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Artificial Immune System Algorithms for Microgrid Energy Management

Yassir El Bakkali[1*], Nissrine Krami [2], **Youssef Rochdi** [3], **Achraf Boukaibat**[4].

[1,2,3,4] National School of Applied Sciences, Ibn Tofail University, Kenitra, Morocco.

E-**mail:** [1]elbakkali.yassir@gmail.com , [2] nissrine.krami@gmail.com , [3] youssef.rochdi@uit.ac.ma , [4] achrafbkt@gmail.com .

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KEYWORDS

Microgrid Energy Management System (EMS), T-Cell Algorithm, Power Dispatch, Real-Time Optimization.

ABSTRACT

The integration of variable renewable energy sources (RES), such as solar and wind, into the microgrid through energy storage systems and controllable loads can destabilize the network. These factors cause power supply/demand imbalances, leading to voltage fluctuations and outages. In this article, a new optimization approach is proposed to address these challenges and to effectively manage the energy balance in microgrids.

The study proposes an Artificial Immune System- inspired algorithm to identify optimal solutions and improve the power quality through power dispatch within the microgrid. Using the predicted renewable energy production data, the T-Cell algorithm executes calculations and sends them to a MATLAB environment for real-time simulation, which will make the system flexible in terms of dynamics and optimization of the power distribution using real-time data.

*Corresponding author.

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خوارزميات النظام المناعي الاصطناعي لإدارة الطاقة في الشبكات المصغرة

ياسر البقالي، نسرين كرامي، يوسف رشدي، أشرف بوكعيبات

ملخص: إن دمج مصادر الطاقة المتجددة المتغيرة (RES)، مثل الطاقة الشمسية وطاقة الرياح، في الشبكة الصغيرة من خلال أنظمة تخزين الطاقة والأحمال التي يمكن التحكم فيها, يمكن أن يؤدي إلى زعزعة استقرار الشبكة. تتسبب هذه العوامل في اختلال توازن العرض والطلب على الطاقة، مما يؤدي إلى تقلبات الجهد وانقطاع التيار. في هذه المقالة، يُقترح نهج تحسين جديد لمواجهة هذه التحديات وإدارة توازن الطاقة بشكل فعال في الشبكات الصغيرة.

تقترح الدراسة خوارزمية مستوحاة من نظام المناعة الاصطناعية (T-Cell) لتحديد الحلول المثلى وتحسين جودة الطاقة من خلال إرسال الطاقة داخل الشبكة الصغيرة. باستخدام بيانات إنتاج الطاقة المتجددة المتوقعة، تقوم خوارزمية T-Cell بتنفيذ الحسابات وإرسالها إلى بيئة MATLAB للمحاكاة في الوقت الفعلي، مما سيجعل النظام مرنًا من حيث الديناميكيات وتحسين توزيع الطاقة باستخدام البيانات في الوقت الفعلي

الكلمات المفتاحية نظام إدارة الطاقة في الشبكات المصغرة خوارزمية الخلايا التائية توزيع القدرة التحسين في الزمن الحقيقي

1. INTRODUCTION

The continuous use of fossil fuels, such as fuel oil, coal, and gas oil, for electricity generation raises significant concerns due to their substantial contribution to greenhouse gas emissions. These emissions are a primary driver of global climate change and have led to the implementation of policies aimed at reducing them. As a result, there is a growing necessity to reevaluate traditional electricity networks that heavily rely on these fossil fuels.

In this context, Microgrid (MG) electrical systems have emerged as a promising alternative (Figure 1). Microgrids prioritize the utilization of renewable energy sources, emphasize energy efficiency, and promote localized power generation, making them a sustainable approach to electricity supply. By harnessing renewable energy sources like solar and wind power, microgrids reduce reliance on fossil fuels and contribute to the reduction of greenhouse gas emissions. They achieve efficient distribution of electricity by generating power locally, minimizing transmission losses, and promoting energy efficiency. Moreover, microgrids offer greater control and flexibility in managing energy resources, enabling efficient load balancing and integration of energy storage systems.

The objective of this research is to propose an energy management system (EMS) that effectively operates and optimizes microgrid resources. The EMS aims to perform essential functions, including real-time monitoring, data analysis, and forecasting of Distributed Energy Resources (DER) electricity production and load consumption. It takes into account external factors such as energy market prices and meteorological conditions to make informed decisions and efficiently manage the energy flow within the microgrid. To achieve this, advanced control mechanisms and intelligent algorithms based on the human immune system are employed within the EMS [1]. These mechanisms enable the optimal allocation and utilization of energy resources, ensuring technical constraints are met and power balance is maintained. By dynamically adjusting the energy flow and load management, the EMS enhances the microgrid's overall performance, reliability, and stability.

Such a success of an EMS is, in turn, largely dependent on the chosen optimization algorithm, specifically in terms of rising complexity and uncertainty involved with modern microgrids. Bio-inspired metaheuristic algorithms such as Genetic Algorithms (GA) [2], Particle Swarm Optimization (PSO) [3], and Ant Colony Optimization (ACO) [4] have seen widespread application in microgrid energy management. Each of these approaches has its strengths and limitations. GA has good global search properties and automatically deals with multi-objective problems due to population diversity, but it usually suffers from a low convergence rate and high computational cost. PSO has the advantage of fast convergence and simple implementation, but is trapped in local optima in solving highly nonlinear, complicated problems [5]. ACO is effective at combinatorial optimization, by achieving good exploration as well as exploitation, but requires meticulous parameter tuning and tends to converge slowly in continuous search spaces [6]. Additionally, these algorithms are also primarily implemented in centralized structures, where one optimization agent performs all computation. Such structures are not fault-tolerant by nature and have scalability issues, especially in dynamic and distributed energy environments [7].

To overcome these limitations, this paper presents an innovative combination of the immune- inspired T-Cell algorithm with a distributed Multi-Agent System (MAS) for microgrid energy management. Immune-inspired, the T-Cell algorithm introduces greater global search capacity, faster convergence, and higher resistance to premature convergence [8]. Clonal selection and differentiation processes in the T-Cell algorithm enable efficient exploration of the solution space while preserving solution diversity. With the combination of the MAS framework, the algorithm benefits from distributed decision-making, reduced latency, and fault tolerance against agent failure [9]. As a result, T-Cell + MAS architecture presents a scalable and competitive solution over traditional bio-inspired approaches in dealing with complex, real-time, and fault-sensitive microgrid energy management problems.

In our study, we will use a heuristic algorithm based on T-Cell, inspired by the human immune system. The goal of this algorithm is to find a feasible solution with reduced computational cost. After selecting the optimization algorithm, it is necessary to implement it in a platform that ensures the management of the microgrid (MG). This platform has the role of continuously supervising the MG, coordinating the different DERs (Distributed Energy Resources), and reacting in case of issues to maintain an energy balance. That's why we have chosen to utilize a Multi-Agent System (MAS), which proves to be a suitable solution for this management due to its characteristics that are well-suited for MG management. Several research works in the field of energy have also employed this technique.

To develop and validate the proposed EMS, simulation and modeling techniques play a crucial role. MATLAB's Simulink software provides a powerful platform for building a realistic and accurate representation of the microgrid. Through simulation, the EMS can be tested under various scenarios, including different DER outputs, load patterns, and market conditions. This validation process helps assess the reliability of the EMS, identify potential failure scenarios, and optimize its performance before real-world implementation.

In summary, this paper aims to develop an advanced EMS for microgrids, enabling efficient management and optimization of DER electricity production, load consumption, and energy market price. By integrating renewable energy sources, energy storage, and intelligent control algorithms, the proposed EMS contributes to a more sustainable and resilient energy infrastructure. The validation process using simulation ensures the reliability and effectiveness of the EMS, paving the way for its practical deployment in real-world microgrid applications.

2. PROBLEM FORMULATION AND CONSTRAINTS

This work addresses the challenges of optimizing energy production allocation from generating units to meet varying demands. An essential aspect of our work is the promotion of deeper integration of renewable energy resources (RE), aiming to reduce production costs while utilizing sustainable sources.

To achieve this objective, we are developing an algorithm that identifies the optimal combinations of generators and loads, considering the specific constraints and characteristics of the energy system. Economic aspects are also considered, with a focus on minimizing production costs through an efficient optimization strategy that considers variable costs associated with each generating unit and energy market prices.

Our primary objective is to optimize the allocation of energy production, considering different loads and consumption, while simultaneously promoting increased integration of renewable energy resources. We aim for a more cost-effective, sustainable, and environmentally friendly energy production that effectively and reliably meets energy needs.

To accomplish our optimization objective, the consideration of both the objective function and constraints is essential. The objective function defines the criterion for minimizing production costs, while constraints are conditions that must be adhered to during the optimization process. These constraints encompass factors such as resource limitations, production unit capacities, battery State Of Charge (SOC) levels, and energy demand requirements.

By incorporating both the objective function and constraints, we can formulate a precise and well- defined optimization problem. Our goal is to find a solution that optimizes the objective function while satisfying all stated constraints. This may necessitate the use of advanced optimization algorithms to determine the optimal configuration of system variables that fulfill these objectives. In summary, achieving our optimization objective requires careful consideration of the following objective function and constraints to accurately and efficiently formulate and solve the optimization problem.

2.1. Objective function

The objective function is defined as follows:

$$min \sum_{t=1}^{m} \left(F_t^{PV} + F_t^{W} + F_t^{ES-} + F_t^{G-} - F_t^{G+} - F_t^{ES+} - F_t^{l} - F_t^{cl}\right).\Delta t \tag{1}$$

With m is the optimization and the cost functions described below [2,9,10]:

F_t^{PV} cost function of the PV panels:

$$F_t^{PV} = \sum_{t=1}^{n\,PV} \pi_t^{k,PV}\ P_t^{k,PV} \tag{2}$$

$\pi_t^{k,PV}$: the offer price of the kth PV panel.

$P_t^{k,PV}$: the power generated by the kth.

PV panel during each period.

$$F_t^W = \sum_{t=1}^{n\,W} \pi_t^{k,W} \; P_t^{k,W} \tag{3}$$

$\pi_t^{k,W}$: *the offer price of the kth Wind turbines.*

$P_t^{k,W}$: the power generated by the kth *the power generated by the kth.*

Wind turbines during each period.

F_t^{ES-}, F_t^{ES+} are the cost functions of the battery storage respectively in discharging and charging:

$$F_t^{ES-} = \sum_{t=1}^{n\,ES} \pi_t^{k,ES-} \; (1-\theta_{ES}) P_t^{k,ES-} \tag{4}$$

$$F_t^{ES+} = \sum_{t=1}^{n\,ES} \pi_t^{k,ES+} \; \theta_{ES} \; P_t^{k,ES+} \tag{5}$$

$\pi_t^{k,ES-}, \pi_t^{k,ES+}$: The offer price of the kth battery storage respectively in discharging and charging.

$P_t^{k,ES-}, P_t^{k,ES+}$: the power generated by the kth.

ES-, ES+: battery storage (respectively in discharging and charging) during each period.

θ_{ES} : $w$hen the battery is charging, this binary number is set to 1, and when discharging, it is set to 0.

F_t^{G-}, F_t^{G+} are the cost functions of the power respectively imported and exported from the grid:

$$F_t^{G-} = \pi_t^{G-} \; (1-\theta_G) P_t^{G-} \tag{6}$$

$$F_t^{G+} = \pi_t^{G+} \; \theta_G \; P_t^{G+} \tag{7}$$

π_t^{G-}, π_t^{G+} : The offer price of the grid power respectively in imported and exported.

P_t^{G-}, P_t^{G+}: the power generated by the grid (respectively in importing and exporting) during each period.

θ_G: when the MG is exporting, this binary number is set to 1, and when importing, it is set to 0.

F_t^l , F_t^{cl} are the cost functions of the load and the controllable load respectively:

$$\mathrm{F}_t^l = \sum_{t=1}^{n\,l} \pi_t^{k,l} \; \mathrm{P}_t^{k,l} \tag{8}$$

$$F_t^{cl} = \sum_{t=1}^{n\,cl} \pi_t^{k,cl} \; P_t^{k,cl} \tag{9}$$

$\pi_t^{k,l}, \pi_t^{k,cl}$: the power cost of the load and the controllable load respectively.

$P_t^{k,l}, P_t^{k,cl}$: the power consumed (by the load and the controllable load respectively) during each period.

2.2. Constraints

Power Balance Constraint: The generated power must be equal to the required power demand.

$$\sum_{i=1}^{n} Pi = PD \tag{10}$$

Where:

Pi: is the power generated for each unit within the system.
PD: is the power demand.

These constraints are specific conditions that must be satisfied during the optimization of the system. They encompass various aspects such as capacity limitations of the production units, maximum generation limits for photovoltaic solar and wind energy sources, restrictions on battery charging and discharging, battery State of Charge (SOC) levels, as well as limits on energy import and export to the grid.

Renewable energy resources:

$$0 \leq \sum_{k=1}^{n\,PV} P_t^{k,PV} \leq P_t^{max,PV} \tag{11}$$

$$0 \leq \sum_{k=1}^{n\,W} P_t^{k,W} \leq P_t^{max,W} \tag{12}$$

$P_t^{max,PV}, P_t^{max,W}$: the maximum available power from PV panels and wind turbines.

Maximum discharge limit:

$$\theta_{ES}.P_t^{ES-} \leq P_{max}^{ES-} \text{ , } P_t^{ES-} \geq 0 \tag{13}$$

Maximum charge limit:

$$(1-\theta_{ES}).P_t^{ES+} \leq P_{max}^{ES+} \text{ , } P_t^{ES+} \geq 0 \tag{14}$$

Respectively, the maximum discharge and charge limit take into account the total stored energy.

$$(\theta_{ES}.P_t^{ES-}.\Delta t) \leq E_{t-1}^{ES} \tag{15}$$

$$((1-\theta_{ES}).P_t^{ES+}.\Delta t) + E_{t-1}^{ES} \leq E_{max}^{ES} \tag{16}$$

Energy balance in Energy Storage Systems (ESS):

$$E_t^{ES} = E_{t-1}^{ES} + (P_t^{ES+} - P_t^{ES-}).\Delta t \tag{17}$$

The equality constraint for the battery:

$$E_{min}^{ES} \leq E_t^{ES} \leq E_{max}^{ES} \tag{18}$$

The battery's State of charge:

$$SOC = E_t^{ES} \div E_{tot}^{ES} \tag{19}$$

The inter-connection with the grid

$$(1-\theta_G).P_t^{G+} \le P_{max}^{G+} \, , \, P_t^{G+} \ge 0 \tag{20}$$

$$\theta_G.P_t^{G-} \le P_{max}^{G-} \, , \, P_t^{G-} \ge 0 \tag{21}$$

P_{max}^{G+} $and P_{max}^{G-}$ are respectively the maximum power that could be imported from the grid and the maximum power that could be injected in the grid.

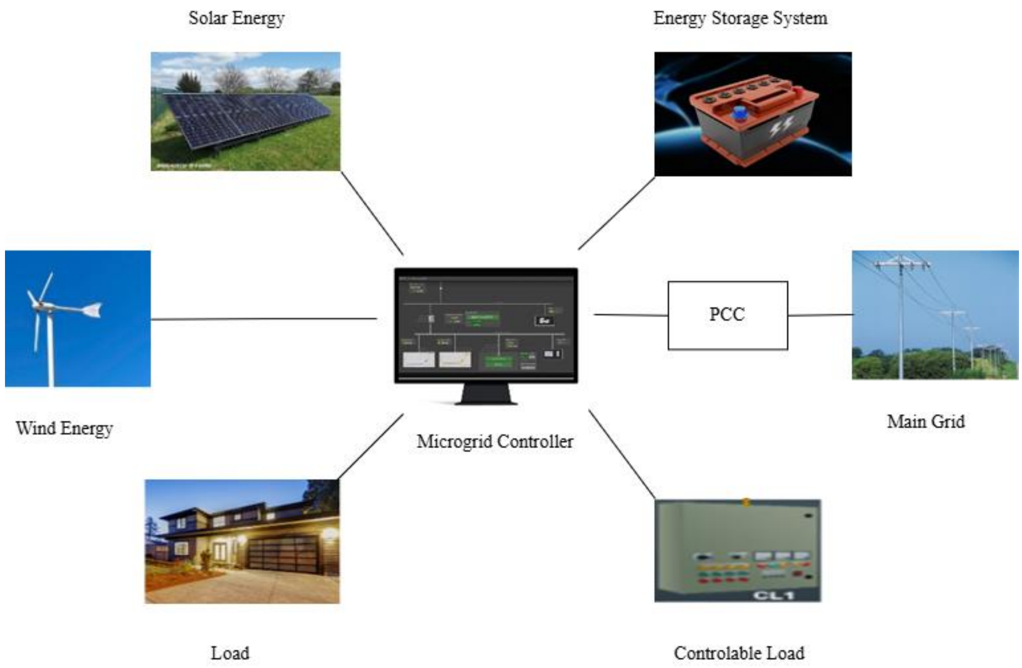

Figure 1: Microgrid architecture.

3. T-CELL ALGORITHM

To solve optimization problems that can have very complex mathematical problems, which often result in long calculation times. But in practice, a solution to an optimization problem must be proposed within reasonable times, which's why there was the appearance of different methods based on AI, such as genetic algorithm (GA) [4,11], ant colony optimization (ACO) [3,12], particle swarm optimization (PSO) [13 -16], neural networks, artificial immune system [17]. concerning classical methods, they have many weaknesses; for example, they are heavy and limited when it comes to complex problems, that is why most research has stopped using these methods.

In our work, we will utilize the T-Cell algorithm, inspired by the human immune system's T cells, which develop in the thymus and undergo clonal selection and differentiation to combat antigens. This biological mechanism is abstracted into a computational algorithm to perform constrained optimization for energy dispatch problems.

Our algorithm simulates the biological immune response through two main operators:

- Proliferation: generation of clones in proportion to the quality (fitness) of the candidate solution.
- Differentiation: variation introduced to the clones to explore the solution space and improve diversity.

The T-Cell algorithm follows a structured sequence of computational steps:

1. Initialization Population: A population of candidate solutions (cells) is initialized, with each decision variable bounded within its respective operating limits.
2. Evaluate Constraints:
   - Equality Constraint Violation (ECV) is calculated as the difference between total generated power, demand, and potential losses: (Total Power Generated – Demand – Transmission Loss). If ECV > 0, it indicates that the generated power exceeds the demanded power, while ECV < 0 suggests that the generated power is lower than the required power.
   - The inequality constraints violation (ICV): The power generated by each generator must remain within the specified maximum and minimum limits.
   - Feasibility Check: The feasibility criterion determines whether a cell is feasible or not. A cell is deemed feasible if the following conditions are met: ECV = 0 and ICV = 0, which means that the generated power is equal to the required power and the decision variables avoid prohibited zones. In other words, if a solution generates less power than required or exceeds the required amount or if the decision variables fall within a prohibited range, then the solution is considered infeasible.
3. Evaluate Objective Function: The value of the objective function for the decision variables. Only feasible solutions are evaluated based on the cost function.
4. Proliferation Process: The proliferation of a cell refers to the quantity of its generated clones.
5. Differentiation Process: The differentiation process involves modifying a certain number of decision variables, which can be referred to as "differentiation".
6. Loop and Update (Reached Max Evaluation): Steps 4–5 are repeated until a pre-set number of objective function evaluations is reached.

The algorithm works in the following way (see Figure 2).

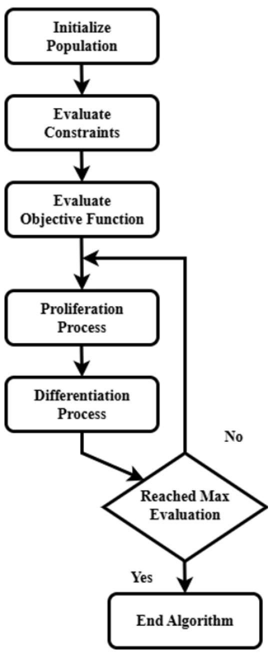

Figure 2: Structured workflow of the T-Cell optimization algorithm.

First, the population is initialized within the limits of the units. Then, ECV and ICV are calculated for each cell, and feasibility is assessed directly from these results. Only feasible candidates proceed to the objective function evaluation. Next, while the number of evaluations has not been reached, the population is then proliferated and differentiated. This cycle is repeated every specified time step.

Figure 2 illustrates the structured workflow of the T-Cell optimization algorithm. This graphical representation provides clarity on the operational logic and facilitates reproducibility and academic rigor in the implementation.

4. MULTI-AGENT SYSTEM (MAS) FOR MICROGRID OPTIMIZATION

The application of Multi-Agent System (MAS) technology in the energy industry has garnered significant attention for its effectiveness in electrical applications. Researchers have dedicated considerable efforts to investigating and refining this technique, recognizing its immense promise. A pivotal article [18] delves into various stages of MAS development, encompassing analysis, design, development, and deployment, highlighting the significance and interest invested in researching and refining this technique. Building upon this research, another noteworthy article [19] explores critical decisions in designing MAS tailored for power and energy applications, providing insights into architectural aspects and mechanisms enabling effective coordination and collaboration among agents. Within the MAS architecture, utility agents like the Agent Management System (AMS) and Directory Facilitator (DF) play vital roles, facilitating seamless communication and coordination among agents. Agents, autonomous entities capable of interacting with the environment, participate in collaborative tasks or compete to achieve distinct goals within MAS, serving various purposes such as solving distributed problems, simulating complex phenomena, and managing work environments [20 - 22]. JADE (Java Agent Development Framework) serves as a crucial platform choice, offering a practical toolkit for developing and deploying intelligent agents within a MAS environment, exemplifying its practicality and effectiveness.

This paper leverages a Multi-Agent System (MAS) framework for microgrid management. Within this framework, a critical role is played by the Optimization Agent (MGO). The MGO integrates the T-Cell Algorithm for efficient optimization. MGO gathers real-time and forecasted data (wind/photovoltaic generation, battery state of charge, load demands) and leverages the T-Cell Algorithm to analyze this data. Based on this analysis, MGO computes optimal setpoints for power generation units and controllable loads, ensuring efficient resource utilization and grid stability. Operating at regular intervals, MGO allows for dynamic adjustments to these setpoints based on changing environmental conditions and load demands. This work implements the MGO agent within the multi-agent platform JADE and MATLAB/Simulink simulation environment, where it interacts with the model and provides optimized setpoints for evaluation of their effectiveness in microgrid management.

To address the defined constraint-based optimization problem, the MAS is structured around specialized agents that collaborate to realize system constraints and optimal control actions in real time; At the core of this architecture is the Microgrid Optimization Agent (MGO), which integrates the constraint-aware optimization process. The MGO gets real-time data from all the sensing agents (the PV Agent, Wind Agent, Battery Agent, and Load Agent) regarding production forecasts, load demands, battery SOC, and grid parameters. According to this data, the MGO formulates the optimization problem as set out in Section 2, including both the objective function as well as constraints (i.e., equations 10 to 21).

The T-Cell algorithm is executed within the MGO to generate optimal setpoints for all controllable elements (i.e., power dispatch, battery charging/discharging, controllable loads); And this Setpoint are sent to the respective execution agents, which independently execute them while still monitoring local constraint conditions—i.e., SOC limits, max generation limits, import/ export limits. In case of deviations or local constraint violations, agents provide feedback to the MGO, which dynamically re-optimizes and re-distributes new control signals. The closed-loop, agent-based approach then not only solves but also enforces in real time the constraint-based optimization problem on a distributed architecture. Centralized decision-making through the MGO and decentralized monitoring of constraints through autonomous agents are both enabled, with guarantees of system feasibility, resilience, and flexibility.

5. RESULTS AND DISCUSSION

The microgrid in Figure 3 incorporates micro-generation technologies, energy storage, controllable loads, storage chargers, and low-voltage network cable simulators (BV). The simulation uses 3 kW photovoltaic panels (PV), a 3 kW micro-wind turbine, a 3 kW energy storage unit, and an LV cable simulator capable of handling up to 50 A of current, with impedance on all three phases (1, 2, 3) and the neutral line. Table 1 offers detailed information about the variables utilized and their respective limit values.

Table 1: Microgrid Parameters.

Variable	Meaning of the variable	Limit values
Ppv	The predicted power generation of the PV system	0 kW ≤ Ppv ≤ 3 kW
Pw	The predicted power generation of the wind turbine	0 kW ≤ Pw ≤ 3 kW
Pbat	The predicted charging or discharging power of the battery	- 3 kW ≤ Pbat ≤ 3 kW
SOC	State of charge of the battery	0 ≤ SOC ≤ 1
Pl	Active power load	0 kW ≤ Pl ≤ 7.2 kW
Pcl	Controllable load	Pcl = 3.6 kW

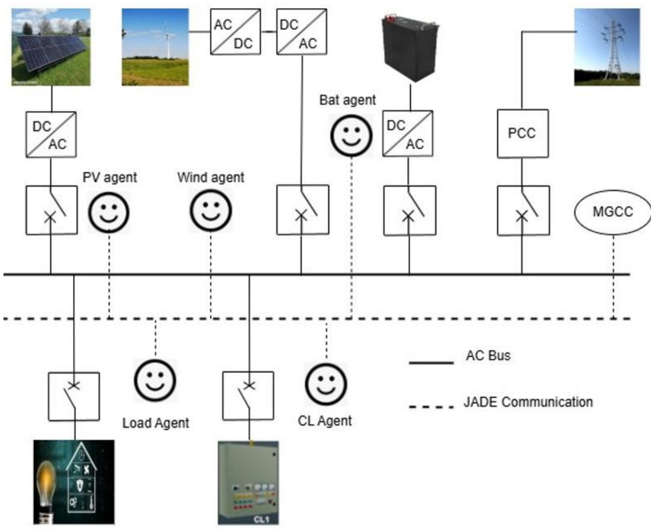

Figure 3: Single microgrid setup.

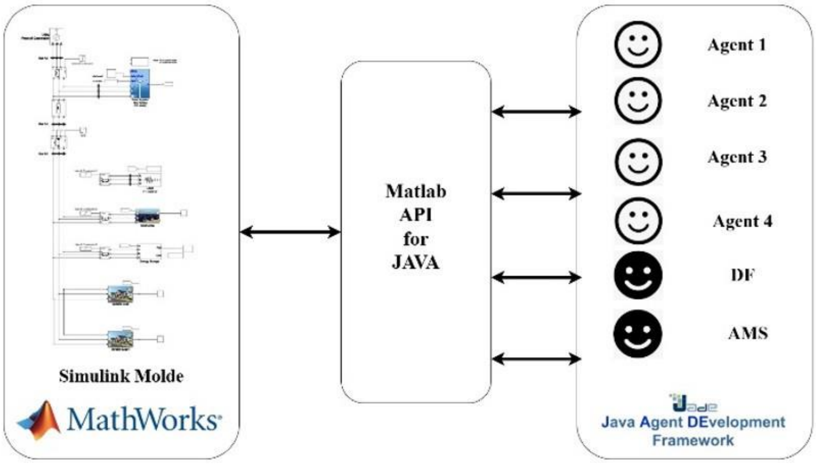

Figure 4: Jade and Simulink interaction scheme.

A MATLAB Simulink model of the Microgrid (MG) was created and combined with JADE to examine the genuine interaction between the agent platform and electrical components. The fusion of JADE with Simulink was achieved using the Java Engine API, enabling Java programs to invoke and assess MATLAB commands. The set points generated within the JADE Multiagent platform will be transmitted via the MATLAB API to the Simulink blocks to establish new references. Figure 4 illustrates the synergy between these two environments.

The simulation outputs presented in Figures 5 and 6 show the performance of the microgrid over different time durations. For each stage, the T-Cell algorithm made the optimization decision, i.e., generation unit setpoints, actions by the battery, and adjustable loads, is described as follows:

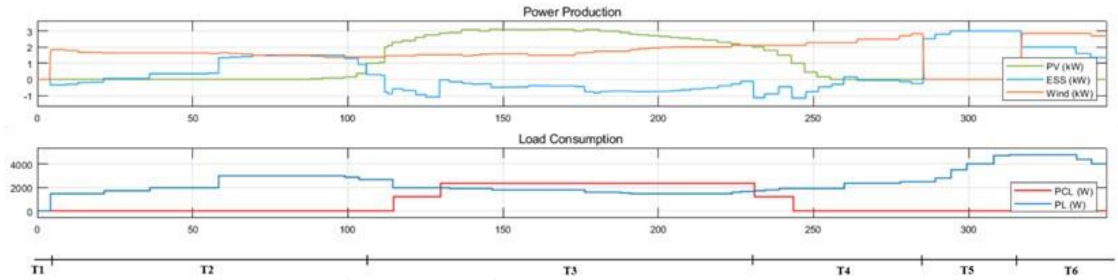

Figure 5: Experimental results for MG power.

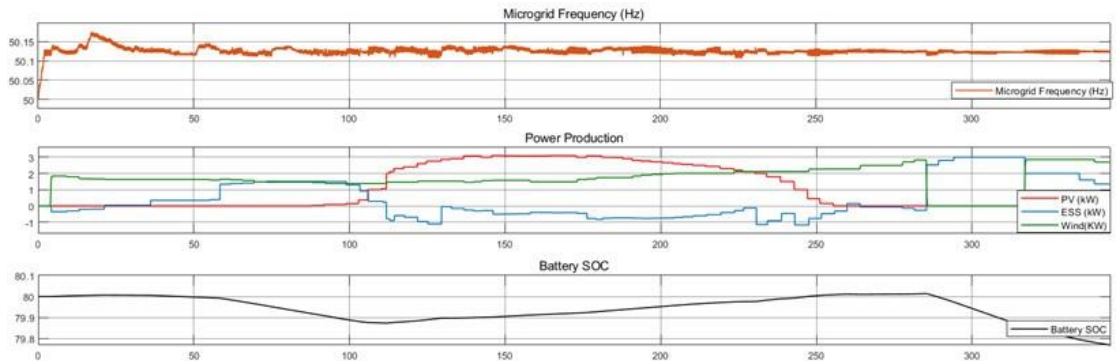

Figure 6: The frequency, SOC (State of Charge) of the batteries during the simulation.

- Phase T1: initially, the wind turbine production is sufficient to provide the full load. The T-Cell algorithm detects a surplus of renewable generation and takes the optimum decision to charge batteries to store excess energy while maintaining the independence of the grid, and avoiding wastage of energy

- Phase T2: As the load gradually increases and even surpasses wind turbine output, the T-Cell algorithm detects the gap and optimally schedules battery discharging to cover the demand gap, and to provide a stable supply without relying on grid imports.
- Phase T3: Photovoltaic production is initiated, supporting the load as well as the wind turbine. The T-Cell algorithm controls the setpoints for charging surplus PV and wind energy in the batteries and activates controllable loads (initial 1200 W, followed by 2400 W) to optimize self- consumption and system efficiency while respecting system constraints.
- Phase T4: When the photovoltaic generation declines, the T-Cell algorithm reduces controllable loads optimally to offer power balance to ensure that the available generation and battery power meet the demand.
- Phase T5: Malfunction in a wind turbine leads to loss of production. The T-Cell algorithm replies by discharging the batteries to feed the load and optimally schedules grid import to cover the remaining shortfall, and to achieve system stability.
- Phase T6: After wind turbine restoration, it continues to supply a portion of the load. The T-Cell algorithm re-optimizes dispatch by lowering grid imports and utilizing the batteries to support the remaining demand, thus restoring system autonomy.

These results prove that at all operating stages, the T-Cell algorithm responds dynamically to the system state, forecasts, and constraints to compute optimal decisions in real-time, which enables optimal energy management, balanced supply, and efficient utilization of the renewable resources.

6. CONCLUSIONS

In conclusion, the integration of Energy Management Systems with the T-Cell algorithm and the Multi-Agent System presents a promising approach for effectively managing microgrids. As microgrids continue to gain importance and gradually replace traditional grids, the need for efficient energy management becomes paramount.

The article highlights the increasing significance of EMS in microgrid management, emphasizing the role it plays in optimizing the operation of power sources, loads, and controllable loads. By considering various objective functions and constraints, mathematical formulation enables the planning and execution of optimal microgrid operations.

Key constraints that must be carefully managed include respecting the maximum and minimum limits of energy production to ensure reliable and profitable performance. Balancing energy production and consumption is crucial, as well as effectively managing the charging and discharging rates of energy storage systems; Technical constraints, such as voltage, current, and frequency parameters, must also be considered to maintain stability and proper functioning within the microgrid.

By incorporating the T-Cell algorithm, the EMS gains stronger capabilities, especially when combined with the MAS framework, which helps distribute power more effectively within the microgrid. The simulation results in MATLAB clearly illustrate the effectiveness of the proposed T-Cell algorithm to dynamically respond to the system variation, forecast renewable energy supplies, and adhere to operating constraints. Each decision phase, from load variability to equipment failures, reflected the algorithm's capacity to maintain the system in equilibrium, maximize renewable self-consumption, and minimize grid import reliance. This highlights the algorithm's added value in terms of responsiveness, flexibility, and performance improvement, and demonstrates its practical relevance and scientific contribution to microgrid energy management.

Looking ahead, future developments aim to effectively manage microgrids, addressing not only power distribution but also voltage variations across network buses to prevent problems and equipment damage. The objective is to achieve optimal power distribution among various equipment and Distributed Generation (DG) sources, ensuring high energy quality in terms of voltage stability alongside efficient energy optimization.

In summary, the combination of EMS, the T-Cell algorithm, and the MAS provides an innovative solution for addressing the challenges of microgrid management. This approach, incorporating energy production forecasts and real-time simulations, ensures efficient and reliable energy management. As the importance of microgrids continues to grow in the context of the energy transition, this methodology offers a promising pathway toward a sustainable future.

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