INVESTIGATING THE USE OF THE RELIABLE COMMITMENT MODEL IN A PIPELINE CONSTRUCTION PROJECT: A CASE STUDY

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Abstract

Current management practices in construction usually undertake the creation of work plans in a very informal fashion, relying heavily on the intuition and experience of the decision-makers. This construction decision pattern has resulted in detrimental effects on project performance. The Reliable Commitment Model (RCM) is a statistical decision-making tool that uses production (objective) data to create work plans, improving their reliability and project performance. The RCM framework is based on lean production principles and supports short-term forecasting of work plans using common site information such as workers, buffers, and plans. The RCM's capability to improve work plan reliability in past building and industrial projects has been proven, but its use in projects of a different nature is yet to be understood. This paper investigated the application of the RCM using a repetitive pipeline construction project as a case study. Thus the study consisted of two units of analysis considering the following activities: 1) open-cut and trenching, and 2) trenchless technology – tunnel-boring. The main finding was that the RCM was able to predict production progress over these activities with certain accuracy, illustrating its potential to improve work plan reliability in pipeline projects. Also, the lessons learned from the RCM implementation in projects of this sort are addressed.

KEY WORDS: Lean Construction, Pipeline projects, Planning Reliability, Reliable Commitment Model, Statistical Models.

1. Introduction

Numerous researchers have stated that the prevalent use of intuition and experience when planning and scheduling projects (Koskela & Vrijhoef, 2000; Sacks & Harel, 2006) severely affects project performance. Gonzalez et al (2009) thus formulated the Reliable Commitment Model as a lean-driven tool to improve the reliability of work plans and decisions through use of statistical multivariate linear regression (MLR) methods. RCM is able to predict project progress at the activity level of work plans constructed, using statistical models and common on-site information collected about resources and conditions. When used in tandem with other lean tools, it assists in the creation of more reliable work plans. This was further

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documented and validated in Gonzalez et al (2010) where the RCM showed proven success in improving planning reliability at the operational level in repetitive projects of the vertical type (multi-storey/multi-residential building projects).

This paper proposed trialing the RCM's validation for use in a repetitive construction project of a non-building and horizontal scope, using pipeline construction as a case study (Wendt, 2012). The goal of the study was thus to explore and analyze the applicability of the RCM in a pipeline project. The ability of the RCM to predict project progress at the operational level in the typical and various activities/processes selected, would serve to verify its applicability and potential use on projects of this type. Thus, only the predictive ability of the RCM was explored, without utilising its capabiity to make decisions and changes to the planning of resources related to the RCM (labor numbers, WIP buffers, and planned progress).

The results and conclusions reached were in alignment with previous research conducted by Gonzalez et al (2009,2010), even when the RCM was only utilized in an observational role on the South-Western Interceptor Project. It must be stressed at this point that the main objective of this research was not to duplicate the findings of past research, but to confirm that the RCM could be utilised for the first time, in repetitive projects of the horizontal type, which had never been investigated historically.

2. Reliable Commitment Model Remarks

One critical lean aspect to improving planning commitment reliability is the analysis of constraints on planned activities that could limit or prevent their execution. The most common constraints are design, materials, prerequisite work, space, equipment, and labor (Ballard 2000). The basic hypothesis for RCM is that the progress of a repetitive activity can be predicted, for a short-term planning horizon, using only three variables: size of labor, buffers (Work-In-Process), and planned progress (Gonzalez et al, 2010).

Statistical analysis using Multivariate linear regression (MLR) models based on historical data are used to implement the RCM, which relate predicted progress (PRP) of an individual process as a dependent variable with the following independent variables: a worker-week (W) which is the total number of days worked by a planned number of workers over the planning horizon for the activity (e.g. a horizon of 1 week or 6 days multiplied by 6 workers in this activity's crew = 36 worker-weeks), buffers (WIP buffer) available at the beginning of the planned week (e.g. if the activity is laying the final coat of seal for a two-coat chipseal road, the buffer is the amount of linear metres which have been sealed with the first coat), and planned progress (PP) estimated for the horizon (using the seal example above, the planned progress may be that in one week, ONE KILOMETRE of road must be sealed with the second coat). In other words, a general expression:

$$PRP=\beta_0 + \beta_1 W + \beta_2 \text{WIP Buffer} + \beta_3 PP \qquad (1)$$

for the RCM is defined. Only significant variables are selected in the models, since including redundant variables may lead to incorrect analysis of scenarios. The variable selection process uses statistical indicators; the coefficient of determination (R^2) and the P-value, leading to a trade-off between the number of variables, and the R^2 and P-values. In general, regression models with the least number of variables, and with the highest R^2 and low P-values are preferred (preferably < 5% or 0.05).

The RCM also replaces the notion of variability in the process' duration of the WIP buffer design stage with the variability or reliability (variability is inversely proportional to reliability) of the commitment planning for the WIP buffer management stage. By doing so, the Actual or Predicted Process Reliability Index (Actual or Predicted PRI) is proposed, which is defined as the ratio between actual or predicted progress (AP or PRP) and planned progress (PP) of a process, varying between 0% and 100% (Gonzalez et al, 2010).

$$\text{Actual / Predicted PRI} = (\text{AP / PRP}) / \text{PP} \tag{2}$$

The Commitment Confidence Level (CCL) (Gonzalez, 2010) measures the commitment accuracy of the activity progress prediction, comparing the predicted PRI with the actual or real PRI and is defined as:

$$CCL_{i,j} = \left(1 - \left(\frac{PredictedPRI_{i,j} - ActualPRI_{i,j}}{ActualPRI_{i,j}}\right)\right) \times 100 \tag{3}$$

where: **$CCL_{i,j}$**= Commitment confidence level for week i and activity j (%).

Actual PRI$_{i,j}$ = Actual or Real Process Reliability Index for week i and activity j. Actual PRI is computed using equation (2).

Predicted PRI$_{i,j}$= Predicted Process Reliability Index for week i and activity j. To calculate the Predicted PRI, PRP replaces AP in equation (2).

Note that CCL does not measure confidence on the net predicted progress of the activity and when less than 0, is set to 0.

Nomographs are an implementation tool for the RCM and are useful in other engineering disciplines such as hydraulics, for the scope of this paper a weekly development of these constitutes an important part of RCM application. A nomograph is constructed by rearranging equations (2) for the Predicted PRI and the general expression (1) above as follows (Gonzalez et al, 2010):

$$\text{Pred. PRI} = \text{PRP/PP} \Rightarrow \text{PRP} = \text{PRI} \times \text{PP} \tag{4}$$

If eq. (1) is substituted into eq. (4):

$$\text{PRP} = \beta_0 + \beta_1 W + \beta_2 \text{WIP Buffer} + \beta_3 \text{PP} = \text{PRI} \times \text{PP}$$

$$\beta_0 + \beta_1 W + \beta_2 \text{WIP Buffer} = \text{PP}(\text{PRI} - \beta_3)$$

$$\Longrightarrow \quad PP = \left(\frac{\beta_0 + \beta_1 W + \beta_2 WIPBf}{PRI - \beta_3}\right) \tag{5}$$

Eq. (5) defines a relationship between PP, W, WIPBf, and PRI. PP can either be defined by the planner or estimated using the RCM (for more RCM details, please refer Gonzalez et al, 2010).

3. Case Study: The South-Western Interceptor Project

The single embedded case study approach was utilized for this research paper (Yin, 2003) and consisted of two units of analysis, open-cut trenching and tunnel-boring. 13 weeks of data for 1000mmΦ High Density Poly-Ethylene (HDPE) pipe and 15 weeks of data for 1800mmΦ Reinforced Concrete Pipe (RCP) installation were collected in the first and second units respectively. Microsoft © Excel™ was the software used with its *Data Analysis* feature to perform statistical analysis on the large amounts of data that were collected, in order to process and obtain the statistical indicators needed to implement the RCM.

3.1. Unit of Analysis One - Open-cut Trenching Section, Pipe Installation and Weld (P) Activity.

Given in Table 1(a) are analysis results for the pipe installation and weld (P), the primary activity of the open-cut trenching section selected from six which were observed and analyzed for this section of works. As outlined by Gonzalez et al (2010), the general heuristics used for selection of the relevant MLR models developed were the minimum combination of dependent variables of W, WIPBf and PP with the coefficient of determination (R^2) values closest to unity, and p-values less than 5% or $\alpha \leq 0.05$.

Table 1(a): Summary of Heuristic-Selected MLR Analysis Results of P Activity; O.C.T. Works.

Activity/ Wk	Selected MLR Model Equation	R-sq	p-value	Pred. CCL	Pred PRI	Actual PRI
P/Wk 5	PRP = -29.88 + 4.06W + 0.54PP	1.00	0.02	0%	21%	37%
P/Wk 6	PRP = -20.75 + 3.30W + 0.53PP	0.99	0.01	100%	100%	100%
P/Wk 7	PRP = -2.22 + 3.73W	0.93	0.00	100%	100%	100%
P/Wk 8	PRP = 3.77 + 3.39W - 0.56WIPBf	0.94	0.00	0%	40%	20%
P/Wk 9	PRP = -22.64 + 3.55W + 3.55WIPBf + 0.48PP	0.96	0.00	0%	44%	46%
P/Wk 10	PRP = -3.30 + 3.70W	0.93	0.00	100%	100%	100%
P/Wk 11	PRP = -3.89 + 3.81W	0.94	0.00	100%	100%	100%
P/Wk 12	PRP = -17.56 + 3.54W + 3.54WIPBf + 0.37PP	0.95	0.00	100%	100%	100%
P/Wk 13	PRP = -12.95 + 3.63W + 3.63WIPBf + 0.28PP	0.94	0.00	100%	100%	100%
	Mean	0.95	0.003	67%	78%	76%

The predicted Commitment Confidence Level (CCL) was added as a further heuristic to be used in the selection process. Figures 1(a) and (b) illustrate RCM prediction performance over the 9-week period following the four-week *warming* period. Note that this period was chosen to ensure enough data was collected to develop more accurate prediction models as the RCM is based on historical site data (Wendt, 2012). An additional and important note was that the research which forms the basis of this paper had introduced additional selection heuristics which aided in the selection of each of the models chosen for investigation.

The averages for the predicted and actual PRI ratios (given in Table (1)(a)) calculated using the MLR models selected for this period are close at 78% and 76% respectively, while the average Predicted CCL is at 67%. As can be seen, the predicted progress (PRP) values follow the actual progress (AP) measurements very closely, in most cases closer than that of the planned progress targets (PP) as indicated by the 2% variation between the predicted and actual PRI averages.

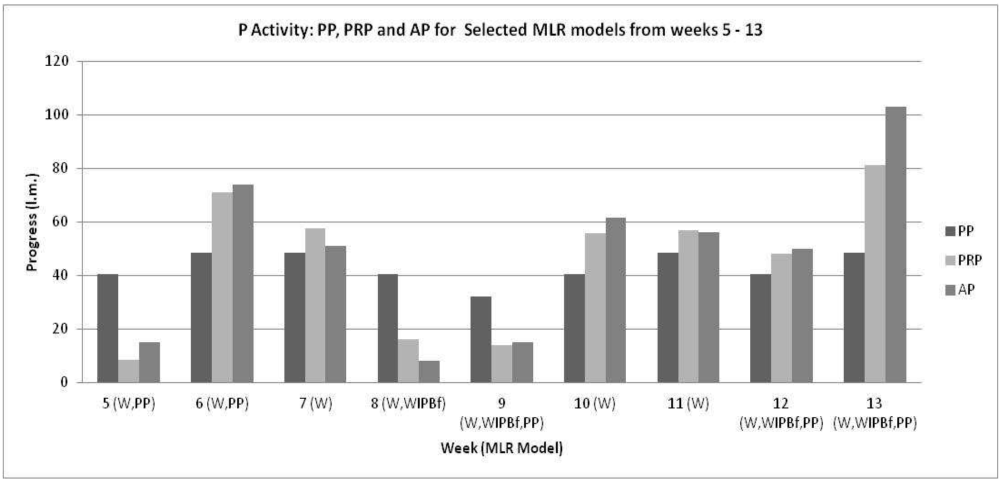

Figure 1(a): 9-week comparison of PP, PRP, and AP for P Activity, O.C.T Section

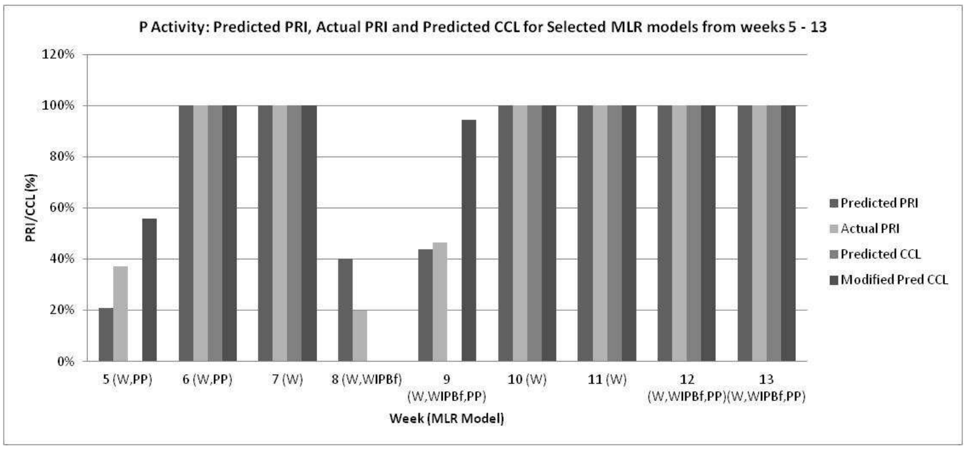

Figure 1(b): 9-week comparison of Predicted PRI, Actual PRI and Predicted CCL for P Activity, O.C.T Section

The nomograph in Figure 1(c) is a week 7 MLR model developed for the P activity. The selected model was of the form PRP = $\beta_0 + \beta_1 W + \beta_3 PP$ ($\beta_2 = 0$), and exhibited the strongest heuristics of all models developed over the 9-week period (R^2 = 0.99, P-value = 0.00, Predicted CCL = 100%).

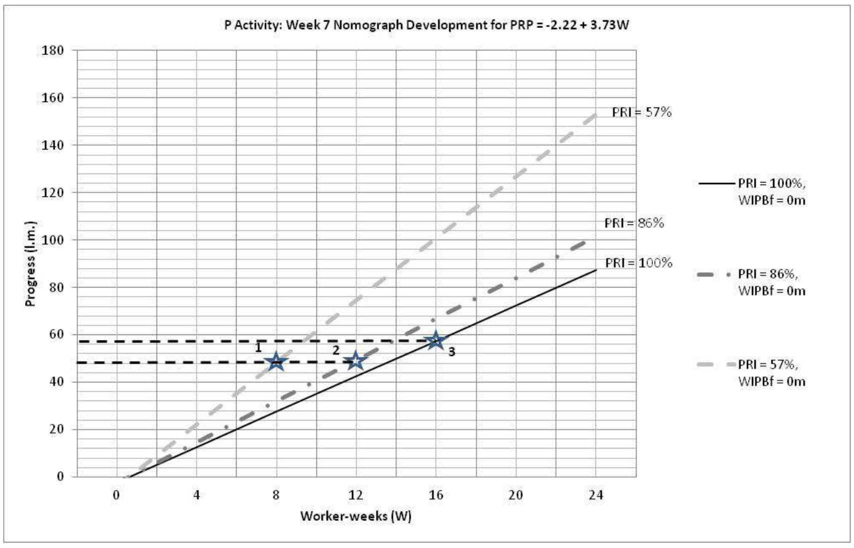

Figure 1(c): Week 7 Nomograph for P Activity

Sensitivity analysis for the nomograph is given in Table 1(b), with planner production scenarios described:

Table 1(b): Sensitivity Analysis with RCM Nomograph for Week 7, P Activity. (Actual W = 16, Actual Progress = 51m, WIPBf = 3.5m)

Point	PP (l.m.)	Plnd W	WIPBf (lm)	Pred. PRI	PRP (lm)
1	**48.4**	**8**	**0**	**57%**	**27.59**
2	48.4	12	0	86%	41.62
3	57.0	16	0	100%	57.00

Note: Bolded data indicates the base case.

- Point 1: This base case defines a PP of 48.4m, and 8 worker-weeks, which from the nomograph implies a PRI of 57% which is not an optimum production frame, therefore based on the RCM MLR equation developed, approximately 27.6m of progress is predicted which would equate to nearly two 15m pipe lengths installed this week.

- Point 2: To improve the reliability of the production frame and achieve a PP of 48.4m, worker-weeks can be increased to 12, resulting in a predicted PRI of 86% or 41.6m. This would imply three pipe installations for the week.

- Point 3: Given actual worker-weeks recorded for week 7 was 16, the predicted PRI resulting would be 100% with a predicted progress of 57m, comparable to the 51m progress actually achieved for the week. Because this marked the end of the planned pipeline section, 51m was the maximum achievable progress for this week.

3.2 Unit of Analysis Two - Tunnel-Boring Section, Pipe Change (PC) Activity.

Given in Table 2(a) below are the analysis results for the pipe change (PC) activity, the primary activity of the tunnel-boring section selected from four activities identified for this section of works.

Table 2(a): Summary of Heuristic-Selected MLR Analysis Results of PC Activity; T.B.M. Works

Activity/Wk	**Selected MLR Model Equation**	**R-sq**	**p-value**	**Pred. CCL**	**Pred. PRI**	**Act. PRI**
[4]*PC/Wk5	PRP = 27.86 + 0.36W - 1.04PP	0.28	0.53	0%	96%	100%
*PC/Wk6	PRP = 34.53 + 0.68W + 0.84WIPBf - 2.31PP	0.59	0.75	0%	27%	100%
*PC/Wk7	PRP = 21.59 + 0.36W + 0.99WIPBf - 0.11PP	0.44	0.71	0%	37%	100%
*PC/Wk8	PRP = 8.30 + 0.71PP	0.21	0.30	80%	93%	77%
*PC/Wk9	PRP = 13.56 + 0.36WIPBf + 0.22PP	0.56	0.13	0%	56%	100%
PC/Wk10	PRP = -2.57 + 1.27PP	0.61	0.01	0%	95%	100%
PC/Wk11	PRP = -8.70+0.58W+0.66WIPBf + 0.29PP	0.74	0.03	95%	78%	74%
PC/Wk12	PRP = -9.03+0.63W+0.80WIPBf + 0.14PP	0.74	0.02	0%	84%	33%
PC/Wk13	PRP = 9.00 + 0.65PP	0.29	0.07	0%	88%	100%
PC/Wk14	PRP = 7.25 + 0.76PP	0.36	0.03	0%	98%	100%
PC/Wk15	PRP = 7.65 + 0.55W	0.30	0.04	Delay	Delay	Delay
	Mean	**0.55**	**0.032**	**19%**	**89%**	**81%**

Week 12 saw considerably slow progress due to hard ground conditions with swelling of the soil surrounding the TBM. These conditions became apparent late in week 11 and carried on into week 12. This resulted in a very low actual progress for the week, and resulted in the delay which carried into week 15 where no work was planned (should have been completed by this time), but work was still being carried out to finish the drive.

The average predicted and actual PRI ratios for the activity over the 10-week analysis period are at 89% and 81% respectively, while the average predicted CCL is at 19%, represented by only two out of the total 10 weeks (8 & 11). Week 8 near the end of drive 2 and 11 in the middle of drive 3.

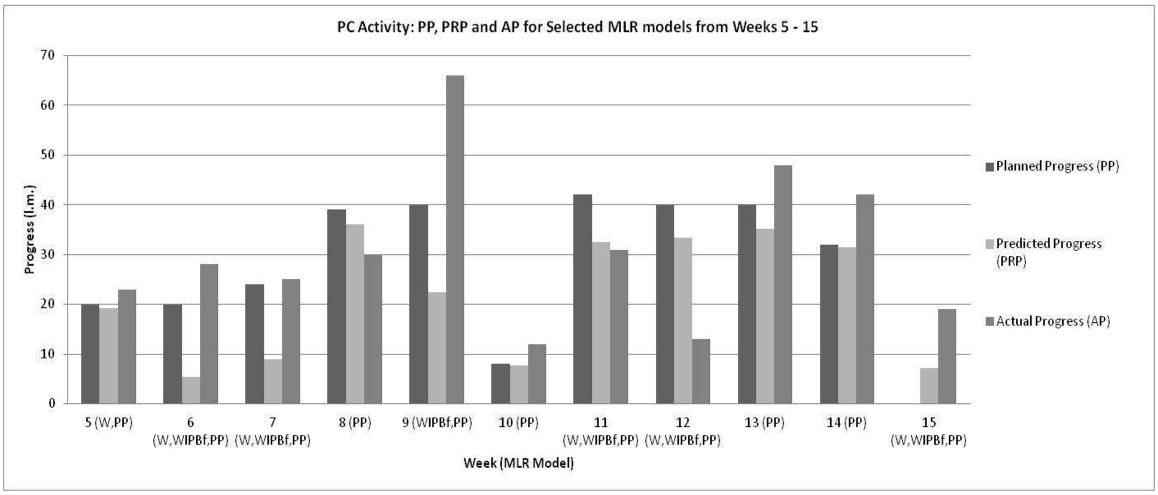

Figure 2(a): 9-week comparison of PP, PRP, AP for PC Activity, Tunnel-boring Section

[4] *Not included in mean calculation due to R-sq and p-value disqualification according to heuristics.

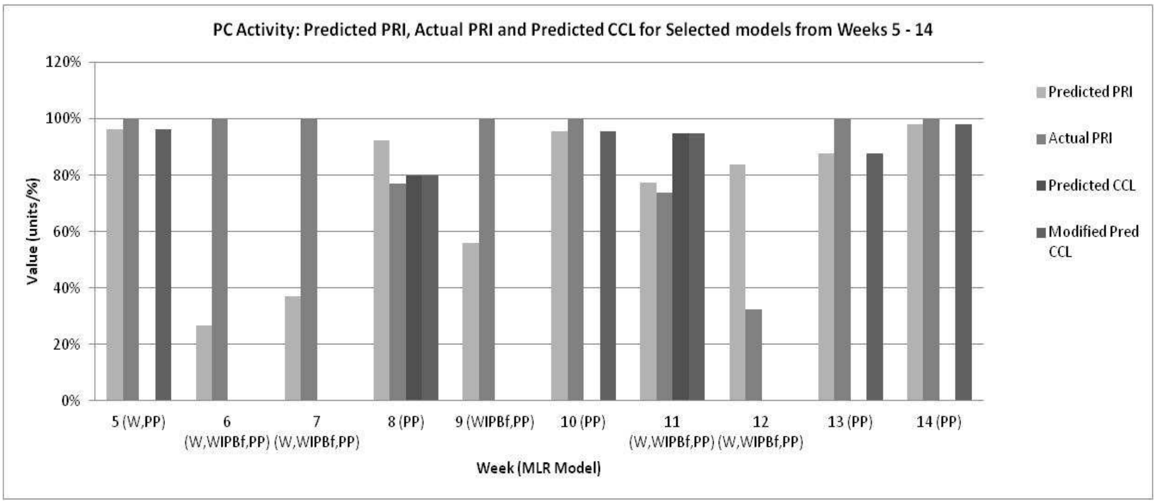

Figure 2(b): 9-week comparison of Predicted PRI, Actual PRI and Predicted CCL for PC Activity, Tunnel-boring Section

Figure 2(c) illustrates the week 11 nomograph developed for the PC activity based on the selected MLR model (PRP = $\beta_0 + \beta_1 W + \beta_2 WIPBf + \beta_3 PP$). Table 2(b) outlines a few of the possible planned production frame approaches which can be undertaken by planners.

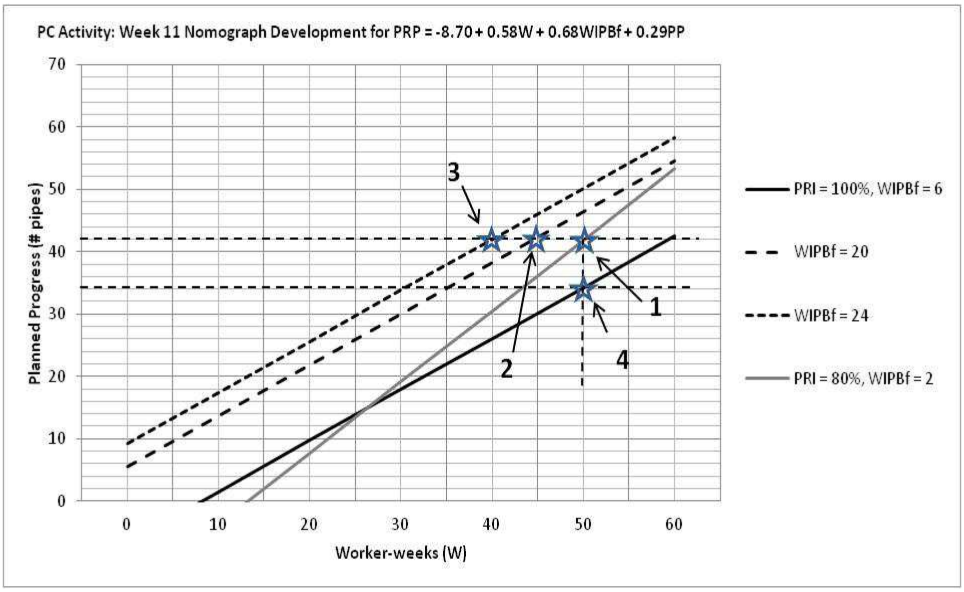

Figure 2(c): Week 11 Nomograph for PC Activity

Table 2(b): Sensitivity Analysis with the RCM for Week 11, PC Activity (Actual W = 50, WIPBf = 6, PP = 42, AP = 31)

Point	PP (l.m.)	Plnd W	WIPBf (lm)	Pred. PRI	PRP (lm)
1	**42**	**50**	**3**	**80%**	**33.6**
2	42	44	20	100%	42
3	42	40	24	100%	42
4	34	50	6	100%	34

Note: Bolded data indicates the base case.

- Point 1: the base case defines PP = 42m, planned W = 50, WIPBf = 2 pipes, and corresponds on the nomograph to a predicted PRI = 80% resulting in a predicted progress of 33.6.
- Point 2: If the planner decreases worker-weeks to 45 and increases WIPBf to 20 pipes, this raises the PRI to 100%, matching PP and PRP.
- Point 3: decreasing worker-weeks further to 40, and increasing the WIPBf to 24 maintains PRI = 100%, and the match between the PRP and PP.
- Point 4: using the actual W and WIPBf measured for the activity, the planned progress was determined from the nomograph to be 34 pipes at a PRI of 100%. This is very close to the actual figure of 31 pipes achieved.

4. DISCUSSION OF RESULTS AND EVALUATION OF A MODIFIED PREDICTED CCL INDICATOR

A significant observation in the results obtained are the exhibition of phenomena similar to that observed in Gonzalez et al (2010) with findings from the building industry where the RCM was employed, with the variation trends observed especially with respect to Figures 1(c) and 2(c) as examples, and through behavior illustrated through the nomograph analysis. The research investigation hence achieved results similar to those conducted by Gonzalez et al (ibid), all from a purely observational approach in its testing. Also, the enhancement of the Predicted CCL indicator to avoid the disqualification of valid measurements improved the Predicted PRIs significantly as compared to those results first obtained with the seminal approach developed.

If Week 9 of figure 1(b) and weeks 5, 10 and 14 of figure 2(b) are examined closely, the average difference between the predicted and actual PRI figures calculated is minute at only 3.25% (2%, 4%, 5%, and 2% respectively), yet the predicted CCL ratios default to zero because of the predefinition: ***if predicted PRI < actual PRI; predicted CCL = 0***. To address this issue, a ***revised*** predicted CCL is proposed:

$$\text{Predicted CCL} = 1 - \frac{abs(Prsd.\ PRI - Act.\ PRI)}{Act.\ PRI} \tag{4}$$

Examination of eq. (4) indicates a validity range of 0 ≤ Pred PRI ≤ 2 x Act PRI or 0 ≤ Act PRI ≤ 2 x Pred PRI where Act PRI ≠ 0. However, this range can be refined by setting a limit (using analysis software) which can set the default zero value if the abs (Pred. PRI – Act. PRI) exceeds a certain limit, within the constraints stated above. In Figure 1(b) it is by default 50%, while in Figure 2(b) it is ***set*** to 60%.

The default value used in Figure 1(b) as well as the 60% threshold in Figure 2(b) reflects a more capable RCM prediction accuracy. Note that the CCL is more evident in a greater number of cases here accounting for 83% as compared to the original 67% average (zero CCL in weeks 5, 8 and 9) for the P activity, and improving the 19% average for the PC activity to 78%.

It is evident from inspection of the modified predicted CCL in the figures that it is clearly a much more transparent indicator of the prediction accuracy of the RCM, as well as the 83% and 78% averages for each activity.

5. CONCLUSIONS

The initial hypothesis for the valid applicability of the RCM into the case study was confirmed with the primary activities utilized as examples of this fact. The R-sq., p-values, Predicted CCL and PRI are confirmation of the fact that the RCM indeed was able to predict with certain accuracy. The exciting prospect of the research is that even though data collection and analysis was executed in a non-intervening manner only to investigate the predictive ability of the tool, the results produced indicate that the power of the RCM can be enhanced further in projects of this nature with more research and careful implementation, keeping in mind that each project is essentially a prototype in nature despite the fact that scopes may be comparable, careful implementation and continuous feedback is necessary to achieve the full benefits of the RCM.

Table 3: Summarised Average Results of Heuristic Indicators for the RCM

Unit/Activity	*R-sq.*	*p-value*	*Pred. CCL (Mod. Pred. CCL)*	*Pred. PRI*
1/P	0.95	0.003	67% (83%)	78%
2/PC	0.51	0.033	19% (78%)	74%

It is believed that through active implementation of the RCM on projects of this nature, that lean practice can be implemented through continuous improvement over a repetitive project through each planning horizon utilising the tools discussed above. The prediction accuracy of the RCM was illustrated here with the average statistics satisfying the requirements for MLR modeling. The involvement of on-site and relevant planning personnel enables the RCM to be implemented with increased efficiency and provides the means to quantitatively determine production frames in order to achieve planned targets. The case study thesis (Wendt, 2012) from which the results were derived also propose an additional ***Site-Specific Variable*** to further enhance RCMs accuracy, and provides an avenue for further exploration in horizontal continuous projects. Construction planning techniques will only serve to benefit from the elimination of intuition and experiential planning called into play in the face of variability and uncertainty, thus promoting waste minimisation and organisational practice improvement, as well as enhancing the channels of communication between on-site and management personnel.

Careful measurement and monitoring systems must be *lived* and through the participation of all involved with the project, construction will one day be able to do away with its wasteful practices and cultures. The internal relationships of the project team must be fostered in an open environment of collaboration and continuous technological advancement, while ensuring the traditional adversarial relationships borne out of a rigid project management practice are eliminated.

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