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# THE OPTIMAL PARAMETER DESIGN FOR A BLOOD SUPPLY CHAIN SYSTEM BY THE TAGUCHI METHOD

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Abstract. *The objective of this study is to design a robust blood supply chain system considering the total cost (TC) and the safety of patients. The freshness of transfused blood affects patient safety. The turnover rate (TR) is used in this study as the index of a patient's safety level. This study examines the blood supply chain system of the Taichung Blood Center of the Taiwan Blood Services Foundation and its contracting hospitals. A robustly designed blood supply chain system considers the input, the optimal approach, and the output. The input stage of the design uses the dynamic Taguchi method to set the signal, noise, and control factors of the blood supply chain system. The approach of this study was to use a neural network (NN) and a genetic algorithm (GA) to determine the results of the output process. The results show that the most robust control combination is a FIFO (first in, first out) blood delivery policy (BDP) where the maximal inventory level (MaxIL) is 600, the minimal inventory level (MinIL) is 80, and the donor arrival rate (DAR) is 120. Finally, the sensitivity analysis is discussed.*
**Keywords:** Blood supply chain system, Patient safety, Dynamic Taguchi method, Neural network (NN), Genetic algorithm (GA)

## 1. Introduction.

The Taichung Blood Center of the Taiwan Blood Services Foundation is Taiwan's best-known facility for collecting, storing, processing, and distributing blood and its related products (i.e., plasma, packed blood cells, serum, etc.). The Taichung Blood Center, as a purchase and distribution center for blood products, serves as the intermediary between blood suppliers (donors) and blood users (hospital patients). It is the blood center's duty to forecast demand and collect adequate supplies; it then receives requests from its contracting hospitals and distributes the blood supplies to the contracting hospitals. Blood donors, the Taichung Blood Center, and the contracting hospitals comprise the blood supply chain system.

Rabinowitz and Valinsky [1] discussed a blood bank inventory system and emphasized the impact of the characteristics of the blood bank system on the design and construction of the simulation. Mole [2] researched the delicate relationship between donors and the Transfusion Service in the UK, and discussed the policy decision to balance the conflicting stock requirements of maintaining high availability and low outdating rates. Operating characteristics include the probability distribution of demand for blood, the scale of the throughput, the disparity between blood shelf-life and ordering intervals, the amount of blood transfused, and the volume of requests received by the blood bank. Vrat and Khan

[3] studied a simulation model incorporating the "desired-beginning-inventory-level" policy to analyze system performance and submitted optimal inventory policy guidelines for a hospital blood bank. They used blood shortage and blood outdating as the two primary important components of measuring effectiveness. Pegels [4] explored technological advances in the preservation and utilization of human blood and researched a variety of operation research techniques to assist in the management of regional blood banks. Kendall [5] studied how well blood bank inventories are controlled on a day-to-day basis. He found that the blood administrator must have an annual plan to attain a blood service organization's goals. Kendall [5] developed the decision method based on multiple objective techniques, and it is especially relevant to healthcare delivery problems. Gregor's [6] simulation used an increase in the amount of available blood, a change in the number of delivery vehicles and a comparison of different types of inventory consignment policies to a direct sale to examine the effect of sending fresher blood supplies as inventories to hospitals with lower probabilities of transfusion. The result showed that the periodic redistribution of a regional inventory yielded lower outdating rates and lower shortage rates. Prastacos [7] approached several important issues from a unified perspective of blood inventory management theory and practice. Sirelson and Brodheim [8] simply used the mean daily demand as a parameter to construct a predictive model which relates base stock levels to shortages and outdating rates.

The variation of the major parameters of blood inventories is taken into account in order to reflect the variation in daily transfusions resulting from unstable demand forecasting. A blood center with a larger blood inventory turnover would have much fresher blood supplies, i.e., a better blood inventory performance. Pereira [9] concluded that the mean and variation of blood usage are the leading parameters in the regional optimization of inventory policies, and that a stochastic model simulated the routine operation of a hospital blood bank inventory being used over a finite number of days [10]. Outdating and shortage rates grew exponentially, which could be partially counterbalanced by increasing the number of blood suppliers. St. Joseph's Hospital [11] developed a computer system to streamline the transfusion process. The system has increased efficiency in record keeping, billing, usage reports, workload distribution and inventory management for the blood bank. Kendall [12] evaluated a regional blood distribution information system designed to improve the management of blood inventory and to maintain adequate inventory levels, which would meet patient demand, keep blood waste to a minimum, provide high-quality blood, and keep regional operating costs at an acceptable level.

Based on the above literature review and significance, the design and plan of a robust blood supply chain system is important for blood centers, hospitals, and patients. Any instability in blood supply or demand could result in a shortage of supply, putting patients' lives at risk [13]. Also, an excess of supply over demand would result in outdating costs [14]. Even the freshness of transfused blood affects the quality of the blood supply chain. Hence, designing an optimal supply chain system is crucial, for it takes costs and lives into account.

In this study, the Taichung Blood Center of the Taiwan Blood Services Foundation is the model used to design and plan a robust blood supply chain system. This study examines the delivery process from donation at the blood center to delivery to hospitals in order to design and plan a robust blood supply chain system. The Taichung Blood Center of the Taiwan Blood Services Foundation is used as a model in order to understand the process of blood supply chain systems, and to determine which factors affect their performance. This study analyzes these factors and uses them to design a more robust system.

The application of the blood supply chain system in this study is based on computation technology in order to construct a dynamic system of blood banking, information acquisition, processing, and management. The computation technology includes the Taguchi method, neural network (NN), and genetic algorithm (GA). This study also sets an optimal combination of factors' levels for a robust blood supply chain system and explores the overall performance of inventory management.

2. **Robust Design for the Blood Supply Chain System.** The researchers developed a strategic plan for Taichung Blood Center's blood supply chain system. The challenge for the Center is to procure the quantity of whole blood needed to produce the blood products needed by the hospitals. The blood center must understand the cost characteristics and the needs of the hospitals.

The design of the supply chain system focuses on the initial step of material flow. The donated whole blood is used to produce many different blood products (e.g., plasma, packed blood cells, serum). Packed red blood cell concentrate (RBC) is the blood product most frequently used by hospitals, and is therefore used as the research product (presented product) in this study. Packed RBC is generally used in the transfusion of internal medicine/surgery; its shelf life is 35 days, and thus it is perishable. Two hundred and fifty *ml* of whole blood (one bag) can produce 150 *ml* (one bag) of packed RBC.

The second step is to construct a simulation scenario for the design of the robust supply chain system. This study assumes that the blood center's demand random variable $D_t$ (uncertain demand in each day $t$) of packed RBC is the Normal probability distribution $N(\mu, \sigma^2)$, in which $\mu$ is the mean ($\frac{\text{bags}}{\text{day}}$) and $\sigma^2$ is the variance ($\frac{\text{bags}^2}{\text{day}^2}$). The study assumes that the donate random variable is fit for Poisson distribution $P(x) = \frac{\lambda^x}{x!}e^{-\lambda}$, in which $\lambda$ is the donor arrival rate of $\frac{\text{bags}}{\text{day}}$ (one donor, one bag of whole blood), and $x$ is the number of donors who donate blood each day. The Exponential distribution is applied here for the transfer Poisson distribution, in order to obtain $x$. The Exponential distribution is defined as $f(x) = \lambda e^{-\lambda x}$. $F(x)$ is the cumulative distribution function of $f(x)$. This study uses $F(x) = \theta$ ($\theta$ is simulated with the Monte Carlo method, between 0 to 1) to obtain the value of $x_t$, in which $x_t$ is the number of donors of whole blood in a given period ($t$).

The study of the performance of the blood supply chain is the third step in the design process. Collection, storage and transportation of blood affect the hospital's total costs and patient safety, which are in turn important issues for robust blood center design. The total cost ($TC$) is expressed as Equation (1) including set-up costs, production costs, holding costs, shortage costs, and outdating costs.

$$TC = O\sum_{t=1}^{T} K + C\sum_{t=1}^{T} Q_t + C_h\sum_{t=1}^{T} I_t + C_s\sum_{t=1}^{T} S_t + C_r\sum_{t=1}^{T} r_t \tag{1}$$

where $O$ is the set-up cost for the production of the packed RBC from whole blood, $t$ is the period of time (each day), and $T$ is the 365th day. $K$ is the production label for the production of the packed RBC from whole blood in the time $t$ (if the packed RBC is not produced, $K$ is 0; otherwise, $K$ is 1). $C$ is the production cost for each bag, $Q_t$ is the quantity of packed RBC produced over period $t$, $C_h$ is the rate of the unit cost of the holding, $I_t$ is the inventory level over period $t$, $C_s$ is the rate of unit cost from a shortage, $S_t$ is the shortage level over period $t$, $C_r$ is the rate of unit cost from outdating, and $r_t$ is the outdating level over period $t$.

Blood freshness is an important factor in studies of patient safety [9,10]. The greater the turnover rate ($TR$), the fresher the blood. Hence, $TR$ is defined as the index of patient safety levels in this paper. Equation (2) shows the formulation of $TR$.

$$TR = \frac{\sum_{t=1}^{T} Q_t}{\sum_{t=1}^{T} I_t \Big/ 365}. \tag{2}$$

Equation (3) shows the production quantity $Q_t$, which is subject to minimal and maximal levels of inventory.

$$Q_t = \begin{cases} 0, & Q_{\min} \le I_{t-1} \le Q_{\max} \\ Q_{\max} - I_{t-1}, & I_{t-1} < Q_{\min} \end{cases} \quad \text{for } t = 1, 2, \ldots, T. \tag{3}$$

The inventory and shortage levels are defined in Equation (4):

$$I_{t-1} + Q_t - D_t = I_t - S_t, \text{ for } t = 1, 2, \ldots, T \tag{4}$$

From the above Equations (1)-(4), we can obtain the decision variable $Q_t$. The values of $O$, $C$, $C_h$, $C_s$, and $C_r$ are set as 200, 50, 10, 100, and 30, respectively.

The three stages of this study for developing a robust design are input, optimal approach and output (see Figure 1). The input stage uses the Taguchi method to plan the signal and control factors of the blood supply chain system. In the second step, a simulation is used to determine the performance of the blood supply chain system. The optimal approach is to use NN and GA to determine the results of the output stage. The NN is used to map the relationship between the input and output data when the relationship is nonlinear, and the GA is used to search for the optimal solution. The output stage includes obtaining the optimal combination of levels of the control factors and deriving the sensitivity analysis of the inventory level for the performance of this blood supply chain system. The three stages are described in further detail below.

**Stage I. Input (The Dynamic Taguchi Procedure)**

The dynamic Taguchi procedure is used to assess the optimal combinations of parameter levels in order to measure the robustness of and to reduce response variation in a dynamic system [13]. Three factors – the signal, noise, and control factors – are considered in the dynamic Taguchi design procedure. The signal factor's levels are adjustable and can be applied once the optimal combination of parameters' levels is determined. Noise factors are parameters that are difficult and expensive for the decision-maker to control. Noise factors deviate the performance from the target specified by the signal factor. Control factors are parameters that can be used to determine the best combination of factor levels based on the experimental system that is least sensitive to the effect of the noise factors [15]. That is, the dynamic Taguchi procedure design is used to obtain the optimal design of control factors' levels based on reducing the noise factor's effect when the signal factor is considered. The followings are the three steps used in the dynamic Taguchi procedure in order to obtain the result of simulation data of the blood supply chain system. The application of the dynamic Taguchi procedure is shown as follows, from Step 1 to Step 3.

***Step* 1. Deciding signal, noise, and control factors**

The first step is deciding the signal, noise, and control factors in the blood supply chain system. The signal factor is the service level (SL): an adjustable SL avoids shortages or waste of packed RBC when the hospital's demand is uncertain. The noise factor is the demand variable (DV). Control factors are blood delivery policy (BDP), maximal inventory level (MaxIL), minimal inventory level (MinIL), and the arrival rate of the donors (DAR). The performances are $TC$ and $TR$. These factors and their levels are listed in Table 1.

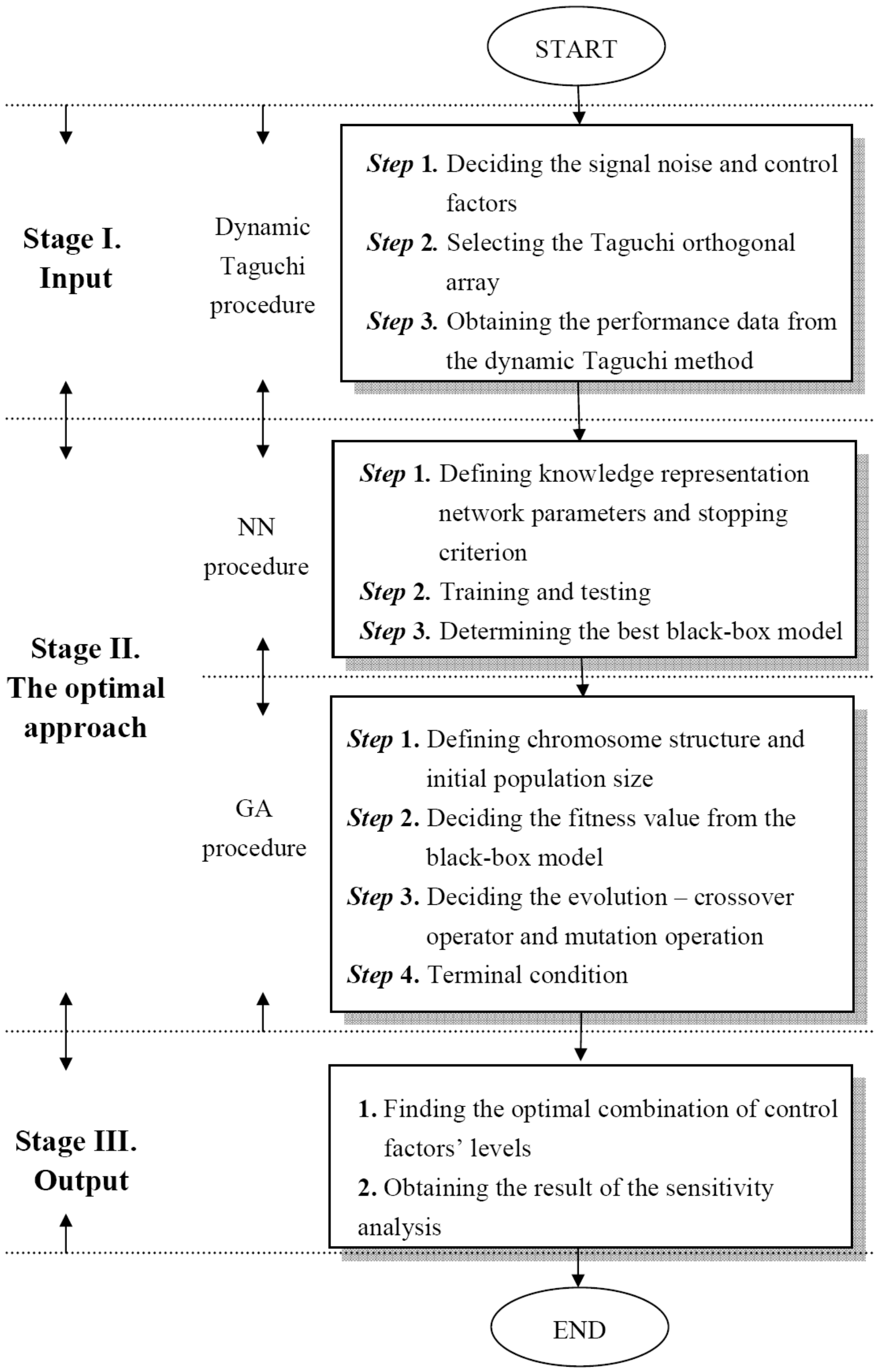


FIGURE 1. The three stages for robust design for the blood supply chain system

***Step* 2. Selecting the Taguchi orthogonal array**

The orthogonal table $L_9$ was selected as the arrangement of control factors, as shown in Table 2. The control factors BDP, MaxIL, MinIL, and DAR were assigned to columns A, B, C, and D respectively. The numbers in the columns represent the factor levels.

***Step* 3. Obtaining the performance data from the dynamic Taguchi method**

Eighty-one responses were generated in each experiment via Equations (1)-(4) for each of the noise and signal factor levels. A total of 4374 ($3*2*9*81$) performance data for $TC$ and $TR$ were generated. Table 2 shows each experiment's performance data, including the minimum, maximum, mean, and standard deviation.

TABLE 1. Experimental factors and their levels

| | | | | |
|---|---|---|---|---|
| Performances | 1 | $TC$ | | |
| | 2 | $TR$ | | |
| Signal factor: SL | Level 1 | 0.8 | | |
| | Level 2 | 0.9 | | |
| | Level 3 | 1.0 | | |
| Noise factor: DV | Level 1 | $N(150, 15^2)$ | | |
| | Level 2 | $N(150, 30^2)$ | | |
| Control factors | | Value | | |
| | | Level 1 | Level 2 | Level 3 |
| BDP | | FIFO | LIFO | – |
| MaxIL | | 600 | 800 | 1000 |
| MinIL | | 80 | 120 | 160 |
| DAR | | 120 | 240 | 400 |

FIFO: First In First Out

LIFO: Last In First Out

TABLE 2. $L_9$ and the data of simulation

| $L_9$ | | | | |
|---|---|---|---|---|
| # | A | B | C | D |
| 1 | **1** | **1** | **1** | **1** |
| 2 | **1** | **2** | **2** | **2** |
| 3 | **1** | **3** | **3** | **3** |
| 4 | **2** | **1** | **2** | **3** |
| 5 | **2** | **2** | **3** | **1** |
| 6 | **2** | **3** | **1** | **2** |
| 7 | **1** | **1** | **3** | **2** |
| 8 | **1** | **2** | **1** | **3** |
| 9 | **1** | **3** | **2** | **1** |

#: Experiment number

The blood supply chain system involves simultaneously optimizing two performances including $TC$ and $TR$. Owing to $TC$ with the-smaller-the best and $TR$ with the-larger-the-best, $TC$ and $TR$ are conflicting with each other, producing a trade-off effect. The desirability function is used here in order to achieve a simultaneous goal. According to the desirability function, $DTC$ is chosen to transfer $TC$ to a 0-1 value as Equation (5), and $TR$ is transferred to a 0-1 value by the $DTR$ formula as Equation (6) [16].

$$DTC = \begin{cases} 1, & TC \le TC_{\min} \\ \left(\frac{TC - TC_{\max}}{TC_{\min} - TC_{\max}}\right), & TC_{\min} \le TC \le TC_{\max} \\ 0, & TC \ge TC_{\max} \end{cases} \tag{5}$$

where $TC_{\min}$ is the lowest value of $TC$ and $TC_{\max}$ is the highest value of $TC$.

$$DTR = \begin{cases} 0, & TR \le TR_{\min} \\ \left(\frac{TR - TR_{\min}}{TR_{\max} - TR_{\min}}\right), & TR_{\min} \le TR \le TR_{\max} \\ 1, & TR \ge TR_{\min} \end{cases} \tag{6}$$

where $TR_{\min}$ is the lowest value of $TR$ and $TR_{\max}$ is the highest value of $TR$.

**Stage II. The Optimal Approach (The NN and GA Procedures)**

This stage includes the NN and GA procedures. The NN procedure establishes the relationship of the noise, signal, and control factors with two performances, the $DTC$ and the $DTR$. The GA procedure is used to obtain the optimal control factors' levels in order to set the optimal conditions of the blood supply chain system.

• **NN procedure**

NNs are popular research tools and used in many areas, for example, telecommunication, signal processing, pattern recognition, prediction, process control, financial analysis. [17]. NNs' processing parallel units are nodes whose structure resembles a human neurological system. The nodes are interconnected so that the knowledge pertaining to the relationship between the input and output nodes are stored in the inner product of synaptic weights. The transfer function is used for the weighted sum of the previous input neuron layers, except the first layer. The transfer function results in a wide-ranging application of NNs. In accordance with the problem's complexity, NNs produce a network architecture named the black-box model. Analysis results show that NNs are effective for addressing complex nonlinear problems if an excellent network architecture and parameters are selected [17,18].

In this study, a Back Propagation Neural Network (BPNN) is used to construct the black-box model of a dynamic multiple performance system by using the experimental data to train the network. The black-box model is constructed as follows.

***Step* 1. Defining knowledge representation network parameters and stopping criterion**

The BPNN consists of input, hidden and output layers. The Network structure is depicted in Figure 2, where there are six input nodes and two output nodes. The six input nodes include signal, noise, and control factors. The input values for the SL levels

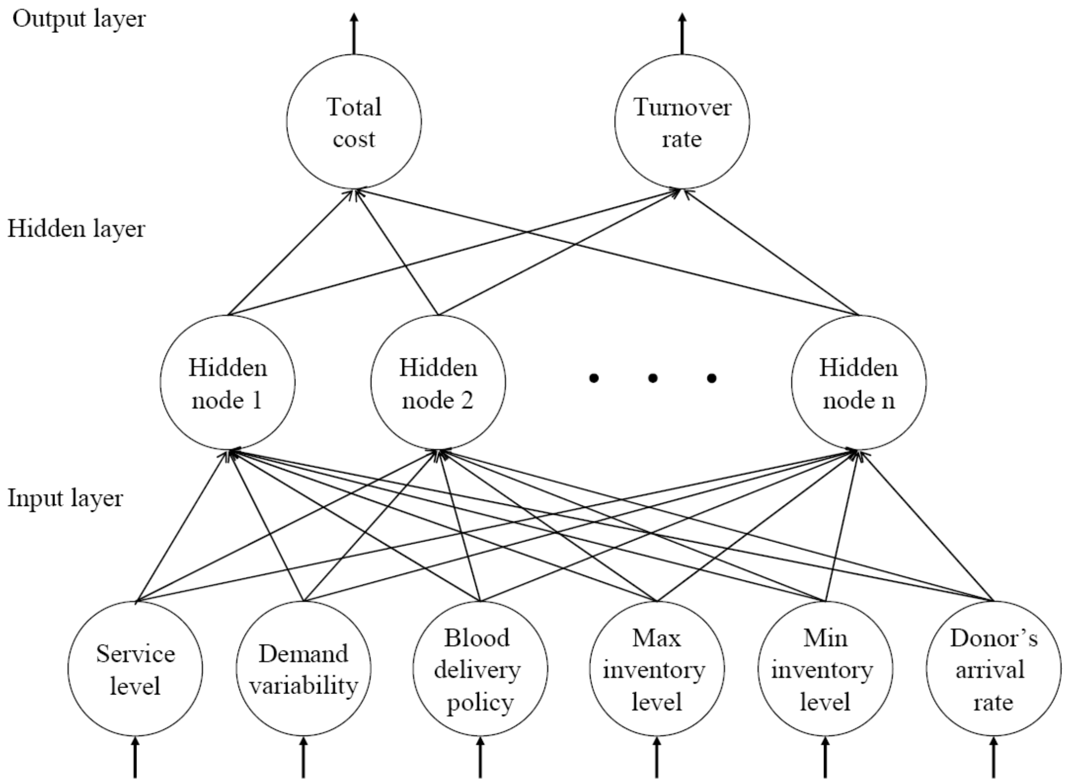


FIGURE 2. BPNN architecture in this paper

1, 2, and 3 are set as 0, 0.5, and 1 respectively; the DV levels 1 and 2 are set as 0, and 1 respectively; the BDP levels 1 and 2 are set as 0 and 1 respectively; the MaxIL levels 1, 2 and 3 are set as 0, 0.5, and 1 respectively; the MinIL levels 1, 2, and 3 are set as 0, 0.5, and 1 respectively; and the DAR levels 1, 2, and 3 are set as 0, 0.5 and 1 respectively. The two output nodes are $TC$ and $TR$. The output value for $TC$ and $TR$ are set as $DTC$ and $DTR$. In addition, the network parameter-learning rate and moment will be set to assist the trained network to attempt to converge and stabilize the training behavior. The stopping criterion is set to lower the root mean square error (RMSE) in the training and testing processes.

***Step* 2. Training and testing**

This study uses the NN software package Pythia (http://www.runtime.org/pythia.htm). The iteration was set to 10,000; the momentum coefficient is set to 0.80; and the learning rate was set to dynamically auto-adjust from 0.03 to 0.3 for rapid effective learning and stable behavior, as observed by mildly varying values of RMSE, in order to obtain the appropriate black-box model. Table 3 lists several candidates of the network architecture when we randomly selected 3937 records (90% of the entire experiment dataset) to be the training pattern and 437 records (10% of the entire experiment dataset) as the testing pattern.

Table 3. The candidates BPN model

| Architecture | RMSE (Training) | RMSE (Testing) |
|---|---|---|
| 6-3-2 | 0.020452 | 0.022105 |
| 6-4-2 | 0.014068 | 0.015142 |
| 6-5-2 | 0.013230 | 0.014022 |
| **6-6-2** | **0.010490** | **0.011982** |
| 6-7-2 | 0.010577 | 0.011995 |
| 6-8-2 | 0.013096 | 0.014120 |
| 6-9-2 | 0.013092 | 0.014086 |
| 6-10-2 | 0.013098 | 0.015223 |
| 6-11-2 | 0.013130 | 0.014394 |
| 6-12-2 | 0.017128 | 0.018008 |
| 6-13-2 | 0.017226 | 0.018904 |

Architecture: input nodes-hidden nodes-output nodes

***Step* 3. Determining the best black-box model**

The architecture 6-6-2 (input nodes-hidden nodes-output nodes) was selected to obtain a better performance because it had the lowest RMSE of training and testing. The weights connected between layers in the NN structure illustrated the relationship between the input factors and output performances. The value of each performance was calculated by the weighted sum connected to the output node and transferred by an activation function (e.g., a sigmoid function). Hence, the weights obtained from a trained BPNN and the activation functions of each node formed the fitness function of the black-box model adopted in the GA optimization procedure.

**• GA procedure**

GA is an optimization methodology created from the concept of Darwinian natural selection and genetics in biological systems for obtaining solutions with nonlinear programming [19]. GA's search techniques for obtaining optimal solutions differ from traditional search techniques, which conduct a point-to-point search route in the solution space: GA uses a set of candidate solutions called population to conduct a series of iterative computations, mimicking the Darwinian principle of "survival of the fittest" to obtain the optimal solution. Also, GA's stochastic nature characteristic enables it to treat larger search spaces with complex problems randomly but efficiently [20]. GA generates a "chromosome", which represents a series of alternate solutions, and can quickly produce a successful solution without testing all possible solutions when the fitness function is evaluated as the performance of the solution. Three main operators – selection, crossover, and mutation – are to improve the fitness of an estimated population when the optimal solution is converged [19].

Once the best black-box model forming the relationship between input factors and output performances is determined, the GA is performed to obtain the optimal levels of the factors combination. The four steps of the GA procedure are as follows.

***Step* 1. Defining chromosome structure and initial population size**

The control factors BDP, MaxIL, MinIL and DAR were limited to values between 0 and 1 and combined into one string (**N**, **O**, **P**, **Q**) to represent the chromosome structure. They were subjected to two or three levels. The **N** value for the BDP levels 1 and 2 are 0 and 1 respectively, and the **Q** value for the DAR levels 1, 2, and 3 are 0, 0.5, and 1 respectively. However, MaxIL and MinIL were not bound to discrete levels in order to search better levels' settings, so the **O** and **P** values are between 0 and 1. Fifty strings were randomly generated to establish the initial population.

***Step* 2. Deciding the fitness function from the black-box model**

The two performances, $DTC$ and $DTR$, need to be integrated into one overall performance as the fitness function to simultaneously optimize dynamic multiple performances by a GA. The larger the fitness value, the higher overall performance of the levels combination of control factors. The fitness function is represented as Equation (7):

$$\text{Fitness function} = \sqrt{DTC * DTR} \tag{7}$$

***Step* 3. Deciding the evolution – crossover operator and mutation operation**

The essential operators, including reproduction, crossover and mutation, should be determined in advance by applying the GA to optimize the levels of the selected control factors. Herein, a "roulette wheel" approach is adopted as the selection procedure. The mutation rate is determined automatically, and the crossover rate is set as 0.5.

***Step* 4. Terminal condition**

The stopping condition of the GA procedure was set to be 3000 iterations or the change in the previous 1000 iterations is less than 1%. When the optimal string (**N**, **O**, **P**, **Q**) is obtained, **O** and **P** must be transformed by Equations (8) and (9) for MaxIL and MinIL levels.

$$\text{MaxIL} = \mathbf{O} * (1000 - 600) + 600 \tag{8}$$

$$\text{MinIL} = \mathbf{P} * (160 - 80) + 80 \tag{9}$$

The optimal levels of the control factors in each combination of signal and noise factors are shown in Table 4. Table 4 also shows the six optimal combinations of control factors' levels which need to be evaluated to derive the most robust combination for the blood supply system.

**Stage III. Output**

The study determined the most robust levels of the control factors for the different combinations of signal and noise factors. To select the most robust levels of control factors, the control levels of the factors in Table 4 were applied to each combination of signal and noise factors and their fitness values were calculated. Table 5 shows six solutions for the different combinations of control factors' levels when all combinations of signal factor's

Table 4. The optimal level of control factors for each combination of signal and noise factors

| Signal factor | Noise factor | Control factors | | | | Overall performance |
|---|---|---|---|---|---|---|
| SL | DV | BDP | MaxIL | MinIL | DAR | Fitness value |
| 1 | 1 | 1 | 600.000 | 80.311 | 1 | 0.769089 |
| 2 | 1 | 1 | 601.152 | 120.000 | 1 | 0.692249 |
| 3 | 1 | 1 | 600.806 | 80.079 | 1 | 0.653263 |
| 1 | 2 | 1 | 600.000 | 120.000 | 1 | 0.723468 |
| 2 | 2 | 1 | 600.000 | 80.071 | 1 | 0.664628 |
| 3 | 2 | 1 | 600.467 | 80.008 | 1 | 0.637590 |

levels and noise factor's levels are considered. Of the results of the comparison of the fitness values among solutions in Table 5, solution 4 has superior fitness values. For example, in solution 4, when $\{\mathrm{SL} = 1, \mathrm{DV} = 1\}$, the fitness value of solution 4 (0.770251) is greater than the other fitness values (solution 1 = 0.769089, solution 2 = 0.768930, solution 3 = 0.769033, solution 5 = 0.769987, and 0.769685). The results show that the most robust levels of control factors are as follows: that BDP is FIFO, MaxIL is 600, MinIL is 80, and DAR is 120.

3. **Sensitivity Analysis.** A sensitivity analysis based on the results of the most robust levels of the control factors combination is provided. Table 6 shows the $TC$-changed percentage and the $TR$-changed percentage for each combination of signal and noise factor's levels when BDP is FIFO, MinIL is 80, and DAR is 120, in the condition that MaxIL is from 600 to 640 with an increment of 4. Generally, when the MaxIL is between 600 and 640, results show that when the SL is fixed, the increasing MaxIL will lead to an increased $TC$-changed percentage. However, when the MaxIL is between 636 and 640, the $TC$-changed percentage decreases in $[\Delta TC(1,2)/TC(1,2)]\%$ and $[\Delta TC(2,2)/TC(2,2)]\%$. Additionally, increasing MaxIL leads to a decreased $TR$.

Furthermore, to explore the effects of noise factor, the $TC$-changed percentage in $[\Delta TC(1,1)/TC(1,1)]\%$ is larger than that in $[\Delta TC(1,2)/TC(1,2)]\%$; the $TC$-changed percentage in $[\Delta TC(2,1)/TC(2,1)]\%$ is larger than that in $[\Delta TC(2,2)/TC(2,2)]\%$; and the $TC$-changed percentage in $[\Delta TC(3,1)/TC(3,1)]\%$ is larger than that in $[\Delta TC(3,2)/TC(3,2)\%$. Also, the $TR$-changed percentage in $[\Delta TR(1,1)/TR(1,1)]\%$ is less than that in $[\Delta TR(1,2)/TR(1,2)]\%$; the $TR$-changed percentage in $[\Delta TR(2,1)/TR(2,1)]\%$ is less than that in $[\Delta TR(2,2)/TR(2,2)]\%$; and the $TR$-changed percentage in $[\Delta TR(3,1)/TR(3,1)]\%$ cannot be compared with that in $[\Delta TR(3,2)/TR(3,2)]\%$. The noise factor phenomenon shows that when a decision maker increases MaxIL in the condition that the SL is fixed, more demand variation will lead to a decrease of $TC$-changed percentage, and there is no steady result of a $TR$-changed percentage.

Table 7 shows $TC$-changed percentage and $TR$-changed percentage in each combination of signal and noise factor's levels when BDP is FIFO, MaxIL is 600, and DAR is 120 in the condition that MinIL is from 80 to 90 with an increment of 1. The results show that generally, when the SL is fixed, increasing MinIL leads to an increase of $TC$-changed percentage. However, when MinIL is between 86 and 90, the $TC$-changed percentage in $[\Delta TC(3,1)/TC(3,1)]\%$ decreases. When MinIL is between 83 and 90, the $TC$-changed percentage in $[\Delta TC(2,2)/TC(2,2)]\%$ decreases. Also, when MinIL is between 81 and 90, the $TC$-changed percentage in $[\Delta TC(3,2)/TC(3,2)]\%$ decreases. However, increasing MinIL leads to a decreased $TR$-changed percentage.

TABLE 5. Comparison of fitness values among solutions

| SL | DV | Fitness Value | | | | | |
|---|---|---|---|---|---|---|---|
| | | Solution 1: BDP = 1, MaxIL = 600.000 MinIL = 80.311, DAR = 1 | Solution 2: BDP = 1, MaxIL = 601.152 MinIL = 120.000, DAR = 1 | Solution 3: BDP = 1, MaxIL = 600.806 MinIL = 80.079, DAR = 1 | Solution 4: BDP=1, MaxIL=600.000 MinIL=120.000, DAR=1 | Solution 5: BDP=1, MaxIL=600.000 MinIL=80.071, DAR=1 | Solution 6: BDP=1, MaxIL=600.467 MinIL=80.008, DAR=1 |
| 1 | 1 | 0.769089 | 0.768930 | 0.769033 | 0.770251 | 0.769987 | 0.769685 |
| 2 | 1 | 0.692940 | 0.692249 | 0.692518 | 0.694258 | 0.693958 | 0.693408 |
| 3 | 1 | 0.653914 | 0.652890 | 0.653263 | 0.655292 | 0.654979 | 0.654284 |
| 1 | 2 | 0.722310 | 0.722101 | 0.722218 | 0.723468 | 0.723205 | 0.722883 |
| 2 | 2 | 0.663689 | 0.662935 | 0.663219 | 0.664904 | 0.664628 | 0.664074 |
| 3 | 2 | 0.637261 | 0.636357 | 0.636687 | 0.638482 | 0.638205 | 0.637590 |

TABLE 6. $TC$ and $TR$ in MaxIL = 600 $\sim$ 640 (incremental 4) when BDP = FIFO, MinIL = 80, and DAR = 120

| MaxIL | 604 | 608 | 612 | 616 | 620 | 624 | 628 | 632 | 636 | 640 |
|---|---|---|---|---|---|---|---|---|---|---|
| $[\Delta TC(1,1)/TC(1,1)]\%$ | 0.169 | 0.159 | 0.149 | 0.138 | 0.127 | 0.115 | 0.102 | 0.089 | 0.076 | 0.063 |
| $[\Delta TR(1,1)/TR(1,1)]\%$ | −0.966 | −0.976 | −0.737 | −0.993 | −0.750 | −0.756 | −1.019 | −0.769 | −0.775 | −0.781 |
| $[\Delta TC(2,1)/TC(2,1)]\%$ | 0.204 | 0.187 | 0.170 | 0.152 | 0.134 | 0.115 | 0.095 | 0.076 | 0.057 | 0.038 |
| $[\Delta TR(2,1)/TR(2,1)]\%$ | −1.408 | −1.429 | −1.744 | −1.475 | −1.497 | −1.520 | −1.231 | −1.562 | −1.266 | −1.608 |
| $[\Delta TC(3,1)/TC(3,1)]\%$ | 0.170 | 0.162 | 0.155 | 0.147 | 0.140 | 0.132 | 0.125 | 0.117 | 0.110 | 0.103 |
| $[\Delta TR(3,1)/TR(3,1)]\%$ | −1.858 | −2.215 | −1.935 | −1.974 | −2.013 | −2.406 | −2.105 | −2.151 | −1.825 | −2.239 |
| $[\Delta TC(1,2)/TC(1,2)]\%$ | 0.130 | 0.113 | 0.096 | 0.078 | 0.060 | 0.042 | 0.024 | 0.006 | −0.011 | −0.029 |
| $[\Delta TR(1,2)/TR(1,2)]\%$ | −1.050 | −1.061 | −0.802 | −1.081 | −0.817 | −1.102 | −0.833 | −0.840 | −0.847 | −0.855 |
| $[\Delta TC(2,2)/TC(2,2)]\%$ | 0.120 | 0.103 | 0.085 | 0.068 | 0.050 | 0.033 | 0.016 | 0.000 | −0.0164 | −0.031 |
| $[\Delta TR(2,2)/TR(2,2)]\%$ | −1.796 | −1.520 | −1.543 | −1.567 | −1.592 | −1.618 | −1.645 | −1.333 | −1.695 | −1.375 |
| $[\Delta TC(3,2)/TC(3,2)]\%$ | 0.070 | 0.069 | 0.069 | 0.069 | 0.069 | 0.070 | 0.070 | 0.073 | 0.073 | 0.075 |
| $[\Delta TR(3,2)/TR(3,2)]\%$ | −1.935 | −1.975 | −2.013 | −1.706 | −2.091 | −2.135 | −1.812 | −2.222 | −1.887 | −1.923 |

$TC(i,j)$: $TC$ when SL = level $i$ and DV = level $j$

$TR(i,j)$: $TR$ when SL = level $i$ and DV = level $j$

$\Delta TC(i,j) = TC(i,j)$ for MaxIL $= N + 4t$ minus $TC(i,j)$ for MaxIL $= N$

$\Delta TR(i,j) = TR(i,j)$ for MaxIL $= N + 4$ minus $TR(i,j)$ for MaxIL $= N$

TABLE 7. $TC$ and $TR$ in MinIL = 80 ∼ 90 (incremental 1) when BDP = FIFO, MaxIL = 600, and DAR = 120

| MinIL | 81 | 82 | 83 | 84 | 85 | 86 | 87 | 88 | 89 | 90 |
|---|---|---|---|---|---|---|---|---|---|---|
| $[\Delta TC(1,1)/TC(1,1)]\%$ | 0.110 | 0.108 | 0.105 | 0.103 | 0.100 | 0.097 | 0.094 | 0.091 | 0.088 | 0.084 |
| $[\Delta TR(1,1)/TR(1,1)]\%$ | −0.723 | −0.484 | −0.732 | −0.490 | −0.493 | −0.744 | −0.499 | −0.754 | −0.505 | −0.508 |
| $[\Delta TC(2,1)/TC(2,1)]\%$ | 0.077 | 0.072 | 0.067 | 0.061 | 0.056 | 0.051 | 0.045 | 0.040 | 0.035 | 0.029 |
| $[\Delta TR(2,1)/TR(2,1)]\%$ | −0.559 | −0.845 | −0.852 | −0.859 | −0.576 | −0.872 | −0.880 | −0.590 | −0.893 | −0.599 |
| $[\Delta TC(3,1)/TC(3,1)]\%$ | 0.016 | 0.012 | 0.008 | 0.004 | 0.001 | −0.002 | −0.005 | −0.008 | −0.011 | −0.013 |
| $[\Delta TR(3,1)/TR(3,1)]\%$ | −0.920 | −0.929 | −0.623 | −0.943 | −0.952 | −0.962 | −0.970 | −0.980 | −0.658 | −0.997 |
| $[\Delta TC(1,2)/TC(1,2)]\%$ | 0.080 | 0.075 | 0.070 | 0.065 | 0.060 | 0.055 | 0.050 | 0.045 | 0.039 | 0.034 |
| $[\Delta TR(1,2)/TR(1,2)]\%$ | −0.785 | −0.526 | −0.796 | −0.533 | −0.536 | −0.811 | −0.543 | −0.546 | −0.826 | −0.554 |
| $[\Delta TC(2,2)/TC(2,2)]\%$ | 0.010 | 0.004 | −0.001 | −0.006 | −0.011 | −0.015 | −0.020 | −0.025 | −0.029 | −0.033 |
| $[\Delta TR(2,2)/TR(2,2)]\%$ | −0.890 | −0.597 | −0.904 | −0.912 | −0.612 | −0.926 | −0.621 | −0.940 | −0.631 | −0.955 |
| $[\Delta TC(3,2)/TC(3,2)]\%$ | −0.038 | −0.039 | −0.041 | −0.042 | −0.042 | −0.043 | −0.043 | −0.043 | −0.043 | −0.043 |
| $[\Delta TR(3,2)/TR(3,2)]\%$ | −0.958 | −0.968 | −0.649 | −0.984 | −0.660 | −1.000 | −1.010 | −0.678 | −1.027 | −0.690 |

$TC(i,j)$: $TC$ when SL = level $i$ and DV = level $j$

$TR(i,j)$: $TR$ when SL = level $i$ and DV = level $j$

$\Delta TC(i,j) = TC(i,j)$ for MaxIL $= N+1$ minus $TC(i,j)$ for MaxIL $= N$

$\Delta TR(i,j) = TR(i,j)$ for MaxIL $= N+1$ minus $TR(i,j)$ for MaxIL $= N$

Furthermore, to explore the effects of the noise factor, the $TC$-changed percentage in $[\Delta TC(1,1)/TC(1,1)]\%$ is larger than that of $[\Delta TC(1,2)/TC(1,2)]\%$; the $TC$-changed percentage in $[\Delta TC(2,1)/TC(2,1)]\%$ is larger than that of $[\Delta TC(2,2)/TC(2,2)]\%$; and the $TC$-changed percentage in $[\Delta TC(3,2)/TC(3,2)]\%$ is larger than that of $[\Delta TC(3,1)/TC(3,1)]\%$. Also, the $TR$-changed percentage in $[\Delta TR(1,1)/TR(1,1)]\%$ is slightly less than that of $[\Delta TR(1,2)/TR(1,2)]\%$; the $TR$-changed percentage in $[\Delta TR(2,1)/TR(2,1)]\%$ is less than that of $[\Delta TR(2,2)/TR(2,2)]\%$; and the $TR$-changed percentage in $[\Delta TR(3,1)/TR(3,1)]\%$ cannot be compared with that of $[\Delta TR(3,2)/TR(3,2)]\%$. The noise factor phenomenon shows that when MinIL increases and SL is fixed, more demand variation leads to an increase of $TC$-changed percentage, and there is no steady result toward a $TR$-changed percentage.

4. **Conclusion.** In this study, the authors proposed to design a robust blood supply chain system, taking $TC$ and patient safety into account in the blood supply chain system. The advantages of the proposed system over other studies [1-14] are as follows. First, previous studies only explored blood inventory policies, rather than designing a blood supply system or taking the concept of a supply chain into the design. However, the proposed supply chain system can increase the overall efficiency of the blood supply. Second, previous research only considers the cost concept in the blood supply, without taking patient safety into consideration. However, in Taiwan today, patient safety is a crucial issue in hospitals, for they strive to improve service quality and patient satisfaction [21,22]. This study uses patient safety as a performance value and $TR$ as the index of patient safety levels. Simultaneously, the $TC$ and $TR$ are considered as performance values in the blood supply chain system.

Based on the above two advantages in the supply of blood, this paper considered that financial viability and patient safety must be considered to promote a greater cooperative effort from all hospitals throughout the system when designing a blood supply chain system. A three-stage process was used to resolve the optimal combinations of parameters' levels for the blood supply chain system. Optimizing the selected parameter levels requires developing a model capable of accurately describing input-output behavior and capturing the range of the input-output parameter levels. Therefore, this study proposes an optimal approach that combines NN and GA to identify the nonlinear relationship between the input and output parameters and obtain a near-optimal combination of parameter levels.

The results show that the most robust level of control factors are that BDP is FIFO, MaxIL is 600, MinIL is 80, and DAR is 120. Also, sensitivity analysis shows two important points: first, when the SL is fixed, increasing either the MaxIL or MinIL leads to a decreased $TR$-changed percentage; and second, the noise factor phenomenon shows that when the SL is fixed and MaxIL is increased, more demand variation leads to a decreased $TC$-changed percentage. Nonetheless, when the SL is fixed and MinIL is increased, more demand variation leads to an increased $TC$-changed percentage.

Furthermore, from the results of Table 5 and the sensitivity analysis of Table 6, the contribution of the three-stage process for the proposed algorithm in the study shows that, traditionally, the dynamic Taguchi method has been most widely applied to product design and manufacturing in the industry [23,24]. This study applies the dynamic Taguchi method to the design of a blood supply chain system and considers an adjustable SL for practical application in blood supply policy. This is an innovative idea for the dynamic Taguchi method in service system design. Second, the dynamic Taguchi method for obtaining the optimal combination of parameters' levels is used only to treat discrete levels of control factors: it cannot treat continuous levels. This paper uses NN and GA to obtain the optimal combination of parameters' levels, which suits both discrete and continuous levels of control factors. Even if the factor levels are continuous, the obtained solutions are not confined between the upper and lower bounds of the levels [25,26]. Third, this paper uses NN to map input and output factors because NN is suitable for solving nonlinear problems. Recent studies have shown that the hybrid approach integrates NNs for solving dynamic Taguchi problems: the solutions are better than those obtained with the traditional dynamic Taguchi method [27]. Fourth, the dynamic Taguchi method can only be used to solve a single response: this paper can solve either multiple responses or a single response. For example, in this paper, two responses – $TC$ and $TR$ – are solved.

In this paper, the authors widely applied the dynamic Taguchi method, NN, and GA to the blood supply chain system. Future studies can use this paper's innovative ideas to design different supply chain systems and to explore problems with setting system parameters' levels. Also, different signal factors, control factors, and responses can be used in the blood supply chain systems. The limitation for this paper is that the signal factor's levels and control factors' levels are based on the decision makers of the blood supply chain system. However, the noise factor's levels are based on the external environment, and thus a designer must consider the variations of the external environment when adjusting the optimal parameter levels.

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