Predicting project duration using a coupled artificial neural network and Taguchi method approach

Previsão da duração do projeto usando uma rede neural artificial acoplada e abordagem do método Taguchi

Predicción de la duración de un proyecto mediante una red neuronal artificial acoplada y el método Taguchi

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Larbi Bendada
Master in Mechanics
Institution: Department of Mechanics, Laboratory of CMASMTF, University of Oum El Bouaghi
Address: Oum El Bouaghi, Algeria
E-mail: bendada_larbi@yahoo.fr

Mourad Brioua
Doctor in Mechanicals Engineering
Institution: Department of Mechanics, Laboratory LRPI, University of Batna 2
Address: Batna, Algeria
E-mail: m.brioua@univ-batna2.dz

Mohamed Razi Morakchi
Doctor in Industrial Maintenance
Institution: Faculty of Technology, Laboratory of LGE, University of M'sila
Address: M'sila, Algeria
E-mail: mohamed.razi.morakchi@usherbrooke.ca

Ibrahim Djouani
Doctor in City Management
Institution: Faculty of Technology, Laboratory of LGE, University of M'sila
Address: M'sila, Algeria
E-mail: ibrahim.djouani@univ-msila.dz

ABSTRACT

Accurate project duration prediction is increasingly important for management because it defines the expected timeline for project realization. This study utilizes an integrated approach combining neural networks with the Taguchi method to forecast the time required to complete projects within predetermined deadlines. The methodology involves modelling and simulating the network of project activities to estimate the total average project duration. The neural network model uses input variables such as success probability, effort, and learning factor.
to predict the total time necessary for project completion. The total average project duration is the output variable that is critical during the design phase. Subsequently, the Taguchi method optimizes the neural network’s outputs, incorporating mean squared error (MSE) values to enhance predictive accuracy. This study underscores the efficacy of artificial neural networks (ANNs) as predictive tools, demonstrating their ability to meticulously estimate project duration. The proposed method’s efficiency and applicability are demonstrated by MATLAB simulation analyses, highlighting its effectiveness in precise deadline estimation. In the realm of engineering, ANNs stand tall as formidable predictive tools, their efficacy underscored by this study’s successful application. By harnessing ANNs and simulation data, this research crafts a predictive model adept at estimating the average total duration of projects. Through meticulous consideration of crucial parameters like the probability of success and effort factors, the model emerges as a beacon of accuracy within the design domain. Future research will explore the effects of additional parameters on activity networks and alternative transfer functions, as well as the potential integration of reinforcement algorithms to improve resource allocation, risk management, and project outcomes through online training data.

**Keywords:** Artificial Neural Networks. Taguchi Method. Project Duration Prediction. Project Management. Optimization.

**RESUMO**

A previsão precisa da duração do projeto é cada vez mais importante para o gerenciamento porque define o cronograma esperado para a realização do projeto. Este estudo utiliza uma abordagem integrada que combina redes neurais com o método Taguchi para prever o tempo necessário para concluir projetos dentro de prazos pré-determinados. A metodologia envolve modelar e simular a rede de atividades do projeto para estimar a duração média total do projeto. O modelo de rede neural usa variáveis de entrada como probabilidade de sucesso, esforço e fator de aprendizagem para prever o tempo total necessário para a conclusão do projeto. A duração média total do projeto é a variável de saída crítica durante a fase de design. Posteriormente, o método Taguchi otimiza os resultados da rede neural, incorporando valores de erro quadrático médio (MSE) para aumentar a precisão preditiva. Este estudo ressalta a eficácia das redes neurais artificiais (RNAs) como ferramentas preditivas, demonstrando sua capacidade de estimar meticulosamente a duração do projeto. A eficiência e aplicabilidade do método proposto são demonstradas por análises de simulação MATLAB, destacando sua eficácia na estimativa precisa de prazos. No domínio da engenharia, as RNAs se destacam como ferramentas preditivas formidáveis, e sua eficácia é ressaltada pela aplicação bem-sucedida deste estudo. Ao aproveitar RNAs e dados de simulação, esta pesquisa cria um modelo preditivo capaz de estimar a duração média total dos projetos. Através da consideração meticulosa de parâmetros cruciais como a probabilidade de sucesso e fatores de esforço, o modelo emerge como um farol de precisão no domínio do design. A investigação futura irá explorar os efeitos de parâmetros adicionais nas redes de atividades e funções de transferência alternativas, bem como a integração potencial de algoritmos de reforço para melhorar a alocação de recursos, a gestão de riscos e os resultados do projeto através de dados de formação online.

RESUMEN
La predicción precisa de la duración de los proyectos es cada vez más importante para la gestión, ya que define el plazo previsto para su realización. Este estudio utiliza un enfoque integrado que combina redes neuronales con el método Taguchi para predecir el tiempo necesario para completar los proyectos dentro de unos plazos predeterminados. La metodología consiste en modelizar y simular la red de actividades del proyecto para estimar la duración media total del proyecto. El modelo de red neuronal utiliza variables de entrada como la probabilidad de éxito, el esfuerzo y el factor de aprendizaje para predecir el tiempo total necesario para completar el proyecto. La duración media total del proyecto es la variable de salida crítica durante la fase de diseño. Posteriormente, el método Taguchi optimiza las salidas de la red neuronal, incorporando valores de error cuadrático medio (ECM) para mejorar la precisión de la predicción. Este estudio subraya la eficacia de las redes neuronales artificiales (RNA) como herramientas de predicción, demostrando su capacidad para estimar meticulosamente la duración de los proyectos. La eficiencia y aplicabilidad del método propuesto se demuestran mediante análisis de simulación en MATLAB, destacando su eficacia en la estimación precisa de plazos. En el ámbito de la ingeniería, las RNA se erigen como formidables herramientas de predicción, y su eficacia queda subrayada por el éxito de su aplicación en este estudio. Aprovechando las RNA y los datos de simulación, esta investigación elabora un modelo predictivo experto en estimar la duración media total de los proyectos. Gracias a la meticulosa consideración de parámetros cruciales como la probabilidad de éxito y los factores de esfuerzo, el modelo emerge como un faro de precisión en el ámbito del diseño. Futuras investigaciones explorarán los efectos de parámetros adicionales en las redes de actividad y funciones de transferencia alternativas, así como la posible integración de algoritmos de refuerzo para mejorar la asignación de recursos, la gestión de riesgos y los resultados de los proyectos mediante datos de entrenamiento en línea.


1 INTRODUCTION

The evolving industrial landscape, characterized by intensified market competition and escalating manufacturing system complexities, presents formidable challenges for new product launches. Companies striving for innovation face immense pressure to accelerate product development timelines while upholding high-quality standards, placing significant strain on their workforce (Cho & Eppinger, 2005). In mega-projects, managing complex designs or constructions
entails coordinating a multitude of tasks across various disciplines. As design process complexity increases, iterative adjustments become imperative to refine workflows, necessitating that project managers anticipate and mitigate potential task failures to ensure timely project realization. While traditional tools like GANTT and PERT diagrams are widely used, they often fall short in supporting the iterative nature of design processes, where tasks may require revisiting to refine previous steps (Li, 2013) (Larbi et al., 2022). To address these challenges, several models have been developed to represent iterative design processes, with notable studies exploring sequential, parallel, or coupled methodologies (Ray et al., 2023). The iterative approach has proven instrumental in analyzing and optimizing product development timelines. Utilizing meta-models and response surface methods within composite plans has effectively aligned product development processes with project goals, as evidenced by satisfactory performance across various test indices (Singh; Kottath, 2021). Concurrently, studies have leveraged data from neural networks to analyze recovery operations’ impact on project cost, time overruns, and contractual claims, enhancing decision-making frameworks for improving project outcomes (Mukrimaa et al., 2021). Recent research in smart buildings has underscored the efficacy of Artificial Neural Networks (ANN) in optimizing energy consumption through intelligent occupancy detection (Ray et al., 2023). This method, highlighted by a study achieving accuracies of 98.5% and 97.5% for closed and opened door scenarios respectively, holds promise for enhancing energy management strategies in building automation systems. In (Ginanjar et al., 2022), prediction of power consumption utilization in cloud computing data centers using Kalman Filter parameters with Genetic Algorithm is explored, aiming to optimize energy consumption and extend network lifespan. Furthermore, advancements in estimating software project durations showcase the utility of machine learning techniques, such as Bayesian regulation and Levenberg-Marquardt training algorithms, within neural network frameworks to enhance prediction accuracy (Khalid et al., 2017). Additionally, optimization of microgrid performance using the Ant-Lion Optimization (ALO) algorithm, emphasizing the integration of intelligent control techniques like Unified Power Quality Conditioner (UPQC) and comparing it with a Fuzzy Logic Controller (FLC) (Nagaraju & Chandramouli, 2024). Optimization techniques have also been
applied in the field of robotics, particularly in solving and optimizing the kinematic modeling of continuum robots. For instance, Particle Swarm Optimization (PSO) has been utilized for continuum robot kinematic modeling, as demonstrated in (Morakchi et al., 2022). A recent study demonstrated the superior performance of the Bonobo optimizer (BO) in optimizing the placement and sizing of photovoltaic distributed generators (PDGs) and capacitors (CPs) in power distribution systems (Pham et al., 2023). Moreover, previous research has showcased various applications of Neural Networks across diverse domains. For example, in (Altintas et al., 2021), researchers developed an Adaptive Neural Network (CSANN) to tackle complexities in job-shop scheduling, enabling effective control strategies. Moreover, in (Kamat et al., 2021), ANN tools in MATLAB were utilized to predict the material removal rate of AISI M2 Steel, optimizing parameters for hard turning processes. Similarly, authors in (Godwin et al., 2023) employed an ANN approach to analyze and enhance performance parameters of different IC engines. Additionally, in (Saghir et al., 2021) a neural network-based model was utilized to forecast the compressive strength of concrete containing Industrial By-products. Furthermore, (Gómez-García et al., 2021) utilized the HPA data analysis method combined with ANN to aid risk management processes in the construction industry. In (Mohamed Razi et al., 2022; Mohammed Razi et al., 2022; Morakchi et al., 2023) integration of IoT for optimizing the data logging through accelerometer. In the field of health management, such as in (Arbi et al., 2024), the Constrained Linear Model Predictive Controller (CLMPC) suggests a method suitable for smartphone applications in diabetes self-management. Furthermore, in (Ghemari et al., 2022; Razi et al., 2022) parameter optimization used to enhance accelerometer performance and its influence on vibratory analysis. Lastly, (Djeffal et al., 2023, 2024) using of Artificial Intelligence such as deep learning and PSO to optimize the continuum robot. While the integration of Neural Networks with the Taguchi method for project deadline predictions remains limited, our study proposes a novel approach to address this gap. By combining a neural network with the Taguchi method, we estimate project deadlines effectively. Using artificial neural
networks, we model the project’s average total duration obtained from simulation data, considering input variables like success probability, effort and learning factors. This integrated method simulates project duration, focusing on critical data during the design phase. The method simulates project average total duration using Neural Networks with inputs such as success probability and learning factors, and outputs focusing on critical project duration data during the design phase. Simulation results are then modeled and validated using advanced neural network configurations, demonstrating the potential of this integrated approach to streamline project management and optimize outcomes. The remainder of this paper is organized as follows: Section 2. provides an overview of activity network modeling and the simulation techniques used for predicting project deadlines. Section 3. discusses the modeling approach used in this study, focusing on project duration prediction using ANN. Section 4. provides details the application of Taguchi method and discusses the results of this optimization. Section 5. details the application of Taguchi method and discusses the results from this optimization. Finally, The Section 6. reviews the potential of ANN method for predicting project deadlines and evaluates its effectiveness through Mean Squared Error (MSE) analysis, highlighting how errors are minimized using the Taguchi method.

2 ACTIVITIES NETWORK MODELING

This section introduces a model for activity network process modeling. It involves a sequence of activities, each connected through feedback loops and iterative cycles. The model explores various paths for transitioning between activities and revisiting previous ones as it is depicted in Algorithm 1.
In project management, understanding the flow of tasks and the relationships between different components is crucial for success. The Work Breakdown Structure (WBS) is a fundamental tool used to decompose a project into manageable components, allowing for better planning, organization, and execution. Figure 1 illustrates the hierarchical structure of project management components, starting from the initial demand and progressing through the Statement of Work (SOW), WBS, project networks, and finally, performance.

Figure 1. Horizontal Diagram with Different Colors, Focusing on“Project Networks” and“Performance”

Source: The authors

<table>
<thead>
<tr>
<th>Algorithm 1</th>
<th>Data Processing and Evaluation (ANN with MATLAB nntool)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1: Load data</td>
<td>▶ Inputs : (PS), (E), (LF), Output : average total duration (see figure 2)</td>
</tr>
<tr>
<td>2: Set trainRatio to 0.7</td>
<td></td>
</tr>
<tr>
<td>3: Set valRatio to 0.1</td>
<td></td>
</tr>
<tr>
<td>4: Set testRatio to 0.2</td>
<td></td>
</tr>
<tr>
<td>5: for mm from 1 to 6 do</td>
<td></td>
</tr>
<tr>
<td>6: Divide data randomly into training data (traindata), validation data (valdata), and test data (testdata) based on trainRatio, valRatio, and testRatio</td>
<td></td>
</tr>
<tr>
<td>7: Combine traindata and valdata</td>
<td></td>
</tr>
<tr>
<td>8: for each combination of transfer functions (LOGSIG, PURELIN, and TANSIG), neuron numbers (9, 10, and 18), and learning functions (TRAINLM, TRAININGDM, and TRAINBR) provided by nntool, MATLAB software: do</td>
<td></td>
</tr>
<tr>
<td>9: Predicted MSE values using the Taguchi method</td>
<td></td>
</tr>
<tr>
<td>10: Create the neural network net with input and output layers based on training data, and the specified number of neurons</td>
<td></td>
</tr>
<tr>
<td>11: Train the neural network net using traindata</td>
<td></td>
</tr>
<tr>
<td>12: Simulate net with testdata to get predictions pred2</td>
<td></td>
</tr>
<tr>
<td>13: Calculate the MSE using predictions pred2 and actual values from testdata</td>
<td></td>
</tr>
<tr>
<td>14: end for</td>
<td></td>
</tr>
<tr>
<td>15: end for</td>
<td></td>
</tr>
<tr>
<td>16: Save results to rhendebih.mat</td>
<td></td>
</tr>
<tr>
<td>17: Save data to data1.mat</td>
<td></td>
</tr>
<tr>
<td>18: Plot figure 3, which illustrates the effects of different parameter levels on the mean squared error (MSE) in the system.</td>
<td></td>
</tr>
<tr>
<td>19: Plot figure 4, which estimates the main effect for the S/N ratio for each parameter at three levels.</td>
<td></td>
</tr>
</tbody>
</table>

Source: The authors
2.1 MODEL AND PROCESS PARAMETERS

This paper details a model of an activity network with 100 sequential activities. This model is explored as an illustrative example.

2.1.1 Duration of Activities

Activity durations are not fixed but are indicated by a range between two endpoints. Temporal metrics like the sum, average, and variance of durations are used. Uncertainties in activity durations are modeled using probability distributions such as the Beta distribution, reflecting common project delays and the natural inclination for relaxation periods. Specifically, the triangular distribution is used for its simplicity and relevance, requiring three values for each activity: optimistic, probable, and pessimistic.

2.1.2 Activity Success

Each activity has an assigned probability of success. This accounts for potential disturbances that may prevent activities from meeting their specifications. These probabilities can be represented by various distributions or discrete values.

2.1.3 Activity Failure

Failure of an activity prompts a reconsideration or reevaluation. A secondary probability enables choosing an alternative path for correction.

The document describes a matrix showing the probability of regressing in the process. This 100×100 matrix includes diagonal values set to 1, with each row below the diagonal showing progressively decreasing probabilities, representing the likelihood of stepping back to prior stages.
3 GENERAL STEPS FOR CREATING THE PRC MATRIX

3.1 INITIALIZATION OF THE PRC MATRIX

• define a square matrix PRC of size $n \times n$, where $n$ is the total number of activities;
• initialize the main diagonal of the matrix with values of 1, as each activity has a certain probability of executing itself;
• initialize all elements above the main diagonal with values of 0, as there is no reconsideration towards future activities in a lower triangular matrix.

3.2 CALCULATION OF RECONSIDERATION PROBABILITIES

• for each activity $i$ from 2 to $n$;
• for each activity $j$ from 1 to $i-1$;
• calculate the reconsideration probability from activity $i$ to activity $j$ using a defined rule. For example, the probability can be calculated as:

$$PRC (1)$$

3.3 VISUALIZATION AS A FLOW DIAGRAM

• represent each activity as a node in a flow diagram;
• add arrows to indicate backflows between activities with the calculated probabilities;
• each node should have a self-loop indicating a probability of 1 for the certain execution of the activity.
4 GENERAL ALGORITHM FOR CREATING THE PRC MATRIX

4.1 INITIALIZATION OF THE PRC MATRIX:

The provided pseudocode initializes a Probability of Reconsideration (PRC) matrix of size n × n. First, it creates an empty matrix and sets the main diagonal elements to 1, indicating that each activity is certain to execute itself. Then, it sets all elements above the main diagonal to 0, ensuring that there are no reconsiderations from an activity to any future activity. This initialization establishes the PRC matrix with 1s on the diagonal and 0s in the upper triangular part, preparing it for the subsequent calculation of reconsideration probabilities in the lower triangular part.

Initialize a matrix PRC[n][n] For i from 1 to n:
PRC[i][i] = 1 For i from 1 to n:
For j from i+1 to n: PRC[i][j] = 0 Calculation of Reconsideration Probabilities
For i from 2 to n:
For j from 1 to i-1:
PRC[i][j] = 1 / (i – j + 1)
Representation as a Flow Diagram:

• create a node for each activity;
• add backflow arrows to represent the reconsideration probabilities between activities.

4.2 PROCESS PARAMETERS

A table presents simulation data on the average total duration of the project, listing success probabilities factors influencing effort and learning. The simulation sequences for the average total duration of projects are described by varying levels of success probability (PS), effort (E), and learning factor (CofA). At Level 1, the success probability is 0.795, the effort is 0.00, and the learning factor is 0.6. At Level 2, the success probability increases to 0.825, the effort is 0.05, and the
learning factor is 0.8. Finally, at Level 3, the success probability reaches 0.950, the effort is 0.10, and the learning factor is 1.0.

4.3 DATA STANDARDIZATION

For applying Artificial Neural Networks (ANN) to the data, it is essential to standardize input and output values due to the sensitivity of learning algorithms to data scale. ANN does not require the data’s mathematical description, offering a significant advantage over traditional methods. Data normalization is performed using a specific equation, and the MLP Neural Network Model is implemented in MATLAB, demonstrating both training and testing phases.

5 ARTIFICIAL NEURAL NETWORK

Artificial neural networks (ANNs) are inspired by the human nervous system and have become fundamental in various applications due to their ability to learn from data. These networks are capable of extracting rules and patterns, enabling them to perform tasks such as classification, pattern recognition, and forecasting. A unique advantage of neural networks over other techniques is their ability to simulate a network model and apply it to new, unseen data.

MATLAB offers a robust toolkit for neural network modeling called the Neural Network Toolbox (NNT). This toolbox includes tools for creating, training, and testing neural networks to classify data, uncover hidden patterns, and forecast future outcomes. Although other software like SPSS also offers neural network tools, MATLAB’s Neural Network Toolbox is preferred for its comprehensive feature set.

5.1 PROJECT AVERAGE TOTAL DURATION MODELING USING ARTIFICIAL NEURAL NETWORKS (RDN)

The RdN technique, implemented through ANNs, is extensively used for various scientific and technical applications including model reorganization and
process control. ANNs mimic the processing capabilities of the human brain, which allows for effective behavior modeling and simulation.

Using MATLAB’s Neural Network Toolbox, an ANN model was developed to predict the average total duration of projects. This model is structured with three inputs and one output. The inputs include the probability of success (PS), the effort (E), and the learning factor (LF), while the output is the average total project duration (DTMP). Data from 27 simulation results were used to train the network, which is depicted in Figure 2. The network uses a forward-feeding structure with two hidden layers.

Neural networks utilize various functions to facilitate data processing, including linear transfer and sigmoid functions, defined by the following equations:

1. Linear Transfer Function (Purelin):

   \[ \text{Purelin}(x) = x \]  

2. Sigmoid Function:

   \[ \text{logsig}(x) = \frac{1}{1 + e^{-x}} \]

3. Hyperbolic Tangent Sigmoid Function (Tansig):

   \[ \text{tansig}(x) = \frac{2}{1 + e^{-2x}} - 1 \]
These functions handle the input data as it passes through the network layers.

One of the critical tasks for ANN designers is selecting the number of neurons and layers. The network’s effectiveness is gauged by the mean squared error (MSE), which is minimized during training. The MSE is calculated as shown below:

\[
\text{MSE} = \frac{1}{Q} \sum_{k=1}^{Q} (t(k) - y(k))^2
\]

Here, \( e(k) \) represents the error between the target and the ANN output, \( t(k) \) is the target, \( y(k) \) is the output from the ANN, and \( Q \) is the total number of data points.

6 TAGUCHI METHOD

The Taguchi method is a structured approach widely recognized for optimizing processes and designing high-quality systems. It is particularly favored by engineers and scientists for its simplicity and effectiveness in experiment design, even for those with limited statistical knowledge. This method helps to achieve products and processes that are less sensitive to variations, thereby enhancing quality while reducing development and manufacturing costs. Key tools in this approach include the signal-to-noise (S/N) ratio and orthogonal arrays.

6.1 TAGUCHI ANALYSIS

The signal-to-noise ratio is categorized into three types based on the characteristics being continuous:

a) rating value;
b) minimum value;
c) maximum value.

Where:
- S/N represents the signal-to-noise ratio;
- \( n \) is the number of simulations;
y is the obtained value of project average total duration.

<table>
<thead>
<tr>
<th>Level</th>
<th>Transfer Function</th>
<th>Neurons Number</th>
<th>Training Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>LOGSIG</td>
<td>9</td>
<td>TRAINLM</td>
</tr>
<tr>
<td>2</td>
<td>PURELIN</td>
<td>10</td>
<td>TRAINGDM</td>
</tr>
<tr>
<td>3</td>
<td>TANSIG</td>
<td>18</td>
<td>TRAINBR</td>
</tr>
</tbody>
</table>

These combinations of three transfer functions (LOGSIG, PURELIN, and TANSIG), neuron numbers (9, 10, and 18), and learning functions (TRAINLM, TRAINGDM, and TRAINBR) facilitated by the MATLAB nnTool, have enabled the prediction of MSE values.

To further demonstrate the quality of the models, simulation results are presented, allowing for an in-depth analysis of model robustness and predictive accuracy.

The Figure 3 illustrates the effects of various parameter levels on the mean squared error (MSE) in the system. The x-axis represents the parameter levels, while the y-axis measures their corresponding effect on the MSE.
Key observations include:

- the parameter levels exhibit cyclical patterns of peaks and troughs, indicating that certain parameters consistently have higher effects on the MSE than others;
- peaks around parameter levels 2, 7, 12, 17, and 22 show the highest effects, with values close to 0.027 and 0.029, highlighting their significant contribution to increasing the MSE;
- the troughs, where the effect dips below 0.005, indicate parameter levels with minimal influence on the MSE, suggesting these factors contribute less to overall variability;
- the plot underscores the variability in the impact of different parameter levels, suggesting that some parameters are much more influential in affecting the MSE than others.

In summary, the plot emphasizes the importance of identifying and prioritizing the high-impact parameters (those corresponding to the peaks) for intervention to effectively reduce the MSE and improve system performance. Meanwhile, parameters with minimal effects can be deprioritized, allowing for a more focused and efficient approach to quality improvement.

Table 3. Average Values of Average Total Duration Across Different Levels

<table>
<thead>
<tr>
<th>Levels</th>
<th>A</th>
<th>B</th>
<th>AB</th>
<th>C</th>
<th>AC</th>
<th>BC</th>
<th>ABC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0271</td>
<td>0.0065</td>
<td>0.0007</td>
<td>0.0034</td>
<td>0.0004</td>
<td>0.0040</td>
<td>0.0058</td>
</tr>
<tr>
<td>2</td>
<td>0.0075</td>
<td>0.0255</td>
<td>0.0273</td>
<td>0.0246</td>
<td>0.0292</td>
<td>0.0245</td>
<td>0.0264</td>
</tr>
<tr>
<td>3</td>
<td>0.0028</td>
<td>0.0054</td>
<td>0.0093</td>
<td>0.0093</td>
<td>0.0078</td>
<td>0.0088</td>
<td>0.0051</td>
</tr>
</tbody>
</table>

Source: The authors

For more clarity the results of Figure 4 are presented in Table 3.
Figure 4. Average Values of S/N Ratio for Each Parameter at Different Levels

The simulated results for average total duration values for each parameters are depicted in Figure 3 according to their effect. While Figure 4, estimation of the main effect for S/N ration for each parameters in three levels.

<table>
<thead>
<tr>
<th>Levels</th>
<th>A</th>
<th>B</th>
<th>AB</th>
<th>C</th>
<th>AC</th>
<th>BC</th>
<th>ABC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>59.37</td>
<td>61.88</td>
<td>67.90</td>
<td>63.32</td>
<td>77.86</td>
<td>64.66</td>
<td>64.73</td>
</tr>
<tr>
<td>2</td>
<td>62.12</td>
<td>59.89</td>
<td>57.94</td>
<td>55.91</td>
<td>47.27</td>
<td>61.82</td>
<td>51.77</td>
</tr>
<tr>
<td>3</td>
<td>57.29</td>
<td>57.02</td>
<td>52.96</td>
<td>59.55</td>
<td>53.66</td>
<td>52.31</td>
<td>62.28</td>
</tr>
</tbody>
</table>

Source: The authors

Similarly, For more clarity the results of Figure 5 are presented in Table 4.
The polar plot as it is shown in Figure 5 highlights that AC2, AB2, and A1 have the largest contributions to system variability, with AC2 being the most impactful. ABC2, B2, and C2 also significantly affect variability but to a lesser extent. Moderate contributions come from C3, AB3, BC3, AC3, A2, and B1, while ABC1, B3, ABC3, BC1, C1, A3, AB1, and AC1 show minimal impact. Targeting AC2, AB2, and A1 for quality improvements would effectively reduce overall variability, with additional focus on ABC2, B2, and C2 to ensure comprehensive management. Lower impact parameters can be deprioritized for immediate intervention.

7 CONCLUSION

In the realm of engineering, artificial neural networks (ANNs) stand tall as formidable predictive tools, their efficacy underscored by this study’s successful application. By harnessing ANNs and simulation data, this research crafts a
predictive model adept at estimating the average total duration of projects. Through meticulous consideration of crucial parameters like the probability of success and effort factors, the model emerges as a beacon of accuracy within the design domain.

The integration of mean squared error (MSE) values into the Taguchi method serves as a strategic move to refine the neural network’s predictive prowess. The minimum values observed, such as 0.0028 for Level 3 in A, 0.0054 for Level 3 in B, and 0.0007 for Level 1 in AB, highlight the effectiveness of parameter optimization. Similarly, the maximum values observed, such as 62.12 for Level 2 in A, 61.88 for Level 1 in B, and 67.90 for Level 1 in AB, demonstrate the robustness of the ANN model under various parameter configurations.

This synergistic approach not only mitigates errors but also amplifies the model’s reliability in forecasting project durations. Looking ahead, the trajectory of research is poised to explore a myriad of avenues, from delving into the nuanced effects of additional parameters on activity networks to scrutinizing alternative transfer functions. These endeavors are driven by an unwavering commitment to bolstering predictive accuracy and fortifying the model’s resilience against real-world complexities.

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