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SCHEDULE AND COST FORECASTING MODEL FOR NUCLEAR POWER PLANT PROJECTS

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Abstract: Reliable schedule and cost forecasting is one of the major project management challenges for nuclear power plant projects due to their unique characteristics (e.g., variability of projects portfolio, type of nuclear projects, security and safety requirements). Inaccurate forecasting may bring along schedule delay and cost overrun, and accordingly termination of nuclear power plant's operating license. To overcome these challenges, this study develops a schedule cost forecasting model that is capable of improving the accuracy of cost and schedule estimation for nuclear power plant projects. The forecasting model is designed in two steps: (i) identifying the causal factors of delay for nuclear power plant projects; and (ii) investigating the impacts of identified factors on projects' cost schedule performance by using artificial neural network modeling. The model is also validated by project management portfolio of a nuclear power plant in Michigan – USA. The initial analysis and results are presented and discussed in this paper.

1 Introduction

Nuclear power plants play a vital role in the US power sector by generating about 20% of the total U.S electricity (EIA, 2017). This nuclear power is generated by operating 100 commercial reactors in 61 licensed nuclear power plants (NRC, 2017). In order to maintain the safe operations and maintenance of these nuclear reactors, the operating licenses should be extended and renewed every 20 years by US Nuclear Regulatory Commission (NRC). As of today, the U.S. commercial operating reactors have an average age of about 33 years (NRC, 2017), which addresses that many of the current operating reactors are already in the process of renewing their licenses.

Nuclear power plant operating license renewal requires a full compliance with the US Nuclear Regulatory Commission (NRC) requirements such as safety management, operations, maintenance, refueling, and waste disposal. In order to manage all of these NRC requirements, nuclear power plants develop short term and long term projects portfolio that include capital and maintenance projects. However, these projects that are implemented in nuclear power plant environment have unique characteristics that can be listed as: (i) reprioritization of the nuclear projects that usually results from emergent issues and challenge the safe operations of nuclear power plants, regulatory upgrades to NRC requirements, and recommendation upon inspections; (ii) variability of the nuclear project portfolio that resulted in more fast track projects and a tight portfolio budget; (iii) the classification of the projects (i.e. modifications, maintenance, engineering, and facilities) that each has different design and implementation requirements based on the procedures, the location and the time of the nuclear projects implementation; and (iv) special security and safety procedures required by NRC, (e.g., in- and out-processing for all personnel working inside the plant, materials and equipment staging and storage, special investigation for the project materials and equipment) (Devgun, 2013; PEA, 2015; Jung, 2012). These major distinctive characteristics of the nuclear power plant projects often increase the risk of schedule delay and costs overrun, and lead to inconsistency and unpredictability of the construction projects portfolio. Therefore, there is an emerging need for a model that provides a reliable and accurate schedule and cost estimation for managing and controlling nuclear power plant projects. Many studies have been conducted to predict the accuracy of schedule and cost forecasting in the construction industry such as residential and commercial building construction (Naik and Kumar, 2015; Jaberi, 2013; Adeli and Park, 2001; Savin and Alkass, 1996). These studies addressed the schedule and cost forecast considering resource leveling, resources constraints and productivity. Even if these studies have great contributions on developing schedule and cost forecasting models for the construction industry, they did not address the aforementioned characteristics and challenges of nuclear power plant construction projects that have major impact on their schedule and cost performance. Accordingly, this study presents schedule and cost forecasting model for nuclear power plant projects. The model will help to provide more reliable schedule and cost forecasts to assure on-time and within budget completion for nuclear power plant projects.

2 Objective

The objective of this study is to develop a model that is capable of estimating the schedule and cost performance of nuclear power plant projects. This model is developed in three main stages: (1) identifying the causal factors of delay for nuclear projects; (2) developing a schedule and cost performance model using Artificial Neural Network; and (3) implementing the model to evaluate and refine its performance on real-case nuclear power plant projects. The following sections of the paper present a brief description of these stages.

3 Identification of Causal Factors of Delay

Deliberative project planning and control is a key strategy to make reliable schedule and cost estimates for construction projects. In operable nuclear power plants, schedule delays and cost overruns, especially in projects that are implemented to meet NRC requirements, can impact the plant’s operating license. Therefore, nuclear power plant projects require an advanced integrated project controls system, with attendant policies and procedures for effectively measuring project performance, and forecasting time and cost (Jung, Moon, & Kim, 2011). This advanced system should enhance the management decision making process to meet projects objectives. In order to achieve that, Alsharif and Karatas (2016) presented a framework that identifies the causal factors of delay in nuclear projects. The framework was validated by conducting a case study at an operable nuclear power plant in Michigan – USA, involved weekly data collection of causal factors of delay for in progress projects. Upon data collection, a more in depth analysis was performed to understand the causal factors of delay that have major impacts on schedule and cost performance of nuclear projects. As a result, thirteen major causal factors of delay have been identified for nuclear power plant projects which are; missing schedule updates, design errors (engineering change request), contractors, vendors, materials, funding, schedule productivity, resource productivity, plant engineering support, rework, owner decision, weather, and other delays due to tools and equipment, poor coordination, or differing site conditions. The framework presented in this study will help decision-makers identifying the impacts of the causal factors of delay to evaluate their impacts on project estimation in terms of schedule and cost.

4 Schedule and Cost Forecasting Model Development

The objective of the proposed model in this study is to predict the reliability of schedule and cost forecasts for nuclear projects. The model presented in this study is developed by utilizing Artificial Neural Network (ANN) analysis, which is a widely used technique in estimation and forecasting to fit the purpose of the schedule and cost forecasting model (Jain and Pathak, 2014). ANN is used to explore and analyze the large quantities of construction schedule and cost data in nuclear power plant project portfolio. Therefore, the model is developed in four main steps: (i) establishing the projects database; (ii) identifying the inputs factors, weights, and outputs factors; (iii) implementing the model using the Artificial Neural Network tool; (iv) evaluating the results, schedule and cost forecasts. Figure 1 shows a flowchart for the schedule and cost forecasting model development.

The first step in developing the model is building the projects database, that includes general information about the project characteristics in nuclear power plant such as project name, project type (modification, engineering, maintenance, and facilities), overall project cost, overall project duration, implementation schedule (i.e. outage or online). The database also includes detailed activity information such as work breakdown structure (WBS), activity type (planning, engineering, implementation, and closeout), activity cost baseline, activity duration baseline, and causal factors of delay.

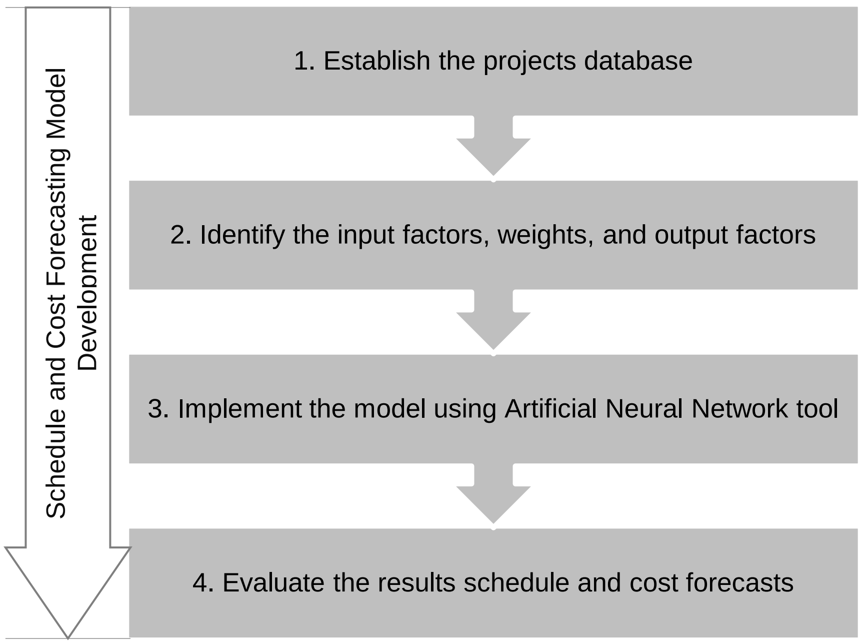

Figure 1: Schedule and Cost Forecasting Model Development Flowchart

The second step is to identify the Artificial Neural Network parameters: the network input factors, neurons weights, and output factors. The project activities durations and cost estimates are defined as the network input factors, the causal factors of delay as weights, and the duration and cost forecasts as output factors as shown on Figure 2. With the input factors and weights determined, the model mapping for predicting the schedule and cost forecasts is defined as:

[1] $(N_1, N_2, N_3, N_n) \Longrightarrow (O_1, O_2)$

[2] $T = f(N_1W_1, N_2W_2, N_3W_3, \ldots, N_nW_n)$

Where N_1, N_2 = input factors which are the activity cost baseline and duration baseline accordingly. N_3 – N_n are the activities attributes and causal factors of delay. W is the weight value of causal factor of delay. O_1, O_2 = output factors which are forecasted cost and schedule performance. T is the target output for schedule and cost forecasts.

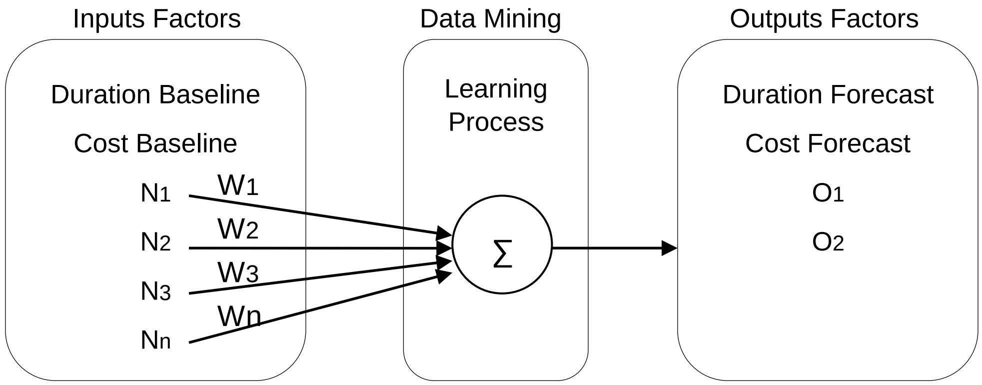

Figure 2: Neural Network Input-Output Mapping

The third step is to implement the model using the Artificial Neural Network technique. The identified network inputs factors and outputs factors and the database are imported to investigate and evaluate the data behaviour based on pre-defined desired outputs factors (i.e. O1: Duration Forecast and O2: Cost Forecast) using the Artificial Neural Networks (ANN). ANN is applied with supervised learning algorithm to train the project database and produce the desired output factors. In this learning process, a set of data is used for validating and testing the reliability of schedule and cost forecast performance of the model.

The fourth step of this model is to evaluate and refine the reliability of schedule and cost forecasts based on the identified causal factors of delay, duration baseline and cost baseline of the nuclear power plants projects.

5 Schedule and Cost Forecasting Model Implementation

To implement and validate the proposed model, real-case nuclear power plant projects data have been collected and recorded weekly at a nuclear power plant in Michigan – USA. A random set of five nuclear power plant projects were selected as a case study to establish a project database and examine the schedule and cost forecasting performance of the developed model. These five projects include modification, engineering, maintenance, and facilities nuclear projects. The cost of these projects ranges from $1.82 million to $9.61 million, durations range from 13 months to 34 months. The total number of activities that are used in training the model is 2,371 activities.

The project database is categorized based on the WBS, cost baseline, and duration baseline which defined as the network inputs factors. Table 1 shows the cost and duration parameters that are used to categorize the duration and cost performance of each project activity. The activities are categorized based on the total cost and total duration required to complete the activity scope of work. For example, if the activity total cost is less than $5,000, its cost category is 1. An activity with total duration of less than 5 days is also categorized as duration category 1.

Table 1: Duration and Cost Categories

Cost ($000)	Cost Category	Duration (Day)	Duration Category
< 5	1	<5	1
5-10	2	5-10	2
10-15	3	10-15	3
15-25	4	15-20	4
25-35	5	20-25	5
35-45	6	25-30	6
45-55	7	30-35	7
55-65	8	35-40	8
65-75	9	40-45	9
>75	10	>45	10

The project database also involves identifying and weighting the causal factors of delay. Table 2 shows an example of a project database. The database includes activity description, WBS, cost baseline value, and duration baseline value for each activity. The WBS is categorized based on the project phases from 1 to 5, where 1 represents initiation activities, 2 represents planning activities, 3 represents designing activities, 4 represents implementation activities, and 5 represents the closeout activities. The duration baseline and cost baseline are categorized using Table 1. The causal factors of delay is then listed and weighted with value 1 if they impacted the activity.

Table 2: Project Database Example

Activity Name	WBS Category	Cost Baseline ($)	Duration Baseline (Day)	Cost Category	Duration Category	Design Error	Resource Productivity	Scope Change
Prepare/approve specifications	3	50,466	37	7	8	0	1	1
Prepare EDP index items	3	9,080	12	2	3	0	1	0
Review design inputs	3	3,456	9	1	2	1	0	1

The project database is imported to the Artificial Neural Network tool. The project database is trained using MATLAB version R2016b, ANN Artificial Neural Network Toolbox, Neural Network Fitting process algorithm. The Neural fitting process utilizes two-layer feed forward network that is trained through backpropagation algorithm, that lead the learning process to pre-defined desired project outputs. The two layers of the network are the hidden layer and the output layer.

The model has three input factors, thirteen weight values, and two output factors. The input factors are the activity WBS category, cost baseline, and schedule baseline for each activity necessary to complete the project scope of work. The weight values represent the expected causal factors of delay that may impact each activity. The output factors are the desired schedule forecast and cost forecast for each activity. The model initial configuration uses ten neurons in the hidden layer to train the data. The ten neurons in the hidden layer is used as a starting point as recommended by the MATLAB Neural Network Toolbox (Mathworks, 2016). In order to validate and test the data, 70% of the data is selected for the training which is 1,659 activities, 15% of the data is used for validation which is 356 activities, and 15% is used for testing the learning process which is 356 activities. The training data is presented to the network during the training to produce the desired outputs by adjusting its error. The validation data is used to measure the network training performance and to stop training when it is no more improving. The testing data is an independent measure to evaluate the overall network performance during and after the training. The model uses the Mean Square Error (MSE) and the Regression R values to determine the accuracy and reliability of the model schedule and cost forecasts.

6 Results and Discussion

The results from the case study implementation by performing 15 training iterations are summarized and presented in Table 3, Figure 3, and Figure 4. Table 3 shows the attributes of the five nuclear projects selected and implemented in this study. In order to analyze the results, the activities cost and duration values are rolled up to the project level. The first column represents the project ID used in the model implementation. The second column shows the type of projects, the third column is the number of activities per project, the fourth column is the total cost baseline, the fifth column is the total duration baseline, the sixth column is actual total cost, and the seventh column is the actual total duration. The eighth and ninth columns of Table 1 show the predicted values for duration and cost for each project based on the model outputs. Figure 3 shows a comparison between the actual values and the predicted values of the duration performance for the projects activities.

Table 3: Nuclear Projects Attributes

Project	Type	Number of Activities	Total Cost Baseline ($m)	Total Duration Baseline (Day)	Actual Total Cost ($m)	Actual Total Duration (Day)	Predicted Total Cost ($m)	Predicted Total Duration (Day)
Project 1	Modification	489	5.65	476	5.52	504	5.62	516
Project 2	Modification	580	9.61	653	9.94	689	10.1	705
Project 3	Engineering	522	2.46	992	2.73	1085	2.95	1113
Project 4	Maintenance	430	1.82	425	1.98	418	2.13	432
Project 5	Facility	350	3.58	388	3.86	432	3.97	445

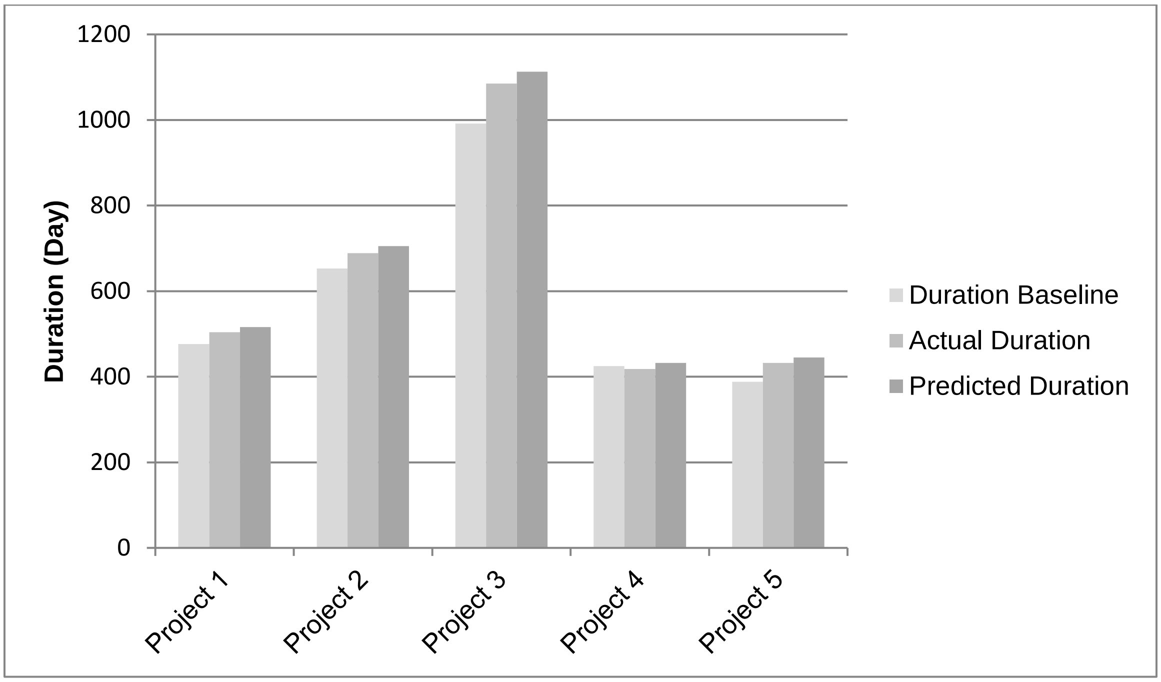

Figure 3: Comparison of Projects Total Duration

Project 1 was designed to complete in 476 days (i.e. duration baseline) and a 10 day time contingency built arbitrary in the project critical path. However, the project was completed in 504 days from the start date. This means 5.9% variation from the original estimate. This variation highlights that the impact of causal factors of delay on the project activities during the project lifecycle and their importance to make more accurate estimations. Therefore, the proposed model in this study, predicted the duration of Project 1 as 516 days based on training the data on the impacts of the expected causal factors of delay. This means that the model is capable of predicting more accurate duration at completion and reduces the forecasting error by 50% (from 5.9% to 2.4%). The original duration estimate for Project 2 was 653 days. However, the project actual duration was 689 days which means 5.5% variation from the original estimate. After training the project database in the proposed model, the predicted duration at completion was 705 days which is 2.3% ahead of schedule. This means that the model was able to identify the potential delay due to the expected impacts of causal factors of delay on the project. Project 3 was estimated to complete in 992 days where the actual duration of the project was 1085 which is about 9.3% behind schedule. However, the predicted value obtained from the model was 1113 days which means if it was used, the project would be 2.5% ahead of schedule. Project 4 was baselined to be completed in 425 days. The actual duration at completion was 418 days. By investigating the project records, it was noticed that the delay was recovered by working overtime and weekends which significantly increased the cost by 8.7%. The predicted duration at completion generated by the model was 432 days with normal working hours. Thus, model was able to predict more accurate duration estimate that can help in more accurate cost estimate. The original duration for Project 5 was 388 days where the project completed after 432 days. This means the project was behind schedule by 11.3%. The model's predicted value for the duration at completion was 445 days which means the forecast improved to about 3%. By comparing the duration baseline, actual duration, and the predicted duration generated by the model, predicted values of projects durations have been improved and are closer to the actual projects duration.

Moreover, the total cost baseline for Project 1 was estimated as $5.65 million. The actual cost was $5.52 million upon the completion of the project. The project was completed under budget. However, after investigating the project records, it was found that the project contingency was inflated by 9% based on expert judgement with little or no risk perception. The project activities were impacted by combinations of causal factors of delay. This resulted in using 74% of the contingency to recover the activities delay and project duration extension. However, after applying the neural network tool, the predicted value of the project total cost was $5.62 million. This value was based on training the project data considering the impacts of causal factors of delay. Even that the predicted value is greater than the actual cost, but it represents more accurate estimates based on risk consideration rather than arbitrary decision. The model was able to predict more accurate cost at completion and improve the forecasting error to 1.8% instead of 2.3%, as shown in Figure 4. The estimate at completion for Project 2 was $9.61 million where the actual total cost was $9.94 million. This means the project was over budget by 3.4%. The predicted value generated by the model was $10.1 million which is more accurate by 1%. Project 3 estimated cost at completion was $2.46 million where the actual cost was $2.73 million which mean 11% over budget. The model predicted cost at completion of $2.95 million. The model was able to improve the forecast to 8% under budget. By analyzing also Project 4, the model predicted $2.13 million for cost at completion which means improving the cost at completion 7.5% under budget. Project 5 was estimated as $3.58 million. The actual cost was $3.86 million which means variance of 10.8% over budget. However, the model predicted $3.97 million for cost at completion. The model was able to improve the forecast to 2.8% under budget.

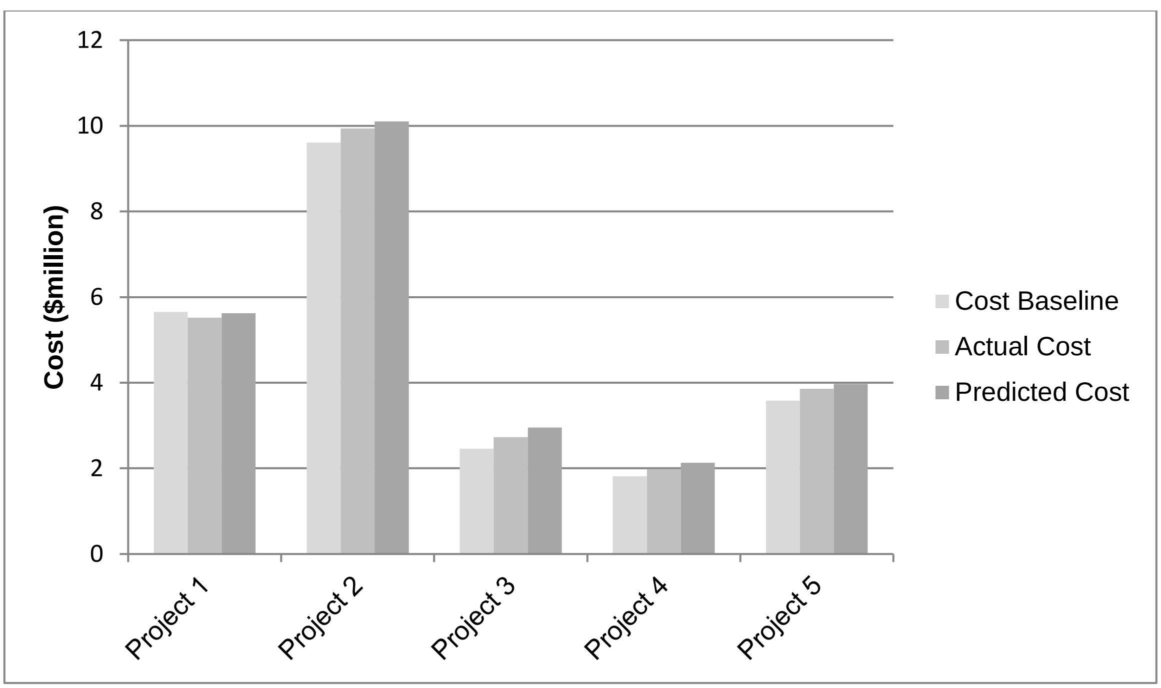

Figure 4: Comparison of Projects Total Cost

The case study demonstrated that the proposed model is able to improve the accuracy of schedule and cost forecast of the nuclear power plant projects. The duration variation reduced from an average of 6% to an average of 2.7%, and the cost variation reduced from an average of 4% over budget to 3.4% under budget. The most important aspect of the results is the ability to predict more accurate schedule and cost performance by considering the risk of common causal factors of delay in nuclear power plant projects.

7 Conclusion

Schedule delay and cost overrun have been a major challenge when managing and controlling nuclear power plants projects due to their unique characteristics and requirements. The risk of schedule delay and cost overrun needs to be identified and analyzed to be considered in projects schedule and cost estimates. Therefore, this paper presents the development and implementation of a schedule and cost forecasting model for nuclear projects. The study demonstrates the benefits of using the Artificial Neural Network technique to train the nuclear projects data considering the impacts of common causal factors of delay in nuclear projects. To validate the model, case study of five nuclear projects at an operable nuclear power plant in Michigan – USA was analyzed, and the results showed that the presented model improves the schedule and cost forecasts of the nuclear power plant projects. The model presented in this study will help decision-makers such as senior management and project managers to have more accurate schedule and cost estimations during the early stages of the project lifecycle. This will also improve the reliability of project management organization by providing more accurate estimates and forecasts. Further analysis is needed to investigate more projects database to improve the performance of the proposed model.

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