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Research Article
Measuring Uncertainties of Project Completion Late Delivery in Environmental Issues

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Abstract

Many uncertainties in multi project construction environment systems are treated as "Controllable" elements, with a variety approaches being used to cope with them. However, modern Construction Industry (CI) has many underlying causes of uncertainty that impact on late delivery of project completion's performance, forcing enterprises into emergency measures to ensure delivery performance. Based upon the results of a survey, this study analyses the uncertainties in the Project Completion Late Delivery (PCLD) that affect customer delivery performance in construction industry, focused on Environmental Issues (EI) such as accidents, unpredictable weather and landform structure. These uncertainties have been quantified and the relative importance to performance has been investigated. The results provide a level of delivery reliability in the prediction of M-factor. It is contended that by concentrating on minimizing the effects of the uncertainties, the underlying causes have not been addressed, resulting in sub-optimization of system performance.

Key words: Measuring uncertainty, late delivery, correlation, linear regression, construction industry

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Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

In the present day dynamic market environment, meeting customer requirements is becoming increasingly important, especially in issues of delivery performance. The ability of industries to satisfy customer cravings in terms of delivery interval, project and product quality are essential to stay in this kind of businesses. During the planning and construction progression, many uncertainties exist to which an enterprise must be able to respond. These dynamic necessities affect the efficient operation and progression of project completion.

Amongst the causes of uncertainty that are reconnoitred within this study are about environmental issues included accidents, unpredictable weather and landform structure. Most of researcher preferred to investigate the tangible causes of uncertainties especially material shortages, labour shortages, machine breakdown, scrap and rework[1-3]. Yet, it is not enough if we assumed only the listed factors of uncertainties that are always faced by industries, such as manufacturing, construction or other types of industry.

Therefore, this study has contributed to explicating on fundamental regression analysis techniques underlying as causes and effect of uncertainty, in an effort to facilitate prediction and classification applications in project completion late delivered. Koh and Saad[4] stand for quantity uncertainty as presented by Wazed *et al.*[5]. Additionally, Koh and Gunasekaran[6] confront of resource breakdown for in-building environment as the factor of uncertainty. While, in the meantime Polat and Ballard[3] found a new discovery regarding these matters, the severe weather and soil condition as the uncertainty factors for construction industry. More factors, reasons and causes that give impacts on project construction performance as discussed by Refsgaard *et al.*[7], particularly weather conditions which can lead uncertainty as earlier as in the planning stage.

There are no specific ways to ignore uncertainties except by reducing, managing and tackling the problems from detailed investigation, such as diagnose and analyse the causes and effects. Frequently, the project will be planned, scheduled and organized using a Critical Path Method (CPM)[8,9] and Program Evaluation Review Technique (PERT)[10]. The project is planned with a simple computer software such as Primawera or Microsoft office package software such as Project and Excel[11].

Uncertainty may always be a big reason for some of construction project late to deliver. Uncertainty can be resulted from lack of information or from disagreement. However, a project needs also to observer several imperceptible matters such as uncertainties to ensure the progression of PCLD is performing better than others.

Uncertainty in PCLD: Uncertainty also refers to measuring the degree of differences between the models and the real system's values respective or between the estimation of variables and their true values. In construction industry, uncertainty also can be referred as complexity and risky of environmental. General definitions of uncertainty presented by Baharum *et al.*[12] from different scientific researches perspectives. Report meeting ministry of climate and energy, geological survey of Denmark and Greenland has discussed five types of uncertainties, which are statistical, scenario, qualitative; recognise ignorance and epistemic arrogance[13] as supported by Walker *et al.*[14]. Figure 1 shows the level of uncertainty as adopted via Baharum *et al.*[15].

MATERIALS AND METHODS

Most of the researchers found out that the uncertainty is difficult to quantify. To ease collection of empirical data, bandwidths for the measurement of level of uncertainties have been introduced. Exponential bandwidths of X<2% until X>30% is pragmatic. This allows coverage of wide span of levels of uncertainties in a very few bandwidths and also highlight the fact that further increment of any bad performance is still deemed bad performance.

For example, a 25% late delivery could be deemed a bad performance and although a record of 30% empirically higher, its effect is equally bad in the context of categorization of the PCLD performance. To enable the benchmarking of levels of uncertainties and levels of PCLD performance, the bands were converted into classification scale, synchronize

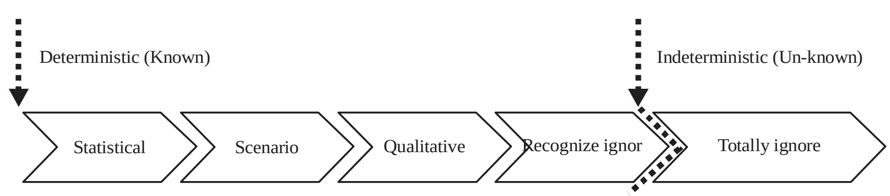

Fig. 1: Uncertainty's scale from "Known" to "Un-known"

Table 1: Benchmarking scale of levels of uncertainty

Benchmark scale	Uncertainty level	Survey bandwidths
1	Statistical	X<2%
2	Scenario	X>2% && X<5%
3	Qualitative	X>5% && X<16%
4	Recognize-ignore	X>15% && X<31%
5	Totally Ignorance	X>30%

with Fig. 1. The level of uncertainty is notated from 1-5 to suite the benchmark the uncertainty level with the bandwidths categorization as shown in Table 1.

A conceptual model that structures and relates uncertainty in cause-and-effect was analysed using a combinatorial methodology of interview and observation. The conceptual model consists of 40 underlying causes of uncertainty and 11 effects, which are contributed towards product tardy delivery.

RESULTS AND DISCUSSION

The importantance of the relation and implication of causes and effects to level of uncertainties and PCLD will be discussed. From the correlated input the predication might be calculates. By assuming the data of uncertainties are normal, the details analysis has been explained.

Relationship between causes and effects: At this stage, the objective was to highlight the approaches used in both low and high uncertainty environments. This would allow subsequent analysis of the relationship between the measures used to cope with the uncertainties and the performance of PCLD for construction industry. All the possible data, the causes and effects that might be playing role in uncertainty is mapped into the Ishikawa diagram to present the relationship among each other's.

Generally, initial model of cause and effect was intellectualized from the construction of an Ishikawa diagram structuring causes and effects of uncertainty in Enterprise Resource Planning (ERP) and on-site environments as shown in Fig. 2 as adopted by Zirawani *et al.*[16]. The details causes and effect on each node is explained together. There are 40 main causes started at inner level, level 3 as shown as following:

Source of causes:

- Rain
  - Type 1: Drizzle
  - Type 2: Raining at evening of the day
  - Type 3: Raining at morning of the day
  - Type 4: Heavy raining
  - Type 5: Pouring raining
- Flood warning: According to water level
  - Type 1: No warning at all
  - Type 2: Yellow
  - Type 3: Red
- Hot and dry
  - Type 1: No cloud-hot
  - Type 2: Hot and dry
  - Type 3: Extremely hot and dry
  - Type 4: Sweltering
- Acts of god
  - Type 1: No
  - Type 2: Yes
- Cold and snowy
  - Type 1: Mild cold
  - Type 2: Cold and snowy
  - Type 3: Snowy and windy
  - Type 4: Extremely snowy and windy
- Soil condition
  - Type 1: Alkaline
  - Type 2: Acidic
  - Type 3: Sandy or swampy
  - Type 4: Very muddy and clayey
  - Type 5: Coarse gravels and hard
- Utilities inside the landform
  - Type 1: Can be deflated
  - Type 2: Item available
  - Type 3: Waiting for Item on delivery
  - Type 4: Waiting for approval before delivery
  - Type 5: Cannot be deflected need to produce another design of item
- Lack of skills
  - Type 1: Certificated
  - Type 2: Moderate
  - Type 3: Poor
  - Type 4: Very poor
- Extra works
  - Type 1: Below than 4 h
  - Type 2: More than 4 h
- Safety matters
  - Type 1: Under control
  - Type 2: When necessary
  - Type 3: Never do the inspection
- Negligence
  - Type 1: Light injury
  - Type 2: Serious injury
  - Type 3: Workers died

In the final data summarization, there are 11 resources that criticize to the type accordingly.

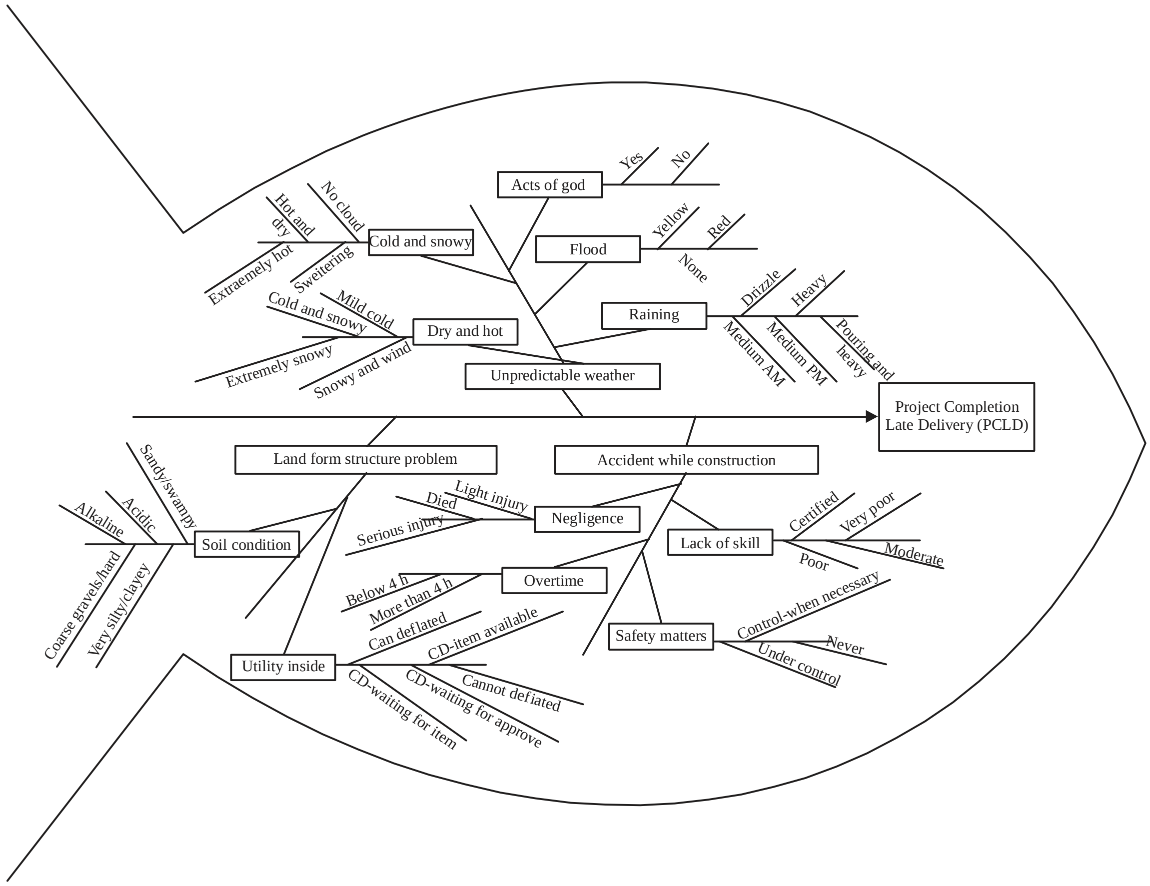

Fig. 2: Ishikawa diagram of cause and effect that uncertainty leading to PCLD in EI

Measure for relative implications of uncertainty: It is inevitable when measuring late delivery of project completion to customers that it is possible to measure what was achieved. Companies use a variety of techniques to cope with uncertainties in order to satisfy their customers and are therefore actively overcoming uncertainties, which then go unrecorded. The level of Project Completion Late Delivery (PCLD) to customer is therefore, a dependent variable, with the disadvantage that dependencies are largely unknown and unrecorded.

Similarly, uncertainties themselves are invariably only partially recorded. For example, the accident may be happen (is only significant) if employees are not concerned about the safety matters. The implication this has on project completion performance is therefore dependent upon when they concern rather than ignorance. Thus, the accident could have no implications or it could cause a delay. Only the latter would ever be recorded and therefore the true incidence of the event is unlikely to be known.

It is not possible to achieve an absolute measure of the implications of uncertainty on PCLD to customer at this stage as both causes and effects are being masked. In this study, the approach taken has been to derive a benchmarking measure of performance allowing comparisons of magnitude to be made in relative rather than absolute terms. To assess the relative implications of uncertainties on PCLD, the use of X and Y as the independents and dependents has to be determine. The M-factor will use to measure the relatives implications of level uncertainties on level of PCLD to customer.

In this case, the level of individual uncertainties (independent variables, X) do not has to directly proportional to the level of late delivery of PCLD to the customers (dependent variables, Y). Plus, the strength of the uncertainties is also need to be determined in the way to measure the implication of the causes and effects, by develop the M-factor.

Examining the relationship of causes and effects: Although, the levels of individual uncertainties, X (causes) do not necessarily directly proportionate to levels of PCLD, Y (effects), X is likely to cause Y. In this study, the variable has been manipulated via translation to the benchmark scale (Table 1). In these contexts, linear regression analysis is suitable to examine the relationship between cause and effect of X and Y. The correlation is use to show the relationship between X and Y is exist or not. While, the linear line of the regression analysis is able to measure the relationship between independent variables and dependent variables, either has relation or not. Then, if the relation is existing, it is also able to measure either the relation is strength or weak.

After the conversion of the result collected from respondents from the survey bandwidths to the benchmark scale for both X and Y, linear regression analysis was carried out. Figure 3 shows the results of the linear regression analysis between X and Y.

Considering the calculated value of correlation factor r ($r^2 = 0.84$ as calculated by Eq. 1), which is equivalent to the r value from the correlation test, it can be inferred that his regression model suggests that there is a goodness of fit on the positive correlation between X and Y:

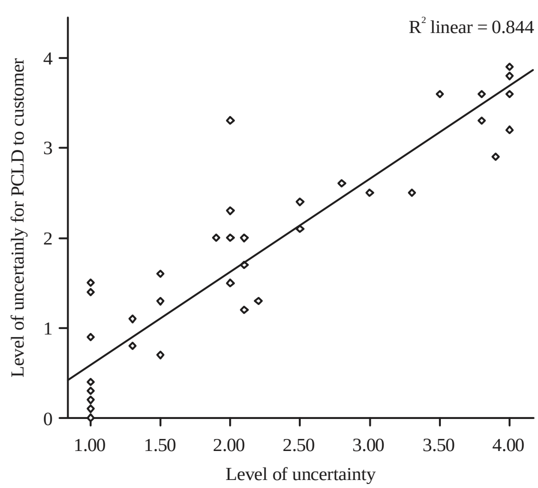

Fig. 3: Linear regression model of X and Y

$$r = \frac{n\left(\sum xy\right) - \left(\sum y\right)\left(\sum y\right)}{\sqrt{\left[n\sum x^2 - \left(\sum x\right)^2\right]\left[n\sum y^2 - \left(\sum y\right)^2\right]}} \quad (1)$$

Then, calculate the value of correlation factor, r:

n = No. of input data of X and Y
C = -0.4243
r = 0.711

Therefore, the equation for the linear regression, r is:

Y = 1.0244X-0.4243
r^2 = 0.8432~0.84

It is also can be understood that the relation between X and Y is highly fortified. It also shows a C intercept value as -0.4243. Figure 4 shows the results of correlation with Pearson correlation between X and Y. The value of correlation factor r (r = 0.91), still shows the goodness of fit on the positive correlation of the relationship between X and Y.

The r and r^2 value signify the ability to predict using the regression line, compared with not using it. This regression model shows a reasonable prediction capability (when r value is closes to 1). The result from the regression analysis do not indicate the statistical significance of the correlation between X and Y. The goodness of fits and its predictability are sufficient in this study to open the usability of using X and Y to derive a benchmark to compare performance of projects and to highlights areas for further examination of causality.

Knowing that the correlation exists between X and Y allowed us to state that X∞Y. Tthe introduction of M-factor to quantify the strength of the relationship resulted in Eq. 2. This study produced M-factor of 1.025. The calculation as following:

Correlations

	Level of uncertainty	Level of uncertainty for PCLD to customer
Level or uncertainty		
Pearson correlation	1	0.919
Significant (2-tailed)		0.000
N	40	40
Level of uncertainty for PCLD to customer		
Pearson correlation	0.919	1
Significant (2-tailed)	0.000	
N	40	40

**Correlation is significant at the 0.01 level (2-tailed)

Fig. 4: Pearson correlation of X and Y

Table 2: Implication relative between X, Y and M-factor

Uncertainty	Coded	X	M-factor value
Drizzle	RAIN1	1.0	1.79
Intermittent on PM	RAIN2	1.9	1.14
Intermittent on AM	RAIN3	3.3	0.66*
Heavy	RAIN4	3.9	0.56*
Pouring and heavy	RAIN5	4.0	0.54*
None	FLOOD1	1.0	2.17
Yellow	FLOOD2	2.1	1.03
Red	FLOOD3	3.8	0.57*
No cloud/hot	DRY1	1.0	2.17
Hot and dry	DRY2	1.5	1.44
Extremely hot and dry	DRY3	2.5	0.87*
Sweltering	DRY4	3.5	0.62*
No	GOD1	1.0	2.17
Yes	GOD2	4.0	0.54*
Mild cold	SNOW1	1.0	2.17
Cold and snowy	SNOW2	2.1	1.03
Snowy and windy	SNOW3	2.8	0.77*
Extreme snowy and windy	SNOW4	4.0	0.54*
Alkaline/non-acidic	SOIL1	1.0	2.17
Acidic	SOIL2	3.8	0.57*
Sandy/swampy	SOIL3	2.2	0.98*
Very silty/clayey	SOIL4	1.0	2.17
Coarse gravels/hard	SOIL5	1.5	1.44
Can deflected	UTILITY1	1.0	2.17
Can deflected: Item available	UTILITY2	1.3	1.67
Can deflected: Waiting for item	UTILITY3	2.1	1.03
Can deflected: Waiting for approve	UTILITY4	3	0.72*
Cannot deflected	UTILITY5	4.0	0.54*
Certified	SKILL1	1.0	2.17
Moderate	SKILL2	1.3	1.67
Poor	SKILL3	2.0	1.08
Very poor	SKILL4	2.0	1.08
Below 4 h	OT1	1.0	2.17
More than 4 h	OT2	2.0	1.08
Under control	SAFE1	1.0	2.17
Control: When necessary	SAFE2	1.5	1.44
Never	SAFE3	2.5	0.87*
Workers: Light Injury	NEG1	1.0	2.17
Workers: Seriuos Injury	NEG2	2.0	1.08
Workers: Died	NEG3	4.0	0.54*

$$y = Mx + b$$
$$M = \frac{y_a - y_b}{x_a - x_b} \tag{2}$$
$$b = -(y_a - y_b)M$$

Where:

y	=	Level of PCLD to customer
x	=	Level of uncertainties
C = b	=	Equal to C intercept
M-factor	=	Relatives implications of level uncertainties on level of PCLD to customer, which M is 1.025

M-factor measures the relative implication of uncertainties on PCLD to customer. The higher is the M-factor, means the greater is the relative implication of the uncertainties measured on the PCLD or vice-versa. For M value of one, the level of uncertainty X is the same as the level of PCLD Y.

A value of M less than one (M<1) means a relatively higher level of uncertainty than the level of customer delivery performance. A value of M greater than one signifies a relatively lower level of uncertainty than the level of PCLD performance. From the results of the survey, the mean of PCLD performance Y has been calculated at 2.65, which denotes a median performance level.

This Y value was used as the baseline to calculate the relative implication on each uncertainty. Table 2 shows the survey of X, Y and M-factor. The result shows there are 15 uncertainties of signifies a relatively high level of uncertainty than the level of PCLD performance, which are RAIN3, RAIN4, RAIN5, FLOOD3, DRY3, DRY4, GOD2, SNOW3, SNOW4, UTILITY4, UTILITY5, SOIL2, SOIL3, SAFE3 and NEG3.

Even though the data for correlation and regression is subjective and the p-value of analysis of variance does not provide the benchmark figure for the practioners, the analysis will be discuss details on the analysis section. The analysis of variance or F-test analysis has been pursued after the regression analysis to find the significance of the uncertainties factors according to the proportion values determination. This analysis is very common for analysts and statisticians when calculating variance for more than 3 variables, at the same time. Hence, the M-factor is introduced to assist the benchmarking in this study.

CONCLUSION

A comprehensive literature review found that many researchers from many of countries using various techniques to tackle the uncertainty with less consciousness on environmental issues. Initially, conceptual model was conceptualized from the construction of an Ishikawa diagram structuring causes and effects of uncertainty in on-site project environments. Uncertainty modelling on PCLD in environmental issues is intentionally to manage the project performance, hence to maximize the customer's satisfaction.

Regression techniques are effective to analyse construction operations in terms of cycle- time prediction and project monitoring. Hence, the M-factor is introduced to assist the benchmarking for further research especially for analytical modelling. There are 15 factors with strength positive relationship, whereby measured by using regression analysis among 40 underlying causes of uncertainty.

In future, the modelling of uncertainty will be carried out through simulation experiments, uncertainty modelling of case study and comprehensive analysis. The significant factor is resulted from analysis of variance between the group and the diagnosis is executed to each causes. The method of analysis execution is exposed.

For analysis, the confidence level of 80% ($\alpha = 0.20$) was set. Analysis of variance (ANOVA) results identified significant evidence that a total of 12 underlying causes of uncertainty affect PCLD in environmental issues. However, this does not mean that those uncertainties with p-values not within 20% do not affect PCLD; instead it simply means that higher confidence was gathered that those identified to be significant have a higher likelihood of resulting in PCLD. The intention of using ANOVA is to establish the existence or otherwise of cause and effect relationships between uncertainties and their outcomes. The use of ANOVA was considered entirely appropriate for this purpose. The data (project construction) derived from the survey were largely based on estimates and the estimates themselves were taken after the application of approaches to cope with uncertainty.

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