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RESEARCH ARTICLE

# Reliable Time Contingency Estimation Based on Adaptive Neuro-Fuzzy Inference System in Construction Projects

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**ABSTRACT** Project scheduling is one of the most essential processes and plays a critical role in determining the success of construction projects. The reliable time contingency enables project planners to effectively address uncertainties and various types of risks that may affect the project duration. The traditional scheduling technique such as deterministic methods and probabilistic methods may not be suitable when used for planning construction projects with uncertainties and risks. This paper proposes a new framework that integrates risk management into project scheduling to establish a more reliable project schedule. The proposed model adopts the adaptive neuro-fuzzy inference system (ANFIS) called the ANFIS-TOOL to model the possibility of risk occurrences integrated with project scheduling in terms of risk lag time (ANFIS-RLT) to generate risk-integrated project duration (RPD). The learning capabilities of adaptive neural networks are utilized to adjust the parameters of the model according to the fuzzy rules, aiming to achieve the most suitable representation of the model. In a real-life case study, a sheet pile wall with a temporary bracing system (SPBS) was applied to demonstrate the application of this technique. The root mean square error (RMSE) was used to validate the accuracy of the model before being applied to real construction projects with a high degree of accuracy. This model can be used as an excellent tool to generate a more reliable schedule baseline in construction projects.

**INDEX TERMS** Adaptive neuro-fuzzy inference system, risk management, time contingency, scheduling.

## I. INTRODUCTION

Project scheduling plays an important role in determining the success of construction projects. Due to uniqueness and complication, construction projects are normally confronted with various types of risks and uncertainties such as labor and machine availability, weather condition, technical accessibility, environmental issues, and other types of risks that may affect the project's accomplishment [1], [2], [3], [4], [5], [6]. Therefore, the process of establishing reliable project scheduling in such risky and uncertain conditions is a major challenge for the project teams.

Many construction engineers endeavor to develop reliable project scheduling techniques, which have the ability to handle risks and complete tasks on time (Contractual deadline). These techniques are necessary to apply effective tools which have the ability to incorporate information from expert judgment and risk management into the project scheduling procedure to deal with risks and uncertainties. However, the present construction scheduling and planning process depends on deterministic methods, such as the Gantt chart (Bar chart) and critical path method (CPM). A Gantt chart is one of the early tools for project scheduling [7]. Although the Gantt chart is widely used for projects with less complexity because of its simplicity, it may not be appropriate for larger or more complex projects. Thus, CPM was developed to use in a wide range of types in construction projects. CPM has been commonly used in practice because of its ability to explain the dependency relationships between activities, finding critical activities or float times, and has been widely

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used by most project management software. However, for more complex or large projects, CPM had been extensively criticized as inadequate in dealing with uncertainties in construction projects [8], [9].

Uncertainty in construction projects is an interesting issue that should be considered in project scheduling. The program evaluation and review technique (PERT) and Monte Carlo simulation (MCS) are probabilistic methods that have been proposed as a supplement to the CPM to operate with uncertainty in construction projects. Activity durations are viewed as random variables that can be represented by probability distributions in both PERT and MCS [9], [10], [11]. Furthermore, to produce the probability density functions, probabilistic methods require historical project information. This procedure is quite impractical because it requires significant time and effort. Using probability theory, the PERT incorporates uncertainty in activity duration [12]. The standard deviation, expected mean duration, and variances for network calculations are calculated using three-time estimates: the optimistic, the most likely, and the pessimistic time estimate. The PERT network calculation is executed in a procedure similar to the CPM calculation. However, this method tends to result in optimistic schedules [13], [14]. Therefore, MCS approach has been developed to overcome this constraint and used to simulate the risk analysis of cost and time in construction applications. With this technique, random variables are implemented as inputs to the modeled systems [15]. This approach is dependent on probabilistic and statistical modeling methods that simulate the randomness of the situation. Estimation of the probability that a specific activity is on the critical path can also be provided by MCS. However, it is a simulation-based process that requires an extensive amount of effort and calculation to reach a reliable output.

Techniques for probabilistic scheduling have been criticized for insufficiency and failing to consider nonrandom uncertainty [16], [17]. Additionally, each project has unique attributes that affect the possibility of risk occurrence and its effects. The historical information that is currently accessible might not be related to the project under consideration or future judgment [18]. In reality, most project planners and experienced experts generally use their knowledge and experiences to determine the activity durations. Thus, fuzzy set theory (FST) has been introduced as an efficient substitute for the random modeling of uncertainty. It is a very effective method because it is more proficient to collect and express the necessary information from experts by accurately capturing their subjectivity, vagueness, and uncertainty in linguistic assessments [19], [20]. Furthermore, compared to the probabilistic technique, the calculations required are significantly faster and less complicated. However, using fuzzy logic alone has limitations when attempting to address various aspects of a construction project management issue. As a result, hybridized fuzzy logic is used by construction researchers to strengthen their abilities in executing dynamic modeling and computation operations [2].

To overcome the limitations of using fuzzy logic alone by applying fuzzy hybrid machine learning, an adaptive neuro-fuzzy inference system (ANFIS) has been developed by Jang [21]. ANFIS incorporates the advantages of an artificial neural network (ANN) with fuzzy inference system (FIS). While ANN has the ability for self-learning, FIS can deal with information in fuzzy language and simulate human brain judgment and decision-making. The learning capabilities of adaptive neural networks are utilized to adjust the parameters of the model according to the fuzzy rules, aiming to achieve the most suitable representation of the model. This process enhances the prediction accuracy and reliability of the model. Furthermore, ANFIS has the ability to deal with uncertainty, vagueness, nonlinearity, and complicated problems which are involved in most construction project management [22], [23].

This study aims to develop a framework that integrates risk management into project scheduling to establish a more reliable project schedule. The ANFIS-TOOL is employed to model the possibility of risk occurrence needed to estimate time contingency affected by risks. The estimation of time contingency, considering risk events and risk factors, is assessed at the activity level. In a real-life case study, a sheet pile wall with a temporary bracing system (SPBS), a soil protection system, is applied to demonstrate the application of this technique.

## II. BACKGROUND AND RELATED WORK

### A. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

ANFIS has been applied in a wide range of construction and civil engineering; however, there is limited research on its application in construction management, especially in the field of project scheduling estimation. For instance, Zhang et al. [24] proposed an ANFIS-based method for predicting the ultimate bearing capacity of single precast reinforced concrete piles, 42 examples of them were collected: 37 examples of them were used for training, and the remaining 5 examples were used for testing the accuracy of prediction. The result indicated that ANFIS could give a high precision prediction. Ebrat and Ghodsi [25] adopt ANFIS to create an intelligent approach to evaluate the main risk factors of construction projects in Iran. The designed model can apply to both quantitative and qualitative factors, learn from experience and historical data, and infer knowledge of future situations by self-learning and updating. Jin [26] developed ANFIS models that are capable of forecasting effective risk-allocation strategies for publicly financed infrastructure projects at a higher degree of accuracy than multiple linear regression models and fuzzy inference systems. Azamathulla and Ghani [27] presented the use of ANFIS to estimate the scour depth at culvert outlets. When compared to the results of regression equations and artificial neural network modeling, the performance of ANFIS was found to be more effective. Najafzadeh et al. [28] used ANFIS model to predict scour depth below pipelines exposed to waves and compared the performance with other techniques, e.g., the group method of data handling (GMDH), the model tree (MT), and empirical equation. Najafzadeh and Azamathulla [29] developed the model called the neuro-fuzzy based group method of data handling (NF-GMDH) was applied to predict the scour process at pile groups due to waves. Azimi et al. [30] used ANFIS, a hybrid of ANFIS system, a genetic algorithm (ANFIS-GA) to estimate the discharge coefficients of side orifices. Chen et al. [31] developed a structural safety evaluation system for in-service tunnels by using ANFIS and the results demonstrated that the evaluation system had high implementation and learning capabilities. Li et al. [32] designed a model based on ANFIS to predict and estimate curtain grouting efficiency, the essential process for improving dam foundations to reduce the deformability of rock masses. Moghayedi and Windapo [23] used an ANFIS, a dependable, and precise advanced machine learning technique, which has been developed based on the data acquired to analyze the influence of uncertainty events on the complete duration of highway construction projects.

More recently, Madani et al. [33] developed techniques and demonstrated a comparison of ANFIS, artificial neural network (ANN), and traditional regression methods in predicting the strength of cementitious mixes. According to the results, ANN and ANFIS performed better than regression analyses. Hasanipanah et al. [34] proposed a new method that integrated the firefly algorithm (FA) for training and optimizing the consequent parameters of the ANFIS, called the ANFIS-FA model, in order to predict the tensile strength of rock. According to the results, the ANFIS-FA can be utilized as a reliable model. Elbaz et al. [35] presented a new model to predict the earth pressure balance (EPB) shield performance during tunneling by integrating an improved particle swarm optimization (PSO) with ANFIS based on the fuzzy C-mean (FCM) clustering method. The results indicated that the improved PSO-ANFIS model showed high precision in predicting the EPB shield performance. Chen et al. [36] applied satin bowerbird optimizer (SBO) algorithms and the teaching-learning-based optimization (TLBO) to optimize the ANFIS model for landslide susceptibility mapping and a total of 152 landslides were identified and randomly separated into two datasets: training (70%) and testing (30%). Onyelowe et al. [37] proposed ANFIS hybrids to predict coefficients of curvature and uniformity of treated unsaturated lateritic soil for sustainable earthworks. Dastgheib et al. [38] employed ANFIS as an effective prediction tool for estimating the completion cost of projects by incorporating the level of risk for qualitative variables into account and comparing it to other types of neural networks. By considering the uncertain conditions, this study enhanced the general estimation of the completion cost formula and the results demonstrated that ANFIS performed an excellent method. Szafranko et al. [39] proposed a new method called CUDA-ANFIS that integrated the ANFIS algorithm with the compute unified device architecture (CUDA) technology to solve problems involved in the evaluation of variants of construction projects, based on the opinions of experts. Peng et al. [40] developed models to apply ANFIS for the prediction and optimization of the flexural behavior of concrete members damaged by corrosion and 107 concrete members were selected to estimate the inputs. The models demonstrated an excellent connection in support of the accuracy of the ANFIS. Based on previous research, it was found that ANFIS has been widely used in civil engineering research and construction, especially in research related to prediction, demonstrating the accuracy and effectiveness of this technique.

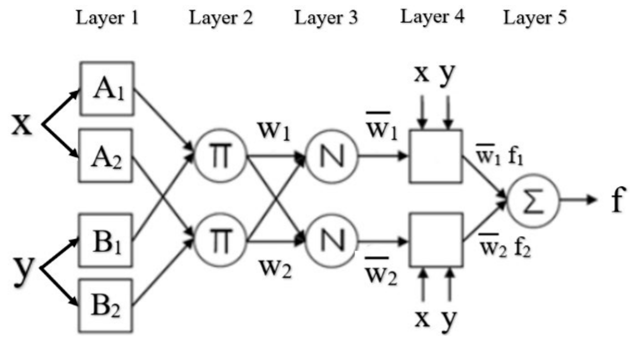

FIGURE 1. ANFIS architecture.

Jang [21] introduced a learning procedure and architecture for constructing a set of fuzzy IF-THEN rules with appropriate membership functions for Fuzzy Inference Systems (FIS) using a neural network learning algorithm and specified input-output pairs. This approach is known as the Adaptive network-based fuzzy inference system (ANFIS). The hybrid learning algorithm, which combines gradient descent and the least-squares method, was introduced to rapidly calibrate and adapt the equivalent fuzzy inference system.

The input in ANFIS is converted into fuzzy membership functions and then combined, with the output membership functions obtained through an averaging process to achieve the desired output. ANFIS assumes a fuzzy inference system under consideration with two inputs (x and y) and one output (z) for the first-order Sugeno fuzzy model, with a common rule set comprising two fuzzy rules used to implement the if-then rules as follows [21]:

$$\text{Rule 1: If } x \text{ is } A_1 \text{ and } y \text{ is } B_1, \text{ then } f_1 = p_1 x + q_1 y + r_1 \tag{1}$$

$$\text{Rule 2: If } x \text{ is } A_2 \text{ and } y \text{ is } B_2, \text{ then } f_2 = p_2 x + q_2 y + r_2 \tag{2}$$

where $p_1, p_2, q_1, q_2, r_1$, and $r_2$ are linear parameters and $A_1$, $A_2$, $B_1$, and $B_2$ are non-linear parameters. The ANFIS architecture consists of five different layers as shown in Fig. 1 [21]. A circle indicates a fixed node whereas a square indicates an adaptive node that parameter is modified during the training or adaptation process.

Layer 1: Nodes in this layer are adaptive node with a node function:

$$O_{1,i} = \mu_{Ai}(x) \tag{3}$$

where $x$ is the input value of $A_i$ node and $A_i$ is linguistic labels. $O_{1,i}$ is the membership function of linguistic variable $A_i$. Any suitable parameterized membership function, such as the generalized bell function [30], [41], may be used as the membership function as follows:

$$\mu_{Ai}(x) = \frac{1}{1 + \left|\frac{x-c_i}{a_i}\right|^{2b_i}} \tag{4}$$

where $a_i, b_i, c_i$ is the function parameter. Changing values of these parameters makes the bell-shaped function varies accordingly and thus, exhibiting various form of membership function for fuzzy set A. Parameters in this layer are referred to as premise parameters.

Layer 2: Each node in this layer is a fixed node designated with the labeled II, and its output is the product of all the incoming signals. Each node output represents the firing strength of a rule:

$$O_{2,i} = w_i = \mu_{Ai}(x)\,\mathrm{x}\,\mu_{Bi}(y), \quad i = 1, 2 \tag{5}$$

Layer 3: Each node in this layer is a fixed node labeled N. In this layer, the ratio of the intensity of the $\mathrm{i}^{\mathrm{th}}$ rule to the intensity of all rules is calculated as follows:

$$O_{3,i} = \bar{w}_i = \frac{w_i}{W_1 + W_2}, \quad i = 1, 2 \tag{6}$$

Layer 4 Every node $i$ in this layer is an adaptive node with node function:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i), \quad i = 1, 2 \tag{7}$$

where $\bar{w}_i$ is a normalized firing strength form layer 3 and $p_i, q_i, r_i$ is the parameter set of this node. Parameters in this layer are referred to as consequent parameters.

Layer 5: There is the only one node in this layer is a fixed node labeled $\sum$, which computes the final output parameter as the sum of all input signals as follows:

$$\text{Overall output} = O_{5,i} = \sum\nolimits_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{8}$$

Technical skills and knowledge of experts in the data set of this system were used for training ANFIS. In this study, the training data will use randomly select from 90% of all data and the remaining 10% will be used for testing the system. The performance of the ANFIS model is validated in terms of the traditional statistical measures, Root Mean Square Error (RMSE) is given below [27], [28], [29], [30].

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(o_i - t_i)^2}{N}} \tag{9}$$

where $t_i$ denotes the value of possibility prediction from ANFIS, while $o_i$ denotes the value of possibility prediction from experts, and $N$ = number of scenarios.

### B. ESTIMATION OF TIME CONTINGENCY

In construction projects, time contingency is a duration considered within the schedule baseline allocated to accommodate identified risks [8]. It can be applied to enhance the flexibility of a schedule that some activities are subject to risk. Time contingency is used to guarantee that the completion of the project will meet the contractual deadline [42], [43]. Because each construction project has unique characteristics, the process of assessing time contingency is one of the most challenging tasks for a project team to complete. The information relating to those risks may not be accessible or entirely comprehended at the time of estimation. In addition, the experiences of project teams and knowledge of the circumstances surrounding the execution of project operations are typically used to estimate time contingency. Generally, time contingency is estimated in different types of techniques. In reality, contractors allocate a portion of the total contract duration as a time contingency. For instance, time contingency can be established through subjective assessments, where individuals rely on their intuitive judgments. When employing subjective judgment, a time buffer of 25-50% of the overall project duration can be arbitrarily allocated and incorporated into the baseline schedule [44]. This buffer is meant to account for uncertainties that may arise during the estimation of the total project duration. In addition, Park and Peña-Mora [42] estimated 20% of the project duration is a schedule contingency and 50% of the schedule contingency can be used for reliability buffering. They developed an effective construction plan that protects against uncertainties by minimizing the possible impact of construction changes using reliability buffering, a simulation-based buffering technique. Furthermore, Zayed et al. [45] develop a model to estimate time contingency using deterministic and simulation-based approaches. The result showed that time contingency is estimated to be 33.70% of the project duration and it is almost 92.50% close to the time contingency of the case study projects.

Critical chain project management (CCPM), an alternate scheduling technique, was created as a result of the application of the theory of constraints (TOC) to project management. The CCPM has been extended and refined several times, and it is being used increasingly in construction scheduling [46], [47]. There are three types of buffers are used: the project buffer (PB), the feeding buffer (FB), and the resource buffer (RB). The project buffer (PB) is placed at the end of the critical chain to prevent the entire project from being delayed. The feeding buffer (FB) is included in the noncritical activities feeding into the critical chain to avoid noncritical activities from delaying those on the critical ones. The resource buffer (RB) is prepared to prevent the critical chain from the lack of critical resources. Typical methods for determining the sizes of these buffers include the cut and paste method (C&PM) and the root square error method (RSEM) [48], [49]. However, some researchers have argued that these types of buffers are insufficient for producing sufficiently reliable schedules for determining various uncertainties and other techniques have been suggested to overcome this limitation [48]. Zhao et al. [49] introduced an innovative critical chain method (ICCM) for project planning and control that integrates genetic algorithms (GA) and fuzzy approaches. The critical chain can be identified using the GA, which is also utilized for determining the optimal start time of each activity. Ma et al. [48] presented an updated CCPM framework to improve the execution of CCPM in construction project management processes. The results demonstrated that the proposed framework performed better than the current buffer sizing approaches by producing buffers with adequate sizes against uncertainty.

Estimating time contingency in the form of a block of time at the end of the project schedule that is distributed for all project activity is not appropriate for project scheduling [8], [43]. For instance, if all parties have access to this information, it could be consumed by the earlier activities and might be exhausted before the project is completed. Thus, Barraza [43] introduced the stochastic allocation of project allowances (SAPA), a probabilistic-based method, based on Monte Carlo simulation to estimate the project time contingency and allocate this time in the activity level. However, this method is based on random variables presented by probability distributions and has been criticized for being inadequate to consider nonrandom uncertainty. To overcome this limitation, fuzzy logic has been used to account for nonrandom uncertainty. Pawan and Lerterapong [8] proposed a new approach for evaluating the time contingency necessary for activities exposed to different risks by using fuzzy set theory. They incorporated fuzzy set theory and risk management to model imprecision and vagueness associated with the impact of risks on activity durations. However, this method does not consider the nonrandom uncertainty of the possibility of risk on activity duration. It may be utilized as a guide for developing risk management strategies in construction projects.

### C. CRITICAL PATH METHOD (CPM)

The Critical Path Method (CPM) is an extensive technique often used for project scheduling because it can present the start and end date of the project. Furthermore, it is also an easy method to understand, clearly describes the relationship of each activity, and can determine the critical lines to indicate which activities cannot be delayed. In this study, CPM has been applied with the precedence diagramming method (PDM), using arrows showing the relationship between different activities. Besides, PDM can be described into four basic types of dependencies or logical relationships between activities, finish to start (FS), start to start (SS), finish to finish (FF), and start to finish (SF). Practically, the most commonly used in project scheduling is the finish to start (FS) relationship because it is a simple format to understand. In this study, CPM was considered integrated with risks in terms of lag time (LT) which is the amount of time a successor activity will be delayed with respect to a predecessor activity [50]. This lag time is associated with risk events and risk factors for each activity called risk lag time (RLT) of activities as shown in Fig. 2.

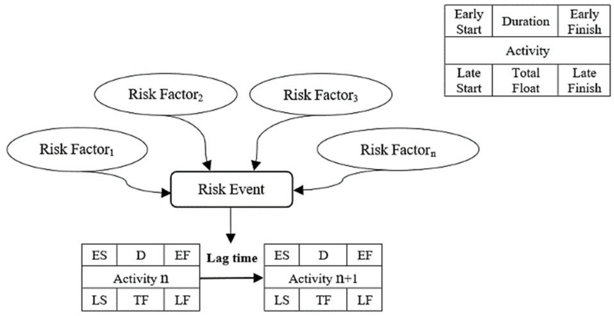


**FIGURE 2.** Integrated CPM (Finish to start) with risks.

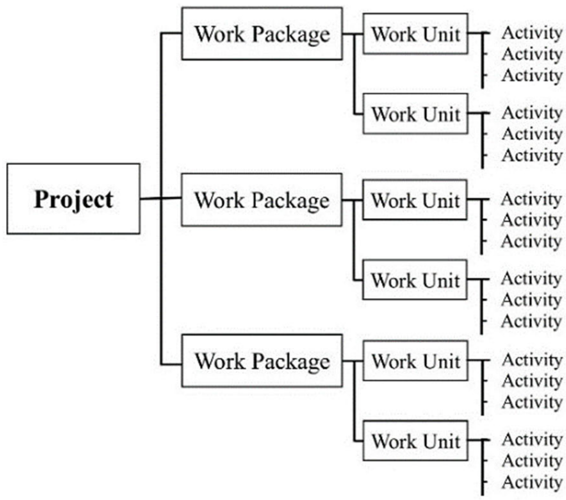


**FIGURE 3.** Work breakdown structure (WBS).

### D. WORK BREAKDOWN STRUCTURE (WBS) AND RISK BREAKDOWN STRUCTURE (RBS)

Work breakdown structure (WBS) is a systematic division of projects into smaller sub-projects in a hierarchical order to be executed by the project team in order to achieve the project objectives and more manageable components [51]. Each sub-project can be further subdivided down to the smallest level, called the activity level. Fig. 3 depicts an example of the typical structure of WBS. Generally, the structure of WBS depends on the size and complexity of each project. If a large project is established, it may consist of smaller projects. On the other hand, if a medium or small project is established, it may consist of only activities that make up a very simple structure.

Risk breakdown structure (RBS) is an essential tool that allows project managers to systematically determine various types of risks and assists the project team in considering the full range of sources from which specific project risks may develop [52]. Similar to WBS, RBS is a hierarchical diagram that divides the risks of projects, starting from the higher level and breaking down into sub-levels of risk. This

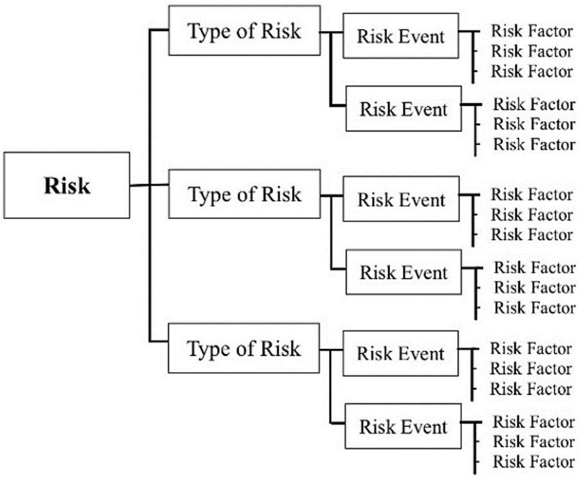


**FIGURE 4.** Risk breakdown structure (RBS).

is helpful when identifying or categorizing specific risks. The project managers may apply RBS to be used for their projects using various RBS frameworks for different types of projects. Frequently, project managers use WBS together with RBS to manage the risks associated with the projects comprehensively and systematically. Fig. 4 shows the typical structure of the risk category that may be established under the risk breakdown structure.

### E. RISK ASSESSMENT

Risk assessment is the estimation of risks that received information from risk identification and risk analysis. The results of the risk assessment analysis will be the basis for determining the guidelines for risk management that may be a result of economic conditions, industry, regulations, and operating environment. The relevance of each risk associated with each level of the organization must be considered because the operations of risk are normally changing. Therefore, good mechanisms are needed to identify and manage the risks of such changes. The risk assessment will assess the possibility and impact of the occurrence. Possibility assessment is the likelihood or frequency of an event occurring. The rating scale of the likelihood or frequency determines the ascending scale and they are different according to the nature of the risk list and the suitability of each organization. Impact assessment is the severity or damage that will occur to the project. If the risk arises, it may affect the loss of money, time, quality, and organizational values.

In this study, the quantitative risk assessment is developed from the framework that considers risk in combination with risk identification and risk analysis in order to estimate the time contingency of the project. Thus, the quantitative risk event estimation of a project in terms of risk lag time can be calculated by multiplying its possibility (P) of occurrence and its impact (I) as given in Eq. 10 [53].

$$\text{Risk (R)} = \text{Possibility(P)} \ \text{x Impact (I)} \tag{10}$$

## III. METHODOLOGY

### A. FRAMEWORK OF RESEARCH

The conceptual framework of the model was developed to establish reliable project scheduling and meet the contractual deadline. Fig. 5 illustrates the framework of this research. For the new project, the project team begins by generating a work breakdown structure (WBS) to consider all activities and the relationships among the projects. Then, the risk breakdown structure (RBS) is evaluated to determine various types of risks that may occur during the construction phase and broken down into sub-levels of risks called risk events and risk factors. The next step will be divided into two major parts: part A and part B. In part A, an ANFIS-based model is established to collect data from experts (Acquisition of data) and develop the most accurate data set for the ANFIS model (ANFIS model development). The processes of ''acquisition of data'' and ''ANFIS model development'' are detailed in the framework. Thus, the outputs of this process are called ANFIS-TOOL, which is an effective tool that has been tested for sufficient accuracy and will be used to predict the possibility of risk occurrence in part B.

In part B, risk-integrated project duration (RPD) is an important process to create a reliable time contingency for the project. This step begins with choosing activities that tend to pose risks and identifying the risk events and risk factors associated with those activities. Subsequently, risk analysis is performed by importing levels of risk factor data into the ANFIS-TOOL system in order to estimate the possibility of risk occurrences. The risk assessment process performed calculations by multiplying the possibility (P) and impact (I) of risk occurrences to calculate the ANFIS risk lag time (ANFIS-RLT) of activities. The next step combines the ANFIS-RLT with the normal project duration (PD), resulting in the risk-integrated project duration (RPD). The project teams will check whether the calculated RPD value agrees with the contract duration (CD). If the RPD value is greater than or close to the CD, then the project is likely to be delayed. Thus, risk response analysis will be introduced to mitigate the risks related to the critical activity and recalculate the above step to generate a modified RPD. When the modified RPD is less than or agrees with the contract duration (CD), the process is complete and increases the likelihood that the project will be finished on schedule.

### B. WORK BREAKDOWN STRUCTURE (WBS)

In this process, the project teams collected detailed information about the construction sequence of a sheet pile wall with a temporary bracing system (SPBS) from reviewing and brainstorming of project teams as well as the information from experts. Thus, the work breakdown structure (WBS) of SPBS can be established in Table 1.

### C. RISK BREAKDOWN STRUCTURE (RBS)

Risk Breakdown Structure (RBS) can help project planners to understand which activities are particularly risky and nec-

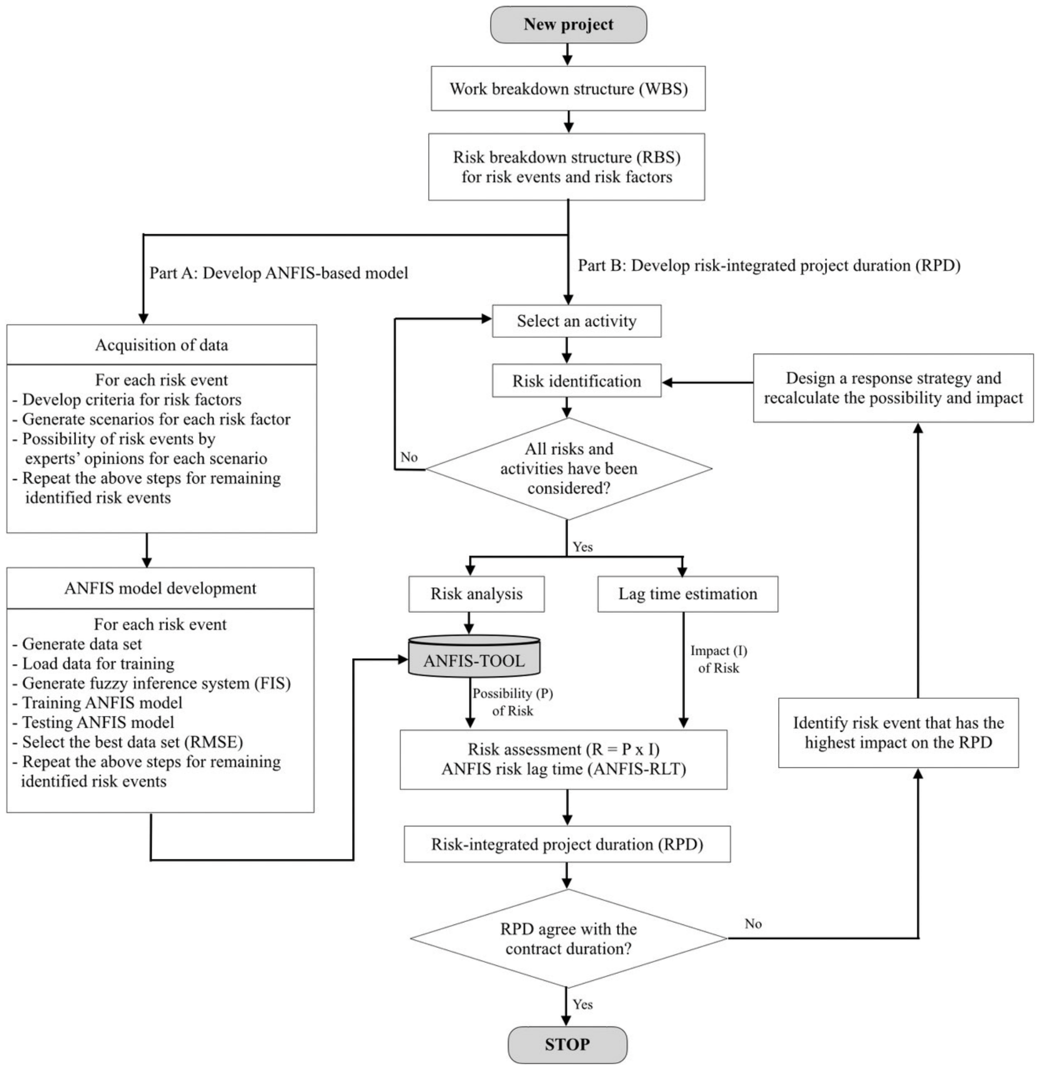


**FIGURE 5.** Framework of research.

essary to consider carefully and systematically. This process is separated into a structure similar to WBS for each activity called the risk breakdown structure (RBS), divided into types of risk, risk events, and risk factors. For a sheet pile wall with a temporary bracing system (SPBS), the RBS can be created in Table 2.

### D. ACQUISITION OF DATA

The acquisition of data is the process of developing the criteria for assessing the rating scale of each risk event based on experts' opinions. A risk factor rating scale has been prepared by using the example of "COVID-19 outbreak at the site", which consists of three risk factors: (1) Distancing and separating of staff, (2) Distancing and separating of labors, and (3) Regulation enforcement. Each risk factor can be rated as three levels. For example, (1) Distancing and separating of staff can be rated as Appropriate (value = 1), Moderate (value = 2), and Not appropriate (value = 3). (2) Distancing and separating of labors can be rated as Appropriate (value = 1), Moderate (value = 2), and Not appropriate (value = 3). (3) Regulation enforcement can be rated as Strict (value = 3), Moderate (value = 2), and Not strict (value = 3). The examples of rating scale criteria for risk factors and their descriptions are shown in Table 3 to Table 5.

This process is to collect data for use in predicting the possibility of risk occurrence. The data collection process was designed according to the terms of IF-THEN rules by setting up a situation of risk factors and receiving the information from five experienced experts who have managed soil protection system with the SPBS method for more than 20 years. The example of an event "COVID-19 outbreak at the site." which involves three risk factors: (1) Distancing and separating of staff, (2) Distancing and separating of labors, and (3) Regulation enforcement was used in this study. Rating Scales associated with each risk factor were developed. Nine scenarios for each expert and a total of forty-five scenarios

**TABLE 1. Work breakdown structure (WBS) of a sheet pile wall with a temporary bracing system (SPBS).**

| WBS | Activity | Description of Activity | Normal Duration (Days) | Previous Task |
|---|---|---|---|---|
| 1 | A | Surveying | - | - |
| 2 | B | Mobilization of machines | - | - |
| 3 | C | Install sheet piles, king posts, and platforms | - | A, B |
| 4 | D | First-layer excavation and bracing | - | C |
| 5 | E | Second-layer excavation and bracing | - | D |
| 6 | F | Third-layer excavation and bracing | - | E |
| 7 | G | Final excavation and lean concrete | - | F |
| 8 | H | Remove bracing | - | G |
| 9 | I | Foundation | - | G |
| 10 | J | RC walls and columns | - | I |
| 11 | K | Remove sheet piles, king posts, and platforms | - | H, J |

| Expert No. | Scenarios No. | Risk Event: COVID-19 outbreak at the site / Risk factors rating scale: Distancing and separating of staff | | | Distancing and separating of labors | | | Regulation enforcement | | | Expert's opinion about "COVID-19 outbreak at the site" |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Not appropriate | Moderate | Appropriate | Not appropriate | Moderate | Appropriate | Not strict | Moderate | Strict | Possibility |
| | | 3 | 2 | 1 | 3 | 2 | 1 | 3 | 2 | 1 | (0-1) |
| 1 | 1 | ✓ | | | ✓ | | | ✓ | | | 0.90 |
| | 2 | ✓ | | | | ✓ | | | ✓ | | 0.80 |
| | 3 | ✓ | | | | | ✓ | | | ✓ | 0.30 |
| | 4 | | ✓ | | ✓ | | | ✓ | | | 0.85 |
| | 5 | | ✓ | | | ✓ | | | ✓ | | 0.50 |
| | 6 | | ✓ | | | | ✓ | | | ✓ | 0.20 |
| | 7 | | | ✓ | ✓ | | | ✓ | | | 0.80 |
| | 8 | | | ✓ | | ✓ | | | ✓ | | 0.40 |
| | 9 | | | ✓ | | | ✓ | | | ✓ | 0.05 |

**FIGURE 6. Example of the expert's opinion about the possibility of the risk event "COVID-19 outbreak at the site."**

for five experts were generated to seek experts' opinions on the possibility of "COVID-19 outbreak at the site."

Possibility data for each risk factor was gathered in the form of linguistic data. This data was converted to fuzzy data. In the conversion of linguistic data to fuzzy data, each data is represented by three linguistic variables, for example, linguistic variables of Distancing and separating of staff, "Appropriate," "Moderate," and "Not appropriate," were modeled using fuzzy membership functions to capture its corresponding risk factors. Using the methodology explained for generating the rule consequences, the rule's antecedents and consequents were generated utilizing the knowledge gained from interviewing SPBS experts. The relative ranking weights of risk factors were within the different rule-based. Fig. 6 shows the example of the first expert's opinion about the possibility (value 0.00-1.00) of the risk event "COVID-19 outbreak at the site." This part can be used to generate a fuzzy rule based on nine rules for the system. Other experts also assess the same process to evaluate the possibilities of the risk events. Finally, repeat the previous steps for the remaining identified risk events.

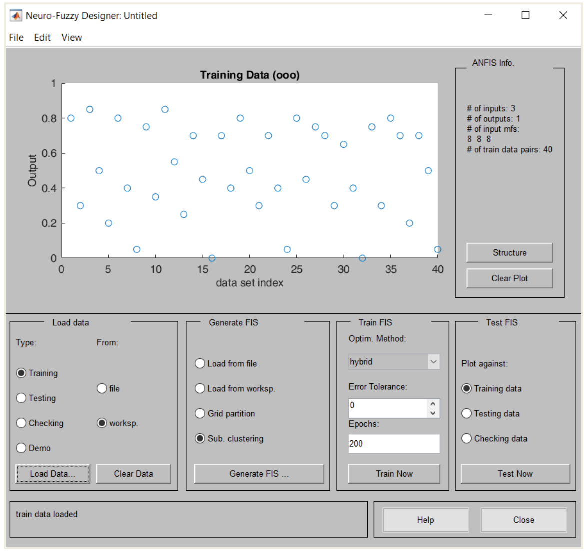


**FIGURE 7. Importing data for training in the ANFIS system.**

### *E. ANFIS MODEL DEVELOPMENT*

Developing the ANFIS model, the data was divided into 4 sets for consideration, namely A, B, C, and D. Each data set was divided into 2 parts for analysis, 90% of data for training (Training data) and the remaining 10% for testing (Testing data). For this research, MATLAB software was used to develop the ANFIS model. From the example risk event "COVID-19 outbreak at the site", a total of 45 scenarios (Table 6) from five experienced experts was separated into 40 scenarios for training (About 90%) and 5 scenarios for testing (About 10%) as shown in Table 7.

The process of training the model with the ANFIS system, utilizing MATLAB software, involves crucial steps as follows: (1) Importing the training data to be used in model creation. (2) Constructing the fuzzy inference system by determining the number and format of the membership functions and initializing the fuzzy rules. (3) Training the model to learn and adjust the membership function formats to minimize the modeling errors, using a Hybrid Learning Algorithm, until the specified number of iterations is reached. In order to provide a clearer understanding of the functioning of the ANFIS system, the researchers have presented and introduced some essential working functions utilized in this research as follows:

Import the training data into the ANFIS system by selecting "worksp." as shown in Fig. 7. Assign the variable name and choose "Generate FIS" as the Sub. clustering model. For example, the import data scenario of data set A for training was 2-9, 11-18, 20-27, 29-36, 38-45.

During the training process, existing data on technical skills and expert knowledge in the database of this system are used to train ANFIS. As a result, ANFIS is capable of accurately describing the relationship between the input and output data. In this case example, the system used three risk factors as inputs: Distancing and separating of staff,

**TABLE 2.** The risk breakdown structure (RBS) assignment of the SPBS.

| Type of Risk | Risk Event | Risk Factor |
|---|---|---|
| R1. Natural Risks | R1E1. COVID-19 outbreak at the site | R1E1F1. Distancing and separating of staff |
| | | R1E1F2. Distancing and separating of labors |
| | | R1E1F3. Regulation enforcement |
| | R1E2. Lightning | R1E2F1. Lightning protection system internal site |
| | | R1E2F2. Lightning protection system external site |
| | | R1E2F3. Lightning zone |
| | R1E3. Fire | R1E3F1. Insufficient fire protection system |
| | | R1E3F2. Fuel around site |
| | | R1E3F3. Environment Temperature |
| | R1E4. Flooding | R1E4F1. Site elevation compared with around area |
| | | R1E4F2. The amount of rainfall |
| | | R1E4F3. Drainage efficiency |
| R2. Construction and Management Risks | R2E1. Neighborhood buildings were damaged | R2E1F1. Vibration from machine |
| | | R2E1F2. Distance between site and nearby building |
| | | R2E1F3. Stability of nearby buildings |
| | R2E2. Complaints from nearby communities | R2E2F1. Noise pollution |
| | | R2E2F2. Air pollution |
| | | R2E2F3. Disturbance from workers |
| | R2E3. Difficulty in accessing the area | R2E3F1. Traffic jam |
| | | R2E3F2. Surface of the existing road |
| | | R2E3F3. Load exceeds the road capacity |
| | R2E4. Survey team error or delay | R2E4F1. Age of device |
| | | R2E4F2. Experience of survey team |
| | | R2E4F3. Out-of-date technology |
| | R2E5. Worker absenteeism | R2E5F1. Worker illness |
| | | R2E5F2. Compensation |
| | | R2E5F3. Rule and regulation |
| R3. Geological Risks | R3E1. Ground movement | R3E1F1. Vibration of machine |
| | | R3E1F2. Insufficient design |
| | | R3E1F3. Improper construction methods |
| | R3E2. Unreliable soil information | R3E2F1. Error from survey teams |
| | | R3E2F2. Unexpected underground objects |
| | | R3E2F3. Insufficient data from owner or designer |
| R4. Equipment Risks | R4E1. Mobile crane failure | R4E1F1. Inexperience of workers |
| | | R4E1F2. Carry overload |
| | | R4E1F3. Lack of maintenance |
| | R4E2. Backhoe failure | R4E2F1. Inexperience of workers |
| | | R4E2F2. Carry overload |
| | | R4E2F3. Lack of maintenance |
| | R4E3. Vibro-hammer failure | R4E3F1. Inexperience of workers |
| | | R4E3F2. Age of Machine |
| | | R4E3F3. Lack of maintenance |

**TABLE 3. Rating scale of risk factor "Distancing and separating of staff."**

| Rating Scale | Distancing and separating of staff | Description |
|---|---|---|
| 1 | Appropriate | If there is appropriate distancing and separating of staff in the site, the possibility of COVID-19 outbreak at the site is low. |
| 2 | Moderate | If there is sometimes appropriate distancing and separating of staff in the site, the possibility of COVID-19 outbreak at the site is moderate. |
| 3 | Not appropriate | If there is no appropriate distancing and separating of staff in the site, the possibility of COVID-19 outbreak at the site is high. |

**TABLE 4. Rating scale of risk factor "Distancing and separating of labors."**

| Rating Scale | Distancing and separating of labors | Description |
|---|---|---|
| 1 | Appropriate | If there is appropriate distancing and separating of labors in the site, the possibility of COVID-19 outbreak at the site is low. |
| 2 | Moderate | If there is sometimes appropriate distancing and separating of labors in the site, the possibility of COVID-19 outbreak at the site is moderate. |
| 3 | Not appropriate | If there is no appropriate distancing and separating of labors in the site, the possibility of COVID-19 outbreak at the site is high. |

**TABLE 5. Rating scale of risk factor "Regulation enforcement."**

| Rating Scale | Regulation enforcement | Description |
|---|---|---|
| 1 | Strict | If the regulation enforcement about COVID-19 disease is strict, the possibility of COVID-19 outbreak at the site is low. |
| 2 | Moderate | If the regulation enforcement about COVID-19 disease is quite moderate, the possibility of COVID-19 outbreak at the site is rather intermediate. |
| 3 | Not strict | If the regulation enforcement about COVID-19 disease is not strict, the possibility of COVID-19 outbreak at the site is high. |

Distancing and separating of labors, and Regulation enforcement. The output was the possibility of "COVID-19 outbreak at the site." The three inputs were given three Gauss membership functions. Fig. 8 shows the displayed function "Fuzzy Logic Designer" of input and output variables in the ANFIS system.

The algorithms for learning that combined generate FIS with the subtractive clustering method (learning 200 cycles to train the model) and optimization with the hybrid method were employed. After the specified number of cycles is completed, the number of clusters resulting is 8 Gauss membership functions and 8 fuzzy inference rules, and the model structure can be created as illustrated in Fig. 9.

The fuzzy rule contains a set of fuzzy IF-THEN rules. Every fuzzy decision rule consists of a set of fuzzy linguistic terms for expressing the values of the attributes. Fig. 10 displays the IF-THEN rules derived from the ANFIS model.

To select the best model, the evaluation is based on the root mean square error (RMSE) value, which is measured from 4 data sets (A, B, C, and D). The Rule Viewer obtained from

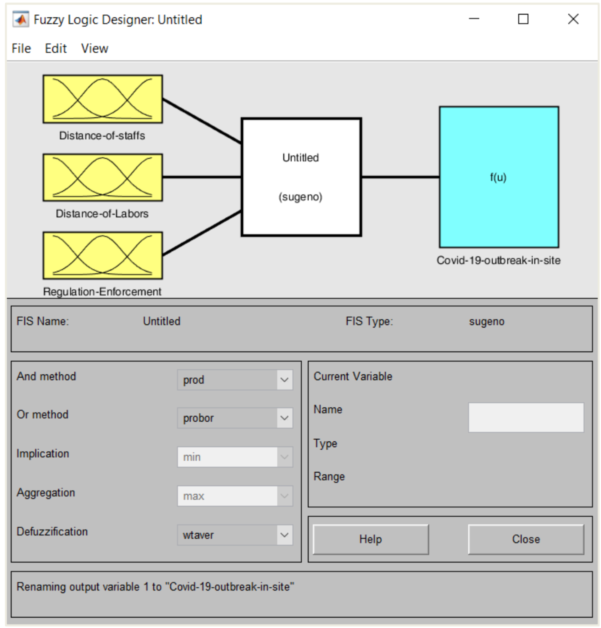


**FIGURE 8. Displayed input and output variables in ANFIS system.**

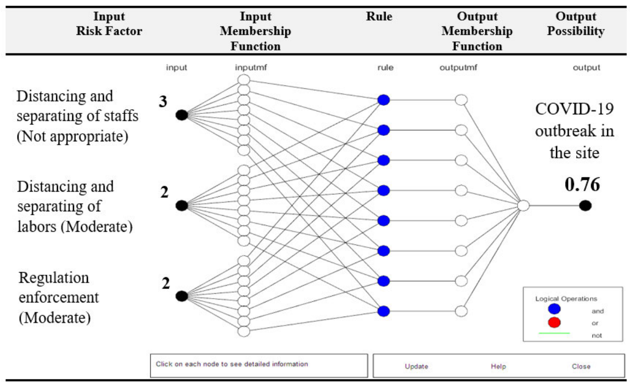


**FIGURE 9. An example model of a prediction possibility of the risk event, "COVID-19 outbreak at the site."**

the ANFIS is then used for further testing of the model as shown in Fig. 11.

### F. SELECT THE BEST DATA SET

The project teams selected the best data set by verifying which data sets are accurate and suitable based on the lowest RMSE value. For testing data, 5 scenarios (about 10%) were not used for training model. On the other hand, this data was used to verify the accuracy of the model. The results of the validation of the example risk event "COVID-19 outbreak at the site" for the accuracy of data sets A, B, C, and D are shown in Table 8. This result showed that data set B has the lowest RMSE (RMSE = 0.0656), or relatively low error value. Thus, this set provided high accuracy and was the most appropriate to use this data set to predict the possibility of a risk event "COVID-19 outbreak at the site."

**TABLE 6. The experts' opinions of risk event "COVID-19 outbreak at the site."**

| Expert No. | Scenario No. | Risk Event: COVID-19 outbreak at the site | | | | | | | | | Experts' opinions about "COVID-19 outbreak at the site" |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Risk factors rating scale | | | | | | | | | |
| | | Distancing and separating of staff | | | Distancing and separating of labors | | | Regulation enforcement | | | |
| | | Not appropriate | Moderate | Appropriate | Not appropriate | Moderate | Appropriate | Not strict | Moderate | Strict | Possibility |
| | | 3 | 2 | 1 | 3 | 2 | 1 | 3 | 2 | 1 | (0.00-1.00) |
| 1 | 1 | ✓ | | | ✓ | | | ✓ | | | 0.90 |
| | 2 | ✓ | | | | ✓ | | | ✓ | | 0.80 |
| | 3 | ✓ | | | | | ✓ | | | ✓ | 0.30 |
| | 4 | | ✓ | | ✓ | | | ✓ | | | 0.85 |
| | 5 | | ✓ | | | ✓ | | | ✓ | | 0.50 |
| | 6 | | ✓ | | | | ✓ | | | ✓ | 0.20 |
| | 7 | | | ✓ | ✓ | | | ✓ | | | 0.80 |
| | 8 | | | ✓ | | ✓ | | | ✓ | | 0.40 |
| | 9 | | | ✓ | | | ✓ | | | ✓ | 0.05 |
| 2 | 10 | ✓ | | | ✓ | | | ✓ | | | 0.90 |
| | 11 | ✓ | | | | ✓ | | | ✓ | | 0.75 |
| | 12 | ✓ | | | | | ✓ | | | ✓ | 0.35 |
| | 13 | | ✓ | | ✓ | | | ✓ | | | 0.85 |
| | 14 | | ✓ | | | ✓ | | | ✓ | | 0.55 |
| | 15 | | ✓ | | | | ✓ | | | ✓ | 0.25 |
| | 16 | | | ✓ | ✓ | | | ✓ | | | 0.70 |
| | 17 | | | ✓ | | ✓ | | | ✓ | | 0.45 |
| | 18 | | | ✓ | | | ✓ | | | ✓ | 0.00 |
| 3 | 19 | ✓ | | | ✓ | | | ✓ | | | 1.00 |
| | 20 | ✓ | | | | ✓ | | | ✓ | | 0.70 |
| | 21 | ✓ | | | | | ✓ | | | ✓ | 0.40 |
| | 22 | | ✓ | | ✓ | | | ✓ | | | 0.80 |
| | 23 | | ✓ | | | ✓ | | | ✓ | | 0.50 |
| | 24 | | ✓ | | | | ✓ | | | ✓ | 0.30 |
| | 25 | | | ✓ | ✓ | | | ✓ | | | 0.70 |
| | 26 | | | ✓ | | ✓ | | | ✓ | | 0.40 |
| | 27 | | | ✓ | | | ✓ | | | ✓ | 0.05 |
| 4 | 28 | ✓ | | | ✓ | | | ✓ | | | 0.95 |
| | 29 | ✓ | | | | ✓ | | | ✓ | | 0.80 |
| | 30 | ✓ | | | | | ✓ | | | ✓ | 0.45 |
| | 31 | | ✓ | | ✓ | | | ✓ | | | 0.75 |
| | 32 | | ✓ | | | ✓ | | | ✓ | | 0.70 |
| | 33 | | ✓ | | | | ✓ | | | ✓ | 0.30 |
| | 34 | | | ✓ | ✓ | | | ✓ | | | 0.65 |
| | 35 | | | ✓ | | ✓ | | | ✓ | | 0.40 |
| | 36 | | | ✓ | | | ✓ | | | ✓ | 0.00 |
| 5 | 37 | ✓ | | | ✓ | | | ✓ | | | 1.00 |
| | 38 | ✓ | | | | ✓ | | | ✓ | | 0.75 |
| | 39 | ✓ | | | | | ✓ | | | ✓ | 0.30 |
| | 40 | | ✓ | | ✓ | | | ✓ | | | 0.80 |
| | 41 | | ✓ | | | ✓ | | | ✓ | | 0.70 |
| | 42 | | ✓ | | | | ✓ | | | ✓ | 0.20 |
| | 43 | | | ✓ | ✓ | | | ✓ | | | 0.70 |
| | 44 | | | ✓ | | ✓ | | | ✓ | | 0.50 |
| | 45 | | | ✓ | | | ✓ | | | ✓ | 0.05 |

**TABLE 7.** **Data sets and Scenarios for training and testing.**

| Data Set | Data scenario (No.) | |
|---|---|---|
| | 40 Training Scenarios | 5 Testing Scenarios |
| A | 2-9, 11-18, 20-27, 29-36, 38-45 | 1-10-19-28-37 |
| B | 1-2, 4-11, 13-20, 22-29, 31-38, 40-45 | 3-12-21-30-39 |
| C | 1-4, 6-13, 15-22, 24-31, 33-40, 42-45 | 5-14-23-32-41 |
| D | 1-7, 9-16, 18-25, 27-34, 36-43, 45 | 8-17-26-35-44 |

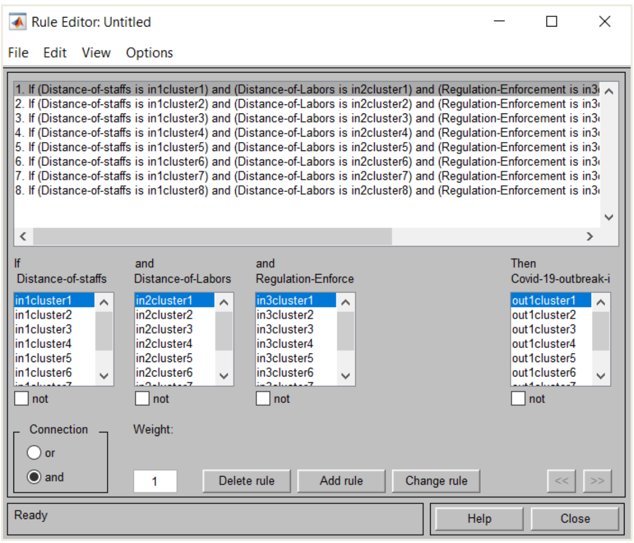


**FIGURE 10.** **Displaying the rules derived from the ANFIS model.**

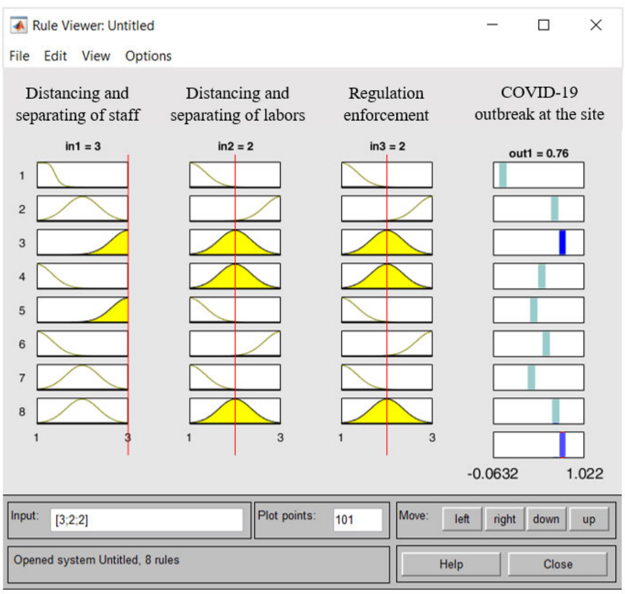


**FIGURE 11.** **Example of testing data using Rule Viewer.**

The purpose of the previous steps is the process for selecting the best possible risk assessment model (ANFIS-TOOL) to predict the possibility of a risk event "COVID-19 outbreak at the site." If the project teams need to assess the possibility of other risk events, they can repeat the previous steps for the remaining identified risk events.

**TABLE 8.** **Validate the accuracy of data sets A, B, C, and D (poss. = possibility).**

| | | Data Set | | | |
|---|---|---|---|---|---|
| | | A | B | C | D |
| Test scenario No.1 | Data scenario | 1 | 3 | 5 | 8 |
| | Expert (poss.) | 0.900 | 0.300 | 0.500 | 0.400 |
| | ANFIS (poss.) | 0.882 | 0.330 | 0.552 | 0.489 |
| Test scenario No.2 | Data scenario | 10 | 12 | 14 | 17 |
| | Expert (poss.) | 0.900 | 0.350 | 0.550 | 0.450 |
| | ANFIS (poss.) | 0.882 | 0.330 | 0.552 | 0.489 |
| Test scenario No.3 | Data scenario | 19 | 21 | 23 | 26 |
| | Expert (poss.) | 1.000 | 0.400 | 0.500 | 0.400 |
| | ANFIS (poss.) | 0.882 | 0.330 | 0.552 | 0.489 |
| Test scenario No.4 | Data scenario | 28 | 30 | 32 | 35 |
| | Expert (poss.) | 0.950 | 0.450 | 0.700 | 0.400 |
| | ANFIS (poss.) | 0.882 | 0.330 | 0.552 | 0.489 |
| Test scenario No.5 | Data scenario | 37 | 39 | 41 | 44 |
| | Expert (poss.) | 1.000 | 0.300 | 0.700 | 0.500 |
| | ANFIS (poss.) | 0.882 | 0.330 | 0.552 | 0.489 |
| **RMSE** | | 0.0814 | **0.0656** | 0.0992 | 0.0713 |

## IV. CASE STUDY

The proposed method was applied to assess risk in the underground construction of a high-rise building with 2 stories underground of 9.2 m depth, 46 stories above ground, and the entire construction floor area (CFA) of 26,868 $m^2$, constructed in Bangkok city. The sheet pile wall with a temporary bracing system (SPBS) was used as an example to explain the application of the developed framework. SPBS has been widely used for underground construction because it was a temporary system or easy to remove and more convenient to use in crowded areas, such as Bangkok. Under the terms of the contract agreement between the main contractor and the subcontractor, the SPBS underground construction of this project was operated by a specialized subcontractor. The subcontractor agreed to finish the project in 130 days (Contract duration) as part of this agreement. As a result, it is essential that the subcontractor should provide a reliable schedule baseline with a high level of performance and accomplishment. Table 9 shows WBS and normal duration for each activity. After that, project planners applied information from the WBS to the CPM diagram and calculated 115 days of project duration as shown in Fig. 12.

### *A. RISK IDENTIFICATION*

Although SPBS is widely used in underground construction projects, there are some types of risks that can affect the

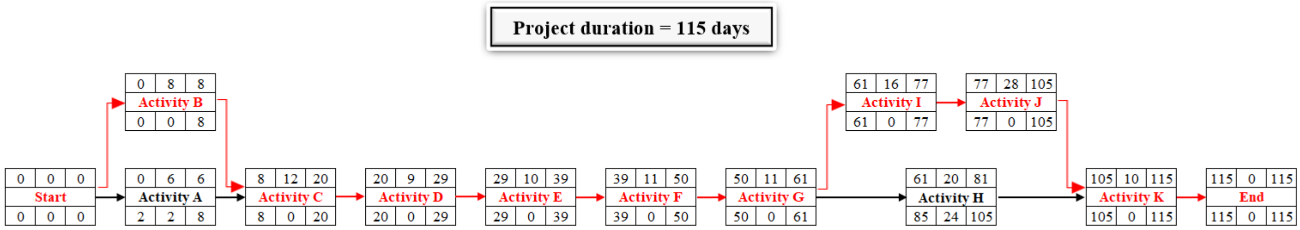


**FIGURE 12. Apply WBS to CPM diagram.**

**TABLE 9. Work breakdown structure (WBS) of sheet pile wall with temporary bracing system.**

| WBS | Activity | Description of Activity | Normal Duration (Days) | Previous Task |
|---|---|---|---|---|
| 1 | A | Surveying | 6 | - |
| 2 | B | Mobilization of machines | 8 | - |
| 3 | C | Install sheet piles, king posts, and platforms | 12 | A, B |
| 4 | D | First-layer excavation and bracing | 9 | C |
| 5 | E | Second-layer excavation and bracing | 10 | D |
| 6 | F | Third-layer excavation and bracing | 11 | E |
| 7 | G | Final excavation and lean concrete | 11 | F |
| 8 | H | Remove bracing | 20 | G |
| 9 | I | Foundation | 16 | G |
| 10 | J | RC walls and columns | 28 | I |
| 11 | K | Remove sheet piles, king posts, and platforms | 10 | H, J |

project duration because the construction of underground structures has various factors to consider, and difficult to predict the risk occurrence. Thus, risk identification (RI) takes part in this process by considering risk events that may occur during the period of construction. For this case example project, the project planners identified four activities that tend to be at risk, Mobilization of machine (Activity B), Remove bracing (Activity H), Foundation (Activity I), and RC walls and columns (Activity J).

Considering the risk events of the project, Mobilization of machine (B) is exposed to a risk event called Difficulty in accessing the area (R2E3). Remove bracing (Activity H) is prone to Ground movement (R3E1). Foundation (I) is tended to Flooding (R1E4). Finally, RC walls and columns (J) are subject to COVID-19 outbreak at the site (R1E1) and Worker absenteeism (R2E5). The CPM diagram calculated 115 days of project duration and identified the risk events in the activities as illustrated in Fig. 13.

### *B. RISK ANALYSIS*

In this step, risk analysis (RA) has been used to consider the possibility of risk occurrence by using effective machine learning, ANFIS-TOOL. Project planners estimated and evaluated the level of risk factors at the project site condition. After that, input the data into the ANFIS-TOOL. The output provided the possibility for each risk event.

Table 10. illustrates the possibility of the risk events (R2E3, R3E1, R1E4, R1E1, and R2E5) that were estimated considering project site condition by project planners and calculated by using the ANFIS-TOOL.

Furthermore, experienced project planners have estimated the impact of risk events in terms of Lag time (LT) estimation if these risks will occur, as shown in Table 11. The CPM diagram calculated a project duration of 140 days (without considering the possibility of risks) and identified the Lag time within the activities, as illustrated in Fig. 14.

### *C. RISK ASSESSMENT*

Risk assessment has been performed to determine the risk lag time (RLT) using Eq. (10) (Risk = Possibility x Impact). The possibility of risk events was received from ANFIS-TOOL in Table 10, whereas the impact of risk was estimated by experienced project planners in Table 11. The results of the risk assessment in terms of RLT are summarized in Table 12. Furthermore, there are two methods to analyze RLT for each activity. The first method is one risk event in one activity. Thus, the RLT of activity Mobilization of machine ($RLT_B$), Remove bracing ($RLT_H$), and Foundation ($RLT_I$) is 2 days, 2 days, and 8 days respectively.

The risk assessment in terms of the risk lag time of the first method (one risk event in one activity) can be calculated as follows:

$$\begin{aligned} RLT_B &= 0.36 \times 4 = 1.44 \text{ or } 2 \text{ days} \\ RLT_H &= 0.25 \times 7 = 1.75 \text{ or } 2 \text{ days} \\ RLT_I &= 0.85 \times 9 = 7.65 \text{ or } 8 \text{ days} \end{aligned}$$

For the second method, multiple risk events are in one activity. Considering activity RC walls and columns, two risk events R1E1 and R2E5 are identified. In this case, risk lag

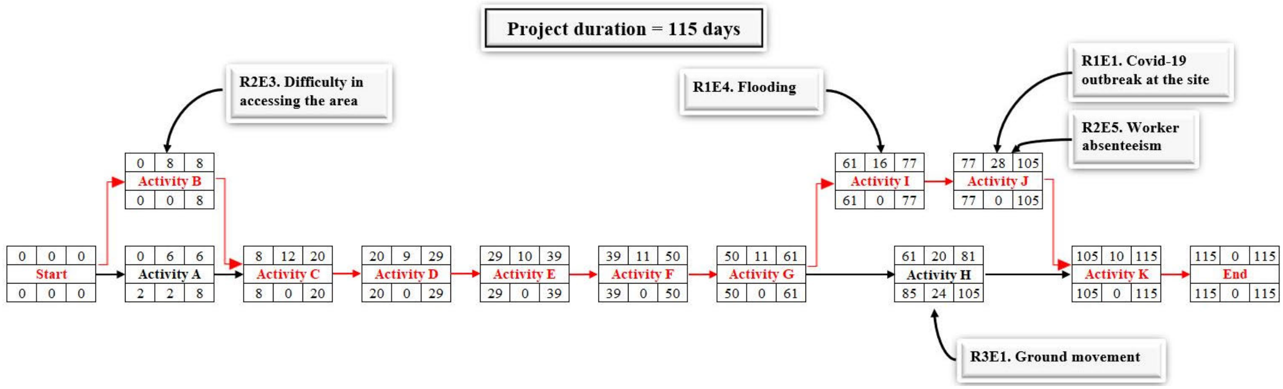


FIGURE 13. CPM diagram and activities exposed to risk events.

TABLE 10. The possibility of risk events from ANFIS-TOOL.

| Activity | Risk Event | Risk Factor | Level of Risk Factor | Possibility of Risk Event from ANFIS-TOOL |
|---|---|---|---|---|
| (B) Mobilization of machine | (R2E3) Difficulty in accessing the area | R2E3F1. Traffic jam | 3 | 0.36 |
| | | R2E3F2. Surface of the existing road | 1 | |
| | | R2E3F3. Load exceeds the road capacity | 1 | |
| (H) Remove bracing | (R3E1) Ground movement | R3E1F1. Vibration of machine | 2 | 0.25 |
| | | R3E1F2. Insufficient design | 1 | |
| | | R3E1F3. Improper construction methods | 1 | |
| (I) Foundation | (R1E4) Flooding | R1E4F1. Site elevation compared with around area | 3 | 0.85 |
| | | R1E4F2. The amount of rainfall | 3 | |
| | | R1E4F3. Drainage efficiency | 2 | |
| (J) RC walls and columns | (R1E1) COVID-19 outbreak at the site | R1E1F1. Distancing and separating of staff | 1 | 0.43 |
| | | R1E1F2. Distancing and separating of labors | 2 | |
| | | R1E1F3. Regulation enforcement | 2 | |
| | (R2E5) Worker absenteeism | R2E5F1. Worker illness | 2 | 0.39 |
| | | R2E5F2. Compensation | 1 | |
| | | R2E5F3. Rule and regulation | 2 | |

TABLE 11. Lag time (LT) is associated with activities and risks.

| Activities | Risk events | Impact of Risk Event in terms of Lag time (LT) (Days) |
|---|---|---|
| (B) Mobilization of machine | (R2E3) Difficulty in accessing the area | 4 |
| (H) Remove bracing | (R3E1) Ground movement | 7 |
| (I) Foundation | (R1E4) Flooding | 9 |
| (J) RC walls and columns | (R1E1) COVID-19 outbreak at the site | 12 |
| | (R2E5) Worker absenteeism | 6 |

time of the activity will be selected from the maximum value RLT. In most cases, risk events tend to occur individually, meaning one event at a time. However, if multiple risk events do occur, they often happen simultaneously or close to each other. Choosing the maximum value will also cover the lag time of other events in the same activity. Therefore, the RLT

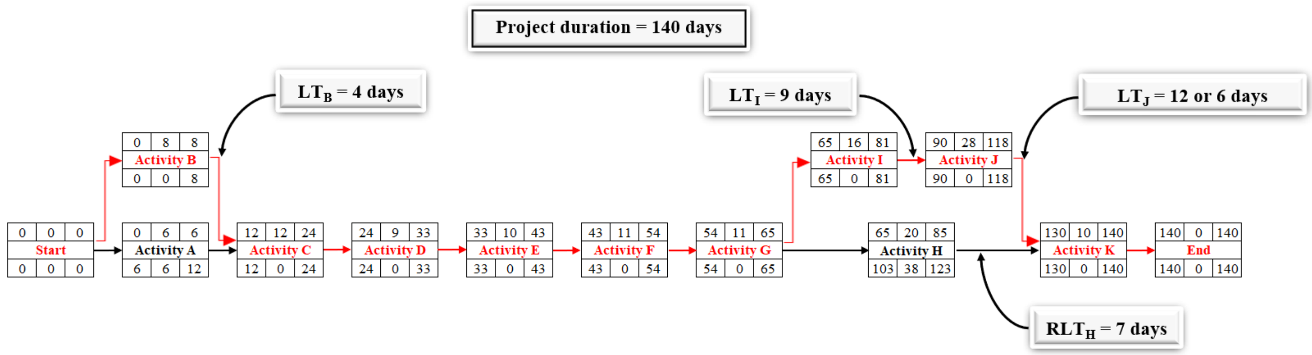


**FIGURE 14.** Input Lag time (LT) into CPM and calculate project duration.

**TABLE 12.** Risk lag time (RLT) is associated with activities and risks.

| Activities | Risk events | Possibility of Risk Event from ANFIS-TOOL | Impact of Risk Event (Days) | Risk = Possibility. x Impact (Days) | Risk Lag Time (RLT) (Days) |
|---|---|---|---|---|---|
| (B) Mobilization of machine | (R2E3) Difficulty in accessing the area | 0.36 | 4 | 1.44 | 2 |
| (H) Remove bracing | (R3E1) Ground movement | 0.25 | 7 | 1.75 | 2 |
| (I) Foundation | (R1E4) Flooding | 0.85 | 9 | 7.65 | 8 |
| (J) RC walls and columns | (R1E1) COVID-19 outbreak at the site | 0.43 | 12 | 5.16 | 6 |
| | (R2E5) Worker absenteeism | 0.39 | 6 | 2.34 | |

of RC walls and columns is 6 days.

$$RLT_J = \text{maximum}[0.43 \times 12 \text{ or } 0.39 \times 6]$$
$$RLT_J = 5.16 = 6 \text{ days}$$

After calculating the RLT for each activity, the next step is a revision of the CPM diagram with RLT. Activities B, H, I, and J used risk lag time (RLT) integrated with the CPM diagram as described in Fig. 15. The adapted CPM (with risks) called risk-integrated project duration (RPD) calculated 131 days of project duration. From the previously assigned contract duration (CD) of 130 days, the RPD is one day more than the contract duration and some of the identified risks may take a serious problem with the contract duration. Therefore, risk mitigation is suggested for the project teams to modify the project duration. For recommendation, risk response analysis will be described in the next step.

### D. RISK RESPONSE METHOD ANALYSIS

For risk response analysis, the project planners select the activity in the critical path because it has the effect of delaying the total project duration. Adjusting the possibility of a risk event is one of the risk management methods that can be performed by adjusting the risk factor. In this case, the project planners determine to mitigate the risks related to the activity Foundation (I) because it is in the critical path and has the maximum possibility of a risk event (0.85) resulting in the maximum value of risk lag time (RLT = 8 days). Activity Foundation is exposed to the risk event "Flooding" because this activity is processing near the rainy season. Risk event "Flooding" consists of 3 risk factors, Site elevation compared with around area (level = 3: Lower), The amount of rainfall (level = 3: Heavy), and Drainage efficiency (level = 2: Fair). The risk factor "The amount of rainfall" is a natural risk that cannot be improved (level = 3: Heavy). However, other risk factors, "Site elevation compared with around area" and "Drainage efficiency" can be improved. The "Site elevation compared with around area" can be improved by filling in the soil around the project and adjusting the soil level within the project area to be closer to or higher than the road level surrounding the project. This will result in a level of risk factor assessment value equal to 1 (level = 1: Higher). In addition, the "Drainage efficiency" can be improved by implementing a better drainage system, installing additional water pumps, and constructing manholes to pump water out of the project.

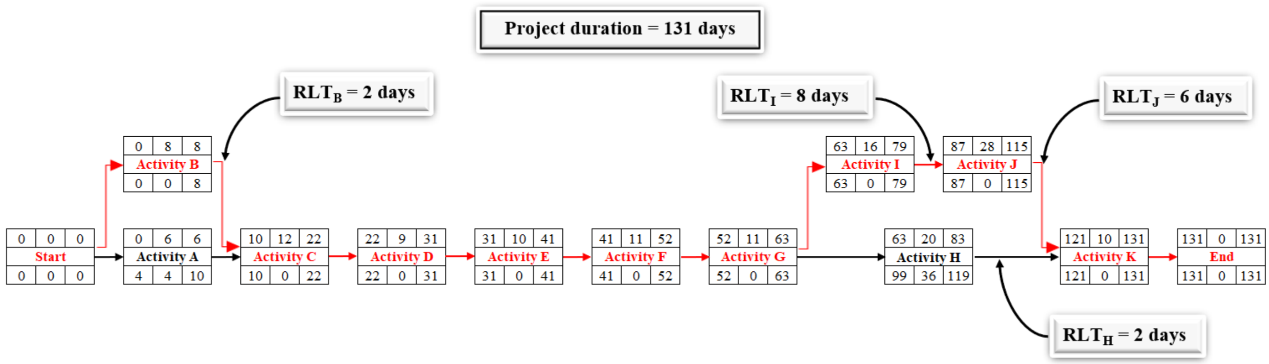


FIGURE 15. Input RLT into CPM and calculate adjust project duration.

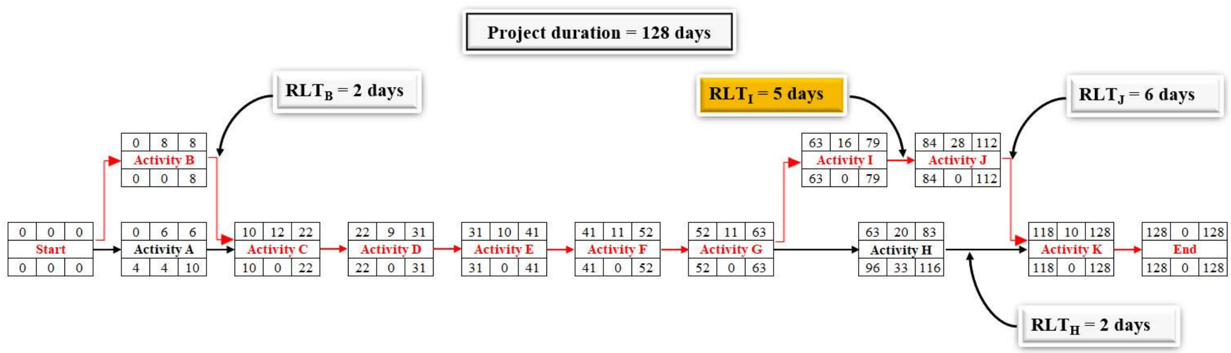


FIGURE 16. Input RLT into CPM and calculate adjust project duration after risk mitigation.

This will result in a level of risk factor assessment value equal to 1 (level = 1: Effective). Thereby, the possibility of the occurrence of "Flooding" decreased from 0.85 to 0.49 and increasing the operation cost of the project.

This step calculates the adjusted risk lag time (RLT) of activity Foundation (I), $RLT_I = 0.49 \times 9 = 5$ days. Thus, the new risk-integrated project duration (RPD) is 128 days as shown in Fig. 16. After the risk mitigation is performed, the RPD is decreased from 131 days to 128 days which does not exceed the contract duration and is more reliable for the project manager to control. If the project planners need to decrease more days, they can select other activities and repeat the same process, Finally, the project planners will compare the cost-effectiveness of increasing costs with reducing the number of operation days caused by risks.

Table 13. illustrates the summary of the project duration for each type of planning/scheduling in this case study. From previous information, under the terms of the contract agreement between the main contractor and the subcontractor, the sheet pile wall with a temporary bracing system (SPBS) underground construction of this project was operated by a specialized subcontractor. The subcontractor agreed to finish the project in 130 days (Contract duration) as part of this agreement. If the project planners of the subcontractor develop a traditional CPM-based project plan that does not incorporate risks into the schedule (115 days), it is possible that various risk events may arise during the actual construction phase. These risk events could potentially lead to project delays. If the project planners develop a plan using the CPM integrated with the impact of risk events in terms of lag time, without considering the possibility of risks (140 days), there is a likelihood that the project duration may exceed the contract duration quite considerably. This situation could lead to dissatisfaction from the owner or the main contractor due to overestimation of this method, potentially affecting the duration of other subsequent activities that may need to be postponed or delayed, in some cases, even resulting in contract termination.

If the project planners develop a project plan with a proposed framework using CPM that integrates with the impact and the possibility (ANFIS-TOOL) of risk events in terms of risk lag time (RLT) (131 days), it is possible that the project duration may not exceed or slightly exceed the contract duration. If the project duration exceeds the contract duration, this proposed framework can be applied to incorporate risk management processes by performing risk response (risk mitigation) to adjust the possibility of a risk event in case some of the identified risks may take a serious problem with the project duration or contract duration. Another advantage of the proposed method is that project planners can make

**TABLE 13. Summary of the project duration for each type of planning/scheduling.**

| Types of planning/scheduling | Project duration | Description |
|---|---|---|
| Traditional CPM | 115 days | The CPM regardless of the risk. |
| CPM (with lag time) | 140 days | The CPM integrates with the impact of risk events in terms of lag time (without considering the possibility of risks). |
| CPM (with risk lag time) | 131 days | The CPM integrates with the impact and the possibility (ANFIS-TOOL) of risk events in terms of risk lag time (RLT) (considering the possibility of risks). |
| Adjusted CPM (by risk mitigation) | 128 days | Performing risk response (risk mitigation) by adjusting the possibility of a risk event in case some of the identified risks may take a serious problem with the project duration or contract duration. |

adjustments at the level of risk factors that contribute to the occurrence of a risk event, in order to modify the possibility of risk occurrence. After the risk mitigation is performed, the adjusted Risk-integrated project duration (RPD) is decreased (128 days) which does not exceed the contract duration (130 days) and is more reliable for the project manager to control. Therefore, the proposed method demonstrates its applicability for project planning and integration of risk management, making it suitable for implementation in construction project planning with systematic and efficient risk considerations.

## V. DISCUSSION AND CONCLUSION

An overly optimistic project schedule could result from failing to provide appropriate time contingency, leading to suboptimal project performance and the potential for delays. The reliability of time contingency represents an essential component of a realistic and dependable schedule. This buffer time can be added to individual activities to improve the overall project schedule. In reality, contractors typically incorporate time contingency into their activity duration to increase schedule robustness. However, in most cases, risks that have an impact on these activities are not systematically identified and analyzed during the estimation process and it is less obvious how estimates are made. Therefore, it is challenging for project planners to strengthen reliable construction schedules. Moreover, most contractors allocate an arbitrary time contingency because they do not have appropriate techniques to account for project risks. The isolation of risk management from project scheduling has the effect of diminishing the project's ability to achieve successful outcomes.

Construction projects have been known well-known for their complexities and uniqueness. In the planning step, the project planners assess the possibility and impact of risk occurrence in the construction to estimate project duration. Predicting the possibility of risks occurring in construction projects is quite difficult. The deterministic methods such as Gantt chart and CPM, as well as probabilistic methods like PERT and Monte Carlo simulation, may not be suitable when used for planning construction projects that involve nonrandom uncertainties and various types of risks. The available historical data or experiments may not be relevant to the current project under consideration or future decision-making because each project is unique. An adaptive neuro-fuzzy inference system (ANFIS) is a more appropriate method that can predict the possibility of risk. ANFIS integrates the explicit knowledge representation of fuzzy expert systems with the learning powers of adaptive neural networks. The proposed ANFIS-TOOL uses the ANFIS system to assess the possibility of risk occurrence in construction projects. In addition, the ANFIS-TOOL undergoes a validation of its model accuracy using the root mean square error (RMSE) method before being applied to real construction projects. This validation ensures that the model will perform at the most optimal performance.

This study presents a newly developed framework that integrates risk management into project scheduling to establish a more reliable project schedule. The proposed framework assesses time contingency at the activity level by identifying project activity risks and analyzing their possibility of occurrence and impact. ANFIS is employed to model the imprecision and vagueness intrinsic to time contingency assessments provided by experts, and a case study of constructing sheet pile walls with a temporary bracing system (SPBS) is employed to demonstrate the effectiveness of the approach. The proposed ANFIS-TOOL is able to assess the level of possibilities based on experts' opinions. The study shows that risk management can be systematically incorporated into scheduling, and ANFIS can be used to model the possibility of multiple risks on activity time contingency with reasonable computation efforts. When compared to such deterministic and probabilistic based approaches, the resulting activity time contingency of this technique is more reliable. Finally, this study introduces an integrated approach for risk management and project scheduling using the ANFIS model, which advances the current practice of time contingency estimations and applies ANFIS in assessing the possibility of risk occurrences on activity durations in real construction projects.

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