

Optimization of Neural Network for Resource Allocation Using Genetic Algorithms

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تحسين الشبكات العصبية لتخصيص الموارد باستخدام الخوارزميات الجينية

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Accepted: 15/3/2025 Published: 30/6/2025

ABSTRACT

ـــــالــة جــــامحة بــابــل للعلــــــوم الصـــرفـة والتط بيقيــة مـجلــة جــــامحة بــابــل للعلــ وم الصــرفــة والتط

<u>Background:</u> In this study, the optimal allocation calculation was adopted to determine the reliability of the neural network, as it is considered a mathematical model whose purpose is to process data and machine learning. This study contracts with the reliability of neural networks and finding the optimal work for them.

<u>Materials and Methods:</u> This research used a genetic algorithm with an exponential cost function to understand how the human brain works, taking into account the cost of each component. Simulating the human brain using genetic algorithms has been the subject of research by many researchers in recent decades.

Results: The results were excellent in terms of improving the neural network allocation and reliability, as all the network elements were taken into account and tested for their reliability well to provide better results in processing. The study was compared to several research papers that addressed reliability testing in other scientific and technological fields, and the comparison was more favorable in terms of numerical results. Conclusion: the study's findings increased the neural network's allocation and dependability. The reliability of each network component is divided by the system optimization problem, which makes use of the most crucial location. Because it involves limitations on both human and material resources (the neural network's reliability).

<u>Key words:</u> Neural networks, genetic algorithms, structure diagrams, and reliability allocation.

INTRODUCTION

The neural network diagram's structure as a complex system was the subject of this investigation, which is a computational model of how the human brain works and consists of three layers: Input layer: In this layer, data is entered (input 1, input 2, input 3) through nodes $(R_1R_2R_3)[1-4]$. Hidden layer: It contains four nodes $(R_4R_5R_6R_7)$ where computational processing is done using activation functions such as ReLU or Sigmoid, and this layer plays a role in extracting patterns or features from the input data [5, 6]. Output layer: It contains two nodes (R₈R₉) that represent the outputs of the network, which are the final results (output 1, output 2) after processing the data in the previous layers. The reliability function for the neural system was designed by calculating the success paths within the connectivity matrices. According to [6-9], all paths are identified using Boolean algebra, followed by removing nodes to create minimal paths [3, 6, 10]. The reliability function is analyzed to understand the level of safety of the applied advanced system. The paper also addresses the mathematical challenge of improving reliability while taking into account the operational history of the network. The reliability requirements of any component of a complex system are determined by its criticality and location optimization. The primary goals are to minimize overall costs while enhancing the system's lifetime and reliability. Some components may require extensive customization, depending on their location in the system, to improve total reliability. Plans face different tests when optimizing mechanical, electrical systems[6,7]. The goal is to enhance the distribution and reliability of the complex neural network architecture while minimizing costs, which can be represented by factors such as weight, size, or other parameters. Many researcher talked about the oxygen supply system within spaceship[1,2]. This research addressed the topic of neural networks and ways to improve them.

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MATERIALS AND METHODS

The best way to address the problem

A key factor in determining the reliability of components is ensuring that the model is costdependent, which proves the validity of the input component. The recommended cost factor settings can be modified, allowing engineers to evaluate how the system evolves over time and determine whether each component meets the basic reliability criteria [2-5]. Additionally, the model must take into account the accuracy of the input system analysis. In larger systems, some scenarios can pose significant challenges, leading to increased workload, especially when it comes to core systems [3]. The outcomes were attained using a genetic algorithm, which helps solve optimization problems in complex neural systems. The exponential model was used to calculate the overheads. Allocation and Optimization of Reliability in Neural Network Construction Figures. We consider the neural network structure diagram, study each component of the system, and calculate reliability and optimal allocation according to the following points:

 $C_i(R_i) = (cost of element);$ $0 \le R_i \le 1 = \text{(reliability as an element)};$ $R_s = (dependability of the system);$



 $C(R_1, ..., R_n) = \sum_{i=1}^n a_i c_i(R_i)$ (is the overall cost of the system, where $a_i > 0$);

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R_G stands for "systems reliability" goal.

We observe the neural network and the distinct roles played by each component of the network, as well as the importance of each input and output location, each with a distinct degree of dependency. The goal is to enable the above network to allocate resources to all or specific components in an appropriate manner. Nonlinear programming is required to solve the network allocation [10].

Minimized
$$C(R_i, ..., R_n) = \sum_{i=1}^n a_i C_i(R_i), a_i > 0.$$

Subject to:

$$R_s \ge R_G$$

$$0 \le R_i < 1 \text{, in which } i = 1, ..., n.$$
 (1)

Study the components of the neural network as a complex system and extract all the success paths in the system. Below is a description of the reliability of a sequential network with n components of the complex network, as shown in the clear form [9].

$$R_{s} = \prod_{i=1}^{n} R_{i}. \tag{2}$$

$$R_{s} = 1 - \prod_{i=1}^{n} (1 - R_{i}).$$
 (3)

Here, $[R_i]$ indicates the dependability of the component, whereas $[R_N]$ indicates the steadiness of the neural network [5]. The steadiness of each complex network with the given p minimal trails will be compared using equations (1) and (2).

$$R_{s} = 1 - \prod_{z=1}^{p} \left(1 - \prod_{i=\alpha}^{\omega} R_{i} \right)$$
 (4)

In this instance, "α" denotes an index of the minimal path's first component, and "ω" denotes its last component [3, 7].

One might apply equation (3) to evaluate the neural network's dependability. The figure 1 shown the neural network structure .

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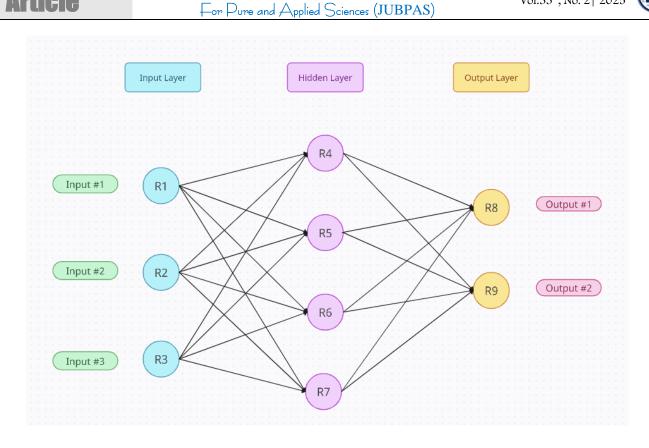


Figure 1. Neural network structure diagram. (in the current study)

Success paths that achieve success without failure within a specified time period and achieve polynomial reliability of the neural network [4-7].

$$\begin{split} R_{s} &= 1 - [1 - p_{r}\{x_{1}x_{4}x_{8}\}] \times [1 - p_{r}\{x_{1}x_{4}x_{9}\}] \times [1 - p_{r}\{x_{1}x_{5}x_{8}\}] \\ &\times [1 - p_{r}\{x_{1}x_{5}x_{9}\}] \times [1 - p_{r}\{x_{1}x_{6}x_{8}\}] \times [1 - p_{r}\{x_{1}x_{6}x_{9}\}] \\ &\times [1 - p_{r}\{x_{1}x_{7}x_{8}\}] \times [1 - p_{r}\{x_{1}x_{7}x_{9}\}] \times [1 - p_{r}\{x_{2}x_{4}x_{8}\}] \\ &\times [1 - p_{r}\{x_{2}x_{4}x_{9}\}] \times [1 - p_{r}\{x_{2}x_{5}x_{8}\}] \times [1 - p_{r}\{x_{2}x_{5}x_{9}\}] \\ &\times [1 - p_{r}\{x_{2}x_{6}x_{8}\}] \times [1 - p_{r}\{x_{2}x_{6}x_{9}\}] \times [1 - p_{r}\{x_{2}x_{7}x_{8}\}] \\ &\times [1 - p_{r}\{x_{2}x_{7}x_{9}\}] \times [1 - p_{r}\{x_{3}x_{4}x_{8}\}] \times [1 - p_{r}\{x_{3}x_{4}x_{9}\}] \\ &\times [1 - p_{r}\{x_{3}x_{5}x_{8}\}] \times [1 - p_{r}\{x_{3}x_{5}x_{9}\}] \times [1 - p_{r}\{x_{3}x_{6}x_{8}\}] \\ &\times [1 - p_{r}\{x_{3}x_{6}x_{9}\}] \times [1 - p_{r}\{x_{3}x_{7}x_{8}\}] \times [1 - p_{r}\{x_{3}x_{7}x_{9}\}]. \end{split}$$



It should be noted that $[R_i = 1]$ occurs if the i-th component works properly, and $R_i = 0$, $\forall i=1,\cdots,9$ occurs when it fails, resulting in $R_i^n = R_i$. [11, 12].

Equation (5) yields the following polynomial when the preceding statement is applied:

$$\begin{split} R_S &= R_1 R_2 R_3 R_5 R_8 + R_1 R_2 R_3 R_5 R_9 + R_1 R_2 R_3 R_6 R_8 + R_1 R_2 R_3 R_6 R_9 + R_1 R_2 R_3 R_7 R_8 \\ &+ R_1 R_3 R_4 R_5 R_8 + R_1 R_2 R_3 R_7 R_9 + R_1 R_3 R_4 R_6 R_8 + R_1 R_3 R_4 R_7 R_8 + R_2 R_3 R_4 R_5 R_9 \\ &+ R_2 R_3 R_4 R_6 R_8 + R_2 R_3 R_4 R_6 R_9 + R_2 R_3 R_4 R_7 R_8 + R_1 R_3 R_4 R_8 R_9 + R_2 R_3 R_4 R_7 R_9 \\ &+ R_2 R_3 R_4 R_8 R_9 - 2 R_1 R_2 R_3 R_4 R_5 R_8 - R_1 R_2 R_3 R_4 R_5 R_9 - 2 R_1 R_2 R_3 R_4 R_6 R_8 \\ &- R_1 R_2 R_3 R_4 R_6 R_9 - 2 R_1 R_2 R_3 R_4 R_7 R_8 - R_1 R_2 R_3 R_5 R_6 R_8 - R_1 R_2 R_3 R_4 R_7 R_9 \\ &- R_1 R_2 R_3 R_5 R_6 R_9 - R_1 R_2 R_3 R_5 R_7 R_8 - R_1 R_2 R_3 R_5 R_6 R_8 - R_1 R_2 R_3 R_5 R_7 R_9 \\ &- R_1 R_2 R_3 R_5 R_6 R_9 - R_1 R_2 R_3 R_5 R_7 R_8 - R_1 R_2 R_3 R_5 R_8 R_9 - R_1 R_2 R_3 R_5 R_7 R_9 \\ &- R_1 R_2 R_3 R_6 R_7 R_8 - R_1 R_3 R_4 R_5 R_6 R_8 - R_1 R_2 R_3 R_5 R_8 R_9 - R_1 R_2 R_3 R_6 R_7 R_9 \\ &- R_1 R_2 R_3 R_6 R_7 R_8 - R_2 R_3 R_4 R_5 R_6 R_8 - R_1 R_2 R_3 R_6 R_8 R_9 - R_1 R_2 R_3 R_6 R_7 R_9 \\ &- R_1 R_3 R_4 R_5 R_6 R_9 - R_2 R_3 R_4 R_5 R_6 R_8 - R_1 R_2 R_3 R_6 R_8 R_9 - R_1 R_3 R_4 R_6 R_7 R_8 \\ &- R_2 R_3 R_4 R_5 R_6 R_9 - R_2 R_3 R_4 R_5 R_7 R_8 - R_1 R_2 R_3 R_7 R_8 R_9 - R_1 R_3 R_4 R_5 R_8 R_9 \\ &- R_2 R_3 R_4 R_5 R_6 R_9 - R_2 R_3 R_4 R_6 R_7 R_8 - R_1 R_2 R_3 R_4 R_6 R_8 R_9 - 2 R_2 R_3 R_4 R_5 R_8 R_9 \\ &- R_2 R_3 R_4 R_6 R_7 R_9 - R_1 R_3 R_4 R_7 R_8 R_9 - 2 R_2 R_3 R_4 R_5 R_8 R_9 \\ &+ 2 R_1 R_2 R_3 R_4 R_5 R_6 R_8 + R_1 R_2 R_3 R_4 R_5 R_8 R_9 + 2 R_1 R_2 R_3 R_4 R_5 R_7 R_9 \\ &+ 2 R_1 R_2 R_3 R_4 R_6 R_7 R_8 + 2 R_1 R_2 R_3 R_4 R_5 R_8 R_9 + R_1 R_2 R_3 R_4 R_5 R_7 R_9 \\ &+ 2 R_1 R_2 R_3 R_4 R_6 R_9 + R_1 R_2 R_3 R_4 R_5 R_8 R_9 + R_1 R_2 R_3 R_4 R_5 R_6 R_7 R_8 \\ &+ R_1 R_3 R_4 R_5 R_6 R_9 + R_1 R_2 R_3 R_4 R_5 R_6 R_7 R_9 + 2 R_1 R_2 R_3 R_4 R_5 R_6 R_7 R_8 \\ &+ R_1 R_3 R_4 R_5 R_6 R_9 + R_1 R_2 R_3 R_4 R_5 R_6 R_7 R_9 + R_1 R_2 R_3 R_4 R_5 R_6 R_7 R_8 \\ &+ R_1 R_3 R_4 R_5 R_6 R_9 + R_2 R_3 R_4 R_5 R_6 R_7 R_9 + R_1 R_3 R_4 R_5 R_6 R_7 R_8 \\ &- R_1 R_2 R_3 R_4 R_5 R_6 R_7 R_9 - 2 R_1 R_2 R_3 R_4 R_5 R_6 R_7 R_8$$

RESULTS AND DISCUSSION

GA IMPLEMENTATION:

Next every iteration, GA makes the fittest members using a predetermined fitness feature The front displays the GA basic flow chart below.

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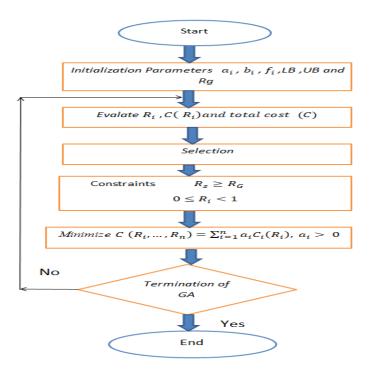


Figure 2. Flow chart of the Genetic Algorithm (in the current study)

Experimental behavior model using a feasibility parameter.

Let $0 < f_i < 1$ be a feasibility factor [12], $R_{i,min}$ be minimum reliability and $R_{i,max}$ be maximum reliability.

$$C_i(R_i) = exp[(1-f_i)\frac{R_{i-}R_{i,min}}{R_{i,max}-R_i}],$$

$$R_{i,min} \leq R_i \leq R_{i,max} \text{ , } i = 1,2,\dots,n.$$

The issue with optimization then is:

$$\label{eq:minimize} \mbox{Minimize } C(R_i,...,R_i) = \sum_{i=1}^n a_i \mbox{ } exp[(1-f_i) \frac{R_{i \mbox{ } -}R_{i,min}}{R_{i,max} \mbox{ } -}R_i], \quad i=1,2,...,n.$$

Subject to:

$$R_s \ge R_G$$

$$R_{i,min} \le R_i \le R_{i,max}$$
, $i = 1, ..., n$.

The table below shows usage of GA and cost function, also shown as histogram in figure 3.

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Table 1: Optimizing reliability allocation with the use of (GA) and a cost function.

Components	Ri	Ci
R1	0.98	744.08
R2	0.98	744.08
R3	0.86	5.54
R4	0.86	5.54
R5	0.86	5.54
R6	0.86	5.54
R7	0.86	5.54
R8	0.97	711.8
R9	0.97	711.8
R _{system}	0.98	2247.92

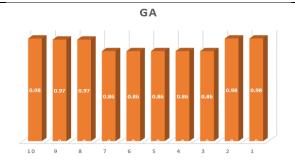


Figure 3: Reliability allocation utilizing GA with an applied exponential((in the current study)



Numerous applications employ neural networks, such as [11, 12].

- 1. Image recognition: this includes identifying faces and differentiating between different animal kinds.
- 2. Speech recognition: this includes text-to-audio conversion.
- 3. Prediction: this includes estimating credit risk or forecasting stock values.
- 4. Classification: dividing emails into regular communications and spam.
- 5. Autonomy: this includes using sensor data analysis to operate self-driving cars.

Of the components in the system, the first and second components were equal at 98% and are considered Level 1, while the seventh and eighth components each had 97%, making them Level 2. The remaining components, which accounted for 86%, were Level 3. As for the cost ratio, it is well known that the higher the reliability of any system, the higher the cost. In other words, the cost is directly proportional to the reliability of the system. This is evident in the table above.

CONCLUSION.

The results of the study improved the neural network's allocation and reliability, as seen in the table above. The system optimization challenge, which utilizes the most important location, divides the dependability of each network component. Due to the fact that it imposes constraints on both human and material resources (the dependability of the neural network), Another way to think of this assignment is as a nonlinear programming challenge. The evolutionary algorithm, which takes into account the locations of different components within the complex network, was used to solve the optimal reliable allocation problem. The table indicates that the components with the highest and lowest dependability assignments were the first and second.



Conflict of interests.

There are non-conflicts of interest.

References

[1] E. K. Muter, "Estimating the reliability bounds of communication network by using sum of disjoint product method." Discrete Mathematics, 2450018, 2024.

JOURNAL OF UNIVERSITY OF BABYLON

For Pure and Applied Sciences (JUBPAS)

- [2] A. Hassan, "Determining reliability signature by minimal cut method for complex-parallel network", Journal of Discrete Mathematical Sciences and Cryptography, https://doi.org/10.47974/JDMSC. pp.1627–1632, 2005.
- [3] M. A.Mellal and E. Zio, "An adaptive particle swarm optimization method for multi-objective system reliability optimization," Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, vol. 233, no. 6, pp. 990–1001, 2019.
- [4] S. A. Abed, H. K. Sulaiman, "Reliability allocation and optimization for (ROSS) of a spacecraft by using Genetic Algorithm" .Journal of Physics: Conference Series. IOP Publishing, p. 032034, 2019.
- [5] R. A. Fadhil. "Improvement of Network Reliability by Hybridization of the Penalty Technique Based on Metaheuristic Algorithms", Iraqi Journal For Computer Science and Mathematics, vol. 5, no. 1, pp. 99-111, Jan. 2024
- [6] F. A.Hashim, E.H.Houssein, K. Hussain, M. S. Mabrouk, and W.Al-Atabany, "Honey badger algorithm: New metaheuristic algorithm for solving optimization problems," Mathematics and Computers in Simulation, vol. 192, pp. 84–110, 2022.
- [7] J. Ma, S. Yu, and W. Cheng, "Composite fault diagnosis of rolling bearing based on chaotic honey badger algorithm optimizing vmd and elm," Machines, vol. 10, no. 6, pp. 469, 2022.
- [8] N.S. Hassan. "Evaluation of the reliability and importance of the units in the minimal cut and minimal pat for a complex network". In AIP Conference Proceedings Vol. 3097, No. 1, 2022.
- [9] F. Alsharify, "A Review of Optimization Techniques: Applications and Comparative Analysis". Iraqi Journal For Computer Science and Mathematics, 5(2), pp.122-134, 2024.
- [10] G. F. Deng and W. T. Lin, "Ant colony optimization-based algorithm for airline crew scheduling problem," Expert Systems with Applications, vol. 38, no. 5, pp. 5787-5793, 2011.
- [11] H. S. Howeidi, "The relationship between importance and redundancy in studying the increasing of a system's reliability". In AIP Conference Proceedings Vol. 2834, No. 1. AIP Publishing, 2023.
- [12] G. Da Col and E. C. Teppan, "Industrial-size job shop scheduling with constraint programming," Operations Research Perspectives, vol. 9, pp. 100249, 2022.

ـــوم الصــرفـة والنطـبيقيــة مـجلــة جـــامعة بـــابــل للعلــوم الصـــرفــة والنطـبيقيــة مـجلــة جــامعة بـــابــل للعلــوم الصـرفــة والنطـــ

الخلاصة

المقدمة: تتناول الورقة التحدي الرياضي المتمثل في تحسين الموثوقية مع مراعاة التاريخ التشغيلي للشبكة. يتم تحديد متطلبات الموثوقية لأي مكون من مكونات النظام المعقد من خلال أهميته وتحسين موقعه. والأهداف الأساسية هي تقليل التكاليف الإجمالية، تهتم هذه الدراسة بموضوع موثوقية عمل الشبكات العصبية وايجاد التوثيق الامثل لها .

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طرق العمل: دراسة مكونات الشبكة العصبية كنظام معقد واستخراج جميع مسارات النجاح في النظام.

الاستنتاجات: يمكن اعتبار هذه المهمة مشكلة برمجة غير خطية. وتم التعامل مع مشكلة تخصيص الموثوقية الأمثل باستخدام الخوارزمية الجينية، والتي تأخذ في الاعتبار مواقع المكونات المختلفة داخل الشبكة المعقدة. تعيينات للموثوقية. وكان تخصيص الموثوقية الإجمالي للنظام (Rs = 0.98 في حين كانت التكلفة الاجمالية للشبكة (2247.92). وتتمثل الفائدة الأساسية لهذا النموذج في أنه يمكن إجراء جميع العمليات الحسابية باستخدام برامج رياضية، تم استخدام إصدار "Matlab" R2020a لاستخراج نتائج التخصيص. وتمت مقارنة الدراسة بعدة اوراق بحثية تناولت اختبار الموثوقية في ميادين علمية وتكنولوجية اخرى . وكانت المقارنة افضل من حيث النتائج العددية .

<u>الكلمات المفتاحية: الشبكات العصبية، الخوارزميات الجينية، مخططات البنية، تخصيص الموثوقية.</u>