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MODELING, TESTING AND VALIDATION OF A HYBRID WARNING SYSTEM FOR COMPLEX LARGE-SCALE INDUSTRIAL PROJECTS IN THE TRANSNATIONAL ENVIRONMENT

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Modeling, testing and validation of an ***Hybrid Early Warning System (HEWS)****, based on the combined use of conventional forecasting and statistical methods, the results of which are integrated as inputs into probabilistic Bayesian Networks, with the goal of issuing early warning of overtaking a critical point that is not within the safety margin set by the project team for cost and time estimates at the completion of CLPTE opens new paths for an integrated understanding of external factor dynamics correlated with internal parameters in a conditional causality map while providing a real-time image of the various scenarios in which CLPTE is headed.*

Keywords: Complex large-scale industrial projects in the transnational environment (CLPTE), Development of new industrial technologies sector, Hybrid Early Warning System (HEWS), Bayesian Networks (BN).

1. Introduction

The practical contribution of this research represents modelling, testing and validation of an Early Warning Hybrid System (HEWS) based on a combination of conventional forecasting and statistical methods whose results are integrated as inputs into Bayesian Probability Networks. The hybrid concept of integrating recorded data, experts/practitioners' opinions, different types of forecasting methods with the dedicated software listed above aims at issuing an early warning of overcoming a critical point that is not within the range set by the project team for cost and time estimates, at CLPTE completion.

2. HEWS conceptual framework. Modeling, testind and validating methodology for Bosch Group Romania - new industrial technology sector

Research methodology has started from the axiom that the best model will be reached when a balance is struck between strengths and weaknesses [10]. The precision and number of variables integrated in HEWS model have played key roles in the validation of the proposed model because a small number of variables can not cover all parts of an uncertainty and risk, but too many variables may interrupt the model's effectiveness [7]. In modeling process of the variables and indices was used a hybrid combination of software, as follows:

- •FMEA - Failure Modes and Effects Analysis - to identify and determine significant external factors that may affect CLPTE performance;
- •AGENARISK - for modeling uncertainties;
- •WinBUGS 14 - for simulating data and establishing probability nodes and tables in Bayesian networks.

In order to obtain the proposed HEWS model, conceptual framework is structured into 5 distinct phases, as follows:

Phase 1: Orientation - At this initial stage, was developed a "checklist," which wanted to be a tool to determine the purpose of HEWS, people involved, the methods and software used and any other key features.

Phase 2: Exploration - At this stage, were explored several determinants factors, external and internal, which could "shape" the future dynamics of CLPTE with applications for industrial technology development, case study - Bosch Romania:

• External factors - in this sub-phase were identified the main factors that could have the greatest impact in terms of time and budget;

• Internal parameters: estimates at completion, both in terms of cost (EAC) and time (EAC(t)) as internal variables for nodes and probability tables within Bayesian Networks;

Phase 3: Integration and modeling of external determinants factors and internal parameters in Bayesian probability networks;

Phase 4: Setting HEWS - establishing nodes and probability tables, as well as intervals for issuing early warnings.

Phase 5: Validation of HEWS model - simulation of external parameters and conditional probability nodes in BN.

Analysing Bosh Group's global performance in 2015[1], 2016 as well as the 2017 projection[2], Bosch emerged from year to year, less in the new industrial development sector where there were successive declines. These represented the reasons to choose Bosch for validating HEWS.

Phase 2 - Exploration:

Exploring external factors - the process of "extracting" the judgments of interviewed experts and practitioners.

After the five experts were identified, they were interviewed on: the final average cost of the project; medium end date of the project completion; the overall uncertainty level of the project, expressed in a qualitative way corresponding to a scale of three values: high, medium and low.

The first two values are related to parameter μ, and the third value is related to the distribution parameter. It should be noted that, from the final average cost corresponding to the CPIf value, the EAC = AC + BCWR/CPIf relationship can easily be derived, where BCWR indicates the value of the remaining work budget.

The same approach was applied to estimate SPI(t)f. The five interviewed managers expressed their opinions/judgments about these three main features of a CLPTE, based on their knowledge and expertise, not only related to the current project, but also to similar projects developed in the past. To reduce distortions, it was important to indicate that the purpose of the interview is to compare the views of experts in order to assess the level of uncertainty affecting the project and it is not extremely significant who provides the most accurate estimation. Regarding the estimate of completion, it was relatively easy to collect the opinions of those interviewed on the future median value of the CPIf and SPI (t) f indices in relation to the remaining work. Above all, the main interest was the logarithm of these values, µk, k = 1, N, which contributes to the equations 1 and 2 to determine the value of the hyper-parameters θ and ʒ of the previous distribution.

Here was taken into consideration a method of moments [5] to estimate hyper-parameters, considering µk, k = 1, N, the logarithm of median values produced as a sample of the previous distribution, computing a mean sample and standard deviation. The logarithm of each index CPIf and SPI(t) f follows median distribution, and then we equal the mean sample and the standard deviation with the mean, as shown in equations 1 and 2.

$$\theta = \frac{\sum_{k=1}^{N}(\mu_k)}{N} \tag{1}$$

$$ʒ = \sqrt{\frac{\sum_{k=1}^{N}(\mu_k - \theta)^2}{N-1}} \tag{2}$$

Alpha and beta hyper-parameters of distribution were chosen in different ways, using a qualitative approach based on the level of uncertainty of the project assessed by the five experts. By dividing the U-level uncertainty into three categories (low, medium and high), corresponding to a range of 1 to 3, it was possible to calculate an average U level for the project uncertainty (the average of the values collected during the survey) which help to determine posterior deviation of the standard deviation CPIf and SPI(t)f. In case study, based on empirical considerations, the hyperparametres α and β are set according to the U-level to obtain: σ= [0; 0.1], corresponding to the low U level; σ= [0.1; 0.3], corresponding to the average U level; σ = [0.3; 0.5], which corresponds to the high U level. Using FMEA a hierarchy of external factors was set up based on the degree of uncertainties and risks, on color codes: red-orange-green.

Table 1

Hierarchy of determinants according to the degree of uncertainty/risk, by color codes: red-orange - green.

Uncertainties and economic Risks		Uncertainties and risks regarding human resources		Uncertainties and risks regulatory/legislative/critical infrastructures		
Raw material prices evolution	Exchange rate evolution	Availability of human resources	Productivity of human resources	Environment	Legislative changes	Critical infrastructures

Table 2

Relationship determinants factors - risks in CLPTE implementation - application for Bosch Romania - development of new industrial technologies.

Raw material prices evolution	Frequency and magnitude of raw material price increases used for the development of new industrial technologies
Exchange rate evolution	The appreciation/devaluation of lion currency against the other currencies
Availability of HR	Availability and expertise of human resources in the development of new industrial technologies
Productivity of HR	
Environment	Frequency of changes in emission standards, industry taxes ... etc.
Legislative changes	Frequency of change of taxes and other taxes
Critical infrastructures	Frequency of critical information infrastructure interruptions

Table 3

The probability of negative impact on costs and program

…SRL	**A**	**B**	**C**	**D**	**E**
Raw material prices evolution	0.417	0.583	0.417	0.583	0.417
Exchange rate evolution	0.250	0.250	0.250	0.250	0.250
Uncertainties and economic Risks	0.333	0.417	0.333	0.417	0.333
Availability of HR	0.167	0.250	0.333	0.083	0.417
Productivity of HR	0.333	0.333	0.333	0.333	0.333
Uncertainties and risks regarding HR	0.250	0.292	0.333	0.208	0.375
Environment	0.056	0.028	0.056	0.083	0.111
Legislative changes	0.028	0.028	0.028	0.028	0.028
Critical infrastructures	0.389	0.389	0.389	0.389	0.389
Uncertainties and risks Regulatory/legislative/critical Infrastructures	0.157	0.148	0.157	0.167	0.176
Impact on CLPTE	0.247	0.285	0,275	0.264	0.295

At first glance, the results show that the probability of exceeding the costs and the project schedule is approx. 25%. Hence, the hypothesis of setting a range of early warnings in the range of 35% - 25%.

Exploring internal parameters:

Generally, during a CLPTE lifecycle, at some point now (Present Time - PT), part of the work is complete and the rest has to be executed. The two components of the estimated completion are: the actual cost of the completed work; estimated Time to Complete (ETC) of the work remained. For utilisation estimates at completition as parameters in HEWS, were followed two sources of information: records of data collected during the performed work, which is the explicit knowledge of the past; the opinions of experts and team leaders on remaining work. It has been demonstrated that the monthly CPIm and SPI(t)m values, obtained as the ratio of the difference between the value recorded at the end of the month and the value collected at the end of the previous month, are normally distributed [8]. This opened the door to establish a confidence interval for the estimate at completion. [9]

$$CPIm = \frac{EV(TP) - EV\ (TP-1)}{AC(TP) - AC(TP-1)} = \frac{EVm}{ACm} \tag{3}$$

$$SPI(t)m = \frac{ES(TP)-ES(TP-1)}{(TP)-(TP-1)} = ESm \tag{4}$$

Table 4

Matrix of cost-time variables

<table>
<tr><th colspan="2" rowspan="2">VARIABLES</th><th colspan="3">Variable TIME</th></tr>
<tr><th>SV>0;
SPI(t)>1</th><th>SV=0;
SPI(t)=1</th><th>SV<0;
SPI(t)<1</th></tr>
<tr><td rowspan="3">Variable COST</td><td>CV>0;
CPI>1</td><td>Before the set deadline;
Under the budget.</td><td>In time;
Under the budget.</td><td>Delayed by the deadline;
Under the budget.</td></tr>
<tr><td>CV=0;
CPI=1</td><td>Before the set deadline;
Whitin the budget.</td><td>In time;
In the budget.</td><td>Delayed by the deadline;
In the budget.</td></tr>
<tr><td>CV<0;
CPI<1</td><td>Before the set deadline;
Over the budget.</td><td>In time;
Over the budget.</td><td>Delayed by the deadline;
Over the budget.</td></tr>
</table>

The above table summarizes the indices and variables together with their respective significance.

Table 5

Synthesis of the formulas used for estimations when finalizing a project.

SITUATIONS	EAC Cost	EAC(t) Time
Future performance differs significantly from previous performance. Two new performance indices, CPIf and SPI(t)f, were introduced for Working Remained (WR).	AC +(BAC – EV)/CPIf	TP +(SAC – ES)/SPI(t)f
Deviations of CV and SV (t) reported at the present time will not affect the rest of the project.	BAC – CV	SAC – SV(t)
Indices CPI and SPI (t) reported at the present time will remain constant until the project is completed.	BAC/CPI	SAC/SPI(t)
The common effect of cost and time performance will be taken into account when calculating the estimate at completion.	BAC/SCI	SAC/SCI(t)
Deviations in the course of the project will be absorbed by appropriate corrective actions and the planned objectives will be achieved.	BAC	SAC

Phase 3: Integration and modeling of external determinants factors and internal parameters in Bayesian probability networks.

The Bayesian approach differs from the conventional predictive methods because it describes probability, such as the degree of conviction someone has in the occurrence of an event. The subjective definition of probability is justified by the probability dependence on the state of information that one has. From the Bayesian perspective, the u parameter of the Probability Density Function (PDF) of a sample of n observations, X = (X1 ... Xn), independently and identically distributed, is a random variable which follows a distribution of Probability called previous distribution.[4] By applying Bayes' theorem, it is possible to write a posterior density function as:

$$f(\theta/x)=\frac{f(x/\theta)*f(\theta)}{\int f(x/\theta)*f(\theta)\,d\theta} \qquad (5)$$

The first step in building a Bayesian graphical model applied to the conventional forecasting is to describe conditional interdependence relationships between different data generated by conventional methods. Win BUGS language used in testing HEWS model is a declarative language to describe parent-child relationships based on the S-curves described above. A complete description of the BUG language can be found in the classic BUGS textbooks [11], but some of the basic features have been illustrated by the simple linear regression model [12].

The main assumptions underlying the model are the independence of the CPIm and SPI(t)m indices and the normal logarithmic distribution. The latter assumption is motivated by the fact that the above indices are affected by a high level of volatility due to changing conditions and factors, month by month, in the internal and external context of each project. The first stage in modeling is data analysis and logarithmic transformation of index values. To this end, the tests developed by Anderson-Darling and Ljung-Box-Pierce are used [3]. Exploratory data analysis techniques accompany the implementation of the two tests. By defining an index as x, the normal logarithmic function is given by:

$$f(x/\mu,\sigma^2) = \frac{1}{\sqrt{2\pi}\,\sigma\, x} e^{-\frac{(\ln(x)-\mu)^2}{2\sigma^2}} \tag{6}$$

Further, the prior distributions for μ parameters and normal logarithmic distribution were chosen. To provide relatively simple flexibility and algebraic calculations, a normal distribution (equation 7) and a reverse gamma distribution (equation 8) were chosen:

$$f(\mu) \sim N(\theta, ʒ^2) = \frac{1}{\sqrt{2\pi}\; ʒ} e^{-\frac{(\mu-\theta)^2}{2\sigma^2}} \tag{7}$$

$$f(\sigma^2) \sim INVG(\alpha,\beta) = \frac{\beta^\alpha}{G(a)\sigma^2(\alpha+1)} e^{-\frac{\beta}{2\sigma^2}} \tag{8}$$

The next step in modeling HEWS model is to calculate the posterior distribution for CPIf and SPI(t)f. Equation 8 can not be solved with a closed formula, so it can be decomposed into two parts, each representing the conditioned posterior distribution of a parameter. After mathematical computation, a normal distribution for (equation 9) and an inverse gamma distribution for (equation 10) are obtained.

$$f(\mu/\sigma^2, x) \sim N\left[\frac{(ʒ^2 * \sum_{i=1}^{n} \ln(xi) + \sigma^2 * ʒ^2)}{\sigma^2 + ʒ^2}, \left(\frac{\sigma \quad * ʒ}{\sqrt{(\sigma^2 + ʒ^2)}}\right)^2\right] \tag{9}$$

$$f(\sigma^2/\mu, x) \sim INVG\left[\frac{n}{2} + \alpha, \frac{1}{2} \sum_{i=1}^{n} (\ln(xi) - \mu)^2 + \beta\right] \tag{10}$$

Both distributions are conditional in terms of data and other parameters. Therefore, equations 7 and 8 can be used to sample samples in the Gibbs process, in the Monte Carlo simulation technique of a Markov chain, which obtains a sample of the posterior distribution [6]. Applying the Gibbs sampling process is based on an iterative algorithm that comprises three main steps:

•were choosen the initial values for μ and σ^2. Initial values do not affect the Gibbs sampling process, because the results of the initial iteration are usually removed (process residual);

•at each iteration j, we generate a random value from the normal distribution in equation 9;

•generating an arbitrary value from the reverse gamma distribution in equation 10.

Then, we return to step 2 as long as the convergence of conditional distributions is reached (appropriate common tests have been used). Once iterations are run (repeat steps 2 and 3 about 400 times), it is possible to obtain the predictive backward density of the CPIf and SPI (t) f indices by introducing I - *m* values of µj and σ^2j obtained by sampling Gibbs, in normal logarithm PDF:

$$f(x_k)\text{TP+1} \approx \frac{\sum_{m+1}^{n} \text{Log}\, N(x_k/\mu j, \sigma^2 j)}{I-m} \tag{11}$$

Thus, a step function is obtained to approximate the predictive backward density for a value grid ranging from 0 to infinity (in practice, a very large number). The terms entered in equation 15 are following:

• I, the number of iterations; a value of 400 is usually sufficient;
• m, the number of values eliminated as a result of the process, usually 100;
• TP + 1, the next time period considered;
• x_k, the values of CPIf and SPI (t) f indices, theoretically from 0 to infinity if the range considered is actually pre-restricted when the value f (x_k) becomes negligible. The PDF should integrate at 1; therefore, the values must be chosen with great care so that the step function approximating the density function could be given by the following relation:

$$\sum_{n=1}^{k} f(x_k)\text{TP} + 1 * (x_{k+1-} x_k) \approx 1 \tag{12}$$

Phase 4: Setting HEWS - establishing nodes and probability tables, as well as intervals for issuing early warnings.

This phase shows how can be correlate in HEWS the external determinants with key internal parameters obtained using the hybrid methods explained in previous sections by setting nodes, probability tables, and intervals for issuing warnings. Thus, were selected 5 (five) key nodes, two internal - CPI and SPI, and 3 external nodes acting as HEWS key inputs for the monthly CPI and SPI trend.

Defining and establishing the probability nodes used in HEWS model simulation as follows:

➢ *Current Schedule Performance Index (SPI) probability nodes:*

The probable SPI node is set to observe the timing trend estimate at completion:

• Under (LowerSide) - if the current SPI value of CLPTE is below a control limit of less than 0.80;

• Over (HigherSide) - if the current SPI of CLPTE is at a control limit greater than 1.20;

• Alright (0.80-1.20) - a "normal" status for which no warnings are issued.

➢ *Cost Performance Index (CPI) probability nodes:*

The probable CPI node is set to observe the cost estimate on completion:

• Under - if the current CPMDT value is lower than the control limit of 0.80;

• Over - if the current CPM value of CLPTE is higher than the control limit of 1.20.
• Safety interval (0.80-1.20) - a "normal" state for which no warnings are issued.

➢ *The "trend" nodes for SPI and CPI:*
These nodes are set to observe the SPI and CPI trends as follows: The "constant" trend - if it deviated from value 1 but stabilized within the confidence interval (the set control limits) or there is no significant change from the previous value. "Upper side" means that it has deflected more than 20% - positive deviation and "lower side" means a negative deviation of 20%.

➢ *Causal Nodes:*
Estimation of effort, labor productivity, availability of material resources, availability and use of critical information infrastructures. If "Higher Side" appears, then the effort has been overestimated, more than the availability of force resources. We have the same situation over the overuse of critical infrastructure. Similar logic is for "Lower Side".

➢ *Time and Cost Performance Observing Nodes:*
These nodes are central intermediate nodes that warn us in three different situations:
• if the project's time and cost situation worsens with the phrase "worsening";
• if the time and cost situation of the project improves with "bettering" or;
• if the situation of the project does not deviate from the plan with the phrase "constant".

➢ *The current warning level node in CLPTE:*
This node is a node that gives the CLPTE manager a complete picture of the CLPTE status at one time, as follows:

- In control;
- Closely monitoring - possible early warnings;
- Return to parameters – recovering;
- Alarming.
-

➢ *Support node for different scenarios:*
It is the last application node that provides a scientific reason to CLPTE managers if they let the project continue in the current form or re-estimate all the cost and time calculations.

Warning tables at different levels in CLPTE.

In the following are presented 4 tables resulting from the relationship of the probability nodes set above with data and information from the external environment. The five warning tables used in HEWS model for monitoring CLPTE (Bosch, the industrial new development sector) in different scenarios are:

Table 6

Printscreen - Conditional probability of time performance - SP and cost - CP.

Shedule performance	Cost performance	LowerSide	Alright	HigherSide
Bettering	Bettering	0	20	80
Bettering	Worsening	50	0	50
Bettering	Constant	0	50	50
Worsening	Bettering	50	0	50
Worsening	Worsening	80	20	0
Worsening	Constant	50	50	0
Constant	Bettering	0	50	50
Constant	Worsening	50	50	0
Constant	Constant	10	80	10

Table 7

Printscreen - Conditional probability of effort estimation.

Shedule performance	Cost performance	ReEstimate	Continue	Suspend
Bettering	Bettering	35	65	0
Bettering	Worsening	65	35	0
Bettering	Constant	25	75	0
Worsening	Bettering	65	35	0
Worsening	Worsening	35	0	65
Worsening	Constant	55	10	35
Constant	Bettering	25	75	0
Constant	Worsening	55	10	20
Constant	Constant	10	90	0

Table 8

Printscreen - The conditional probability of the early warning node.

Shedule ...	Cost Perfo...	Alarming	Closely...	Recovery...	InControl
Bettering	Bettering	0	0	80	20
Bettering	Worsening	20	50	0	30
Bettering	Constant	0	20	50	30
Worsening	Bettering	20	50	0	30
Worsening	Worsening	80	20	0	0
Worsening	Constant	30	40	0	30
Constant	Bettering	0	20	50	30
Constant	Worsening	30	40	0	30
Constant	Constant	0	0	20	80

Table 9

Printscreen - Conditional probability of node support for different scenarios according to the SPI trend

Curent SPI	SPI trend	Bettering	Worsening	Constant
Less	Towards1	65	0	35
Less	Constant	25	25	50
Less	AwayFrom1	0	65	35
Normal	Towards1	50	0	50
Normal	Constant	10	10	80
Normal	AwayFrom1	0	50	50
High	Towards1	65	0	35
High	Constant	25	25	50
High	AwayFrom1	0	65	35

Table 10

Printscreen - Conditional probability of node support for different scenarios according to the CPI trend.

Curent CPI	CPI trend	Bettering	Worsening	Constant
Less	Towards1	65	0	35
Less	Constant	25	25	50
Less	AwayFrom1	0	65	35
Normal	Towards1	50	0	50
Normal	Constant	10	10	80
Normal	AwayFrom1	0	50	50
High	Towards1	65	0	35
High	Constant	25	25	50
High	AwayFrom1	0	65	35

Phase 5: Validation of HEWS model. Early warnings in different scenarios.

Print screens with node values and probability tables obtained from monthly inputs of external nodes for the new industrial development sector - Bosch Romania, are integrated into the chart below, which is the overall framework of HEWS. The values of the probability knots CPI and SPI and their trends in the past months are quantified and the data are used in the WINBag software dedicated to Bayesian networks, then the trends on all nodes are observed and deduced. The node values set in charge of the level Current HEWS alerts are monitored first to check whether there is a real need for some early warnings to take corrective action. In the case of strong beliefs in control, we can not discuss possible early warnings about possible cost or time overruns. However, the proposed HEWS model has the potential to issue early warnings in the "CloselyMonitor" situation, ie before the actual alert, which starts at 35%. In the worst case, if early warnings are not taken into account (the values set for this model are 35% and 25%) since the CloselyMonitor phase, the project reaches the "Alarming" status (10%), which will require decisions such as reassessing costs and time, or even suspending the project (5%). (Annex 1)

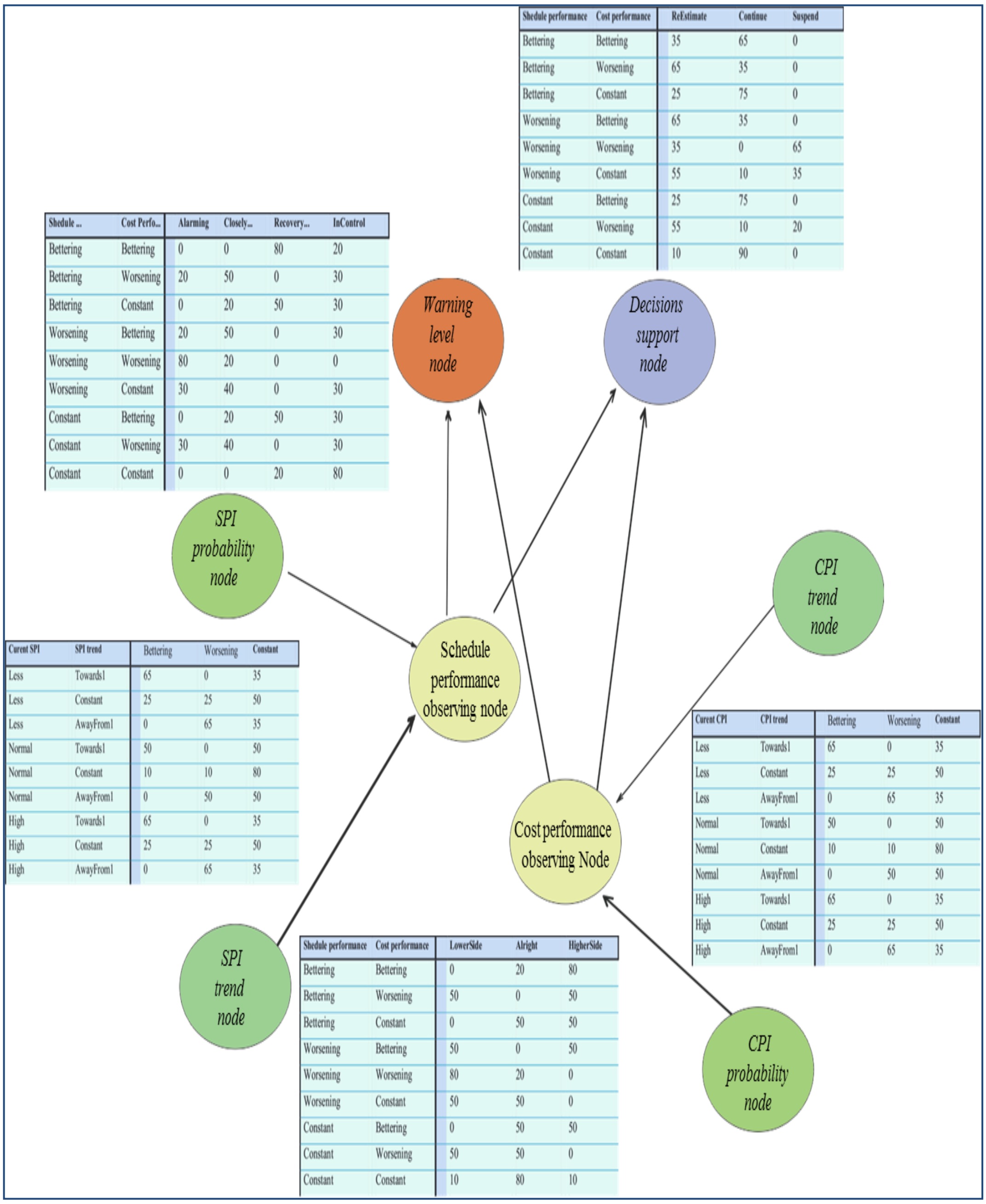

Fig. 1. Representation of conditional probability map consisting of nodes and probability tables.

In table 11, following the data provided by the nodes and the probability tables in HEWS, there are four scenarios in which the project is located, by color code. It was considered that the idea of synthesizing warnings on color code can help CLPTE managers to know the status of the project at all times and, consequently, take necessary corrective actions.

Table 11

Early warning scenarios based on estimates of time and cost parameters

HEWS – Warnings to possible scenarios					
Input variables		Scenario 1 (optimistic)	Scenario 2 (Monitoring/ Early warnings)	Scenario 3 (Closely monitoring/ Early warnings)	Scenario 4 (alarming/ suspension)
1.	SPI	...	...	...	...
2.	SPI Trend	Towards to 1	Towards to 1	Away from 1	Away from 1
3.	CPI	...	...	...	...
4.	CPI Trend	Towards to 1	Away from 1	Towards 1	Away from 1
Parameters monitored					
1.	Time performance	Improvement	Improvement	Worsening	Worsening
2.	Cost performance	Improvement	Worsening	Improvement	Worsening
Results provided by HEWS					
1.	Effort estimation	At the upper limit of the safety margin.	Difficult to estimate	Difficult to estimate	Below the safety margin
2.	Warnings	Recovery	Early warnings/ Closely monitoring	Early warnings/ Closely monitoring	Alarming
3.	Qualitative scenarios	Continuation	Reassessments	Reassessments	Suspension

3. Conclusions

Industry uncertainties are a common phenomenon. The multitude of factors affecting CLPTE, cause-effect relationships between these factors and inherent uncertainties lead to difficult predictions. Despite all researches, issues have remained unresolved due to the lack of a comprehensive hybrid model that can account for causal effects between factors along with the uncertainties that exist. Therefore, an early warning hybrid framework using various conventional and statistical forecasting tools integrated within a BN framework to establish a confidence interval outside which warnings are issued and which consequently lead to the implementation of corrective measures as an instrument strategic planning. The advantages of the new proposed HEWS hybrid model can be summarized as follows:

• Takes into account not only historical data recorded in the past but also expert opinions;

• Defines and sets a time and cost range beyond which warnings are issued;

• The proposed model being made by combining several software packages allows for easier management of input and output data;

• The applicability and effectiveness of HEWS is not limited to projects in the new industrial development sector, research findings suggesting that the same hybrid approach can be applied to other industries sectors in order to improve the process control of the project in terms of time and cost .

• The model provides a very clear understanding of the relationships between the evolutions of the internal parameters correlated with the evolution of the external factors;

• The proposed model provides early warnings, regarding time and budget, in various stages of a CLPTE by modeling uncertainties and variable risk factors;

• Decoding the graphics provided by conventional methods becomes an easy task and non time-consuming for CLPTE managers;

• Provides the possibility of corrective actions based on early warnings in a given situation, and the effect of decisions can be viewed in real time.

Limitations of research

The limitations of the model are largely related to the subjectivity of the project managers interviewed and the confidentiality of the data provided, but also to the limited literature in this chosen research field, as follows:

• First vulnerability of this research is that was assumed from the outset that all the publications and technical reports analyzed from the bibliographic list in different areas of the industrial projects are valid sources and are applicable to the types of industrial projects analyzed in this research. This can be considered an important limitation on the results of this research.

• Second limitation of this research is that were analyzed only 7 major determinants, with its impact and implications on CLPTE. This has limited research into access to various factors that can have important effects on labor productivity in CLPTE. For example, "workplace discrimination between women and men" or "sexual harassment" are some of the factors bypassed by project managers and by the literature. As far as were available such information, there were the posibility to set up other root-based conditional nodes that would have led to additional data on the node responsible for labor productivity.

Further research

A possibility of future research is the development of a web-based decision support system for smartphones, were project managers can enter in project status and will be able to instantly view the distributing probability of estimates at completion.

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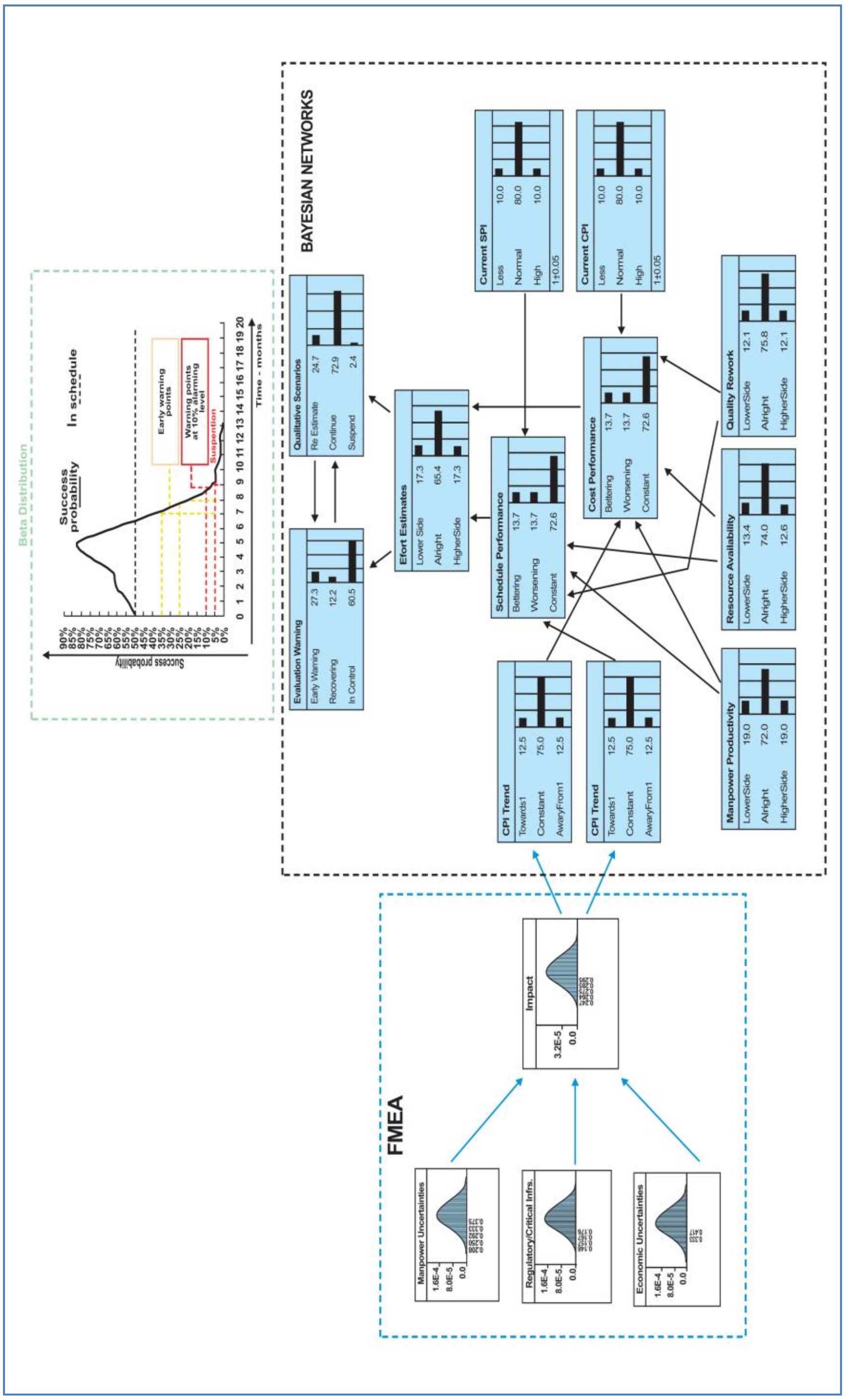

Annex 1. Simulation of external parameters and conditional probability nodes in BN.