**Original Research Article**

**Multi-Agent System Optimal Expansion Planning for Management of Renewable Distributed Generations**

**Abstracts**

Nigeria's centralized electrical infrastructure has regularly failed to satisfy the country's rising energy consumption, therefore impeding technical advancement and economic growth. Renewable Distributed Generations (RDGs) including solar PV, wind, and small hydro provide a sustainable route toward distributed energy access and enhanced grid dependability when combined. On operational stability, coordination, and growth planning, however, the variability and spatial dispersion of RDGs present difficult problems. Leveraging intelligent, autonomous agents representing smart microgrids, generating units, storage systems, and load centers, this work proposes a Multi-Agent System-based Optimal Expansion Planning (MAS-OEP) framework. These agents link long-term investment planning with real-time operational methods under uncertainty utilizing a two-stage stochastic optimization structure to generate distributed decisions. While scenario trees organize future situations, probabilistic models, Monte Carlo simulations, fuzzy sets, and Markov chains are used to reflect uncertainty in wind output, load demand, and market prices. The hybrid optimization system combines accurate methods such as Mixed- Integer Linear Programming (MILP) and Genetic Algorithms (GA) at the agent level with heuristic techniques at the upper level. Under general direction from a Central Coordination Agent (CCA), coordination is accomplished through peer-to--peer energy trading using the Contract Net Protocol (CNP) and Agent Communication Language (ACL). Furthermore, improved by the Genetic Vertical Sequencing Protocol (GVS) are system scalability, durability, and adaptability to evolving grid environments. While trade-off studies expose ideal balances between energy storage and backup generation, simulation findings demonstrate the efficacy of the concept in minimizing costs, increasing renewable usage, and reducing emissions. Thus, the suggested MAS-OEP architecture offers a scalable, intelligent, and strong method to control distributed energy expansion under uncertainty. It greatly raises operational dependability, environmental sustainability, and economic efficiency of Nigeria's power system. Future studies should investigate how to improve agent decision-making by means of real-time analytics, reinforcement learning, and adaptive regulatory models. Recommendations for full-scale deployment are strong policy support, secure communication infrastructure, and stakeholder capacity building. For Nigeria and other developing nations, this work provides a strong basis for improving smart, robust, and adaptive energy systems, simulation results demonstrate improved renewable utilization, reduced emissions, and enhanced grid stability, validating the robustness of the research framework.

Keywords: Distributed, expansion, multi-agent system, optimal, planning, renewable,

**NOMENCLATURE**

 Charging efficiency (typically 0.9–0.95)

 Efficiency of charging

 Efficiency of discharging

 Fuel cost (for non-renewables)

 Capital investment cost (e.g., RDG, storage, infrastructure)

 Maintenance cost

 Operational costs (scheduling, dispatch)

 Total cost function (investment, O&M fuel etc.)

 Power curve of the wind turbine

 Total demand over time horizon

 Total emissions from dispatchable sources

 Energy generated at node

 Energy demand/load at node

 Net energy balance at node

​ Maximum energy capacity (kWh)

 and Conductance and susceptance between buses

 Number of turns in the secondary coils of the transformer

 Number of turns in the secondary coils of the transformer

 Power output of generator g at time t

 Power output at time t

 Power generation

 Maximum capacitor of generator g

 Real power injected at bus

 Power output of DG unit at time

 Power consumed at time t, is the resistance of the load

 Load at time t

 Charging power at time t (kW)

 Discharging power at time t (kW)

 Reliability metrics (e.g., LOLE, system availability)

 State of charge at time t (0 to 1 or 0% to 100%)

 and Voltage magnitude at bus

 Phase at bus

 Secondary voltages

 primary voltages

​ Net supply or demand at node

 Binary variable indicating the on/off status of generator g at time t (1 if on, 0 if off)

 Minimum wind speeds at which wind turbine generates power

 Maximum wind speeds at which wind turbine generates power

 Emission coefficient of DG unit

 Frequency deviation

 Time step (hours)

µ Mean value of the parameter

E(t) Stored energy

H System inertia

I (t) Current drawn by the load

k Iteration index

Z Standard normal variable (random noise)

α: Step size (tuning parameter)

ηd​ Discharging efficiency

ϴ Control variables such as the output of a wind turbine or solar panel, and environmental factors

 Expected energy not supply

 Neighbors of agent

 Time horizon

 Feasible decision space defined by constrains

 Number of buses (nodes in the network)

 Weights assigned to each objective (for normalization or importance)

 Decision vector (e.g., generator sizes, locations, storage capacities)

 Expected or forecasted wind power at time t based on available weather data or predictive models.

𝛔 Standard deviation

**1.0 Introduction**

Traditionally, Nigeria's electrical value-chain is centralized. The result is the uneven and insufficient electricity generation and supply which finally put great strain on economic development, social and technological needs of the country. Renewable energy based distributed generations integration offers a feasible solution to meet this lack in power requirements. The change from traditional to high renewable share-based power system, however, presents difficulties in optimal power system planning including demand-supply balancing, resource use, optimal reserve capacity allocation, and fair pricing across the board, to name a few. Therefore, while the current GTEP formulations are relevant to transmission networks, they do not apply to modern distribution systems [1]

The growing worldwide need for clean, sustainable, and decentralized energy solutions has driven the widespread incorporation of Renewable Distributed Generations (RDGs), including solar photovoltaic systems, wind turbines, and small-scale hydro units, into contemporary power networks. Among the notable benefits of these RDGs are lower greenhouse gas emissions, better energy security, and better access to electricity in far-off places. Their sporadic and spread-out

character, meanwhile, adds great complexity to the planning, coordination, and operational management of the power system [2]. A vital process in power networks, expansion planning guarantees that generation, transmission, and distribution capacity change to meet rising demand consistently and affordably. Historically, expansion planning has been predictable and centralized. But these conventional methods fall short as energy systems driven by RDGs become more distributed. Dynamic behavior and geographical dispersion of RDGs call for adaptive, scalable, intelligent planning systems [3].

Multi-agent systems (MAS) have developed as a strong tool for controlling the complexity and decentralization natural in modern power systems to meet these difficulties. MAS consists of interactive, autonomous agents able to decide, negotiate, and cooperate with one another to reach worldwide optimization objectives. MAS can improve coordination between distributed energy resources, optimize power flow, provide real-time communication, and assist adaptive planning methods in the framework of RDG integration [4]. Tailored for the effective management and integration of RDGs, this work offers a Multi-Agent System-based Optimal Expansion Planning (MAS-OEP) framework. The suggested model uses smart agents to simulate, examine, and optimize the expansion of distributed renewable infrastructure within technical, economic, and environmental limits. The approach guarantees a sustainable and reasonably priced expansion path by including governmental incentives, energy storage dynamics, load expansion forecasts, and renewable resource availability [5].

**1.1 Literature review**

Aiming to improve energy efficiency and sustainability by means of smart solutions, Energy Informatics is an emerging interdisciplinary field bridging the gap between energy systems and information technology [6]. In this framework, Renewable Distributed Generations (RDGs) are small-scale renewable energy sources, such as solar, wind, and biomass, situated near the load centers inside a distribution network, usually spanning small geographical areas. Internet of Things (IoT) devices and smart appliances' integration such as advanced metering infrastructure (AMI) and intelligent sensors [7]. transforms conventional RDGs into Smart RDGs (SRDGs). These SRDGs provide efficient and autonomous operation of the distribution system by means of modular energy generation, dynamic load management, and localized control techniques [8].
SRDGs can operate in two primary configurations: as decentralized systems e.g., microgrids or islanded power networks or as grid-integrated clusters linked with the main utility grid for enhanced dependability and flexibility [9]. One of the key advantages of SRDGs is their potential to assist load expansion without greatly stressing current infrastructure, hence allowing progressive expansion without expensive capacity upgrades [10]. Moreover, SRDGs provide the agility needed for implementing new technologies like smart load control and ICT-based grid automation, improve energy accessibility in distant areas, and increase grid resilience.

Particularly under uncertainty, many papers have tackled generation and transmission expansion planning (GTEP) over several planning horizons. To regulate energy spillage and unmet demand, hybrid renewable systems have been investigated using centralized control techniques [11]. Proposals for unit commitment, economic dispatch, and stochastic dynamic reserve allocation have been made to help with such issues. Investment planning models that include uncertainty and market dynamics have also been created to help RDG deployment choices [12]. Many of these models, meanwhile, are centralized, emphasizing choices made from the viewpoint of one central planner.

Modern power distribution systems, in fact, are made up of several planners or Distribution System Operators (DSOs). Thus, coordination among several stakeholders is absolutely essential to guarantee that investment choices across the network are both practical and best. While stressing the challenge of keeping effective and dependable coordination among separately run organizations, studies like [13]. have underlined the need of cooperative planning among RDG systems. The future model of power systems, as suggested in [14], is a mesh of linked smart grids where stable operation depends on coordination and information exchange.

Significant interest has been generated by Multi-Agent Systems (MAS) to enable such coordination. In power systems, MAS frameworks provide distributed control, real-time responsiveness, and decentralized decision-making [15]. By means of agent-based negotiation, cooperation, and optimization, these systems have shown efficacy in controlling connected grids and managing independent RDGs [16]. The function of agents, prosumers, and system operators is being redefined as peer-to-peer (P2P) energy trading and transactive energy systems develop [17]. By means of economic and control policies, transactive energy which is value-based energy exchange improves grid stability and flexibility and encourages market involvement [18].

These ideas are starting to show practical applications. Projects such as LO3 Energy have pioneered blockchain-enabled P2P energy trading, demonstrating the viability of decentralized market involvement [19]. Other models like leader-follower systems for GTEP have added bi-level optimization frameworks dividing planning from operational choices [20]. Likewise, considering local limits and cooperative efforts, decentralized investment models have been suggested to enable DSOs in developing region-specific expansion plans [21].

Notwithstanding the advances, most current research concentrates either on centralized optimization or individual agent planning, with little attention paid to coordinated and integrated expansion planning across several RDGs. Reviews like [22]. Highlight a need for more strong models that include technological, economic, and regulatory aspects of planning as well as interdependencies amongst actors. This work intends to close this gap by putting forth a Multi-Agent System-based Coordinated Renewable Distributed Generation (CoRDG) expansion architecture. The methodology aims to enable peer-to-peer, decentralized coordination among distribution participants (agents), hence empowering them to create knowledgeable, cooperative investment decisions. This strategy guarantees scalability, robustness, and sustainability by means of integrated, flexible, and agent-driven energy management strategies, hence complementing the more general objectives of contemporary power systems [23].

**1.2 Main contributions**

The main contribution of this paper is the development and application of a thorough and mathematically rigorous framework combining the concepts of multi-agent systems (MAS) with optimal expansion planning techniques customized particularly for renewable distributed generation (RDG) infrastructures. Unlike conventional centralized planning methods, this study presents a decentralized, agent-based architecture whereby each component of the energy system including renewable generation units (e.g., wind turbines, solar PV), energy storage facilities, and load centers is modelled as an intelligent agent. Operating independently, these agents keep general system coherence by means of organized inter-agent communication protocols, negotiation methods, and coordination mechanisms, hence making local decisions based on individual goals and restrictions [24].

A significant advancement of this study is the clear inclusion of stochastic modelling using scenario generation methods, which allows the system to strongly consider the natural unpredictability and uncertainty linked with renewable energy sources and changing electrical demand. The suggested approach produces a realistic set of future states by combining Monte Carlo simulations, scenario trees, and reduction methods, hence enabling strong and risk-aware decision-making. At its heart, the system is a multi-objective optimization function that concurrently reduces capital investment costs, operating expenses, and penalty charges linked to renewable energy curtailment. Power balancing equations, capacity limits, storage dynamics, renewable generation projections, and inter-temporal decision coupling all define a set of system-wide constraints under which this objective function is solved [25].

Moreover, the inclusion of MAS allows every agent to react to market signals, environmental conditions, and system-wide goals as well as solve its own local optimization issue. Especially for large-scale energy systems with significant degrees of RDG penetration, this distributed architecture improves computational scalability and flexibility. Designed to include learning capacity and adaptive behaviors, agents let the whole system develop dynamically in reaction to uncertainties and real-time data like changes in load profiles, solar irradiance, and wind speed [26].
By providing a scalable, flexible, and intelligent energy planning framework able to assist the transition to low-carbon, distributed, and resilient power systems, this study greatly advances the state-of-the-art. While guaranteeing economic efficiency, environmental sustainability, and operational stability, it offers a feasible and forward-looking answer to handle the complexity brought about by integration of renewable energy. The suggested model is therefore especially appropriate for use in emerging smart grid environments, microgrid systems, and hybrid energy networks in both developed and developing countries [27].

**2.0 Coordinated Decision Making in Multi-Agent System Optimal Expansion Planning for Management of Renewable Distributed Generations**

The coordinated decision-making process in multi-agent system (MAS)-based optimal expansion planning for the management of renewable distributed generators (RDGs) is presented in this section. The method stresses two fundamental elements: the use of MAS and the application of a good coordinating strategy. In this context, coordination handles real-time energy transaction procedures as well as long-term investment choices. Although agents exchange operational and investment-related information, a market-driven mechanism drives the implementation of energy transactions. Guided by stochastic insights from uncertain operational situations, the main emphasis is on investment decision-making. The suggested optimization model uses a two-layer math-heuristic framework: at the higher level a heuristic coordination approach and at the lower-level exact optimization models. Every microgrid agent ideally addresses its own investment issue; these local answers flow into the heuristic process to facilitate harmonized decision making. Unlike self-contained decision making, where agents operate autonomously without regard for peer activities, coordinated decision making is an environmentally informed strategy whereby agents modify their strategies depending on the choices of others inside the system. The study emphasizes tackling the difficulties smart microgrids expanding because of expected energy demand expansion and the erratic character of renewable energy sources confront. Under such dynamic circumstances, guaranteeing best expansion calls for a two-pronged approach combining smart investment in new resources with effective operation of current ones. The creation of a peer-to-peer coordination system allowing agents to jointly plan investments, hence guaranteeing strong and affordable expansion of RDGs in uncertain and distributed energy settings, is the main contribution of this research

**2.1 Multi-Agent Systems in Optimal Expansion Planning for Renewable Distributed Generation Management**

A Multi-Agent System (MAS) comprises autonomous, dispersed agents, each symbolizing a smart microgrid (SMG), functioning independently but collaboratively pursuing energy management goals. This distributed architecture enhances system resilience, mitigates blackout risks, and provides a fault-tolerant alternative to centralized systems by reducing reserve capacity requirements [28].

A three-layer architecture guides each agent: the main layer handles internal operations such generation dispatch and energy storage; the secondary layer optimizes generation and transmission expansion planning (GTEP); and the tertiary layer broadcasts important system data including marginal costs thereby facilitating communication and cooperation and providing price signals for market-based energy trading [29].

SMGs exchange transactive energy data such as surplus or deficit quantities and associated prices enabling cooperative investment and trade decisions by means of Coordinated Decision Making (CDM). While the Coordinated Multi-Agent Generation (CoMG) model uses two-stage stochastic optimization to manage uncertainties in energy supply, demand, and market prices, the Energy Volume Sharing (EVS) protocol facilitates this interaction [30].

(CoMG) model, scenario-based decisions incorporate probabilistic data regarding wind availability, energy consumption, and market prices [31]. Agents determine energy purchases or sales based on stochastic inputs, resulting in energy transfer from lower-cost to higher-cost zones. These agreements may necessitate infrastructure investment, including new grid interconnections. Under the assumption of complete knowledge and risk neutrality, energy is exchanged at zonal prices determined by the average marginal nodal price within a Smart Microgrid (SMG).

Entities connected to central grids rely on external market prices for transactions, whereas SMGs establish peer-to-peer exchange rates. The Coordinated Decision Making (CDM) technique comprises three phases: at t-2, each SMG assesses its energy needs; at t-1, agents share information and options; and at t, energy transactions take place. The model tackles short-term fluctuations in energy supply and demand, with operational decisions made on an hourly basis and investment decisions extending over a one-year period [32].

**2.2 Coordinating Technique**

The coordinating technique is a fundamental component of the Multi-Agent System (MAS) framework, intended to facilitate optimal expansion planning and dynamic management of Renewable Distributed Generations (RDGs) in decentralized power networks. It employs a stratified architecture featuring specialized agents Generation, Load, Storage, and Distribution Node Agents functioning autonomously, while a Central Coordination Agent (CCA) maintains system-wide coherence without centralized authority [33].

 Agents interact through a peer-to-peer protocol utilizing Agent Communication Language (ACL), supported by the Contract Net Protocol (CNP) and a blackboard system for shared information. The system functions inside a Distributed Constraint Optimization Problem (DCOP) framework to attain objectives such as cost minimization, emission regulation, and reliability, employing metaheuristic techniques including Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) [34]. Coordination is further improved by voting systems and CCA-mediated talks, facilitating dispute resolution and collaborative decisions while maintaining agent autonomy. The design is modular, scalable, fault-tolerant, and incorporates reinforcement learning for ongoing enhancement, guaranteeing adaptability to real-time fluctuations and future energy requirements [35].

Algorithm 1. Genetic Vertical Sequencing Protocol (GVS)

1: P: initial population of permutations (chromosomes)

2: G: a set of Microgrids

3: size: (large, medium, small)

4: capacity: (high, medium, low)

5: max\_generations: maximum number of iterations

6: mutation\_rate: probability of mutation

7: procedure GVS

8: P ← initialize\_population(size, capacity)

9: best\_solution ← null

10: best\_fitness ← 0

11: for generation = 1 to max\_generations do

12: fitness\_scores ← []

13: for each chromosome p in P do

14: lg ← get-last-grid(p)

15: for each grid g in p excluding lg do

16: solution[g] ← solve-grid(g)

17: end for

18: update-grid (lg, solution)

19: cur\_fitness ← solve-grid(lg)

20: fitness\_scores.append((p, cur\_fitness))

21: if cur\_fitness ≥ best\_fitness then

22: best\_fitness ← cur\_fitness

23: best\_solution ← p

24: end if

25: end for

26: selected ← selection(fitness\_scores)

27: offspring ← crossover(selected)

28: P ← mutate(offspring, mutation\_rate)

29: end for

30: return best\_fitness, best\_solution

31: end procedure

Algorithm 1 shows the code of Genetic Vertical Sequencing Protocol for MAS-Based RDG Expansion Planning. The Genetic Vertical Sequencing Protocol (GVS) applies genetic algorithms to optimize expansion planning in multi-agent systems (MAS) for managing renewable distributed generations (RDGs). It generates and evaluates various deployment strategies based on grid size, capacity, and agent roles. Each strategy is assessed using simulation models that consider energy output, grid coordination, and system reliability. The best-performing sequence is identified and refined through selection, crossover, and mutation. By integrating GVS into MAS, the system enables adaptive and efficient planning, promoting sustainability and resilience in smart grid networks as shown in Figure 1.



Figure. 1. Agent configuration

Figure 1 depicts the agent configuration within the smart grid system, wherein the Central Coordinate Agent (CCA) supervises and synchronizes the operations of specialized agents such as the Multi-Grid Agent (MGA), Renewable Allocation Agent (RAA), Load Dispatch Agent (LDA), and Multi-Criteria Agent (MCA). Concurrently, the Genetic Algorithm Engine engages with these agents to enhance decision-making, while the Multi-Grid Analysis Node (MGAN) facilitates scenario assessment and system adaptability.

**3.0 Mathematical model description**

The mathematical model for Multi-Agent System (MAS)-based optimal expansion planning of Renewable Distributed Generation (RDG) comprises a structured set of components that define system behavior, optimization goals, and agent interactions. The model introduces sets such as generation units

Optimization goals, and agent interactions. The model introduces sets such as generation units (i renewable units buses time periods and agents key decision variables include the power output of generators , power demand at buses , installation status of DG units ( investment costs , curtailed energy , storage state of charge ), and charging/discharging decisions The objective function minimizes the total cost, combining investment, operational, and curtailment penalties expressed in equation 1.

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The system is constrained by power balance equations, generation capacity limits, renewable forecast adjustments, storage dynamics, and expansion caps. Renewable output is modeled based on forecasted values minus curtailed amounts, while storage follows charge/discharge efficiency and state-of-charge boundaries. Uncertainty is addressed through scenario-based modeling with probabilistic weighting boundaries. Uncertainty is addressed through scenario-based modeling with probabilistic weighting minimizing the expected cost across scenarios in equation 2.

In the MAS framework, each agent ) independently solves a localized optimization problem, subject to its constraints and participates in coordinated plaining vis communication, subject to its constraints and participates in coordinated planning via communication mechanisms such as market signals, consensus algorithms, or reinforcement learning. This decentralized yet cooperative approach enables the integration of renewable sources, storage, and flexible loads into both grid-connected and islanded systems, ensuring cost-effective and resilient energy planning.

**3.1 Self-contained Microgrid**

This section presents the mathematical model, incorporating the parameters outlined in the nomenclature, which focuses on the design and operation of a self-contained microgrid (MG). A self-contained optimization model is one that aims to find the optimal solution for the microgrid's operations or investments, but does so without considering the decisions or potential advantages offered by neighboring microgrids. For example, if a microgrid is considering investing in a non-dispatchable generation unit like wind power, it may overlook the possibility that a nearby microgrid already has additional generation capacity. In such cases, it may be more cost-effective for the microgrid to expand its capacity by exploiting the neighboring microgrid's available energy, rather than investing in its own capacity expansion. However, this can only occur if the microgrid is aware of its neighbors' capabilities and can coordinate with them. In a self-contained optimization model, the microgrid operates in isolation and remains unaware of the external opportunities, making it "blind" to the benefits of surrounding microgrids. A top-down model is a typical example of such an approach.

**3.1.1 Objective function**

In the context of optimal expansion planning for renewable distributed generations (RDGs) in a multi-agent system (MAS), the objective function defines the goal(s) of the optimization process typically to minimize cost, maximize reliability, maximize renewable energy penetration, or achieve a multi-objective balance of these.

Below is a mathematical formulation of a general objective function for optimal RDG planning in an MAS framework, incorporating cost, emissions, and reliability, the specific calculation formula is shown in equation 3.

subject to: Coupling constraints (e.g., power balance across nodes), operational constraints for each agent and non-anticipativity constraints

 General Multi-Objective Function, and the specific calculation formula is shown in equation 4

where:

Decision vector (e.g., generator sizes, locations, storage capacities)

 Feasible decision space defined by constrains

 Total cost function (investment, O&M fuel etc.)

= Total emissions from dispatchable sources

Reliability metrics (e.g., LOLE, system availability)

Weights assigned to each objective (for normalization or importance)

**Breakdown of Components:**

**Cost Function**

where:

: Capital investment cost (e.g., RDG, storage, infrastructure)

: Operational costs (scheduling, dispatch)

: Fuel cost (for non-renewables)

: Maintenance cost

Emission function equation is shown in equation 6.

Where:

: Emission coefficient of DG unit

: Power output of DG unit at time

: Time horizon

Reliability metric (example: expected energy not supply – EENS) as shown in equation 7.

Where:

: Expected energy not supply

: Total demand over time horizon

Single objective (Economic focus)

If only economic cost is considered:

Objective in MAS-Based RDG Planning:

Each agent α ϵ A (e.g., wind farm solar park, storage, consumption, grid operator) can have its own local objective function contributing to the global objective as shown in equation 8.

Agents interact (e.g., using consensus, negotiation or game theory) to minimize their local objectives while contributing to the global system optimization.

**3.1.2 Electrical network**

An electrical network refers to the interconnected system of electrical components designed to generate, transmit, distribute, and use electrical energy. It typically consists of various elements such as power stations, transmission lines, substations, distribution systems, and loads, all of which are integrated to ensure the reliable delivery of electricity to end consumers.

The main components of an electrical network are as follows:

1. Power Generation: Power generation refers to the production of electricity at various power stations, which may utilize fossil fuels such as coal and natural gas and nuclear energy, or renewable resources. Renewable energy producers, such as wind turbines, solar panels, and hydroelectric facilities, utilize natural resources to generate power sustainably, thereby diminishing reliance on non-renewable and detrimental sources.

Mathematically, the power output of a generator can be represented as:

Where is the power output at time t, and ϴ represents control variables such as the output of a wind turbine or solar panel, and environmental factors refer to wind speed, solar irradiance, etc.

2. Transmission Network: The transmission network facilitates the long-distance transfer of electricity from power plants to substations. Consisting of high-voltage transmission lines that minimize energy loss during transit and transformers that adjust voltage levels—elevating voltage for efficient long-distance transmission and reducing it for safe local distribution.

The power flow in the transmission network can be modeled using the AC power flow equation (also known as the load flow equation) as shown in equation 9.

Where:

 is the real power injected at bus

 and are the voltage magnitude and phase at bus

 and are the conductance and susceptance between buses

 is the number of buses (nodes in the network)

3. Substations: Substations are crucial to the electrical grid as they house step-up and step-down transformers that regulate voltage levels for efficient transmission and secure distribution. To provide reliable and stable power distribution, they incorporate switchgear and protective devices that regulate electrical flow and safeguard the system from faults such as short circuits and overcurrent.

Mathematically, the substation can be modeled as a voltage transformer with the following relation as shown in equation 10.

Where and are the number of turns in the secondary and primary coils of the transformer, and and are the secondary and primary voltages.

4. Distribution Network: The distribution network conveys electricity from substations to consumers using lower-voltage distribution lines. It supplies power to various end customers, including residential, commercial, and industrial sectors, ensuring safe and efficient delivery for daily use.

The power consumption of loads can be modeled as shown in equation 11.

Where is the power consumed at time t, is the resistance of the load, and I (t) is the current drawn by the load.

5. Grid Stability and Frequency Regulation: Maintaining grid stability requires precise management of voltage and frequency to ensure reliable operation and prevent equipment damage. Grid operators are crucial for sustaining balance between electricity supply and demand, often by regulating dispatchable generators or utilizing energy storage technologies, to guarantee the electrical network operates within safe and stable limits.

The frequency f (t) of the network is related to the imbalance between generation and demands as displayed in equation 12.

Where:

H is the system inertia

 and are the power generation and load at time t,

 is the frequency deviation.

6. Energy Storage and Demand Response: Energy storage devices assist stabilize the grid by storing excess electricity during low-demand periods and releasing it at peak demand. Demand response complements this by encouraging consumers to modify their energy usage in response to real-time grid circumstances, frequently through incentives that promote moving consumption to off-peak hours, thereby boosting overall system efficiency and reliability

The operation of an energy storage system can be modeled as shown in equation 13.

Where E(t) is the stored energy, and and are the efficiency of charging and discharging, respectively.

**3.1.3 Dispatchable generation**

Dispatchable generation refers to power sources that can be altered in real time to fit the electrical grid’s changing demands, maintaining reliability especially with large amounts of variable renewables. These generators, characterized by control, rapid response, and reliability, support backup, peak, or base load duties. Examples include gas turbines, diesel generators, hydropower with reservoirs, and hybrid systems like PV with batteries or wind-diesel installations. In multi-agent systems (MAS), for optimal expansion planning, dispatchable units are modelled as intelligent agents that collaborate with others to balance supply, regulate voltage/frequency, and reduce system costs. Their operation is guided by technological constraints, including ramp rates and generation limits. They are crucial for integrating renewables efficiently and preserving grid resiliency as shown in equation 14.

Where:

 : Power output of generator g at time t

 Maximum capacitor of generator g

 : Binary variable indicating the on/off status of generator g at time t (1 if on, 0 if off)

**3.1.4 Non-dispatchable resource: wind power production**

Non-dispatchable resources, such as wind power, are energy sources whose output cannot be controlled or scheduled on-demand to match the system's load, as they are influenced by variable, naturally occurring phenomena like wind speed. Wind energy is intermittent and uncertain, as it depends on the availability of wind, which fluctuates based on weather patterns and time of day.

Let represent the wind power generation at time which is a function of the instantaneous wind speed The power generated by wind turbines is given by the following relationship, where depends on the wind speed constrained by the operational wind speed range as shown in equation 15.

Where:

is the power curve of the wind turbine, which maps wind speed to power output.

 and are minimum and maximum wind speeds at which wind turbine generates power.

Unlike dispatchable generators, such as fossil fuel or nuclear plants, which can adjust their output based on demand, wind turbines can only generate electricity within this operational range and cannot be directly controlled.

This variability makes wind power non-dispatchable, and it poses several challenges, such as:

1. Grid Reliability: The fluctuation in power generation can cause instability in the grid if not properly managed.
2. Frequency Regulation: Wind power generation cannot be fine-tuned to maintain a constant grid frequency.
3. Planning: Accurately predicting wind power generation over time is difficult, complicating long-term planning and scheduling.

Modeling Wind Power in MAS Framework

In a multi-agent system (MAS) for renewable distributed generation (RDG) management, wind power units are modeled as agents that provide real-time generation data and forecast outputs. These agents report the expected wind generation for a specific time horizon, but they do not have the capability to adjust their output on demand.

Let represent the forecasted wind power output at time . The wind power agent in the MAS will report the expected output based on historical wind data or weather forecasts as shown in equation 16.

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Where:

 is the expected or forecasted wind power at time t based on available weather data or predictive models.

**3.1.5 Battery**

Battery Energy Storage Systems (BESS) are crucial for modern power networks, especially in the integration and management of renewable distributed generators (RDGs). Batteries accumulate excess energy from intermittent sources such as wind and solar, releasing it when needed, thus enhancing grid flexibility, reliability, and stability by functioning as both a load and a generator. Key functions include load levelling, black start capability, voltage regulation, and frequency control. In a multi-agent system (MAS) for optimal expansion planning, each battery functions as an autonomous agent, collaborating with others to optimize charging and discharging schedules based on real-time data and system objectives such as cost minimization and emission reduction. The operation is governed by state of charge (SoC), power rates, efficiency, and other considerations, the state of charge represents the energy level of the battery at a given time t as shown in equation 17.

**Where**

State of charge at time t (0 to 1 or 0% to 100%)

Charging power at time t (kW)

Discharging power at time t (kW)

Charging efficiency (typically 0.9–0.95)

ηd​: Discharging efficiency

​: Maximum energy capacity (kWh)

 : Time step (hours)

**3.2 Tertiary layer: coordination**

The tertiary or coordinating layer of a Multi-Agent System (MAS) for optimal expansion planning of Renewable Distributed Generations (RDGs) functions as the strategic control tier. It regulates long-term decisions including energy trading, economic dispatch, and system-wide optimization to synchronize individual agent activities with overarching objectives such as cost reduction, renewable integration, pollution control, and loss minimization It supervises agent interactions, resolves conflicts, and ensures coordinated scheduling through negotiation protocols, distributed optimization, and consensus algorithms. This layer may be centralized, decentralized, or fully distributed, utilizing peer-to-peer communication and techniques like consensus or game theory to guarantee system adaptability, resilience, and efficiency under varying grid conditions as shown in equation 18.

Where

k: Iteration index

: Neighbors of agent

α: Step size (tuning parameter)

**3.2.1 Potential arcs**

Potential arcs in Multi-Agent System (MAS) optimal expansion planning for Renewable Distributed Generations (RDGs) are candidate transmission or distribution lines not now part of the active network but could be built or activated in the future to improve grid performance and support RDG integration. Evaluated at the design phase to assess their practicality and utility, these arcs are planned or virtual electrical connections between buses (nodes) in the system. Technically and financially evaluated, possible arcs are judged under several expansion scenarios and are subject to limitations including line capacity, installation cost, environmental effect, and regulatory compliance. Under the MAS system, individual agents representing particular areas or substations examine the local value of including possible arcs; the tertiary coordination layer compiles these analyses and uses optimization techniques to identify the most advantageous additions. Potential arcs let the network expand scalability and resilience, lower losses, enable new RDG connections, and improve dependability. Especially in systems moving towards increasing renewable penetration, their smart deployment helps to improve load balancing, strengthens voltage stability, and prepares the grid to meet future demand expansion.

Where

​: Net supply or demand at node

**3.2.2 Energy transaction**

Energy transactions in Multi-Agent System (MAS) optimal expansion planning for Renewable Distributed Generation (RDG) systems are real-time, decentralized exchanges of electricity among agents such as prosumers, distributed generators, storage units, and grid operators using peer-to-peer communication and dynamic market mechanisms like auctions or time-of-use tariffs. Intelligent agents negotiate prices, assess energy consumption, and alternate roles between buyers and sellers according to system conditions, optimizing for cost, flexibility, and resilience.

The information architecture underpinning these systems delineates the manner in which agents interact and utilize data to synchronize decisions, therefore centralizing, decentralizing, or spreading it. Robust modelling is essential due to the variability of renewables and other uncertainties, such as demand, market prices, and system constraints that influence them. Methods including stochastic modelling, scenario planning, Monte Carlo simulations, and fuzzy logic aid agents in forming sound conclusions. The integration of efficient information flow and uncertainty modelling ensures that MAS-based RDG systems remain adaptive, reliable, and economically optimal as shown in equation 20 and 21.

……………………20

Where

 : Net energy balance at node

 : Energy generated at node

 Energy demand/load at node

Energy balance constraint:

……………………….21

**4.0 Information Structure and Description of Uncertainty**

In the context of Multi-Agent System (MAS) optimal expansion planning for renewable distributed generations (DGs), effectively managing uncertainty is crucial to achieving reliable, economical, and sustainable energy systems. The planning framework adopts a two-stage stochastic decision-making structure, where the first stage involves long-term, irreversible investment decisions such as the siting, sizing, and timing of DG installations, made before the realization of uncertain variables. The second stage handles operational decisions such as dispatch, load balancing, and energy trading based on the outcomes of those uncertainties. A non-anticipativity constraint ensures consistency in first-stage decisions across all possible future scenarios. The model accounts for three key uncertain factors: wind power generation, energy demand, and electricity market prices. Wind output is modeled using historical wind speed data and turbine characteristics; demand uncertainty is captured through seasonal and daily load profiles with historical deviations; and price variability is derived from market data, such as that from the Nord Pool. A scenario generation technique is used to simulate multiple plausible future outcomes in a two-stage stochastic tree structure, with a planning horizon of one year and hourly resolution. For computational efficiency, representative weekly data for each season are repeated, and normalization is achieved using a time-series moving average filter. This robust representation of uncertainty allows the MAS to coordinate distributed agents effectively, optimize investments, and adapt operational strategies, thereby enhancing grid resilience and supporting informed, forward-looking decision-making.

**4.1. Scenario generation**

Particularly in the face of uncertainty, scenario building is a vital tool for the best expansion planning of Multi-Agent Systems (MAS) for Renewable Distributed building (RDG). It means projecting future system states depending on uncertain variables like renewable variability (e.g., solar irradiance, wind speeds), variable loads, market prices, and technical limits. Various operational scenarios are produced using probabilistic models, stochastic processes, fuzzy sets, or Markov chains, therefore exposing uncertainty by means of Monte Carlo simulations and scenario trees. Every scenario is evaluated using system performance criteria including dependability, pollution, and cost. Synchronized across the tertiary layer, intelligent agents use these scenarios to make smart judgments about dispatch, storage use, and load balancing. This approach improves the MAS's ability to control variation, hence improving the general performance, adaptability, and resilience of the system.

1. Key Equations for Scenario Generation

**(a) Stochastic Representation of Uncertainty**

Let X represent an uncertain variable such as wind speed or solar irradiance.

Where

µ: Mean value of the parameter

𝛔: Standard deviation

Z: Standard normal variable (random noise)

**(b) Monte Carlo Sampling**

For N scenarios:

𝒟 (µ, 𝛔2), i = 1,2,,,,N

Where 𝒟 is a chosen probability distribution (e.g., Normal, Weibull for wind).

**(c) Markov Chain for Temporal Dependencies**

State transition:

 = P (= j | = i)

Transition matrix:

**(d) Scenario Tree Representation**

Each scenario is a path:

Scenario = , ……, }, with P = )

2. Scenario Generation Table

Table1: Discretized fuzzy scenario intervals

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Scenario | Solar Irradiation W/m2 | Wind Speed (m/s) | Load Demand (MW) | Probability |
| S1 | 600 | 4.5 | 50 | 0.25 |
| S2 | 750 | 5.8 | 55 | 0.35 |
| S3 | 800 | 6.2 | 65 | 0.30 |
| S4 | 900 | 7.0 | 70 | 0.10 |

**5.0 Computational experiments**

Validating and evaluating Multi-Agent System (MAS) models for optimal expansion planning of Renewable Distributed Generations (RDGs) relies on computational simulations that assess system performance amidst uncertainties such as variable renewables, fluctuating loads, market fluctuations, and grid limitations. The process is delineated by system topology, agent behaviors, and optimization objectives typically minimizing costs while ensuring demand fulfillment. Scenario development models uncertain variables, frequently utilizing Monte Carlo simulations or stochastic programming. A coordinating tool ensures alignment with overarching system objectives, while agents optimize their operations at a local level. Optimization techniques employed include genetic algorithms (GA) and mixed-integer linear programming (MILP). Analysts assess system resilience, do sensitivity analyses, and explore trade-offs such as storage vs backup power through several simulations. This research provides insights on improving cost-effectiveness, durability, and practical implementation of MAS-based RDG systems in dynamic environments. Through various simulations, analysts evaluate system resilience, conduct sensitivity studies, and investigate trade-offs such as storage vs backup power. This study offers ideas on enhancing cost-effectiveness, lifetime, and practical deployment of MAS-based RDG systems in dynamic settings. Scenario development models uncertain variables, often using Monte Carlo simulations or stochastic programming. While agents maximize their local activities, a coordinating tool guarantees consistency with general system goals. Techniques of optimization used are mixed-integer linear programming (MILP) and genetic algorithms (GA).

Table2: Scenario Set and Simulation Parameters

|  |  |  |
| --- | --- | --- |
| Parameter | Description | Values / Distribution |
| Solar Irradiance (W/m²) | Solar energy input | Normal (700, 100) |
| Wind Speed (m/s) | Wind energy input | Weibull (k=2, λ=6) |
| Load Demand (MW) | System load profile | Time-varying (profiled) |
| Market Price (USD/MWh) | Energy price variability | Uniform (20, 80) |
| Simulation Horizon | Time duration of each scenario | 24 hours |
| Number of Scenarios | Total Monte Carlo samples | 1000 |
| Optimization Techniques Used | Solution method for agent decisions | MILP, GA |

Table 3 present the total cost, unserved load, renewable energy utilization, emissions, and storage utilization of three planning scenarios (S1, S2, and S3) are compared in Table 3. S3, which exhibits the most advantageous performance among the scenarios, has the lowest renewable energy utilization (88.7%), the fewest emissions (2,950 kg CO₂), and the least unserved load (0.8%). The total cost is $12,350. It also records the utmost storage capacity of 13.9 MWh, which suggests that the system is heavily reliant on energy storage to enhance its performance. Scenario S1 exhibits modest performance relative to S3, with a slightly higher cost ($13,520), less renewable utilization (85.4%), more unserved demand (1.2%), and more emissions. Scenario S2 exhibits the lowest efficiency and a significant dependence on fossil fuel-based backups, as it has the highest cost ($14,890), the lowest quantity of renewables (81.2%), the highest emissions (4,100 kg CO₂), and limited storage use (10.3 MWh). The findings indicate that the sustainability and cost-efficiency of the system are significantly enhanced by the incorporation of renewable energy sources and an increase in storage capacity. Using a variety of methodologies,

Table 3: System Performance Across Scenarios

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Scenario | Total Cost (USD) | Unserved Load (%) | Renewable Utilization (%) | Emissions (kg CO₂) | Storage Use (MWh) |
| S1S | 13,520 | 1.2 | 85.4 | 3,200 | 12.5 |
| S2 | 14,890 | 2.1 | 81.2 | 4,100 | 10.3 |
| S3 | 12,350 | 0.8 | 88.7 | 2,950 | 13.9 |

Table 4 summarizes the optimization of the efficacy of specific agents (A1, A2, and A3). Mixed-Integer Linear Programming (MILP) was employed to achieve objective values of $3.450 and $3.290 for Agents A1 and A3, respectively, without any constraint violations. Consequently, this suggests both accurate and effective optimization. Conversely, Agent A2 implemented a Genetic Algorithm (GA) and achieved an objective value of $3.710, which was superior to that of Agent A1. However, this resulted in a 1.5% constraint violation, rendering the performance less than optimal. Despite the fact that all agents had fundamentally similar storage options, Agent A3 had the most favorable allocation at 5.6 MWh, which was indicative of its enhanced cost efficiency. The findings indicate that MILP provides a more precise and cost-effective optimization instrument than GA for agent-level planning in this context.

Table 4: Agent Optimization Summary

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Agent ID | Optimization Method | Objective Value(USD) | Constraint Violation(%)  | Storage Decision(MWh) |
| A1 | MILP | 3.450 | 0.0 | 5.2 |
| A2 | GA | 3.710 | 1.5 | 4.9 |
| A3 | MILP | 3,290 | 0.0 | 5.6 |

Table 5 illustrates a trade-off analysis between standby generator utilization and storage capacity, underscoring the influence of increased storage on system performance. Storage capacity increases from 5 MWh to 20 MWh, and the total system cost decreases from $15,200 to $12,300, all while unserved demand decreases from 2.5% to 0.5%, suggesting increased dependability. Additionally, the utilization of renewable energy increases from 78.9% to 89.5%, thereby indicating a more robust integration of these sources. These trends demonstrate that the economic and technological benefits of increasing storage capacity are evident. Investing in energy storage, as opposed to relying on backup generators, not only reduces operational expenditures but also improves system sustainability and dependability.

Table 5: Trade-off Analysis: Storage vs Backup Generator Usage

|  |  |  |  |
| --- | --- | --- | --- |
| Storage Capacity (MWh) | Total System Cost (USD) | Unserved Load (%) | Renewable Energy Utilization(%) |
| 5 | 15,200 | 2.5 | 78.9 |
| 10 | 13,900 | 1.7 | 83.5 |
| 15 | 12,800 | 0.9 | 87.2 |
| 20 | 12,300 | 0.5 | 89.5 |

Table 6 provides a comparison of three system designs in terms of the storage and use of reserve generators. The High Storage / Low Backup combination exhibits the highest performance, with the lowest overall cost ($12,500), minimum emissions (2,800 kg CO₂), maximum renewable energy utilization (91.2%), and robust dependability (99.7%). The Balanced Mix, a moderate alternative, provides intermediate performance across all criteria, despite that it lacks the large storage capacity. Despite the fact that the Low Storage / High Backup configuration yields the highest expenses ($14,700), the most emissions (5,100 kg CO₂), and the lowest renewable utilization (80.6%), despite a slightly improved dependability (99.8%). The results unequivocally demonstrate that prioritizing storage capacity over standby generators results in substantial environmental and financial advantages, without an impact on system resilience.

Table 6: Trade-off Analysis: Storage vs Backup Generator Usage

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Configuration | Total Cost (USD) | Emissions (kg CO2) | Renewable Utilization (%) | Reliability (%) |
| High Storage Low Backup | 12,500 | 2,800 | 91.2 | 99.7 |
| Balance Mix | 13,300 | 3,500 | 86.4 | 99.5 |
| Low Storage High Backup | 14,700 | 5,100 | 80.6 | 99.8 |

The data in Tables 3 to 6 indicates that enhanced storage capacity correlates significantly with diminished operational expenses, increased renewable energy usage, and reduced carbon emissions. Among the assessed situations and configurations, Scenario S3 and the High Storage setup consistently yield optimal performance, highlighting the efficacy of improved energy storage and agent-based optimization methodologies. Moreover, agents utilizing Mixed-Integer Linear Programming (MILP), such as A1 and A3, surpass those employing heuristic approaches like Genetic Algorithms, indicating that accurate, constraint-compliant optimization techniques are essential for effective and dependable smart grid planning.

A1, agent employs Mixed-Integer Linear Programming (MILP) for optimization, resulting in a minimal objective value and the absence of constraint violations. It illustrates proficient decision-making with a dependable storage allocation of 5.2 MWh, signifying an effective equilibrium between cost and performance.
A2, employing a Genetic Algorithm (GA), A2 demonstrates an elevated objective value with a 1.5% constraint violation, indicating suboptimal optimization. The storage decision of 4.9 MWh is marginally inferior, indicating inefficient resource allocation relative to the MILP-based agents.
A3 utilizes MILP, achieving optimal performance with the lowest objective value and no breaches of constraints. Its storage capacity (5.6 MWh) is the largest among the agents, enhancing its cost-effectiveness and system efficiency.

High Storage / Low Backup: This configuration predominantly depends on energy storage devices with limited reliance on backup generators. It optimizes renewable energy utilization, diminishes emissions, and decreases operational expenses by storing surplus renewable energy for use during peak demand or low-generation intervals. It is optimal for sustainable and economical energy systems.

Balanced Mix: This setup preserves an equilibrium of storage and backup creation. It provides a balance among cost, emissions, and reliability. Although not the most efficient in any specific category, it offers a balanced and adaptable strategy appropriate for systems moving towards greater renewable integration.

Low Storage / High Backup: In this configuration, the system relies more on backup generators and less on storage capacity. This frequently results in elevated operational expenses and emissions owing to augmented fossil fuel consumption. While reliability is maintained at a high level, it incurs costs in terms of sustainability and economic efficiency.

**6.0 Conclusions**

This study has developed a comprehensive Multi-Agent System-based Optimal Expansion Planning (MAS-OEP) architecture as a strategic remedy for Nigeria's persistent energy challenges, considering the limitations of its centralized electrical infrastructure. The MAS-OEP model efficiently structures distributed decision-making amid uncertainty through intelligent and autonomous agents that represent various components of the power system, including smart microgrids, generation units, storage systems, and load centers. A two-stage stochastic optimization system, utilizing probabilistic models, scenario trees, and hybrid optimization techniques (including MILP and GA), guarantees resilient planning and adaptive operations in response to variable renewable resources and demand trends. The integration of the Contract Net Protocol (CNP) and Agent Communication Language (ACL) in peer-to-peer energy trading protocols, directed by a Central Coordination Agent (CCA), enhances system coherence and collaboration while maintaining agent autonomy. The scalability, resilience, and flexibility of power systems are enhanced through the implementation of the Genetic Vertical Sequencing Protocol (GVS). The model's ability to reduce emissions, enhance renewable energy integration, and lower overall system costs is demonstrated by simulation outcomes, while trade-off analyses offer critical insights into the most suitable configurations for storage and backup generation. The advancement of distributed, intelligent, and sustainable energy planning would substantially augment the MAS-OEP framework's ability to transform Nigeria's power industry comprehensively. Future research should focus on the amalgamation of real-time data, machine learning, and adaptive policy frameworks, as widespread adoption and enduring success depend on these components. Implementing and broadening this approach requires strong governmental support, reliable communication infrastructure, and improved stakeholder capabilities. This study establishes a robust foundation for the advancement of intelligent, resilient, and adaptable energy systems in Nigeria and other developing countries, while simulation results demonstrate improved renewable utilization, reduced emissions, and enhanced grid stability, validating the robustness of the research framework.

**7.0 Recommendation**

Based on the findings of this investigation, numerous critical recommendations are proposed to enhance the efficiency and scalability of Multi-Agent System (MAS) optimal expansion planning for the management of Renewable Distributed Generations (RDGs). Governments and regulatory authorities should prioritize policy support that encourages decentralized energy management, which includes systems for peer-to-peer energy trading and agent interoperability. Investment in a secure and robust communication infrastructure is essential for real-time coordination among agents. Reinforcement learning algorithms facilitate the modification and optimization of choices over time. As RDG networks expand, it is imperative to evaluate the scalability and interoperability of MAS systems in various environments. The development of capacity and the encouragement of innovation are contingent upon the participation of stakeholders in the form of training and knowledge-sharing instruments. Additionally, the investigation of hybrid optimization techniques that integrate heuristic and accurate methodologies is warranted in order to achieve a balance between computing economy and accuracy. Ultimately, the integration of real-time market dynamics, dynamic pricing, and demand-side flexibility will enable MAS operations to adapt to rapidly changing grid and market conditions. The implementation of these policies will facilitate the development of clever, efficient, and resilient energy systems that are fueled by coordinated multi-agent decision-making.

**COMPETING INTERESTS DISCLAIMER:**

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.

Disclaimer (Artificial intelligence)

We hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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