Application of Neural Network Algorithms in Networked Microgrids' Operation Optimization and Control

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Abstract: - Neural Network algorithms have significant applications in microgrid operations optimization and control to provide cheap, robust, and reliable energy to end-users. These algorithms are inspired by artificial neural networks (ANNs). In this paper, we have proposed a neural network algorithm (NNA) based on the unique structure of ANNs. Neural network algorithms have the capability to generate new candidate solutions using the complicated structure of ANNs and their operators. Improvised exploitation and each parameter in the asymmetric interval are iteratively converged theoretically in the context of convergence proof. In this paper, we have demonstrated the scheduling problems for networked microgrids solved by using artificial neural networks (ANNs) along with the biological nervous systems approach. The neural network algorithm (NNA) is designed by using a specific structure of ANNs. NNA has the capability to take the benefits using complicated structure of ANNs to generate the enhanced solution. The designed code supports and implements a neural network-supported optimization algorithm. The proposed algorithm finds optimal solutions by utilizing solutions that are based on certain rules produced by machine learning neural networks.

Key-Words: - Microgrids, Optimization Application, Operation, Scheduling and Trading, Fault Tolerance, Machine Learning Algorithms Applications, Networked Microgrids.

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1 Introduction

Climate change is leading to a threat to power systems by introducing potential challenges of more electricity demand and impacts on the power equipment's installed. In addition, overloading and overheating may occur due to the convergence of these climate change factors. To resolve these issues, we need to enhance the capability of the power network to face such weather conditions commonly known as enhancing the power system resilience. Power system resilience can be enhanced by using several methods such as strategic planning approaches and system hardening methodologies. A notable and rare solution is integrating controlled and smart technology based on establishing networked microgrids (NMGs) strategically. NMGs are capable of transferring both power and information across the microgrids. We can configure and link the multiple microgrids according to our needs like ring, star, or full configuration. Each configuration of networked microgrids has its own benefits of reducing operational costs and improving power supply resilience as compared with independent microgrids, [1].

Networked microgrid configuration and networked microgrid optimization and control can drastically affect the operational cost by using detailed exploration of problem modelling, and objective functions with constraints. The comparative analysis of algorithms supports the strengths and limitations of NMGs configurations, optimization, and control of NMGs operations. In this paper, we have offered a more realistic and comprehensive description of problem modeling, its optimization, and control to make stable and reliable

NMGs operations for meeting the energy requirements, [2].

For this purpose, machine learning techniques seem to be good approaches to finding effective prediction of uncertainty parameters. There are several algorithms to find the optimal parameter making the cost function optimal. The distributed networked microgrids have more operational characteristics like less computing time and more secure energy availability as an optimal solution, [3]. We can model the uncertain parameters of distributed networked microgrids including the loads, and output power using machine learning effective methods, [4].

The paper has Section II describing the microgrid operation optimization problem and its machine learning solutions. Section III describes machine learning in microgrids' operation optimization and control. Section IV gives findings for NMGs configuration, optimization and control based on comparison of Genetic Algorithms and Neural Network Algorithms. Conclusions and future directions are mentioned in Section V.

2 Microgrids Operation Optimization Problem and Machine Learning Solutions

Microgrid operation optimization problems can be solved by using machine learning algorithms as shown in Figure 1, [5]. The machine learning algorithms find regression and classification-based solutions for microgrids. In this context, networked microgrid operation optimization and control are considered more reliable machine learning solutions to provide stable and available energy to end users due to their statistical behavior. In statistical problems, machine learning algorithms are considered optimal solutions due to their regression and classification properties, [6].

2.1 Networked Microgrids Operation Optimization and Control Framework and Problem Description

Networked microgrids consist of distributed energy resources, battery energy management systems, and local loads for their operation and control scenarios. Networked microgrids have the ability to achieve complete performance and expected outcomes by processing information about forecasting data and information about market transactions. The constraints for networked microgrid optimization and control have significant characteristics and limitations of operation based on the set rules for the implementation of strategies. The optimization cost function of networked microgrids can take shape as per the requirements in actual scenarios. We have optimization objectives and measurement indications based on four aspects:

- Economic Benefits
- Environmental Impacts
- Power Quality Affects
- Demand Requirements

We can categorize the optimization model into various properties of formulated problems like objective functions, decision variables, and constraints. These properties are helpful in deciding the appropriate optimization method for the optimization model. For example, if we have one cost function or objective function, we need to solve a single optimization problem, and it will give one optimal solution. Alternatively, for multiple objective functions, we have a multi-objective optimization problem to be solved, and it gives multiple optimal solutions. Then we can transform the networked microgrid optimization problem into a mathematical formula in order to optimize the model. The implementation of the algorithm to the model is based on the complexity of the optimization problem, [7].

2.2 Machine Learning Algorithms

Machine learning algorithms are used to find statistically complex optimization problems that are difficult to solve by using other methods. They are applicable to both regressed and classified problems. Unlike traditional optimization problems, machine learning algorithms explore the random factors properties to solve the optimization problem getting optimal solutions. Recently, several machine learning algorithms have been designed and developed with a chain of algorithms and their enormous applications in networked microgrids, [8].

2.2.1 Machine Algorithms for Single Objective Optimization

The single objective optimization has only one objective function for optimal solution. Both supervised and unsupervised machine learning algorithms can be applied to get the optimal solution of a single objective function. The list of supervised and unsupervised machine learning algorithms is shown in Figure 1. Decision Trees, Naive Bayes Classification, Support vector machines for classification problems, Random Forest for classification and regression problems, Linear regression for regression problems, Ordinary Least Squares Regression, Logistic Regression, and Ensemble Methods are supervised machine learning algorithms that can be used for single objective optimization process.

2.2.2 Machine Learning Algorithms for Multi-Objective Optimization

Multi-objective optimization is mostly referred to as a complex optimization problem that consists of two or more conflicting objective functions simultaneously. In this case, the improved performance of one objective function can degrade the other objective function. Multi-objective functions are considered favorable for coordinating trade-offs between the objective functions and getting the solutions making all the objectives optimal as much as possible. Moreover, single-objective functions are optimized giving one optimal solution while multi-objective problems give a set of Pareto optimal solutions which is the case of this research paper. So, machine learning algorithms can identify a bunch of pareto optimal solutions in the presence of constraints instead of the single objective solution.

The most attractive supervised and unsupervised machine learning algorithms for multi-objective optimization problems are support vector machines and independent component analysis respectively. In addition, we can use Decision Trees, Naive Bayes Classification, Random Forest for classification and regression problems, Linear regression for regression problems, Ordinary Least Squares Regression, Logistic Regression, and Ensemble Methods. Unsupervised algorithms involved in multi-objective optimization problems of networked microgrids are K-means for clustering problems, A-priori algorithm for association rule learning problems, Principal Component Analysis, and Singular Value Decomposition.

2.3 Networked Microgrids Operation Analysis

The networked microgrids have their two categories of operations: dynamic networked microgrids and pre-defined networked microgrids.

In dynamic networked microgrids, an advanced structure for microgrids is adapted to define the boundaries and their adjustment to create balance in generation and load. These networked microgrids are flexible in the context of optimization of operations which are real-time, efficient use of resources and system demands to make the system more reliable. Similarly, dynamic networked microgrids had the capability of auto-detection, self-healing, fault tolerance, and reconfiguration in case of restoring the power system network supply. In this work, we have used a multi-objective system which is considered as dynamic networked microgrids providing the real-time coordination, interconnection of components, load balancing, and optimal sharing of powers in the microgrids of networked microgrids.

The pre-defined networked microgrids have the ability for consistent network configuration and consistent switching without considering the system operating conditions and priorities of customers. The system boundaries are determined with the help of supply adequacy, coverage, and reliability scores. These are operated by using pre-defined rules and agreements. In the case of grid-connected system, the power sharing is carried out by using these rules and agreements. Community microgrids are considered as pre-defined networked microgrids. Community microgrids are connected to each other with pre-defined connections, agreement for power sharing, and strategies for its operations to meet the loads for the community.

As we have used dynamic networked microgrids approach, if we compare it with predefined networked microgrids. It provides more flexible conditions and boundaries for real-time changes in generation and loads. This also enhances the system resilience, and reconfiguration of networked microgrids to resolve the faults, isolation from the main grid, and provide uninterruptable power to the loads. Energy efficiency and cost-effectiveness are improved in dynamic networked microgrids by optimizing the use of distributed energy resources. Dynamic networked microgrids scalability has the property of integration of new microgrids and distributed energy resources. This process enables the management of the voltage and frequency and balancing of loads. In short, dynamic networked microgrids have more advantages over pre-defined networked microgrids, [1].

2.4 The Review Methodology in this Paper

We have reviewed the literature systematically and categorized the optimization and control into two phases deployment and operation phase for networked microgrids in order to enhance processing time, [9].

The deployment phase consists of component selection, system sizing, and parameter configuration while the operation phase has more focus on real-time scheduling and planning. However, optimization of networked microgrids has no such clear boundaries for any comprehensive strategy and planning.

3 Machine Learning in Microgrids' Operation Optimization and Control

Machine learning algorithms have significant worth for operation optimization and control in networked microgrids, [10]. There are two phases for optimization and control i.e., the deployment phase and the operation phase.

3.1 The Deployment Phase of Networked Microgrids Operation Optimization and Control

The deployment phase of networked microgrids finds the actual performance of microgrids and their capability to handle future perspectives of microgrids in networked microgrids. The cost-effective networked microgrid system is formulated in this research work with the help of several microgrids connected to networked microgrids. Different demands at different times have several operation response times as per the requirements. We need to compare the performance and analyze the complete parameters regarding cost-benefit approach. The main focus of the deployment phase is to formulate a reliable, cost-effective, and environment-friendly networked power system to supply reliable and stable power to the main grid and directly connect loads.

3.1.1 System Sizing and Component Selection

The performance parameters, size, and model of networked microgrids can give the cost of networked microgrids even with a limited budget for system components. Machine learning algorithms are commonly used for determining cost-effective system components. We have several applications of machine learning algorithms for sizing and component selection in the deployment phase of networked microgrids.

The system sizing and component selection in networked microgrids is a statistical problem to be classified or regressed. These tasks are daily-based maintenance costs to predict the equipment's reliability. For deployment of the networked microgrids optimization and control, applications of supervised and unsupervised algorithms in sizing and component selection are most common due to their classification and regression properties.

3.1.1.1 Multi-Objective Machine Learning Techniques

The environmental conditions and economic structure define the indications of the design of networked microgrids operation. Networked microgrids are also considering reliabilities and uncertainties for the system. Hybrid machine-learning techniques can enhance the optimization and control of networked microgrids. The indicators differences including the annualized cost and expected load loss and energy loss, power supply probability, and electricity cost are involved to determine the feasibility and decision-making.

3.1.2 Parameters Configuration

Parameters configuration is compulsory in order to get the optimal cost function as per the requirement of power and topology of the networked microgrids. We have configured the networked microgrids as a star, ring, and full configuration to get the feasible results as per our requirements.

Machine learning classification algorithms are commonly used to configure the parameters of networked microgrids in order to optimize the operational cost. These classification algorithms may be supervised or unsupervised. For example, if we have five networked microgrids, we have to configure the parameters of each microgrid to get a full optimal solution of all five microgrids in networked microgrids, [11].

3.1.2.1 Multi-Objective Machine Learning Techniques

To get optimal solutions in multi-objective optimization, we need to configure the parameters optimally for the size and topology of networked microgrids. Optimal decision variables affect can be tested by conducting a sensitivity analysis. Multi-objective algorithms have the ability to reduce the computational time in treating all objectives simultaneously or independently. The result in multi-objective functions is a set of optimal solutions rather than a single solution giving many choices to minimize the cost for decision making.

3.2 The Operation Phase of Microgrids Operation Optimization and Control

The operation phase of networked microgrid optimization and control is considered a full reflection of the deployment stage. To realize the operation economy of the networked microgrids and meet various operation constraints, the utilization energy rate is maximized. Similarly, the operation of networked microgrids is more relevant to end users of load. In the operation phase, we have two stages planning and real-time scheduling.

3.2.1 Planning

Networked microgrid optimization and control is a complex task due to more data prediction and component runtime characteristics to settle the optimal energy scheduling points. The advanced prediction of scheduling response with the networked microgrids can reduce the operating cost of networked microgrids. We can use machine learning algorithms in the operation phase for networked microgrid optimization and control.

We can plan the operation of networked microgrids by using supervised and unsupervised machine learning algorithms in the operation phase of optimization. Optimal scheduling points are based on the statistical nature of networked microgrids having the parameters of time scaling, and energy output as required.

3.2.1.1 Multi-Objective Machine Learning Techniques

For multi-objective optimization problems, we can find the optimal energy and scheduling scheme for networked microgrids. For multi-objective functions, we can obtain a set of pareto optimal solutions minimizing the operational cost of networked microgrids.

3.2.2 Real-Time Scheduling

Short-term operations can lead the scheduling process in networked microgrids to minimize energy production costs and balance the real-time power generation and demand. If there is an uncertain data prediction, scheduling can be failed severally. There are enormous applications of machine learning algorithms in real-time scheduling in the operation of networked microgrids.

Networked microgrids can only have effective and efficient operation and control when they have real-time and short term microgrids parameter settings adjustments to respond to the demand. Machine learning algorithms are simple to apply for real-time scheduling of the operation of networked microgrids.

3.2.2.1 Multi-Objective Machine Learning Techniques

In the islanding mode of one or more microgrids in networked microgrids, the multi-objective optimization problem can arise to be optimized to get the optimal results of droop-regulated islanded microgrids. By using supervised and unsupervised machine algorithms, we can find the optimal strategy to maximize the utilities or profit and eventually minimize the cost of operation of the networked microgrid, [12].

4 Neural Network Algorithm in Microgrids' Operation Optimization and Control

Scheduling problems for networked microgrids are solved by using artificial neural networks (ANNs) along with biological nervous systems approach. The neural network algorithm (NNA) is designed by using a specific structure of ANNs. NNA has the capability to take the benefits using the complicated structure of ANNs to generate the enhanced solution, [13]. The designed code supports and implements a neural network-supported optimization algorithm. The proposed algorithm finds an optimal solution by utilizing solutions that are based on certain rules produced by machine learning neural networks, [14].

The Pseudocode and process of the main loop for the neural network algorithm (NNA) in MATLAB is as follows:

There are three steps in this process (i), (ii) and (iii):

i) Process Explanation

The process explanation is further consisting of two more steps as follows:

a) Initialization
   - Initialize the population of solutions (pop), the weights (w), and the parameters.

b) Main Loop
   - For each iteration (max_it), the algorithm updates the solutions and the weights based on certain rules.
     a. Solution Update: - Create new solutions by updating the positions of the solutions (XP) based on the weighted average (w*XP).
     b. Weight Update: - Update the weights (w) based on certain rules to encourage exploration and exploitation.
     c. Input Solutions Update: - Update the input solutions (XP) based on certain rules to encourage exploration and exploitation.
     d. Bias Reduction: - Reduce the bias (beta) to encourage exploration and exploitation.
     e. Constraint Handling: - Apply constraint handling to ensure that the updated solutions (XP) are within the feasible region.

f. Objective Function Evaluation: - Evaluate the objective function values for the updated solutions (XP).
g. Selection: - Select the new population of solutions based on the objective function values and the constraint violations.

ii)Explanation of Parameters and Variables

The parameters and variables can be explained as follows:

- max_it: Maximum number of iterations
- npop: Population size
- nvars: Number of variables
- w: Weights
- wtarget: Target weights
- beta: Bias parameter
- LB, UB: Lower and upper bounds of the variables
- Epss: Tolerance for constraints
- pop: Initial Population of solutions
- XP: Current population of solutions
- x_pattern: Pattern of solutions
- XTarget: Best obtained solution called target solution.
- my_fitness_function: Objective function

4.1 Neural Network Algorithm (NNA)

We can demonstrate the neural network algorithm in Figure 1(a) and Figure 1(b) which is a complete representation of the Artificial Neural Networks (ANNs). Mostly there are three errors that occurred in ANN.

1- Training Error
2- Validation Error
3- Test Error

Mostly, we can find these errors with the help of loss function, for example, mean square error. Due to these errors, ANN is not able to learn and model the data which is nonlinear and has complexity. Due to such difficulties, we have used the NNA algorithm to find the results. This algorithm is the unique structure of ANN which gives the new candidate solutions to the problem.

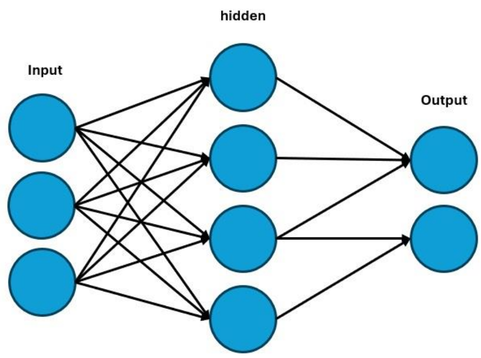

Fig. 1(a): Shows the Artificial Neural Networks (ANNs)

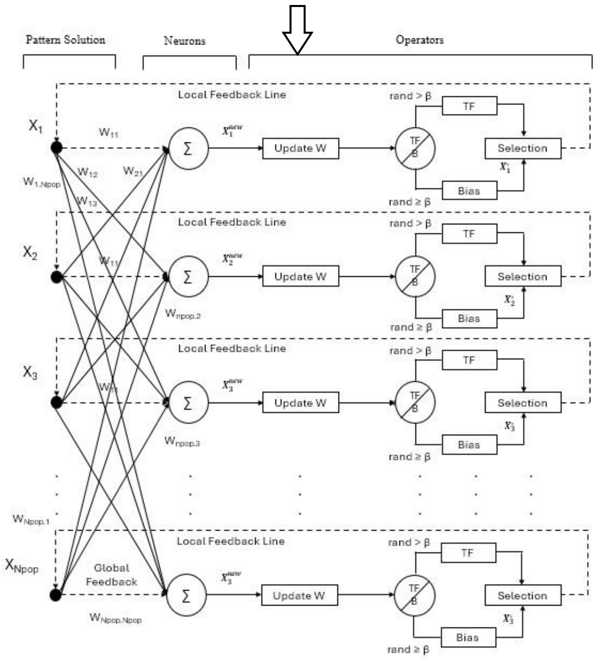

Fig. 1(b): Shows the Neural Network Algorithm

4.2 Steps of the NNA

We can take advantage of ANNs in the context of NNA inspiration by the structure and concept of ANNs. The complete process of the NNA is described in Figure 2 (Appendix) for all processes.

NNA has the ability for global search to find the best solution. It is an unsupervised algorithm that has the property of a self-learning process to find the best solution. There are two major properties of NNA algorithms. These can be used for opposite-based learning These are using tunable parameters for exploration and exploitation to find the better solution in each learning cycle, [15].

iii) Pseudocode

The pseudocode for MATLAB simulation is shown in Figure 3 (Appendix).

5 Results: Comparing Neural Network with Genetic Algorithm in the Full, Line, Ring and Star Topology

The results obtained from the heuristic technique genetic algorithm [16] and machine learning neural network algorithm are obtained during the simulation and optimization process. These results are compared with each other in order to get a better understanding of the operation optimization of networked microgrids, [17].

Table 1 and Table 2 are the results obtained by using genetic algorithm and neural network algorithm respectively. Both Table 1 and Table 2 shows the comparative values for each parameter optimized for networked microgrids in full configuration case.

Table 1. Genetic Algorithm Results for Networked Microgrids Full Configuration (Total Energy Cost: 2385.977863 (2385.977863) USD per hour)

E_gen	E_c	Generation	Transmission	Total
9.82671	11	674.004	5.0698	679.074
9.82671	11	674.004	5.0698	679.074
9.82671	11	674.004	5.06981	679.074
4.51988	1	348.757	0	348.757
E_Gen Contingency	11.0000	11.0000	11.0000	

Table 2. Neural Network Algorithm Results for Networked Microgrids Full Configuration (Total Energy Cost: 2385.977868 (2385.977700) USD per hour)

E_gen	E_c	Generation	Transmission	Total
9.82679	11	674.01	5.07039	679.08
9.82656	11	673.994	5.07039	679.064
9.82656	11	673.994	5.0704	679.064
4.52008	1	348.769	0	348.769
E_Gen Contingency	11.0000	11.0000	11.0000	

Table 3 and Table 4 are the results obtained by using genetic algorithm and neural network algorithm respectively. Both Table 3 and Table 4 shows the comparative values for each parameter optimized for networked microgrids in line configuration case.

Table 5 and Table 6 are the results obtained by using genetic algorithm and neural network algorithm respectively. Both Table 5 and Table 6 shows the comparative values for each parameter optimized for networked microgrids in ring configuration case.

Table 3. Genetic Algorithm Results for Networked Microgrids Line Configuration (Total Energy Cost: 2395.864618 (2385.864618) USD per Hour)

E_gen	E_c	Generation	Transmission	Total
9.84599	11	675.356	10.9136	686.27
9.86512	11	676.777	2.37163	679.148
9.84599	11	675.356	10.9136	686.27
4.44291	1	344.176	0	344.176
E_Gen Contingency	12.0884	10.4558	10.4558	

Table 4. Neural Network Algorithm Results for Networked Microgrids Line Configuration (Total Energy Cost: 2395.864618 (2385.864618) USD per hour)

E_gen	E_c	Generation	Transmission	Total
9.97596	11	686.773	3.86197	690.635
9.95049	11	684.182	15.8345	700.017
9.89254	11	678.956	37.2654	716.222
4.181	1	328.62	0	328.62
E_Gen Contingency	10.4515	12.0970	10.4515	

Table 5. Genetic Algorithm Results for Networked Microgrids Ring Configuration (Total Energy Cost: 2395.864618 (2385.864618) USD per hour)

E_gen	E_c	Generation	Transmission	Total
9.84599	11	675.357	10.9135	686.27
9.86512	11	676.777	2.37163	679.148
9.84599	11	675.356	10.9136	686.27
4.4429	1	344.176	0	244.176
E_Gen Contingency	**12.0884**	**10.4558**	**10.4558**	

Table 6. Neural Network Algorithm Results for Networked Microgrids Ring Configuration (Total Energy Cost: 2395.864618 (2385.864618) USD per hour)

E_gen	E_c	Generation	Transmission	Total
9.84599	11	675.356	10.9136	686.27
9.86512	11	676.777	2.37163	679.148
9.84599	11	675.356	10.9136	686.27
4.44291	1	344.176	0	344.176
E_Gen Contingency	10.4515	12.0970	10.4515	

Table 7 and Table 8 are the results obtained by using genetic algorithm and neural network algorithm respectively. Both Table 7 and Table 8 shows the comparative values for each parameter optimized for networked microgrids in star configuration case.

Table 7. Genetic Algorithm Results for Networked Microgrids Star Configuration (Total Energy Cost: 2423.250826 (2423.250826) USD per hour)

E_gen	E_c	Generation	Transmission	Total
9.89492	11	679.154	38.9772	718.131
9.92592	11	681.858	4.24867	686.106
9.92592	11	681.858	4.24867	686.106
4.25324	1	332.907	0	348.907
E_Gen Contingency	12.0884	10.4558	10.4558	

Table 8. Neural Network Algorithm Results for Networked Microgrids Star Configuration (Total Energy Cost: 2423.250826 (2423.250826) USD per hour)

E_gen	E_c	Generation	Transmission	Total
9.89492	11	679.154	38.9771	718.131
9.92592	11	681.858	4.24865	686.107
9.92592	11	681.858	4.24865	686.107
4.25324	1	332.906	0	348.906
E_Gen Contingency	12.0884	10.4558	10.4558	

6 Conclusion

The proposed algorithm neural network is run by using the code which is optimizing the problem in order to find the optimal solution by utilizing a population of solutions and updating each solution supported by certain rules. The proposed algorithm basically and encourages exploration and exploitation by updating the solutions and weights supported by certain rules. This also reduces the bias to find the optimal solution. The proposed methodology neural network algorithm (NNA) consists of dynamic optimization modeling based on the structure and concept of artificial neural networks (ANNs). NNA is getting benefits from ANNs unique structure in order to solve complex optimization problems. The optimal results show NNA's ability to find the minimum of multi-modal functions having minimum probability to be trapped in local minima and it is verified from the results section.

Future work includes updating the weight matrix and the transfer function operator can be used. The learning and updating weights in ANNs can be the further learning approaches in ANNs such as reinforcement learning, gradient descent learning, and competitive learning, and further learning versions can be derived from NNA. Optimization problems including transportation, scheduling, and energy saving can be the next topics for NNA to solve.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

APPENDIX

Pseudocode:

```
matlabCopy code
FMIN = zeros(max_it, 1);
XP = zeros(npop, nvars);
tic x_pattern = pop;
for ii = 1:max_it % Creating new solutions
        for jj = 1:npop
         XP(jj, :) = x_pattern(jj).position;
        end
x_new = w * XP;
XP = x_new + XP; % Updating the weights
        for i = 1:npop
         w(:, i) = abs(w(:, i) + ((wtarget - w(:, i)) * 2 .*
         rand(npop, 1)));
        end
        for i = 1:npop w(:, i) = w(:, i) ./ sum(w(:, i)); %
         Summation of each column = 1
        end
% Creating new input solutions
        for i = 1:npop if rand < beta % Bias for input
         solutions
         N_Rotate = ceil(beta * nvars);
         xx = LB + (UB - LB) .* rand(1, nvars);
         rotate_postion = randperm(nvars);
         rotate_postion = rotate_postion(1:N_Rotate);
                 for m = 1:N_Rotate
                         XP(i, rotate_postion(m)) =
         xx(m);
        end
% Bias for weights
         N_wRotate = ceil(beta * npop);
         w_new = rand(N_wRotate, npop);
         rotate_position = randperm(npop);
         rotate_position = rotate_position(1:N_wRotate);
        for j = 1:N_wRotate w(rotate_position(j), :) =
         w_new(j, :);
        end
        for iii = 1:npop w(:, iii) = w(:, iii) ./ sum(w(:, iii));
         % Summation of each column = 1
        end
         else % Transfer Function Operator
                 XP(i, :) = XP(i, :) + (XTarget.position -
         XP(i, :)) * 2 .* rand(1, nvars);
         end
end
% Bias Reduction
        beta = beta * 0.99;
        if beta < 0.01 beta = 0.05;
        end
XP = max(XP, X_LB);
XP = min(XP, X_UB);
        for jj = 1:npop x_pattern(jj).position = XP(jj, :);
        end
% Calculating objective function values
        for i = 1:npop [x_pattern(i).cost, c] =
         my_fitness_function(x_pattern(i).position);
        x_pattern(i).const = sum(c(c > epss));
        end
% Selection
        POP_New = [pop; x_pattern];
        X_Minus = []; aa = [POP_New.const];
        COST_MINUS = [POP_New(aa <= epss).cost];

        if ~isempty(COST_MINUS) X_Minus =
         POP_New(aa <= epss);
        [~, INDEX_M] = sort(COST_MINUS);
        X_Minus = X_Minus(INDEX_M);
        end
X_PLUS = [];
SUM_C_PLUS = aa(aa > epss);
        if ~isempty(SUM_C_PLUS) X_PLUS =
         POP_New(aa > epss);
        [~, INDEX_P] = sort(SUM_C_PLUS);
        X_PLUS = X_PLUS(INDEX_P);
        end
wtarget = w(:, 1);
POP_New = [X_Minus; X_PLUS];
x_pattern = POP_New(1:npop);
pop = POP_New(1:npop);
XTarget = POP_New(1);
% Best obtained solution so called Target Solution
% Display disp(['Iteration: ', num2str(ii), ' Fmin= ',
         num2str(XTarget.cost), ' Sum_Const= ',
         num2str(XTarget.const), ' beta= ',
         num2str(beta)]); FMIN(ii) = XTarget.cost;
end
toc
```

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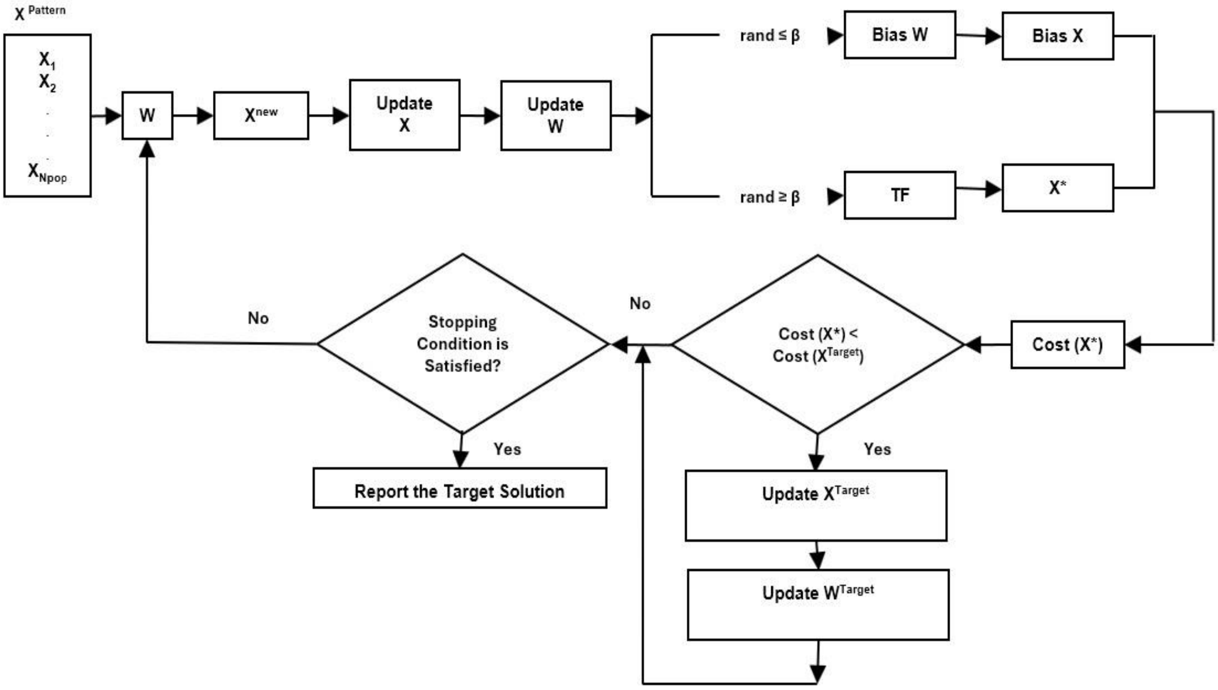

Fig. 2: Process of NNA

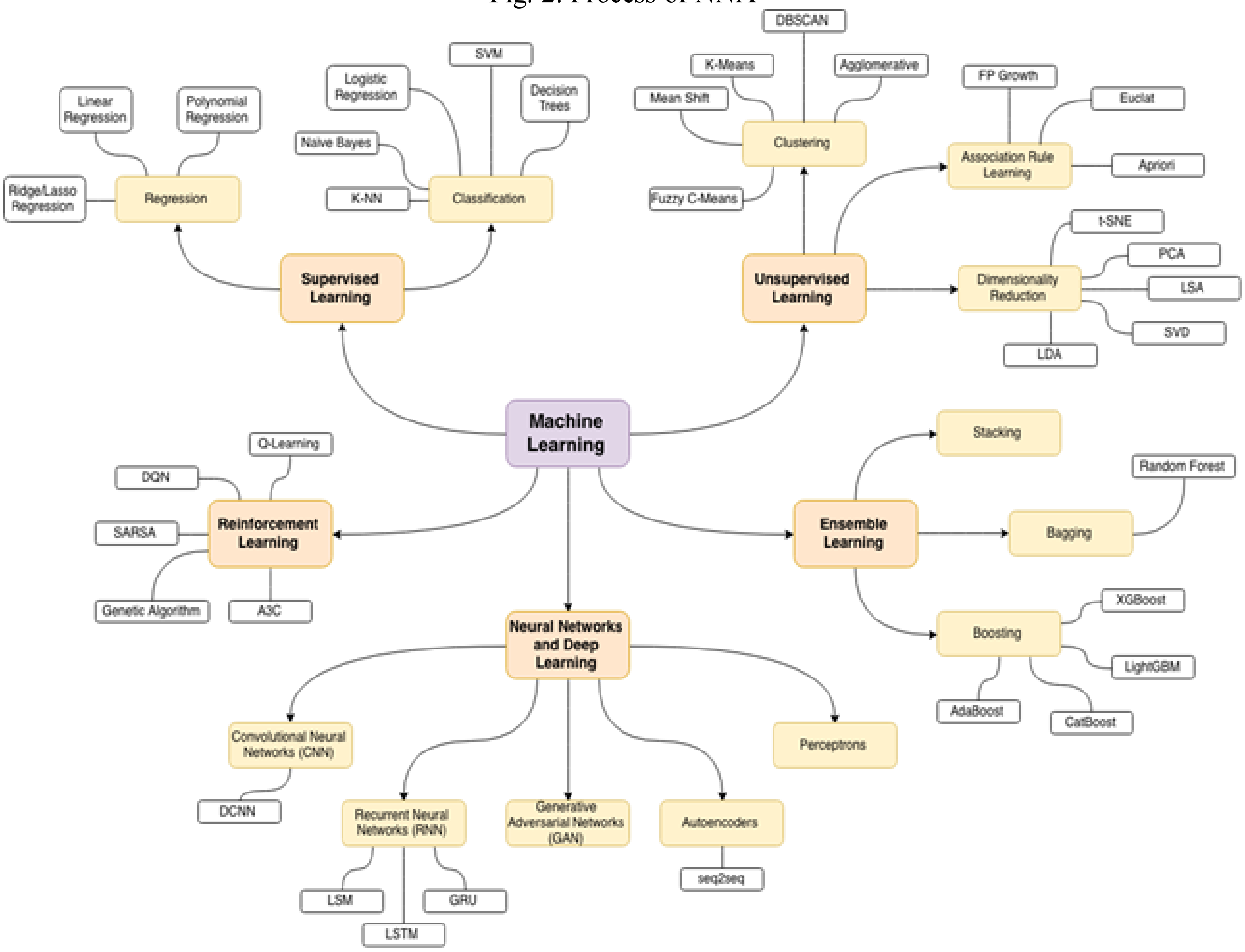

Fig. 3: Pseudocode for MATLAB simulation