



OPTIMIZATION OF POWER SYSTEM RELIABILITY IN WIND FARMS USING A HYBRID HEURISTIC ARTIFICIAL NEURAL NETWORKS AND UNIVERSAL MOMENT GENERATING FUNCTIONS

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ABSTRACT

This paper presents an innovative approach to optimising the reliability of electrical systems associated with wind farms by integrating advanced methods, including the Universal Moment Generating Function (UMGF), artificial neural networks (ANN), and the Harmony Search (HS) algorithm. The study focuses on modelling multi-state systems to address the complexity of wind energy production, which involves stochastic variability and degradation phenomena. The proposed methodology combines reliability assessment techniques with cost constraints to determine the most economical system configuration that meets specified reliability levels. Through simulations involving various subsystems (wind turbines, transformers, transmission lines), the authors demonstrate that their hybrid approach effectively balances investment costs and system reliability. The results indicate that maximizing reliability incurs higher costs, with the optimal compromise found at a reliability level around 97%, corresponding to a minimal investment of approximately 30,400 MDA (Million Dinars Algerian). Overall, this integrated optimization framework offers a practical, flexible solution for designing cost-effective, reliable wind energy systems, contributing valuable insights to renewable energy planning and reliability engineering.



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I. INTRODUCTION

The fundamental goal of an electrical energy system is to deliver reliable power to end-users at minimal cost, while maintaining acceptable levels of service quality and system continuity [1]. In our modern society, electricity is indispensable, serving as the backbone of economic activities, technological development, and daily life. The volume of electrical energy produced is often regarded as a barometer of a nation's economic health; developed countries typically generate surplus energy relative to consumption, necessitating continuous expansion and optimization of power infrastructure to meet increasing demand [2]. Achieving a balance between supply and demand with high reliability remains a critical challenge, emphasizing the importance of strategic planning rooted in reliability engineering and quality of service considerations. Conventional approaches to energy generation predominantly rely on fossil fuels and nuclear power, which have historically been the primary resources for new projects. However, these sources are now facing critical depletion fossil fuel reserves are diminishing at an alarming rate, reaching thresholds that threaten energy security and sustainability.

While nuclear energy was once viewed as a promising alternative due to its high capacity and low operational costs, concerns about long-term radioactive waste management, safety risks, and escalating costs have prompted a shift away from nuclear solutions. Additionally, both fossil fuels and nuclear energy significantly affect the environment through greenhouse gas emissions and other pollutants [3]. In response to these challenges, renewable energy sources have gained considerable prominence as sustainable alternatives that provide clean power without depleting finite resources. They offer numerous advantages, including minimal environmental impact and the potential for decentralised generation. Nonetheless, renewable sources such as solar and wind are inherently intermittent and stochastic, characterised by natural fluctuations that must be carefully managed within the grid. Among renewable options, wind power has demonstrated remarkable growth since the early 1990s, driven by technological advances and proactive policy measures, and today it stands as one of the most economically competitive renewable energies. It plays a vital role in reducing greenhouse gas emissions and combating climate change [4], [5].

II. LITERATURE REVIEW

However, integrating and operating wind energy systems presents unique challenges. The structural complexity of wind turbines, given their height, accessibility issues, and specialised maintenance requirements, necessitates sophisticated reliability and maintenance strategies [6]. Moreover, the degradation and failure of turbine components occur randomly and are difficult to predict precisely, complicating reliability assessments and decision-making processes. As a result, reliance on expert judgment and qualitative data is often necessary to effectively design and optimise maintenance schedules and system configurations. Therefore, advanced reliability modelling and optimisation methods are essential to enhance the performance, availability, and cost-effectiveness of wind energy systems [7]. In this context, our research proposes a comprehensive approach to model the reliability of multi-state wind energy systems. We utilise the Ushakov technique, also known as the Multi-State System (MSS) analysis, along with the Universal Moment Generating Function (UMGF), which effectively captures the probabilistic behaviour of systems with multiple failure modes or performance degradation levels. These methods are particularly suitable for complex systems with numerous redundancy configurations and variable performance states. The core contribution of this work lies in integrating these reliability modelling techniques with metaheuristic optimisation algorithms, specifically Harmony Search (HS). HS is a nature-inspired algorithm that mimics musical improvisation and is well-suited for solving combinatorial and continuous optimisation problems within complex search spaces. Our approach aims to determine the optimal system configuration, considering component reliability, performance, and cost, that minimises total investment while satisfying predefined reliability constraints. Many studies have been done on this subject. According to [8] present a stochastic meta-heuristic model (SMM) for the multi-criteria allocation of wind turbines (WT) in a distribution network to enhance network reliability. Also, by [9] applied a Water Cycle Algorithm (WCA) as a metaheuristic optimisation for a decoupling strategy to improve the efficiency of the original dual-loop Reliability-Based Design and Optimisation (RBDO) algorithm. And, the same authors [10] propose an intelligent optimisation-inspired Support Vector Regression (SVR) modelling strategy to construct a high-precision approximation model for offshore wind energy. In [11] explore the application of machine learning techniques to improve the reliability of the offshore wind farm. Finally, by [12] compare the performance of twelve metaheuristics (MHs) on wind farm layout optimisation (WFLO). The structure of this paper is as follows: the initial section introduces the Harmony Search optimisation method, followed by a detailed description of the reliability assessment process under cost constraints. Subsequently, we present simulation setups and discuss the results, including sensitivity analyses and cost-reliability trade-offs. The paper concludes with reflections on the efficiency of the proposed approach and future directions for wireless and renewable energy system optimization.

III. HARMONY SEARCH OPTIMIZATION COMBINED WITH ANN MLS ALGORITHM

Solving an optimisation problem involves systematically exploring the feasible solution space, defined by a set of constraints, to identify the optimal solution(s) that minimise or maximise a performance criterion, commonly referred to as the objective function. This function provides a quantitative measure of the solution's quality, efficiency, or accuracy. Formulating such problems necessitates the clear identification of known parameters, referred to as problem data, and unknown decision variables. These elements are mathematically interconnected through constraints and objective functions expressed as equations or inequalities. When decision variables vary over continuous domains, the problem is classified as a continuous optimisation task [13]. In the context of neural network modelling, optimisation techniques are fundamental for training processes, hyper parameter tuning, and performance enhancement, particularly when approximating complex nonlinear functions. The challenge frequently involves modelling nonlinear systems of the form $f: \mathbf{R}^K \rightarrow \mathbf{R}$, where analytical solutions are often unavailable or impractical. Among the most effective neural network architectures for such tasks are Multilayer Perceptron (MLPs) and Radial Basis Function (RBF) networks. This study emphasises the use of MLPs owing to their strong approximation capabilities, flexibility, and generalisation performance [14]. An MLP consists of an input layer, one or more hidden layers, and an output layer. Each neuron (i), as shown in Fig. 1, comprises a weighted summation component followed by a nonlinear activation function $g(\cdot)$, which introduces nonlinearity and enables the network to learn complex mappings. The collective interaction within and across layers allows the MLP to approximate highly nonlinear functions with arbitrary accuracy, under suitable conditions [15]. The training of the neural network typically employs supervised learning via the back propagation algorithm, which iteratively adjusts the synaptic weights to minimise a loss function—usually the mean squared error—between the network's outputs and the predefined ground-truth data. For each training example, the desired output is explicitly known, and the error signal propagates backwards through the network layers to update the weights using gradient descent. Training continues until the error falls below a designated threshold or stops decreasing significantly. Initial weights are randomly assigned to ensure diversity in the search space and to promote convergence towards an optimal or near-optimal solution [16]. Despite its efficiency, back propagation can be sensitive to the initial conditions and prone to stagnation in local minima. To address these limitations, integrating meta-heuristic algorithms into neural network training has gained prominence. In this context, the Harmony Search (HS) algorithm is employed to optimise the neural network parameters.

Inspired by the improvisation process in musical harmony, HS maintains a harmony memory, an evolving population of candidate solutions, which is iteratively refined through three key steps: memory consideration, pitch adjustment, and randomisation. These mechanisms balance exploration and exploitation during the search process, increasing the likelihood of converging on globally optimal solutions. Coupling HS with neural network training leverages the global search strengths of metaheuristics, leading to improved convergence, enhanced approximation, and greater robustness against local minima. The resultant neural network architecture, optimised via the harmony memory, is depicted in Fig. 1. This hybrid methodology effectively combines the learning capabilities of neural networks with the global search efficiency of metaheuristics, making it particularly suitable for tackling complex nonlinear modelling and optimisation problems with multiple constraints.

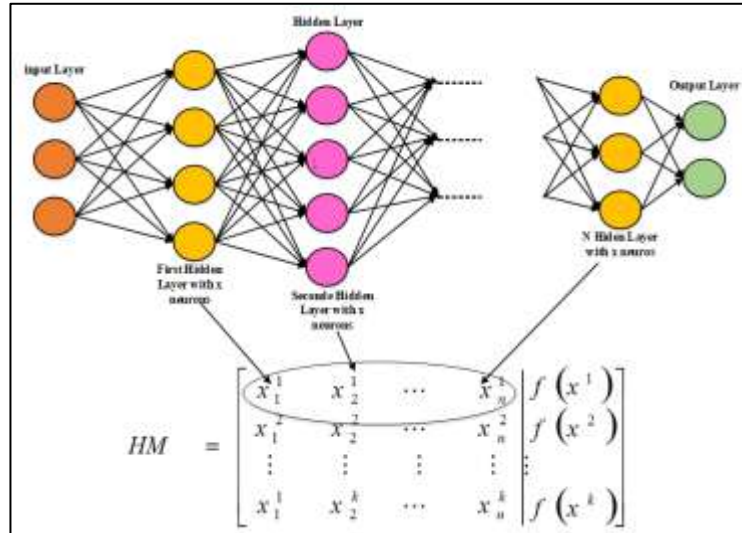


Figure 1: Determining the parameters of the neural network using HS.

Source: Authors, (2026).

Here, the same activation function g is used in both layers. The superscript of n , θ , or w refers to the layer, first or second. The output, 1,2, i y_i of the MLP network becomes.

$$y_i = g\left(\sum_{j=1}^3 w_{ji}^2 g(n_j^1) + \theta_j^2\right) = g\left(\sum_{j=1}^3 w_{ji}^2 g\left(\sum_{k=1}^n w_{kj}^1 x_k + \theta_j^1\right) + \theta_j^2\right) \quad (1)$$

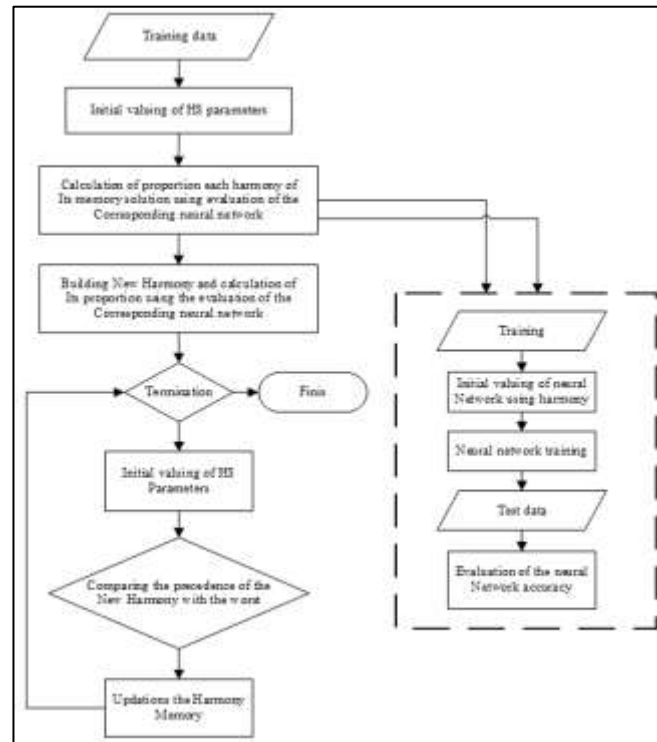


Figure 2: Flow-chart of ANNHS.

Source: Authors, (2026).

III.1 IMPROVING RELIABILITY UNDER THE CONSTRAINTS OF AN ALLOCATED BUDGET FOR AN ELECTRICITY NETWORK

In modern power grids, operational reliability can fluctuate across multiple performance levels, allowing the system to continue functioning even in partially degraded states. Specifically, a component's failure does not necessarily result in a complete outage; it may reduce capacity or performance. For example, a generation unit typically operates at its nominal capacity, ensuring maximum availability under optimal conditions. However, when failures occur, they can lead to either full system outages or partial reductions in capability. This behaviour exemplifies the multi-level operating nature of a power system. A Multi-State Power System (MSPS) is an electrical network capable of operating at multiple performance levels, providing a nuanced representation of operational states ranging from fully operational to complete failure. As documented in reference [17], this modelling approach enables a more precise evaluation of system reliability and resilience across diverse failure scenarios.

III.2 RELIABILITY ASSESSMENT UNDER ECONOMIC CONSTRAINTS

In power system design, there exists an intrinsic economic trade-off between system reliability and operational costs. An increase in reliability levels typically correlates with higher investment costs for more robust components and redundancies, while the costs of customer interruptions tend to diminish as reliability improves. Historically, utility companies have predominantly focused on minimising operational and infrastructure costs; however, integrating reliability considerations into economic planning requires a comprehensive quantitative framework. The cost-of-reliability approach emerges as an effective methodology, enabling decision-makers to balance the financial investment required for reliability enhancement with the economic and societal costs of outages and service disruptions [18].

III.3 QUANTITATIVE EVALUATION OF RELIABILITY WITH A PREDETERMINED BUDGET

The proposed methodology aims to identify the optimal configuration of a power system that maximises cost-efficiency, i.e., minimises total investment, while satisfying explicit reliability constraints. This involves the strategic selection and placement of system components, including generation units, transformers, transmission lines, and distribution elements. The approach considers augmenting existing infrastructure by adding or replacing components, recognising that increasing system reliability invariably requires additional capital expenditures. Achieving the targeted reliability level thus entails a trade-off between capital investment and performance, with the optimal solution being the configuration that maximises reliability-to-cost ratio within a predefined financial limit. This optimisation process is particularly pertinent in systems characterised by variable or uncertain load demands, as in renewable energy integration. Modifications to the system are primarily driven by changes in load profiles and service requirements, necessitating adaptive and intelligent optimisation techniques capable of navigating complex, high-dimensional solution spaces.

III.4 FORMAL PROBLEM FORMULATION AND DESIGN STRATEGY

The core challenge in designing reliable wind farm-integrated power systems is formulating a mathematical model that captures the multifaceted nature of system costs and reliability metrics. Specifically, the problem involves minimising the aggregate capital expenditure associated with system components—such as turbines, transformers, and transmission lines—subject to reliability constraints expressed as probabilistic or deterministic availability thresholds. Mathematically, the problem can be formulated as follows:

$$\min C(x) \text{ subject to } R(x) \geq R_{\text{target}} \quad (2)$$

Where x represents decision variables characterizing component selections and configurations, $C(x)$ denotes the total investment cost, and $R(x)$ signifies the system's reliability metric (expressed as a probability of system availability or a system performance index). The target reliability level R_{target} is predetermined based on operational standards or regulatory requirements. In this context, the reliability assessment incorporates system-wide reliability modelling techniques, such as multi-state system representations and probabilistic analysis, to evaluate the reliability contribution of each component and subsystem under various failure modes. The fundamental goal is to identify a configuration that maximises achievable reliability within the allocated budget, thereby optimising the economic efficiency of wind energy integration. To solve this complex, NP-hard optimisation problem, the Harmony Search (HS) algorithm, an evolutionary metaheuristic inspired by musical improvisation, has been employed. Its global search capability, combined with its flexibility to handle discrete and continuous variables, makes it particularly suitable for this application. The solution framework involves initialising a population of candidate configurations, iteratively refining them using a harmony memory, and applying a reliability-driven cost evaluation to guide the search toward an optimal balance between investment and system performance [19]. This systematic approach enables stakeholders to make informed investment decisions by quantifying the trade-offs between system reliability and capital expenditure, ultimately facilitating the deployment of cost-effective, high-reliability wind farm power systems.

IV. DETAILED SYSTEM DESCRIPTION FOR OPTIMIZATION

The system consists of five interconnected subsystems within a wind farm power network as shown in Figure 3 [20].

- 1 Power Generation SS1: 10 wind turbines convert wind energy into electricity, with variations in capacity and reliability considered.
- 2 Voltage Step-up SS2: Four medium-to-high voltage transformers elevate generated power for transmission.
- 3 High-Voltage Transmission SS3: Five HV lines transport electricity from turbines to substations or load centers.

- 4 Step-down Transformers SS4: Four HV/MV transformers regulate voltage levels for distribution reliability.
- 5 Distribution Network SS5: Seven MV lines deliver electricity from substations to consumers.

The design aims to optimise component selection (types and quantities) to balance cost and reliability, ensuring the entire system meets specified availability standards. This involves analysing failure rates and performance parameters to determine the most efficient configuration within budget constraints, thereby facilitating resilient, cost-effective wind power integration into the grid.]

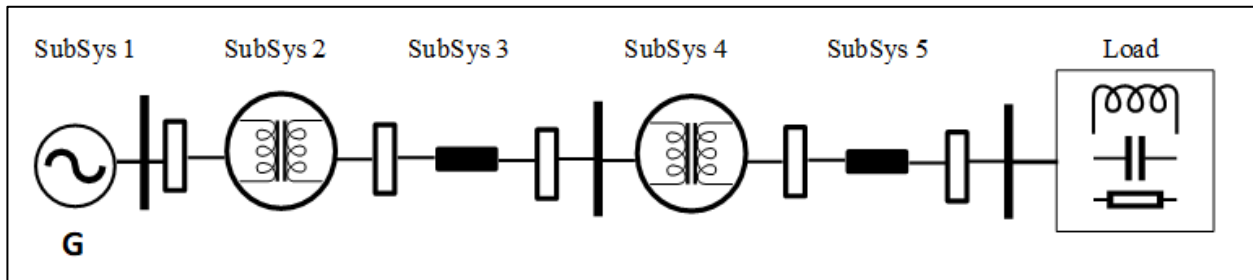


Figure 3: Synoptic diagrams of the electro-energy system associated with the Wind farm.
Source: Authors, (2026).

Table 1: System version component data available on the market.

Sub-system	Versions	Reliability A (%)	Cost C(mln MDA)	Performance (Capacity) (MW)
Wind farm	1	0.992	7.735	8
	2	0.986	6.475	7
	3	0.994	6.698	8
	4	0.988	6.290	8
	5	0.980	6.146	7
	6	0.991	4.484	6
	7	0.992	3.926	5
Transformer HT	1	0.994	2.805	21
	2	0.990	2.272	21
	3	0.997	2.594	15
	4	0.991	2.569	15
	5	0.998	1.857	11
Lines HT	1	0.971	1.985	19
	2	0.997	1.983	17
	3	0.991	1.842	17
	4	0.976	1.318	15
Transformer HT/MT	1	0.978	0.842	19
	2	0.986	0.875	19
	3	0.978	0.745	17
	4	0.983	0.654	15
	5	0.981	0.625	15
	6	0.971	0.608	15
	7	0.985	0.492	13
	8	0.973	0.415	13
Lines MT	1	0.984	0.456	17
	2	0.993	0.432	15
	3	0.989	0.364	13
	4	0.981	0.283	11
	5	0.968	0.242	11

Source: Authors, (2026).

IV.1 DEMAND LEVEL (LOAD)

Consumer demand is estimated at a maximum power of 30 MW on the electricity grid. A minimum load level relative to a consumption of 10 MW describes the power consumed during off-peak hours. Two intermediate levels have been chosen, namely 15 and 20 MW. Each level usually corresponds to a cumulative annual duration. The demand parameters are illustrated in the following table and figure Figure 4:

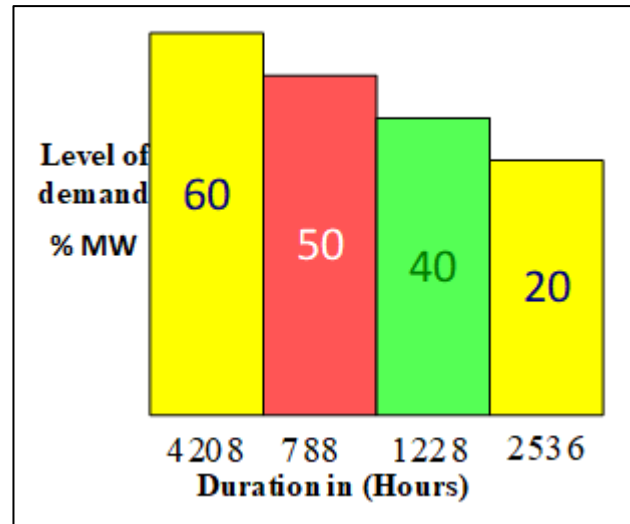


Figure 4: Level and duration of demand.
Source: Authors, (2026).

Table 2: Table states.

State	State1	State2	State3	State4
Level of demand (%)	60	50	40	20
Duration (hours)	4208	788	1228	2536
Probability (%)	41.66	8.33	33.33	16.66

Source: Authors, (2026).

We apply the load-coupled reliability optimization method to determine, with minimum cost, a system configuration that satisfies the desired reliability.

IV.2 SOLUTION APPROACH TO OPTIMAL PARK DESIGN

A comparison can be drawn between the optimal architecture of a power network and the process of improvising music: just as improvisation features numerous harmonies that symbolise different power system design options, harmony itself represents the specific configuration of the network design vector. Each musical instrument corresponds to a subsystem in the power system, with the instrument's pitch indicating the value of a design variable, such as the type and technology of electrical components, without considering their physical placement. A more harmonious sound signifies a local optimum, while an even better harmony indicates the global optimum. Figure 3 illustrates the five core subsystems (stations) that make up the electrical power generation system supplying electricity to consumers. The entire dispatch operation of this system, involving five key design variables, is depicted in the figure. The process begins with selecting the first design variable.

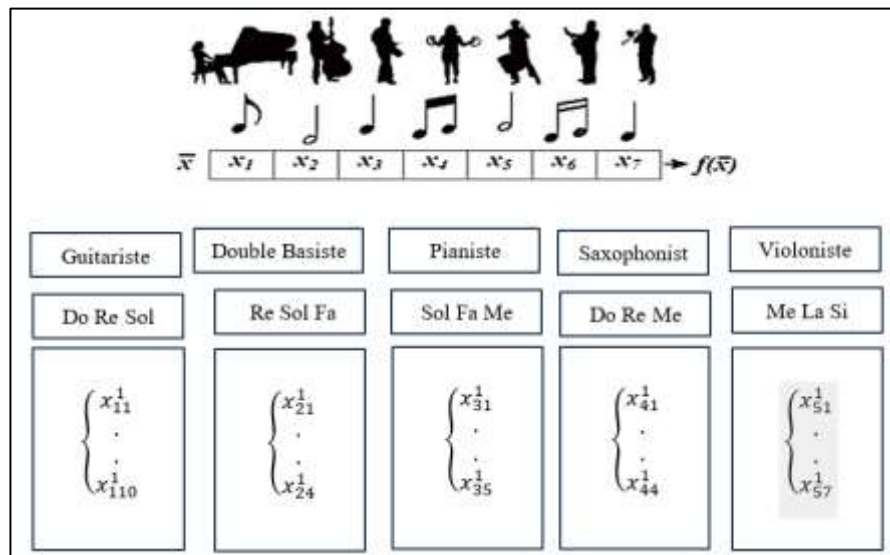


Figure 5: Distribution of variables with respect to musical notes.
Source: Authors, (2026).

In our reliability optimization problem, we need to choose the optimal combination of elements to minimize the total cost while satisfying the reliability constraint. The elements can be selected from any combination of available components, each characterized by reliability, capabilities, and cost. In the first stage, one or more components are selected, and a vector solution is chosen (randomly) in each subsystem. In this step, the electro-energy system design (grid and wind farm) is optimized. The worst design is eliminated, and the new design is incorporated if the newly selected electro-energy system design is superior [21], [22]. Each row of the harmonic memory matrix represents a candidate electro-energetic system design. The elements of this matrix represent the number of component technologies [23].

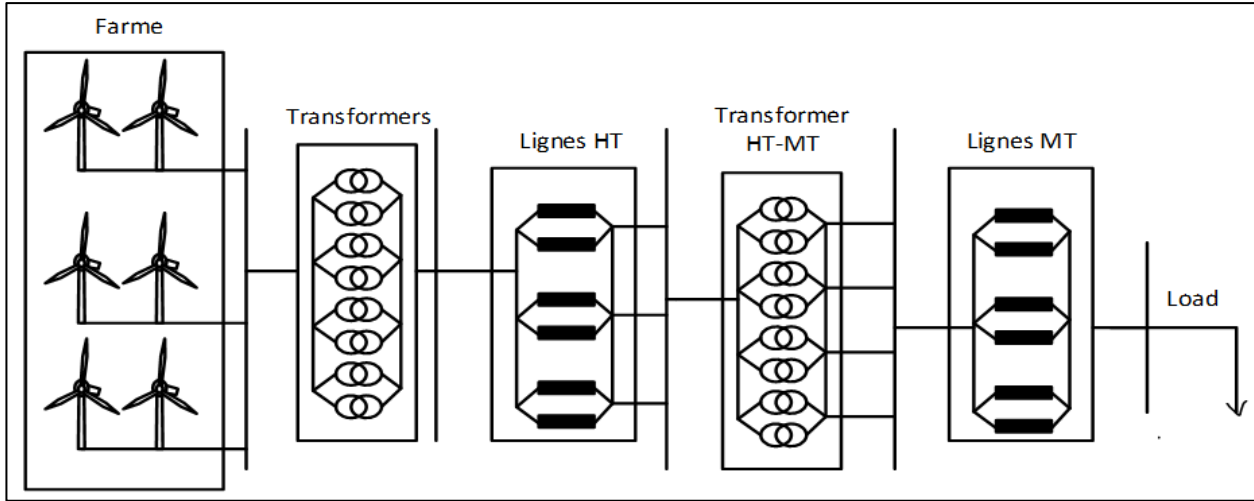


Figure 6: Parallel-series electro-energetic system.
Source: Authors, (2026).

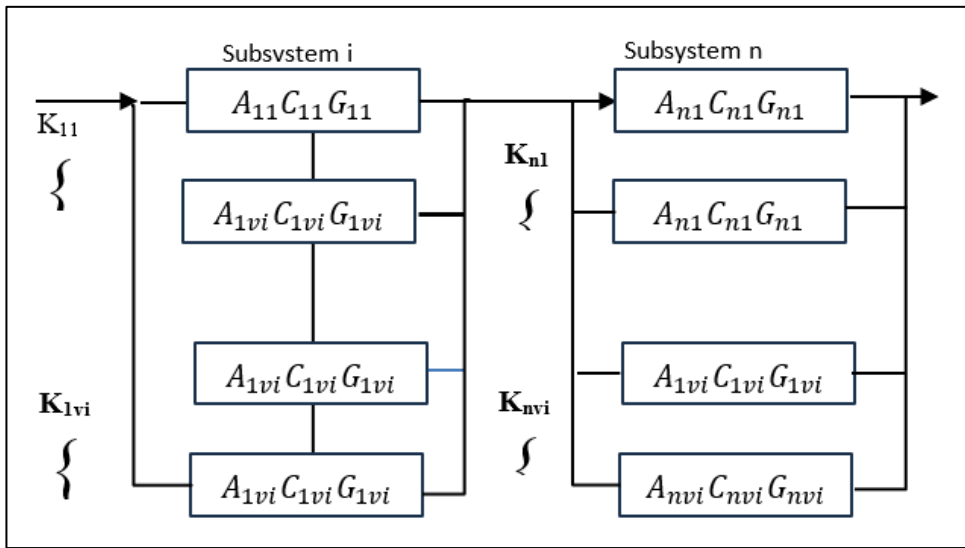


Figure 7: Subsystem parallel-serial different versions and number components.
Source: Authors, (2026).

Each subsystem C_i contains several elements or components connected in parallel. For each subsystem i , there are different versions of the elements (generators, transformers, and lines) available on the market. For each subsystem of elements, different versions and number of components can be chosen. For each subsystem i , the elements are characterized by their cost (C_{iv}), reliability (R_{iv}), and performance (G_{iv}) according to their version. With: v :Version i : Subsystem all components in the subsystem belong to the v . The structure of the element belonging to subsystem i is defined by the number of components in parallel (of each version).

V_i : The version of the type of component i

k_{iv} : The number of elements in parallel in each subsystem

k_{iv} For $1 \leq v \leq V_i$

C_{iv} : The cost of each element

The structure of the entire system is defined by the vectors $k_i, k_i = \{k_{iv}\}$ with $1 \leq i \leq n$ and $1 \leq v \leq v_i$. For a set of vectors, the total cost of the system is given by the following expression:

$$C = \sum_{i=1}^n \sum_{v=1}^{v_i} k_{iv} C_{iv} \quad (3)$$

The problem of planning the multi-state expansion of the electro-electric power system in the initial period can be formulated as follows:

Find the minimum cost of configuring the electrical power system $\{k_1, k_2, \dots, k_n\}$, such that the corresponding availability is greater than or equal to the specific availability A_0

$$\text{Minimize } C_0 = \sum_{i=1}^n \sum_{v=1}^{v_i} k_{iv} C_{iv}$$

Under constraints $A(k_1, k_2, \dots, k_n, D, T) \geq A_0$

We apply the load-coupled power system optimization method to determine an optimal structure from the point of view of investment cost, while satisfying the prescribed level of reliability. Each component of the subsystem is characterized by the following parameters:

G_i : represents the performance or capacity in MW

A_i —Represents the availability of the item in question.

C_i —Represents the cost as a % of the investment for each item.

The design algorithm consists of the following steps:

IV.3 INITIALIZING SEARCH HS

The HS algorithm parameters are set in this step: the harmony memory size (HMS), the considered harmony memory ratio (HMCR), the pitch adjustment ratio (PAR), and the stopping criteria (improvement count). These settings are selected based on the issue.

IV.3.1 Harmony Parameters:

IV.3.1.1 Initialize the Memory of the Search HS Harmony:

The HS matrix features randomly produced designs like HMS, each vector denotes vector solutions of a power design in H.M. $x_{1k}^1, x_{2k}^2, \dots, x_{gk}^{HMS}$ The (HM) preserves the best configurations of the systems in the research process. We are left to calculate the network design having an initial cost relative to the initial stage C_0 and calculate the availability of the initial network design at the initial stage A_0 [24].

IV.3.1.2 Improve a New Harmony:

A new harmony $[x^{nv}] = x_{11}^{nv}, x_{12}^{nv}, \dots, x_{gk}^{nv}$, is improvised by H.M. among the entire available technologies of each subsystem on the list $[Y_{AT}]^2$. Three rules are used for the generation of a new harmony. H.M. consideration, launch adjustment, and random generation. In the consideration of H.M., the value of the first lattice design variable $[x_{g-1}^{nv}, 1]$ for a new harmony is chosen at any H.M. of value $(ie, \{x_{1k}^1, x_{2k}^2, \dots, x_{gk}^{HMS}\})$ where the entire technology available on the market is denoted $[Y_{AT}]^2$ HMCR. It is applied as follows:

$$\begin{cases} x_{1k}^1 \in \{x_{gi}^1, x_{gi}^2, \dots, x_{gi}^{HMS}\} & \text{Si } \text{ran} \leq \text{HMCR} \\ x_{gi}^1 \in Y_{AT} & \text{Si } \text{ran} > \text{HMCR} \end{cases}$$

The (ran) is a random number with uniform distribution generated between the interval [1,0], If the number (ran) is less than the value of HMCR, the i^{iem} network design variable of the new fleet design $[x_{gk}^{nv}]$ is selected. The current values are stored in the i^{iem} H.M. column Otherwise; the i^{iem} redesign network design variable $[x_{gk}^{nv}]$ is selected from the list $[Y_{AT}]$.

The design variable of the New Harmony $[x^{nv}] = x_{11}^{nv}, x_{12}^{nv}, \dots, x_{gk}^{nv}$ is obtained by the memory considered, it is examined to determine whether the pitch should be adjusted or not. The launch adjustment is made by "PAR", the PAR is studying better system design in the vicinity of the current system design. It is applied as follows:
Adjustment Pitch Decision

$$PAD \text{ POUR } x_{gi}^{nv} \begin{cases} \text{oui si } \text{ran}_1 \leq PAR \\ \text{no si } \text{ran}_1 > PAR \end{cases}$$

The (ran1) is a randomly generated number produced, it is uniformly distributed over the interval [0,1]. If this random number is less than the PAR, the x_{gi}^{nv} is replaced by its list of neighbouring elements of the same technology. If this number is not less than the RAP, it x_{gi}^{nv} remains the same.

IV3.1.3 Harmony Memory Update:

If the new $[x^{nv}] = x_{11}^{nv}, x_{12}^{nv}, \dots, x_{gk}^{nv}$ harmony is better than in H.M., the new lattice design is included in H.M., and the existing harmony is excluded from H.M. In this process, it should be noted that the matrix of H.M. is handled by the objective function without constraint and the same lattice design is not allowed in H.M. more than once.

V. RESULTS OBTAINED BY THE ANNHS ALGORITHM, UMGF:

The natural objective function is to determine the minimum-investment design configuration that satisfies the reliability constraints at each stage. The full results obtained by the proposed ANNHS and UMGF harmony research for indicated values A0 are shown in Table 5.3. The latter outlines the optimal initial system design and the corresponding optimal power at each stage for expansion planning to achieve the desired A0 reliability levels. Tables 3 and 4 illustrate the calculated cost and reliability index for the corresponding network design. After running our program, we obtained the results. This summarizes the results for the reliability thresholds 0.97, 0.98, and 0.99. We see that increasing reliability increases cost. Therefore, to achieve better reliability, we must invest more. The high price for a high-reliability level of 0.99 is 30,890 MDA. Meanwhile, for a reliability level of 0.97, the cost is reduced to 30,741MDA. Since our goal is to achieve good reliability at a lower price, the best configuration is the one with a reliability constraint of 0.97. (97% reliability constraint: reliability is 0.943, cost 30.675 million DA), (98% reliability constraint: reliability is 0.968, cost 30.720 million DA), (99% reliability constraint: reliability is 0.987, cost 30.751 million DA), Choosing a more reliable structure results in a structure that is too expensive (from an investment perspective), and vice versa: a cheaper structure entails a loss of reliability. In our work, we propose structures with different levels of reliability, giving investors a choice and facilitating their decision-making regarding a particular investment. The intelligent optimization and optimal budget are 30,400 MDA. This amount represents the absolute minimum investment cost to build the wind farm system described in the research paper, while meeting your reliability requirement (having a risk of failure, or LOLP (loss of load probability), of less than 1%). Our method shows that any configuration costing less than 30,400MDA will not be reliable and will not comply with the specifications (LOLP < 1%). It is not necessary. Spend more to get an even more reliable system, but that would be an "overinvestment". The budget of 30,400 MDA makes it possible to achieve the set objective.

Table 3: Best configuration and Strategy optimization.

ID	Equipment Type	Cost Per Unit	Performance (Capacity)	Reliability (Availability)	Strategic
1	Wind turbine Type 1	1 000 MDA	2 MW	92.00 %	more economical, but the least and the least reliable.
2	Wind turbine Type 2	1 800 MDA	3 MW	95.00 %	(optimal) Excellent cost/performance compromise.
3	Wind turbine Type 3	2 500 MDA	4 MW	97.00 %	the most efficient and reliable, but the most expensive.
1	Transformer Type 1	800MDA	10 MVA	99.50 %	the optimal solution) Cheapest option, already very reliable.
2	Transformer Type 2	1 200 MDA	15 MVA	99.80 %	More expensive option for a marginal gain in reliability.
1	Line Type 1	500 MDA	20 MW	99.60 %	(the optimal solution) Cheapest option, very reliable.
2	Line Type 2	900 MDA	35 MW	99.90 %	Almost twice the price for a very small improvement in reliability.

Source: Authors, (2026).

Table 4: Optimal Allocation of the 30,400 MDA Budget for Wind Turbine Sub systems.

This 30,400MDA must be allocated, item by item, to build the optimal solution [2 1 1 1 1]		
System equipment	Purchase: Type	Budget
SS1 subsystem (Production -Wind turbines)	Type 2	18 000 MDA (10 x 1800MDA)
SS2 subsystem (Production -Wind turbines)	Type 1	3,200MDA (4 x 800MDA)
SS3 subsystem (Production -Wind turbines)	Type 1	2,500MDA (5 x 500MDA)
SS4 subsystem (Production -Wind turbines)	Type 1	3,200MDA (4 x 800MDA)
SS5 subsystem (Production -Wind turbines)	Type 1	3,500MDA (7 x 500MDA)
Total verified: 18000 + 3200 + 2500 + 3200 + 3500 = 30 400 MDA		

Source: Authors, (2026).

V.1 DETAILED BUDGET ALLOCATION ANALYSIS

1) SS1 Subsystem (Generation – Wind Turbines): Strategic Significance: This component represents the principal capital expenditure within the system. The optimization process correctly prioritized energy generation capacity by allocating most of the investment budget to ensure a robust and reliable power production foundation, thus emphasizing its critical role in system performance and reliability.

2) SS2 Subsystem (Medium-Voltage/High-Voltage Transformers): Strategic Significance: The selected configuration favoured the most cost-effective option, leveraging the high inherent reliability of Type 1 transformers, which are deemed sufficient for the operational demands once generation is secured. This reflects an economic optimization aligned with maintaining system dependability without unnecessary expenditure.

3) SS3 Subsystem (High Voltage Transmission Lines): Strategic Significance: Similar to the transformer selection, the choice of transmission infrastructure was driven by cost-efficiency, supported by the already high levels of reliability observed in existing high-voltage lines, thus minimizing expenditure while ensuring transmission system robustness.

4) SS4 Subsystem (High Voltage/Medium Voltage Step-down Transformers): Strategic Significance: The allocation reflects a focus on economical solutions for non-critical components, balancing reliability with cost considerations, and avoiding overinvestment in elements with marginal impact on overall system resilience.

5) SS5 Subsystem (Medium Voltage Distribution Lines): Strategic Significance: The cost distribution indicates a strategic approach to economizing on non-essential system components, optimizing overall expenditure while maintaining adequate levels of distribution reliability across the network.

V.2 INTERPRETATIONS OF THE OPTIMIZATION RESULTS BY THE HS ANN MLS ALGORITHM:

The design of an electrical power system integrated with a contemporary wind farm must achieve an optimal balance between cost-efficiency and operational reliability, ensuring that consumers are supplied with electricity in an economically viable manner while adhering to predefined safety and reliability standards. To identify the minimal capital investment configuration that satisfies the specified reliability criteria, conventional deterministic approaches are insufficient because the problem is complex and multimodal. Consequently, metaheuristic algorithms, particularly the Harmony Search (HS) algorithm, are employed to effectively navigate the solution space. The HS parameters have been calibrated as follows: Harmony Memory Size (HMS) = 30, Harmony Memory Considering Rate (HMCR) = 0.95, Pitch Adjustment Rate (PAR) = 0.65, with a maximum of 1000 iterations (NI). Post-execution analysis yields results summarised in Table 5-3, which details the trade-offs between reliability thresholds 0.95, 0.97, and 0.99, and their corresponding system costs. The findings confirm a positive correlation between system reliability and investment cost: achieving a reliability level of 0.99 necessitates a substantial investment of approximately 20.438 MDA, whereas a reliability target of 0.97 is attainable at a lower cost of approximately 18.957 MDA. Therefore, from a cost-benefit perspective, the configuration constrained to a 0.97 reliability threshold presents the most favourable compromise. Specific results are as follows:

- 1) At a 95% reliability constraint, the actual reliability is 0.943, with a total system cost of approximately 18.957 MDA.
- 2) At a 97% reliability constraint, the reliability reaches 0.968, with the cost marginally increasing to 19.167 MDA.
- 3) At a 99% reliability constraint, the reliability approximates 0.987, with the cost rising significantly to 20.438 MDA.

Selecting a more reliable system architecture entails higher capital expenditure, whereas opting for a less costly design involves compromised reliability, a critical consideration for investors. Our analysis offers a spectrum of reliability-efficient configurations, enabling stakeholders to make informed decisions aligned with their strategic investment objectives. By balancing reliability requirements against economic constraints, one can optimize system design, thereby minimize the investment outlay while ensure an acceptable reliability level for wind farm power supply projects.

VI. CONCLUSION:

The discrete methodology employed advantages Harmony Search optimisation integrated with an advanced Artificial Neural Network employing Multi-State Layered Systems to determine the optimal configuration and sizing of wind energy systems. This approach addresses a complex yet prevalent challenge in the energy sector: optimising the design and layout of wind farm power systems under cost and reliability constraints, with the objective of improving performance metrics such as system availability.

The core of the methodology involves formulating this as a cost-optimisation problem constrained by target reliability levels, necessitating a sophisticated solution strategy that combines meta-heuristic algorithms with intelligent learning models. Specifically, the proposed framework utilises the HS algorithm to explore and identify the most suitable series-parallel configurations of electrical components within the power grid, aiming to minimise total capital investment while satisfying predefined reliability criteria. The HS algorithm's search space is governed by key parameters, availability, rated capacity (performance), and cost of electrical components, while the ANN MLS provides adaptive intelligence, guiding the search process based on learned operational behaviours and system demands. Importantly, the number and types of electrical elements in series and parallel arrangements are dynamically defined based on variations in consumer load profiles, ensuring practical applicability. This methodology facilitates the resolution of critical reliability challenges by maintaining flexibility in the diversity of electrical component technologies that can be combined within the system architecture. The amalgamation of the Universally Generated Moments Function with the HS algorithm enables comprehensive analysis and optimisation of multi-state systems, without restricting component heterogeneity. The primary objective remains the determination of the cost-minimal system configuration that achieves the desired availability level, with the approach demonstrated effectively in the context of renewable energy sources such as wind turbines. This integrated UMGF-HS framework proves to be a robust and pragmatic solution for addressing redundancy and optimisation issues in complex power systems. Its capacity to minimise total investment costs while ensuring specified reliability standards underscores its potential as a versatile tool for renewable energy system planning and optimisation, paving the way for more efficient, economically sustainable energy infrastructure.

VII. AUTHOR'S CONTRIBUTION

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