid strength by incorporating renewable resources and smart controls. Hence, the amount contributes to the fact that it is possible to critically discuss the role of fossil fuels in the contemporary energy system and how the use of AI in managing microgrids can support an easier, more effective shift to clean energy independence in a remote environment.

6.6 Adaptive AI Control and Temporal Load Variability

The analysis of cumulative load trend (Figure 6, Figure 9) and the energy demand changes within a 15-minute interval allows showing the non-stationary and non-linear energy demand in island microgrids. The origins of these fluctuations are rather diverse since they depend on weather conditions, human activity rhythm, and abnormalities of functioning. This kind of variability needs a very flexible control policy that can react on a real time basis when something happens that is not expected. The Multi-Agent AI System will be the best in this aspect as it will introduce decentralized agents which will oversee assets and load sections. These participants share information to decide together to find an approach to the generation, storage, and demand [54]. Another example, at the times when the load is low, the AI system would be able to store the extra output of renewable facilities in the batteries and during the times of high demand it would be able to release stored energy or even to selectively power the fossil-based generators. This kind of responsiveness makes the grid stable under even erratic loads. The data reported (15-minute intervals) indicates the need for frequent monitoring and control which is impossible to achieve with the help of traditional control systems. These agents can also learn with time trends and be able to change schedules of dispatches to expectation behaviors in the future [55]. This has the benefits of improvement of peak-shaving, low curtailment and long life of equipment. The study of temporal load variation supports the effectiveness of intelligent, autonomous control systems [56]. It proves that MAAI strategy will be more efficient in the operation, able to adapt to uncertainties at a higher level, and more reliable than others to make island microgrids successful in complicated real-world situations.

6.7 Ethical Consideration

The use of the Multi-Agent AI System in the island microgrids requires specific attention to the ethical aspects, especially data privacy, transparency, and non-discriminative access to energy. Since the system is very much based on the real-time collection and processing of data, the insufficient attention to the confidentiality and integrity of the user-distinctive patterns of energy consumption become the top priority [57]. Also, the functionality of the AI agents involving decision-making would need to be viable based on transparency and understanding to establish confidence in the stakeholders and the end-users. When integrating renewable sources, the action should not lead to consolidating energy injustice as it must make sure that all communities within the microgrid receive the same benefit in terms of enhanced reliability and sustainability [58]. Ethical deployment Similarly to algorithmic bias, system decisions should not cause harm to a specific group of people because of technology and economic divisiveness, as AI systems begin to gain greater authority over vital resources, mechanisms of governance and oversight must be put in place to maintain accountability, security, and public good across the lifetime of the microgrid.

7. Future Work

The use of the Multi-Agent AI System in the operation of energy dispatch in island microgrids has demonstrated positive results based on its flexibility, efficiency, and sustainability [59]. There are several directions where this solution can be further improved and optimized to enhance the level of robustness, scalability, and flexibility of the proposed system. Integration of real-time weather forecasting with IoT sensor networks and improvement of the precision of renewable energy forecasting are some of the most interesting fields that need to be pursued in future. The feature of such a system, which could be greatly enhanced by the addition of high-resolution weather data and edge-based sensing devices, is the ability to respond in real time to sudden generation or load changes and engage in more effective real-time decision-making [60]. AI-driven demand response mechanisms implementation is another crucial path. Such mechanisms would enable agents to not only regulate the supply, but also influence and influence demand of the users, proactively and dramatically, through dynamic pricing, incentives and load-shifting mechanisms. This two-way coordination would also increase energy balance during peak times or renewables under-performance [61]. Other opportunities that future work may pursue include the use of a blockchain-based platform to allow multiple island microgrids to coordinate by using secure, decentralized networks to either exchange excess generation or storage capacity. This would enhance overall system resilience, eliminate redundancies, and develop a collaborative energy ecosystem. Also, there is the need to examine cybersecurity considerations of multi-agent communication in the critical infrastructure. Since agent-based systems are decentralized by their very nature, the communication protocols applied to it need to be secured and guarded against malicious intervention to an extent that creates reliability and trustworthiness [62]. Finally, there is a need to implement and validate the pilot version of the Multi-Agent AI System on a large scale and in varying geographical and climatic conditions to assess the functioning of the system within the limits of its operational capabilities [63]. Such deployments will yield useful field data that will be used to improve algorithms, agent behaviors, and coordination strategies. Moving forward, the future research is targeted at improving predictions, adding demand-side flexibility, secure inter-microgrid collaboration, and real-life validation of the framework to achieve the progress of intelligent, sustainable islanded microgrids.

8. Conclusion

This study has proved that a Multi-Agent AI System is useful in coordinating the dispatch of storage- and renewable-based energy resources in island microgrids. The present system with the use of decentralized intelligence and live decision-making based on real-time information greatly increases the flexibility, reliability, and sustainability of isolated networks with respect to their energy. The system incurs optimum energy balancing between the supply and the demand through integration of a wide range of energy resources including wind, biomass, and fossil gas, emphasizing on renewable based inputs. The findings based on advanced visualizations through Python, Tableau, and Excel shows clearly that the multi-Agent allows dynamic flexibilities to change generation and load patterns, which is important in an islanded setting, which is not grid connected. The capability of such a system to optimize energy flows, minimize the demand on fossil fuels, and provide supply security supports the practical viability of such a project in the real world. Energy generation profile analysis, demand fluctuation analysis, and agent-based control strategy analysis led to the fact that the model will become a blueprint of a smart microgrid system in the future [64]. Specifically, the decentralized nature of the coordination between agents allows the autonomous decisions, not only reacting to the current conditions but also preparing and predicting those ahead, which increases the overall energy efficiency and grid stability. The modular structure of the proposed framework promotes some scalability and compatibility with new technologies like smart meters, batteries, and adaptive pricing systems. The results of the current study would be a valuable contribution to the current tendency to shift towards clean and decentralized power systems and its application in remote or disaster-prone territories with restricted or absent access grid power. With the current shift of the global energy industry towards a larger ambition of focusing on renewable sources and distribution of infrastructure, implementation of AI-powered multi-agent strategies in microgrids will be at the forefront. This study paves the way to future research on the development of intelligent energy management searching systems that can be used to meet global sustainability requirements but, at the same time, can provide sound, independent power supply in remote microgrid networks.

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