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Prediction Of Project Schedule Performance Index for Trans South Java Road Project Lot 7 Blitar Regency Using Bayesian Network

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A B S T R A C T

The south coast of Indonesia has considerable potential and competitiveness in the field of tourism. This encourages the government to strive to improve tourism infrastructure through the construction of the South Coast Road. In its implementation, project reporting must be measured and controlled to assist project management in identifying problems and factors that affect project activities. This research aims to identify the most influential factors on Schedule Performance Index and develop a prediction model using the Bayesian Network. 5 main factors that affect project performance, such as Heavy Equipment, materials, Implementation and Work Relations, Labor, and Environment are used to are set 13 scenarios to detect the behavior of each factor appropriately. The factor is confirmed to the respondent to ensure that the factor occurs in the project. The study's results obtained Bayesian Network approach can be used to assess the condition of the JLS Lot 7 Blitar Schedule Performance Index (SPI) with an accuracy of around 80%. The dominant factor affecting SPI is the condition of the Heavy Equipment. The condition of the Heavy Equipment will affect the condition of SPI so closely that the contractor must maintain the performance of the heavy equipment so that the project performance is always in good condition. The identification results are expected to help in better decision-making and project risk management.

1. Introduction

The southern coast of Indonesia has considerable potential and competitiveness in the tourism sector. Natural beauty, culture, tourism facilities, and a strategic location are strong attractions for domestic and foreign tourists. This makes this area an attractive tourist destination as well as a source of state revenue. Therefore, the government is trying to improve tourism infrastructure in the south coast region to facilitate tourist access.

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The South Coast Road (Pansela) is a road that stretches from Banten Province to East Java with a length of 1,604 km. In the East Java region, the Pansela Road construction is divided into four sections, namely sections 6, 7, 8, and 9. Development Project Section 7, Tulungagung - Serang - Malang, is on the Tambak Rejo - Serang Beach road for 12.85 km. The construction of a new road on the south coast, where not much work was done but was hampered by heavy terrain. The terrain conditions in section 7 of the JLS are diverse and challenging because it crosses mountainous and hilly areas. The hilly topography, rocky ground, and steep slopes make this area require considerable work and special techniques.

Management and control of project activities must be carried out properly to ensure that the activities and implementation are appropriate. Less than optimal impact control can impact quality, quantity, cost, and time failures [1]. The project must design information systems to measure achievements, compare actual performance, and analyze deviations so that the project team can take corrective action through the effective and efficient use of resources [1]. Based on previous research, several factors influence performance progress in highway construction projects[2][3][4].

One of the important things to do to ensure that the project goes according to plan is to report project progress regularly. In this case, the measurement and control of project reporting are very important to ensure that the information conveyed in project reporting is accurate, relevant, and timely. In addition, measurement and control of project reporting can also assist project managers in identifying problems and factors that affect project activities. So that corrective actions can be taken more quickly and on target.

Earned Value Management (EVM) is a performance measurement method to measure and monitor project progress. EVM compares a project's actual performance with planned performance in terms of cost, schedule, and quality to determine whether the project is running well or having problems in practice. EVM uses actual data and project planning to measure project performance objectively. Using actual cost data, EVM can calculate how well the project is running and the estimated cost and remaining schedule (estimate at completion). However, EVM is unable to predict sudden major changes in the project environment.

Some studies try to combine multiple predictions in one model [5]. Combined methods for predicting project time performance are usually more accurate than focusing solely on standard time performance formulas because one way can overcome the weaknesses of the other [6][7]. Bayesian is one method, artificial intelligence that is able to calculate the possible relationship between random variables by combining knowledge of statistics and graph theory,

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which has proven to be a powerful method for analysis, optimization, evaluation, engineering, and prediction [8][9][10]. The Bayesian method can control project costs and time by utilizing historical and actual information to estimate progress and project costs and remaining time. In this context, the Bayesian method can help plan and manage projects more effectively. Many studies have been conducted on Bayesian applications, including seismic hazard studies, soil corrosivity prediction, forensic assessment of bridge collapses, diagnostics of nuclear power plants, and others [11][12][13]. To improve the accuracy of project time, performance predictions must involve factors that affect project performance. BN models can detect many interrelated factors and simultaneously direct temporal relationships to related factors. Bayesian models can be used to estimate the completion of an ongoing project by looking at and approaching the actual behavior of objects[14][6]. The advantage of BN modeling is that it can update, integrate other new data, and handle network updates with probabilistic information to make technical decisions under uncertain conditions[15][16][17]. Bayesian people can predict the probability of an event based on previous events [18].

This research aims to identify the factors most influencing SPI and develop a prediction model using the BN method. In this case, BN is used as a statistical analysis method that can combine quantitative and qualitative data and identify causal relationships between observed variables so that the results of the identification are expected to help in better decision-making and project risk management.

2. Research Method

The method used in this study is the Bayesian Network (BN) to predict a Schedule Performance Index (SPI) supported by an analysis of the factors affecting the performance of the Lot 7 Blitar Southern Cross Road development. Lokasi Proyek Pembangunan Jalan Trans Jawa Selatan Lot 7 Tulungagung – Serang – Malang located on the Tambak Rejo – Serang Beach road along 12.85 km with a duration of an implementation plan for 131 weeks. The project is implemented by PT. PP mulai 14 April 2020 sampai dengan 12 Oktober 2022. This study uses primary data (field surveys and interviews with respondents) and secondary data (project schedules, project reports, and SPI), which will be analyzed using the Bayesian method.

The various factors will be confirmed to the respondent to ensure that these factors occur in the project. Respondents were determined using purposive random sampling in which respondents were selected from contractor employees with good experience and knowledge of project monitoring. The chosen factors will be used as variables used to model SPI predictions. The schedule data on weeks 1 to 121 resulted in the SPI value, which is converted into category

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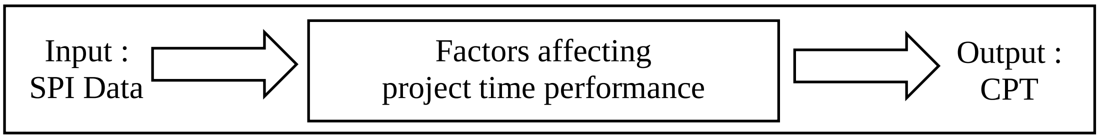
probability ("Good," "Medium," "Fail"). To determine the category utilized critical contractual references [19].

The project's SPI data will be analyzed according to the DAG results by looking for a correlation between the SPI value and the factors that influence it. The conditional probability transition (CPT) value is derived from the probability of each element affecting the performance of the JLS Lot 7 Blitar project by reference to the probability impact matrix [20].



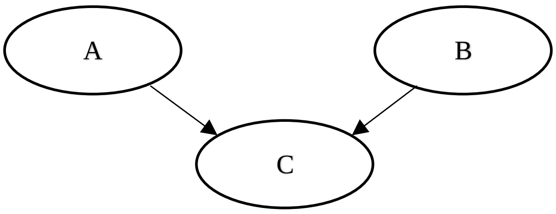
Sources: Author Research Method.

Figure 1. SPI Data Mining Model.

The simulation is processed after the SPI prediction output data is retrieved from BN modeling and compared to the SPI schedule data. The validation model uses the match/no-match approach [11]. The model compares the prediction results of the proposed model with the benchmark data (project SPI timeline) in terms of the classification "match" or "no match." The scenario model studies the effect of changes in the behavior of factor conditions that affect the SPI, and the BN model arranges in 13 scenarios (See Table 7). The scenario model determines how each factor's condition can affect the SPI when it is set to extremes.

2.1 Bayesian Theory

A Bayesian network consists of two parts: (1) a directed acyclic graph (DAG) which represents a visual component of the relationships among a group of dynamically changing input variables and a set of impacted outputs; and (2) a set of conditional probability tables (CPT) of the values of the observed and measured conditional probabilities about the occurrence of events that cause the impact to happen.



Sources: Author Research Method.

Figure 2. Simple Bayesian Network.

The operating results of the *Bayesian network* can be obtained by distributing the probabilities of all variable relationships in the case study under study. For example, the combined probability distribution of the simple *Bayesian network* is shown in **Figure 2.** as follows :

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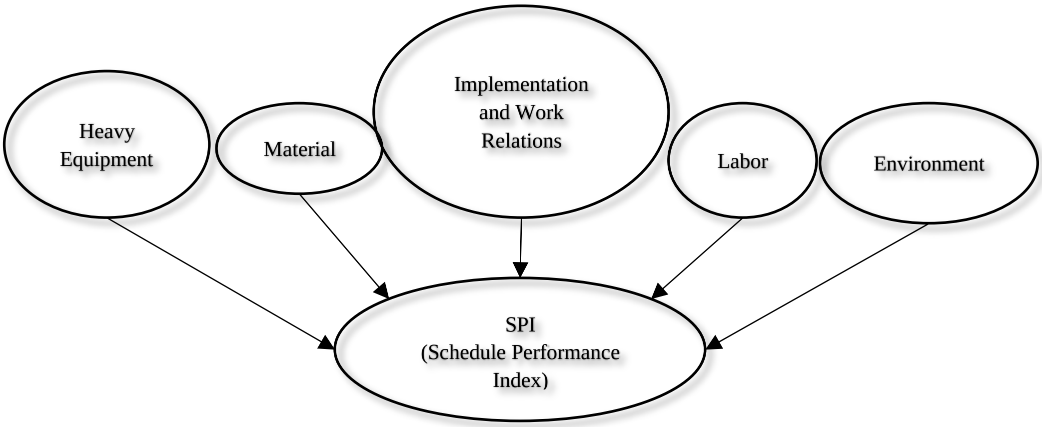
$$P(A, B, C) = P(C \mid A, B)\, P(A,B) = P(C \mid A, B)\, P(A \mid B)\, P(B) \quad (1)$$

The relationship between parent and child nodes falls into two categories, superficial logical relationships such as "and," "or," where conditional probability nodes can be computed directly through logical analysis. While in the other model, each parent node affects the child node by synthetic action, with conditional probability tests usually given by experienced people or experts [8].

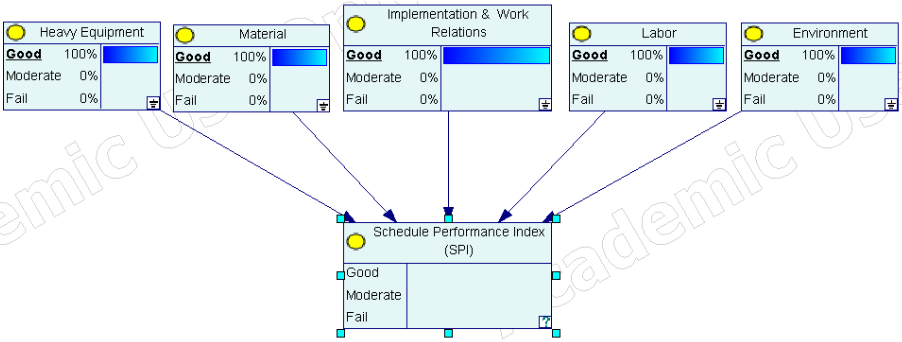
2.2 Direct Acyclic Graph (DAG)

The charts are arranged in a DAG to relate the variables of one node to another. DAG can produce a CPT (Conditional Probability Table) which will be used to predict the model's SPI value. The model's results will be validated to ensure the model follows the actual behavior of these factors. If the validation is not fulfilled, the DAG will be adjusted again until the model output meets the validation test. Researchers used GeNIe Academic Version 4.0 software to simplify creating a DAG structure. See the reference book [21]. GeNIe can find the most critical factors affecting performance by analyzing past and future events [22]. The GeNIe software has a straightforward interface for modeling Bayesian networks [23].



Sources: Author Research Method.

Figure 3. DAG Structure Creation.



Source: GeNIe 4.0 Software.

Figure 4. DAG Structure Creation in GeNIe 4.0 Software.

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Five factors affect SPI per week, but the node still needs to fill in data on the results of expert assessments for the approach to SPI (see **Figure 3**). After filling in the data on the node every week, it is necessary to fill in the CPT to get the expected SPI weight. The GeNIe software can show the node that has been given input data and not (see **Figure 4.**).

2.3 Conditional Probability Transition (CPT)

Once the DAG is complete, Bayesian Networks asks the CPT to determine the probability of an event. CPT is calculated based on the possibility between nodes. Here are several steps to complete the CPT.

Step 1: Review data analysis of five factors affecting project schedule or SPI performance from respondent data at weeks 1 to 121 as input data.

Step 2: Assign a number to each *Schedule Performance Index data* and separate them into two groups, namely 80% (weeks 1 to 95) for modeling and 20% (from weeks 96 to 121) for data testing.

Step 3: CPT is calculated based on the 80% data model.

Based on realizing schedule performance versus time, researchers specifically modeled Bayesian to predict performance conditions or the Schedule Performance Index (SPI) with a value approach of factors affecting project performance [14][24].

$$SPI = EV/PV \quad (2)$$

The performance data report can measure SPI condition by a score of > 1 for good condition, 1- 0.90 for moderate condition, and < 0.90 for poor condition. The factor scoring approach for SPI is based on the Contract Critical in Construction Service Procurement; see **Table 2.** [19]. Factor conditions affecting performance in the field are measured by visual inspection, which is 1 – 0.95 "Good condition," 0.95 – 0.80 "Moderate condition," and < 0.80 "Fail condition" according to factor analysis and probability – impact matrix, see **Table 3.** [20].

Table 1. Performance Index Analysis.

Indeks	Nilai	Keterangan
SPI	>1	Project performance earlier than planned
	<1	Project performance is slower than planned
	=1	Project performance is on schedule

Source : Widiasanti, Manajemen Konstruksi [1].

Table 1. is a construction management method used to compare the completion of field works and work schedules for a given period. The SPI calculation is obtained by formula (2).

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Table 2. The SPI Value.

Index	Score	Information
	>1	Good
SPI	1 - 0.90	Moderate
	< 0.90	Fail

Source : SCM Permen PU No. 07/PRT/M/2011 [19].

The value SPI in **Table 2.** was obtained in the realization of the JLS Lot 7 Blitar Time Schedule. These limits are assessed based on the Critical Contract rules [19]. **Table 3.** provides values for the factors that affect project performance as an approach to SPI. The assessment is based on the Probability Impact Matrix: PMBOK (2000)[20]

Table 3. The Conversion SPI Value to SPI Category.

Index	Probability	Category
	1 - 0.95	Good
Power Factor	0.95 - 0.80	Moderate
	< 0.80	Fail

Source: Author's analysis (2022).

Table 4. provides the probability of equipment and material factors, which are determined based on expert judgment. It also implemented other factors. Then, this data is correlated with SPI data based on the performance report. This data is filled on for each node in CPT to calculate SPI predictions using the GeNIe software.

Table 4. CPT Equipment and Materials.

Heavy Equipment	Probability	Material	Probability
G	0.714	G	0.889
M	0.143	M	0.111
F	0.143	F	0

Source: Author's analysis (2022).

Table 5. shows the CPT model used to help users calculate the expected probability for each node. The CPT automatically follows the child node and parent node models created, assuming all weights equal 1.0. The proportion of importance is determined through analysis supported by previous research [25] and expert verification.

Table 5. CPT Schedule Performance Index (SPI).

Equipment	**G**	**G**	**G**	**G**	**G**	**G**	**G**	**G**	**G**
Material	**G**	**G**	**G**	**G**	**G**	**G**	**G**	**G**	**G**
Implement & Works	**G**	**G**	**G**	**G**	**G**	**G**	**G**	**G**	**G**
Labor	**G**	**G**	**G**	**M**	**M**	**M**	**F**	**F**	**F**
Environment	**G**	**M**	**F**	**G**	**M**	**F**	**G**	**M**	**F**
Good	0.872	0.868	0.864	0.860	0.856	0.852	0.848	0.844	0.840
Moderate	0.102	0.119	0.027	0.112	0.130	0.030	0.122	0.140	0.032
Fail	0.026	0.013	0.109	0.028	0.014	0.118	0.030	0.016	0.128

Source: Author's analysis 2022, GeNIe 4.0. Software.

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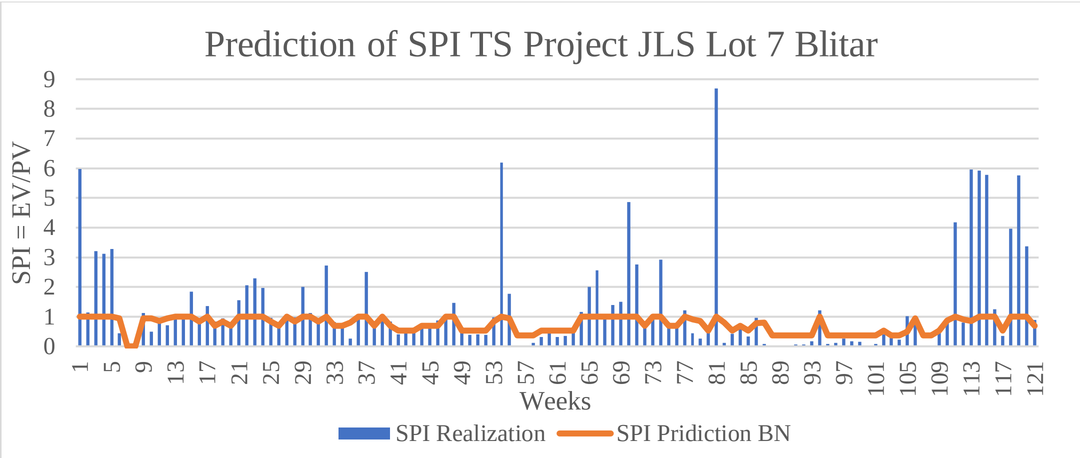
3. Results and Discussions

This discussion is divided into simulation, Validation, and Scenarios with the following description:

3.1 Simulation Model

In the model simulation, actual SPI and Bayesian SPI will be presented, which serves to compare actual schedule performance with prediction results from the Bayesian network model. In this simulation, the actual SPI is calculated based on the actual data obtained during the project execution. In contrast, the Bayesian SPI can be calculated based on predictions generated by the Bayesian network model.



Source: Author's analysis (2022).

Figure 5. SPI - Schedule JLS Lot 7 Blitar and SPI Prediction Results for BN Modelling.

Figure 5 shows the realized SPI value and the predicted SPI value using the BN method. When the prediction results are analyzed, they show similarities to the realized value. However, remember that the predicted SPI value cannot exceed one in the BN method because 1 is considered the maximum value for SPI. Comparing these two SPIs can evaluate the extent to which predictions from the Bayesian network model are accurate in predicting project schedule performance. The accuracy between the actual SPI value and the predicted SPI value using the BN method is measured using the Mean Absolute Percentage Error (MAPE) evaluation metric.

3.2 Validation Model

The validation model uses SPI from 121-week schedule data assessed compared to BN modelling data. The validation results are presented in Table 6. The results show that the BN model can be applied to predict SPI for ongoing projects with an accuracy of 80%. If the value of Mean Absolute Percentage Error (MAPE) ≤ 30%, then the prediction model is accurate or feasible [17].

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Table 6. Validation Model Based on BN.

Weeks	**SPI Base**	**SPI Base on**	**Validation**	**Weeks**	**SPI Base**	**SPI Base**	**Validation**
96	F		OK	108	F	F	OK
97	F	F	OK	109	F	F	OK
...	...	...	...	110	F	M	Not OK
...	...	...	...	111	G	G	OK
...	...	...	...	112	F	M	Not OK
103	F	F	OK	113	G	M	Not OK
104	F	F	OK	...	...	...	...
105	G	F	Not OK	...	...	...	...
106	F	M	Not OK	...	...	...	...
107	F	F	OK	121	F	F	OK
			BN Modeling	25	Data		
			Total Error BN	5	Data		
			Valid Value	20	Data		
			Total SPI Value	25	Data		
			BN Model Accuracy	**80**	**%**		

Source: Research Result (2022).

Table 6. shows that the model validation was carried out by conducting a simulation in weeks 95 to 121; there were 5 data errors, then 20 valid data. The model accuracy is known to be 80%. Predictive Bayesian modeling results with 80 % accuracy can help contractors estimate project time, provide early warning information about project delays, and provide alternative and priority decisions when adopting policy solutions or accelerating construction.

3.3 Scenario Model

The scenario use factors that affect SPI (see **Table 7**.) are Heavy Equipment (HE), materials (M), Implementation and Work Relations (IWR), Labor (L), and Environment (E). Based on these factors, this study arranges 13 scenarios to detect each factor's behavior appropriately.

Table 7. Scenario Model Based on BN.

Scenario	HE	M	IWR	L	E	SPI Based on BN		
						G	M	F
						1 - 0.95	0.8 - 0.95	< 0.8
1	G	G	G	G	G	98 %	2 %	0 %
2	M	M	M	M	M	45 %	50 %	5 %
3	F	F	F	F	F	1 %	20 %	80 %
4	G	F	F	F	F	66 %	7 %	27 %
5	F	G	F	F	F	23 %	15 %	61 %
6	F	F	G	F	F	9 %	18 %	73 %
7	F	F	F	G	F	4 %	19 %	77 %
8	F	F	F	F	G	2 %	78 %	20 %
9	F	G	G	G	G	34 %	53 %	13 %
10	G	F	G	G	G	76 %	19 %	5 %
11	G	G	F	G	G	91 %	7 %	2 %
12	G	G	G	F	G	96 %	4 %	1 %
13	G	G	G	G	F	97 %	1 %	2 %

Source: Author's Analysis (2022).

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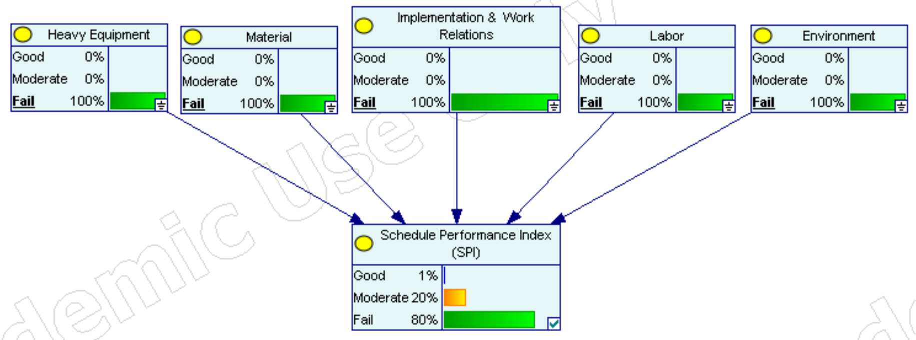
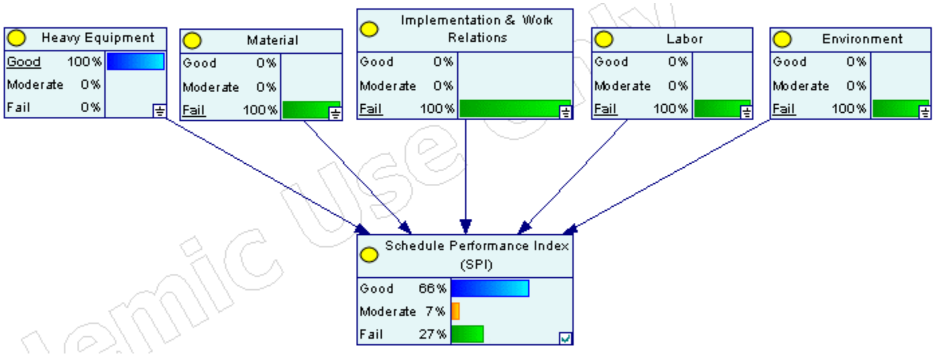


Source: Author's Analysis (2022).

Figure 6. SPI-BN Predictive Modeling Scenarios 3.

Scenario numbers 1 to 3 are designed for all factors to be changed to the "Good," "Moderate," and "Fail" positions. The SPI prediction value obtained is likely to occur if all conditions are changed to "Good" in HE, M, IWR, L, and E "(G = 98%, M = 2%, and F = 0%)". This indicates that if all factors are in the "Good" position, the project schedule performance will likely be good and according to plan.



Source: Author's Analysis (2022).

Figure 7. SPI-BN Predictive Modeling Scenarios 4.

In Scenarios 4 to 8, all factor conditions are set to "Fail", but only one is set to "Good," starting from H, M, IWR, L, and E. The result shows good conditions when the good scenario is set on the Heavy Equipment SPI prediction value factor. SPI prediction value will produce file conditions if the scenario is well applied to material factors, Implementation and Work Relations, and labor. SPI prediction value will produce moderate conditions if the scenario is applied to environmental factors well. This shows that Heavy Equipment is a major influential factor in SPI.

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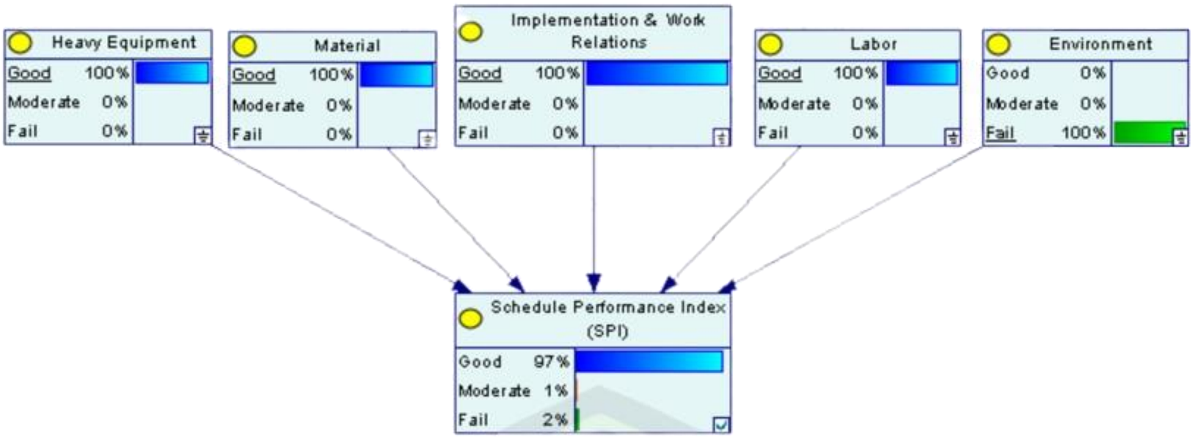

Source: Author's Analysis (2022).

Figure 8. SPI-BN Predictive Modeling Scenarios 13.

In scenarios 9 to 13, all conditions are positioned on "Good", and only one of the factors is set to "Fail" in turn on each factor. The prediction value shows a moderate condition when the failed scenario is set to the Heavy Equipment SPI factor. The SPI prediction value will produce a good condition if a good scenario is applied to material factors, Implementation and Work Relations, and labor. The SPI prediction value will produce moderate conditions if a good scenario is applied to environmental factors.

4. Conclusion

The Bayesian Network approach can be used to assess the condition of the JLS Lot 7 Blitar Schedule Performance Index (SPI) with an accuracy of around 80%. The dominant factor affecting SPI is the condition of the Heavy Equipment. The condition of the Heavy Equipment will affect the condition of SPI so closely that the contractor must maintain the performance of the heavy equipment so that the project performance is always in good condition. The identification results will help better decision-making and project risk management.

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