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Improving Planning Reliability and Project Performance Using the Reliable Commitment Model

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Abstract: Commitment planning reliability at an operational level is a key factor for improving project performance. In the last 15 years, the Last Planner System, a production planning and control system based on lean production principles, has improved commitment planning reliability in the construction industry. However, many construction decision makers continue to rely on their experience and intuition when planning their commitments, which hinders their reliability. The reliable commitment model (RCM) is proposed to improve commitment planning reliability at the operational level by using statistical models. RCM is an operational decision-making tool based on lean principles that supports short-term forecasting commitment planning using common-site information such as workers, buffers, and plans. RCM was tested in several case studies, demonstrating its production forecasting capabilities and its ability to help increase commitment planning reliability and improve project performance. RCM also supports workload and labor capacity matching decisions. RCM has the potential of becoming a useful production decision-making tool.

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Introduction

Planning has traditionally been a topic of much interest among academics and practitioners in project management due to its impact on performance during the execution phase. In construction, however, the focus has been on the development of planning tools rather than on the theoretical issues promoting its improvement (Laufer et al. 1994). This has resulted in inadequately managed projects and poor performance (Ballard 2000; Koskela 2000).

How planning decisions are made to manage variability in construction projects is one of the most relevant theoretical issues requiring more attention (Laufer et al. 1994). In construction projects, variability affects production rates, labor productivity, schedule control, cost control, etc. Although the detrimental effects of variability in construction are well known (Ballard 1993; Tommelein et al. 1999; among others), the traditional construction planning process does not explicitly consider variability, since projects are incorrectly assumed to be static, leading to poor management decisions (Tommelein et al. 1999).

The last planner system (LPS) is a production planning and control system based on lean production principles, which allows overcoming previous issues in construction planning (Ballard 2000). In turn, lean production is a management philosophy focused on adding value from raw materials to finished product. It allows avoiding, eliminating, and/or decreasing waste from the value stream. In particular, reducing one of these wastes, variability, is the core of lean philosophy (Womack and Jones 1996). LPS helps decrease the negative impacts of variability by promoting improved planning reliability and a stable production environment. As a result, reliable work plans, or commitment planning in LPS jargon, are developed at an operational level.

On the other hand, when construction projects outsource some of the work, which is quite frequent, commitment planning must be agreed between contractors and subcontractors. Since the relationship between them is often opposing and noncollaborative, contractors should strive to obtain reliable commitments from the subcontractors (Maturana et al. 2007). Also, many contractors assign work to subcontractors based on their intuition and experience resulting in unreliable commitments (Bustamante 2007; Sacks and Harel 2006). This is a prevalent pattern in planning and decision making in construction (Laufer et al. 1994), which may reduce planning reliability at the operational level.

To help improve planning reliability, this paper proposes a decision decision-making tool based on lean principles, called the reliable commitment model (RCM), which uses statistical models to make commitment planning at an operational level more reliable. RCM allows forecasting commitment planning for short-term periods using information about workers, buffers, and plans. RCM can also complement LPS at an operational level.

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There are several methods that have been used in construction to predict and improve future performance, using past information. Some of the most important ones are: *virtual prototyping*, which is a computer-aided design process concerning digital product models and realistic graphical simulations of construction processes (Huang et al. 2007); *first run study*, which is a trial execution of a process in order to determine the best means, methods, sequencing, etc., to perform it, using the popular plan-do-check-act (PDCA) or Shewart's cycle (Ballard and Howell 1994); and *discrete event simulation modeling*, which dynamically describes systems evolving instantaneously at separate points in time by using computer support to optimize construction operations (Martínez 1996). On the other hand, RCM uses a simpler approach focused on making more reliable production predictions using historical on-site data, which can provide almost immediate feedback. This is an important requirement to make RCM a practical on-site operational tool.

The following sections describe the objectives, research methodology, and literature review, as well as the theoretical and practical foundations of the RCM. Then, the validation process for the RCM is addressed. Finally, the RCM effects on planning issues such as improving planning reliability/project performance and matching load with capacity are addressed.

Research Strategy and Methodology

The main objective of the research presented here was to develop an operational decision-making tool to improve reliability of commitment planning and project performance at an operational level that could also help make commitment planning for both contractors and subcontractors more reliable.

The case study approach (Yin 1994), supported with statistical analysis of data obtained from several construction sites, is used to validate the theoretical coherence of the RCM and to determine the impact on project performance of using RCM. The research methodology consisted of four stages: (1) statement of theoretical foundations and practical framework for the RCM, (2) definition of case studies, where repetitive processes in multifamily residential, multistory building, and industrial projects were studied, (3) RCM development and validation process where multiple linear regression (MLR) techniques were applied, using weekly on-site information from case studies, such as planned and actual workers, buffer sizes and planned/actual progresses at activity level to construct and validate MLR models, and (4) analysis and evaluation of RCM impacts on planning reliability/project performance and load/capacity matching using several case studies.

Last Planner Basics

LPS acts over the following four project planning levels: initial planning or master plan, phase schedule, lookahead planning, and commitment planning or work plans. The initial planning or master plan produces the initial project budget and schedule, and provides a coordinating map that "pushes" completions and deliveries onto the project. The phase schedule produces more detailed and manageable plans from master plans with high complexity level, creating phase schedules based on targets and milestones from that plan and helping to maximize value generation in the process planning and for all involved. The lookahead planning (breakout of master plan or phase schedule) focuses on controlling the flow of work through the production system, detailing and adjusting budgets and schedules "pulling" resources into play. Commitment planning or work plans (short-term period) determines the activities and scheduled work that will be done on-site (operational level) according to the status of resources and prerequisites (more details about LPS stages see Ballard and Howell 1998, 2003; Ballard 2000).

The traditional management approach for work plans defines activities and schedule work that will be done, in terms of what should be done from a master plan, with *no real consideration for what a crew is actually able to do*. The ability of a crew to reliably perform work depends on the stability of the so-called workflow. In construction, workflow can be characterized by crews moving from location to location and completing the work that is prerequisite to starting work by the following crew (Tommelein et al. 1999). In turn, a stable workflow depends on construction preconditions such as resources (design, components and materials, workers, equipment, and space) and prerequisites (completed work of upstream activities) that should be available whenever they are needed (Koskela 2000). However, workflow variability could negatively affect crews' performance, causing idle time or ineffective work (Tommelein et al. 1999).

LPS helps overcome the aforementioned problems by providing a predictable production environment, decreasing workflow variability, and creating reliable work plans to maximize project benefits. The overarching criterion in the LPS is that activities should only be committed if they can be performed (i.e., all construction preconditions must be available), transforming what should be done into what can be done, from which a work plan can be formulated, helping to promote a production environment based on commitment and trust for contractors and subcontractors, among other stakeholders in the process planning. Thus, work plans will be based on achievable assignments serving as a commitment to what will actually be done. The following criteria are critical for the assignments: (1) they are well defined; (2) the right sequence is selected; (3) the right amount of work is selected; and (4) the work selected is practical or sound, that is, it can be done according to the availability of construction preconditions considered during the lookahead planning (Ballard 2000).

This paper focuses on project planning reliability. LPS uses the percentage of plan completed (PPC) as a planning reliability index. PPC is the ratio between actual completed activities and planned activities. A low PPC means unreliable planning and a high PPC the opposite. From a lean production perspective, PPC is also a measure of workflow variability. A low PPC is an indicator of a highly variable workflow, and a high PPC indicates a stable and predictable workflow.

Relationship between Planning Reliability and Project Performance

LPS has been applied in numerous projects around the world in the last 15 years and a wide range of performance improvements have been reported (Alarcón et al. 2005; Liu and Ballard 2008; González et al. 2008b; among others). The main assumption is that an increase in planning reliability, measured through PPC, should improve project performance and productivity. Recently, several researchers have demonstrated a positive and strong relationship between planning reliability and performance at project level (González et al. 2008b; Liu and Ballard 2008).

Due to the limited evidence linking the changes in planning reliability with changes in productivity at the activity level, an in-depth study was carried out by González et al. (2008b). Sacks and Harel (2006) addressed a similar issue, but from a theoretical perspective. González et al. (2008b) proposed a reliability planning indicator at the activity level, called process reliability index (PRI), which measures actual production progress against planned production, and is defined as

$$\mathrm{PRI}_{i,j} = \left(\frac{\mathrm{AP}_{i,j}}{\mathrm{PP}_{i,j}}\right) \times 100 \tag{1}$$

where $\mathrm{PRI}_{i,j}$=process reliability index for week i and activity j (%) ($i=1,\ldots,n$; $j=1,\ldots,m$); $\mathrm{AP}_{i,j}$=actual progress for week i and activity j ($i=1,\ldots,n$; $j=1,\ldots,m$); and $\mathrm{PP}_{i,j}$=planned progress for week i and activity j ($i=1,\ldots,n$; $j=1,\ldots,m$).

PRI ranges between 0 and 100%. If AP is larger than PP, PRI is set to 100%. Since a strong and positive relationship between PRI and productivity at the activity level was found, it was concluded that increasing planning reliability not only improves performance at the project level, it also improves it at the activity level, which confirmed that LPS promotes performance improvements in a project as a whole (for more details see González et al. 2008b).

Matching Load and Capacity

Matching load with capacity is critical for productivity of production systems in construction (Ballard 2000; Thomas and Horman 2006). According to Ballard (2000), where load is the amount of work in a specified time assigned through planning to crews, while capacity is the amount of work a crew can do at any point in time with the tools, work methods, and conditions available on-site. Matching load with capacity is difficult since production variables, such as actual resource utilization and production rates of crews, are frequently unknown a priori, given their changeable behavior caused by wastes in conventional practices (Ballard 2000). This can lead to a poor load and capacity balance and productivity losses.

Whenever load and capacity estimates differ from the actual ones, the planner must either adjust load to match capacity by delaying or accelerating workflow, adjust capacity to match load by decreasing or increasing resources; or a combination of the two. In general, the decision of which option to choose will depend largely on the site conditions of projects and practicality. LPS can assist in this process through the lookahead planning in which assignments are analyzed to satisfy critical criteria, among other LPS procedures (see more details in Ballard 2000).

In many cases, matching load and capacity is not easy. There are two main difficulties, which will be explained using LPS concepts for the sake of clarity, although it is important to note that LPS does not specify a method for matching load and capacity. First, it is difficult to accurately determine *the right amount of work* to perform by crews in work plans based only on the experience of project personnel, which can be biased (Spetzler and Von Holstein 1975). In contrast, if historical data are used, it may not be accurate enough, due to changes in current construction practices (Ramírez et al. 2004). Second, it may not be an easy task to verify whether *work is practical or sound* in work plans (i.e., all construction preconditions are ready for crews to perform work). For instance, the number of site workers supplied by subcontractors to a specific project depends on business demands, i.e., labor resources can be moved to other projects whenever it is more profitable for the subcontractor (Sacks and Harel 2006). As a result, labor resources may not be ready or available, and in the correct amount, when required in a project. Another example is when the work of a crew in repetitive activities depends on the work units or buffer created by an upstream crew. Sometimes this buffer is not available when needed, or is insufficient (Tommelein et al. 1999). This can reduce crew performance by starvation of work units. We will later show that RCM can support the load and capacity matching decisions at the operational level.

Reliable Commitment Model Framework

Most people tend to describe problems through simplistic models of reality, given their limitations for manipulating large amounts of information (Spetzler and Von Holstein 1975). In construction, this phenomenon is prevalent in its decision-making processes leading to erroneous and poor decisions (McGray et al. 2002). For instance, labor productivity is usually estimated assuming that work progress in projects is stable, while in reality it is highly variable (Sacks and Harel 2006). This is due to decision makers' tendency to oversimplify the objective information that available production data provides and rely on intuition and experience (McGray et al. 2002).

In practice, work plans are frequently imposed or "pushed" on to subcontractors independent of the planning process and/or production conditions, due to the noncollaborative relationship that often exists between contractors and subcontractors (Maturana et al. 2007). In addition, since subcontractors' work sizing by contractors is affected by their aforementioned decision biases, subcontractors tend to react by continuously changing their own estimates, and even their resource allocations (Sacks and Harel 2006). The LPS is helping to change from an adversarial relationship between contractors and subcontractors to a more collaborative one, which has beneficial impacts on all parties and also improves the reliability of planning (Alarcón et al. 2005; Ballard 2000). The objective of the proposed RCM framework is to help make commitment planning for both contractors and subcontractors more reliable, whether they use the LPS or not.

RCM is based on lean principles and focuses on reducing the variability in production by improving planning reliability, and promoting a pull production system by matching load with capacity. It is also more oriented to repetitive activities. The first version of the RCM was proposed by Mundaca (2006), and later elaborated and improved by Bustamante (2007) and González et al. (2008a). The conceptual and mathematical framework, as well as the RCM process validation and its application methodology, is described next.

Conceptual Framework

A key step of the LPS for improving work plan reliability is the analysis of constraints on planned activities that could prevent its execution. The most common constraints are design, materials, prerequisite work, space, equipment, labor, and plans (Ballard 2000), which basically represent construction preconditions. RCM regards several of these constraints as variables to predict activity progress. These variables were determined using a database with information of the results of the LPS implementation in 77 construction projects (industrial and building), from 12 Chilean construction companies, carried out by the Production Management Center (GEPUC) during a 3-year period, from 2001 to 2003 (Alarcón et al. 2005).

The LPS provided the reasons for noncompletion (RNC) data of work plans that were used to define the RCM variables. The RNC data provided valuable information on which constraints were mainly affecting the execution of work plans. At the end of the LPS implementation period, there were three RNC that had an average incidence of almost 50%: lack of labor, lack of buffer, and poor planning. These RNC are related to several constraints, such as labor, buffer (prerequisite work), and planned progress (plans). This led to RCM's basic hypothesis, which is that the progress of an activity can be predicted, for a short-term planning horizon, using a model with at least three variables: labor, buffer, and planned progress. The following section describes the mathematical elaboration of this relationship.

Mathematical Framework

MLR is used to estimate the activity progress at the operational level, based on historical data, since the "true" behavior of the phenomenon is not known, and the family of linear models is very flexible and often used (Seber and Wild 1989). Therefore, MLR allows the formulation of the general expression $y=\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_n x_n+\varepsilon_i$, where y=dependent variable; x_i=independent variables; β_i=corresponding parameters of the dependent variables; and ε_i=random error. Only significant variables are selected in the models, since including redundant variables may lead to incorrect analysis of scenarios. The variable selection process uses 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, MLR models with the least number of variables, and with the highest R^2 and low P-values are preferred. Thus, predicted progress in RCM is given by the following MLR model:

$$\mathrm{PRP}=\beta_0+\beta_1 W+\beta_2 \mathrm{WIPBf}+\beta_3 \mathrm{PP} \tag{2}$$

where PRP=predicted progress for an activity in a short-term planning horizon of one workweek. W=number of workers for an activity in a short-term planning horizon. W is the sum of workers in the planning horizon. For instance, if the planning horizon is one workweek of 5 days, and there are five worker days, W is 25 workers. WIPBf=available work-in-process buffer for an activity at the beginning of the planning horizon, which is the number of work units performed by the preceding crew (González et al. 2009). For instance, the WIPBf for the painting activity, which depends on the wall-stucco activity, is the work produced by the wall-stucco activity, measured at the beginning of the planning horizon, before painting begins. PP=planned progress for an activity in a short-term period of one workweek. The units for PRP, WIPBf, and PP may be m^2, m^3, linear meters, houses, apartments, etc.

The prediction accuracy of RCM is measured by two indicators: the PRI, defined earlier, and the predicted/planned commitment confident level (CCL), which are defined as

$$\text{Predicted CCL}_{i,j}=\left[1-\left(\frac{\text{predicted PRI}_{i,j}-\text{actual PRI}_{i,j}}{\text{actual PRI}_{i,j}}\right)\right]\times 100 \tag{3a}$$

$$\text{Planned CCL}_{i,j}=\left[1-\left(\frac{\text{planned PRI}_{i,j}-\text{actual PRI}_{i,j}}{\text{actual PRI}_{i,j}}\right)\right]\times 100 \tag{3b}$$

where predicted/planned $\mathrm{CCL}_{i,j}$=CCL for week i and activity j (%) for both predicted and planned PRI; predicted $\mathrm{PRI}_{i,j}$=predicted PRI for week i and activity j, which replaces AP in Eq. (1) by PRP; planned $\mathrm{PRI}_{i,i}$=planned PRI for week i and activity j, which is estimated by decision makers based on their experience given a planned progress, although this value can be between 0 and 100%, planners usually aspire to a 100% planned PRI; actual $\mathrm{PRI}_{i,j}$=actual PRI for week i and activity j, which is computed using Eq. (1); predicted/planned CCL measures the activity commitment accuracy for the predicted/planned PRI, relative to actual PRI. Note that CCL does not measure confidence on the progress of activities. If predicted/planned PRI is less than actual PRI the predicted/planned CCL is set to 0.

Nomographs for the Reliable Commitment Model

RCM was originally implemented through nomographs, which relate mathematical and graphically planned progress with the other production variables (Bustamante 2007; González et al. 2008b). For this it is better to rewrite PRI as

$$\mathrm{PRI}=\left(\frac{\mathrm{PRP}}{\mathrm{PP}}\right)\Rightarrow \mathrm{PRP}=\mathrm{PRI}\times \mathrm{PP} \tag{4}$$

If Eq. (2) is replaced in Eq. (4), PP can be expressed as

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

Eq. (5) establishes a relationship between PP and W, WIPBf, and PRI. PP can be either planned by decision makers or estimated by the RCM. Similarly, PRI can be either planned or predicted. Fig. 1 illustrates a nomograph for a repetitive housing project, showing the interaction between the different variables involved. Nomographs are commonly used in engineering disciplines (e.g., hydrologic engineering) and can be easily applied by construction decision makers, such as project managers, which can use it to plan activity progress for a given resource frame. In the next section we will illustrate how the RCM and its nomographs can be used.

RCM Methodology Application

Fig. 2 depicts the RCM methodology, which has been tested in repetitive building projects (González et al. 2008a). A computer prototype was developed to support the implementation of the RCM methodology in projects. The main stages of the RCM, which are performed weekly, are the following:

1. Selection of activities: a set of activities should be selected by managers in order to improve their planning reliability. From a lookahead planning window the activities can be selected based on different project priorities and requirements.
2. Initial data collection: weekly production data are gathered for each activity. At the beginning of each week project managers estimate PP, planned PRI, and planned W, and measure the WIPBf size, which are required to predict. At the end of the week, AP and actual W are measured.
   - Decision Block (i) is deployed to analyze if there is enough data (points) to construct the first MLR model (see comments in Fig. 2).
3. Selection of the best MLR model: after 2 weeks, the available data can be used to start the statistical analyses to define the best MLR model. To construct a MLR model, AP, PP, WIPBf sizes, and actual W are used.
   - Decision Block (ii) allows collecting for more information in Stage 2, when it is not possible to get valid MLR models.
4. Definition of nomographs: after selecting the best MLR model, Eq. (5) is used to construct nomographs as the one shown in Fig. 1.

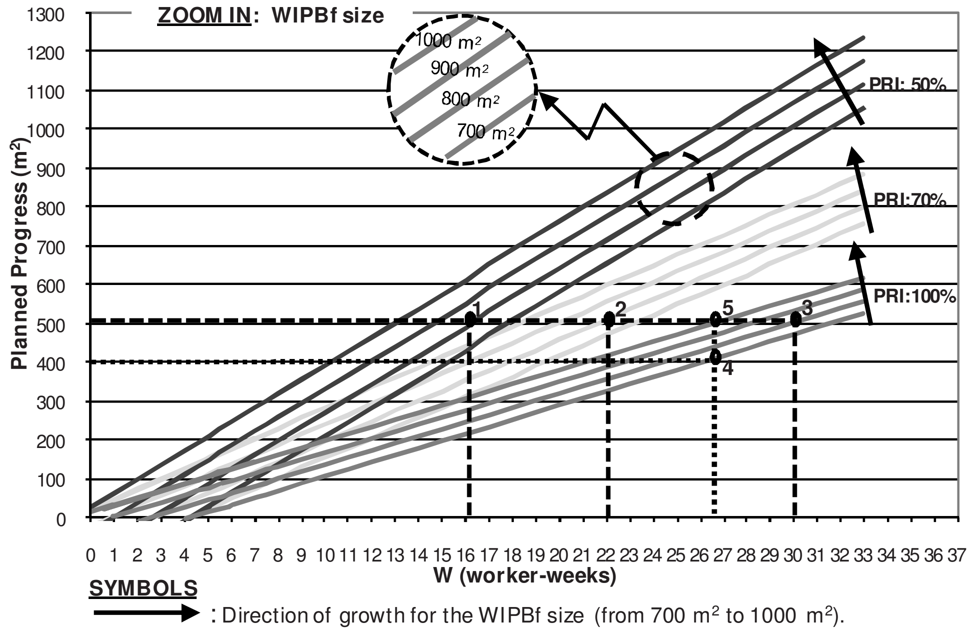

Fig. 1. General nomograph to estimate planned progress based on the RCM

5. Definition of a base case: the base case is determined by applying the RCM and its nomograph to the initial data. Fig. 1 shows Point 1 as the base case defined by the initial data. Table 1 shows a detailed description of inputs (PP, planned W, and WIPBf) and outputs (predicted PRI and PRP). The base case is in boldface, where the PP of 500 m^2 has a predicted PRI equal to 50%, i.e., PRP is 250 m^2.
   - Decision Block (iii) asks if the predicted PRI is lesser than 100%. If the answer is yes, Decision Block (iv) follows, i.e., actions can be taken to achieve a better predicted PRI (or not). If the answer is no, Stage 6 follows, where non-actions are performed. For the example in Table 1 the answer is yes.
6. Keep production frame of base case: production frame (PP, planned W, and WIPBf) is kept for the predicted PRI, if it satisfies the project manager's preferences.
   - Decision Block (iv) asks whether the production frame is kept. If the answer is yes, Stage 6 (nonaction) follows. If the answer is no, Stage 7 follows to state new production frames.

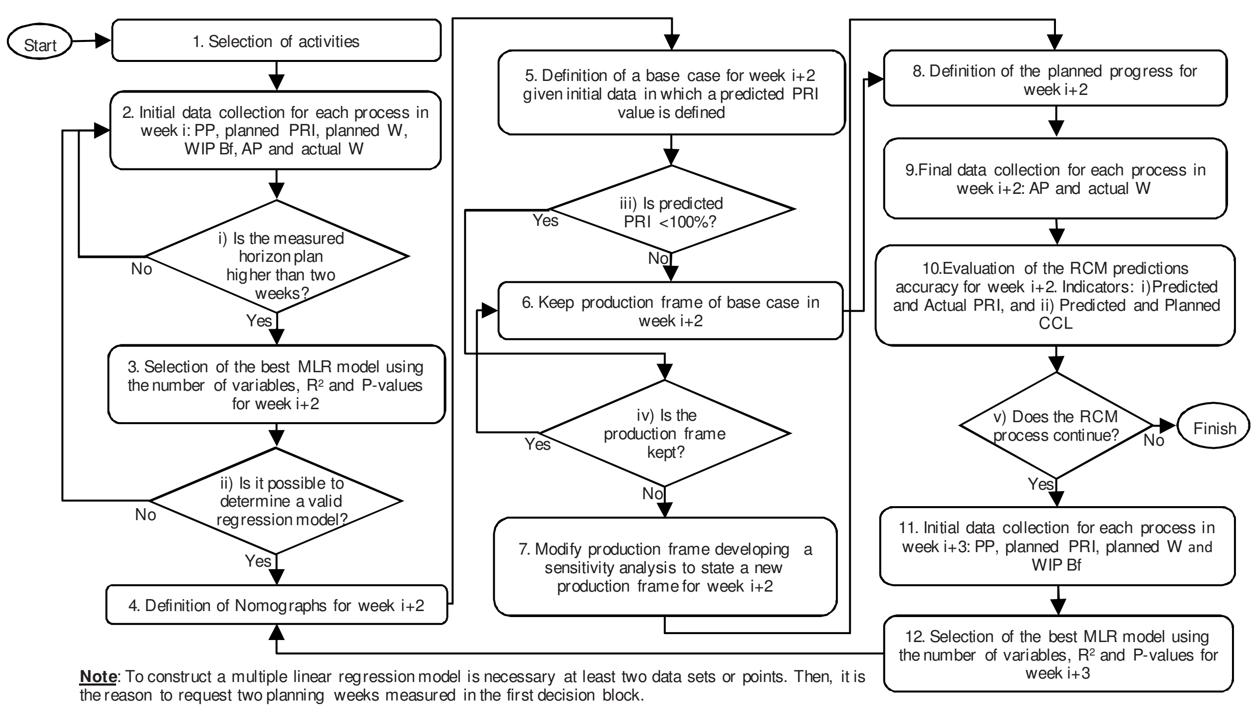

Fig. 2. Methodology to implement the RCM

Table 1. Sensitivity Analysis with the RCM

Point	PP (m^2)	Planned W (worker weeks)	WIPBf (m^2)	Predicted PRI (%)	PRP (m^2)
1	**500.0**	**16.0**	**800.0**	**50.0**	**250.0**
2	500.0	22.0	800.0	70.0	350.0
3	500.0	30.0	800.0	100.0	500.0
4	400.0	26.5	700.0	100.0	400.0
5	500.0	26.5	1000.0	100.0	500.0

Note: Data in boldface indicate the base case.

7. Modify production frame developing a sensitivity analysis: usually actions should be performed to try to improve predicted PRI to make it closer or equal to 100%. Fig. 1 shows the information use to perform actions and Table 1 describes the sensitivity analysis performed. A strategy could be to increase the W levels to achieve higher predicted PRI values (Points 2 and 3 in Fig. 1 and Table 1). Another strategy could be to decrease PP to 400 m^2 (Point 4 in Fig. 1 and Table 1), given an intermediate level for W, a lower WIPBf size, and a predicted PRI of 100%. However, Fig. 1 shows a third strategy, moving from Point 4 to Point 5, in which only increasing the WIPBf size from 700 to 1,000 m^2, increases the PP level to 500 m^2 from 400 m^2 with a predicted PRI of 100%. Table 1 shows that the level of W does not change for Points 4 and 5. Finally, project managers select a predicted PRI value and a production frame from the sensitivity analysis according to their preferences, taking into account labor cost for a higher W level, and time to produce a higher WIPBf size, among others.
8. Definition of the planned progress: by using production frame from Stage 6 or Stage 7, a planned progress is estimated at the beginning of each week. Project managers can decide to either use the RCM prediction as planned progress or keep their own estimate. Gradually they should tend to use the RCM estimate.
9. Final data collection: the final data are gathered at the end of each week, which is necessary for further RCM predictions. The data measured are AP and actual W.
10. Evaluation of the RCM predictions: Once a labor week has finished, the main accuracy measures for the RCM prediction are computed, that is, predicted and actual PRI and predicted and planned CCL. This is a key stage to evaluate the quality of RCM predictions. Finally, the RCM process is repeated in Stage 11 (similar to Stage 2 without AP and actual W information) and Stage 12 (similar to Stage 3 without intermediate decisions) until the activity has been completely executed.

RCM Role for Improving Planning Reliability and Project Performance

The use of RCM's statistical models to predict production behavior in projects should increase planning reliability at the activity level, which should help improve project performance both at the project and activity level. Common sense suggests that if a set of activities individually increases its planning reliability, and this set structures the entire project, then planning reliability at the project level should improve resulting in better project level performance. Previous empirical evidence by González et al. (2008b) supported this notion. Therefore, planning reliability and project performance improvement at the activity level, using RCM, should also reach the project level.

Matching Load and Capacity with the RCM

The RCM allows matching load with capacity by either fixing load or capacity and developing sensitive analyses for the free variable according to actual production conditions, or studying the effect of several construction preconditions that can prevent the performance of an activity to mitigate its impact. Both mechanisms will be illustrated using Fig. 1.

In the first mechanism, load as planned progress in Fig. 1 can be fixed to determine the capacity level as worker weeks required to meet the amount of work planned. Another variable involved in the estimation of load is the planned PRI, which can be included to visualize the impact of planning reliability over capacity levels. If the capacity is limited, i.e., the number of worker weeks is constrained by the subcontractor's needs, the load can be adjusted to a certain amount of work given a planned PRI. There can also be a third option in which both load and capacity are simultaneously matched according to the decision makers' preferences. Also, the extent for which both load and capacity can change week to week is determined by the information statically processed in the RCM.

In the second mechanism, the RCM explicitly manipulates several construction preconditions as number of workers and buffer levels. The first precondition is analyzed using the first mechanism. The analysis of buffer levels is one the most interesting characteristics of the RCM previously studied by González et al. (2008a). For instance, Fig. 1 shows the influence of the buffer size (WIPBf) over labor productivity given the planned progress (load) and planned PRI. A larger buffer improves labor productivity and therefore reduces the number of worker weeks. On the other hand, for the same number of worker weeks, a higher planned progress can be achieved with a larger buffer because of the improvement in labor productivity, i.e., capacity is increased. RCM can therefore suggest using other production variables to solve the load-capacity matching problem. Overall, RCM improves the decision-making process for matching load with capacity.

Validation Process

RCM was validated in two stages. The first stage tested the robustness and theoretical coherence of the mathematical formulation of the RCM. The second stage validates the application of the RCM.

First Stage of Validation

RCM was preliminarily validated over three repetitive building projects, and a total of 15 activities analyzed. LPS was used in the planning processes of these projects (Bustamante 2007). Only 8 activities had significant results, which are shown in Table 2. Historical information of activities was collected during a predetermined period (from 6 to 9 weeks) for each activity. Then, MLR models for this period were constructed, obtaining a specific mathematical expression with available data (partially following the RCM methodology). In practice, RCM is a dynamic process that may result in different MLR models and/or different parameters values, from one week to another, depending on the data. This validation stage used the information available at the end of the entire analysis period to produce only one MLR model, where model responses and real behavior were compared in a backward process that determined weekly predicted PRIs and CCLs. The mean predicted PRI and CCL are shown in Table 2.

Table 2. Results of First-Stage Validation Process

Types of project[a]/activity	Analysis period (weeks)	Regression model, R^2, P-value test model[b,c]	P-value test parameters[b,c]	Mean actual PRI (%)	Mean predicted PRI (%)	Mean predicted CCL[d] (%)
P_1/stucco	7	PRP=205W−788.5; R^2: 91.0%; P:0.0001	P_W:0.0009	77.0	78.0	95.0
P_1/floor ceramic	6	PRP=13.2W−4.3; R^2:85.0%; P:0.009	P_W:0.009	75.0	77.0	93.0
P_1/wall ceramic	6	PRP=13.3W+59.1WIPBf+0.3PP−24.5; R^2:99.0%; P:0.012	P_W:0.008; P_{WIPBf}:0.039; P_{PP}:0.028	70.0	70.0	98.0
P_1/interior painting	7	PRP=23.0W+8.7WIPBf−0.1PP+131.6; R^2:72.0%; P:0.226	P_W:0.307; P_{WIPBf}:0.536; P_{PP}:0.827	89.0	89.0	96.0
P_2/floor ceramic	9	PRP=19.0W−17.2; R^2:91.0%; P:0.00006	P_W:0.0001	72.0	76.0	77.0
P_2/wall ceramic	8	PRP=24.2W+17.5; R^2:92.0%; P:0.0002	P_W:0.0002	74.0	75.0	92.0
P_3/masonry	8	PRP=23.5W−305.7; R^2:87.0%; P:0.002	P_W:0.0023	77.0	77.0	89.0
P_3/slab concrete	8	PRP=0.716W+1.2; R^2:95.0%; P:0.0008	P_W:0.008	84.0	85.0	96.0
			Mean	77.3	78.4	92.0

[a]P_1 and P_2=multistory building; P_3=multifamily residential building.

[b]To an α=0.05 (confidence level of 95%).

[c]There is statistical significance if $P \le \alpha$ value.

[d]It is considered only the predicted CCL to analyze its soundness to measure commitments accuracy from the predictions.

Most of the MLR models showed in Table 2 had good statistical indicators (R^2 and P-values). The interior painting activity, however, had only regular statistical indicators due to difficulties in obtaining accurate on-site measurements. Also, the mean predicted PRI was very close to the actual PRI. The mean CCL of 92.0% demonstrated the accuracy of RCM for describing production behavior and for predicting fulfillment of planning commitments. Not all the models used all the variables. W is the most frequently used variable, followed by a combination of W, WIPBf, and PP. In some cases, on-site production may be very sensitive to a lack of WIPBf. PP is used in only two cases; however, it is relevant since PP describes the contractor/subcontractor commitment that should be collaboratively acquired. The best results of the regression model selection process were obtained using the least number of variables and the higher R^2-value. This heuristic was effective and consistent with the P-value test. Actually, Bustamante (2007) showed that the best regression model could be selected without considering the P-value.

Second Stage of Validation

In the second stage, RCM was applied, using a computer prototype, in five repetitive building projects and one industrial project, with a total of 17 activities analyzed. LPS was also used in all of these projects. The results of 15 of these activities with significant results are shown in Table 3. The RCM was applied weekly. At the end of the 2nd week, MLR model construction began; therefore, a large amount of data related to them was generated during the *analysis period* for each activity (ranges from 8 to 17 weeks). The predicted and actual PRI and CCL are shown in Table 3. In general, reliable predictions were developed from the 4th week, with all possible combinations of variables (W, WIPBf, and PP) being used in the MLR models. The main results showed a difference of only 4.3% between mean actual and predicted PRI values. Mean predicted CCL reached 76.7%, ranging from 62.8 to 89.5%, which was considered good. This application of the RCM showed that it could make reliable predictions, which improved the commitment planning process.

Case Studies of RCM Impacts

We show next the results of the application, using a computer prototype, of the RCM in two case studies.

Table 3. Results of Second-Stage Validation Process

Types of project[a]/activity	Analysis period (weeks)	Mean actual PRI[b] (%)	Mean predicted PRI[b] (%)	Mean predicted CCL[c] (%)
P_4/floor-wall ceramic	8	67.1	81.4	70.0
P_5/plastering	12	88.0	88.8	78.8
P_5/partitions	14	70.0	80.9	67.5
P_5/floor-wall ceramic	11	73.4	90.4	62.8
P_6/plastering	17	73.6	78.4	81.6
C_1/steel disassembly	10	79.4	79.7	76.2
C_1/roof and siding installation	17	82.5	85.5	72.7
C_1/painting	17	84.7	85.3	80.7
C_2/north formwork	13	84.1	80.1	77.3
C_2/south formwork	14	88.0	87.9	89.5
C_2/north steel bars installation	13	87.2	92.3	80.3
C_2/south steel bars installation	14	86.3	83.7	77.0
C_3/formwork	14	88.6	86.0	85.7
C_3/steel bars installation	13	89.3	96.7	83.0
C_3/masonry	14	77.2	86.8	67.8
	Mean	81.3	85.6	76.7

[a]C_2, P_4, and P_5=multistory building; C_3 and P_6=multifamily residential building; C_1=industrial project; and P_n and C_n indicates different construction companies.

[b]Estimated from the week where the RCM begins to define the MLR models.

[c]It is considered only the predicted CCL to analyze its soundness to measure commitments accuracy from the predictions.

Table 4. RCM Application Data: Case Study A

Week	Planned worker weeks	Actual worker weeks	WIPBf (lm)[a]	Planned progress (lm)	Predicted progress (lm)	Actual progress (lm)	Predicted PRI (%)	Actual PRI (%)	Planned CCL[b] (%)	Predicted CCL (%)	R^2 (%)	Selected variables
1	25	10	1,848	722		265		36.7	0			
2	25	10	1,583	722		280		38.8	0			
3	25	15	1,303	722	295.9	280	41.0	38.8	0.0	94.3	100.0	WIPBf
4	25	17	1,023	722	290.1	561	40.2	77.7	71.3	51.7	74.0	WIPBf
5	25	35	1,614	722	289.8	999	40.1	100.0	100.0	40.1	65.0	WIPBf
6	15	24	1,191	433	405.6	630	93.7	100.0	100.0	93.7	94.0	W
7	15	24	993	433	400.2	378	92.4	87.3	85.4	94.1	94.0	W
8	25	40	1,066	722	636.0	703	88.1	97.4	97.3	90.5	79.0	W
9	25	37	904	722	573.1	428	79.4	59.3	31.3	66.1	69.0	W
10	25	36	476	722	524.0	482	72.6	66.8	50.2	91.3	48.0	W
11	25	15	972	722	438.2	283	60.7	39.2	0.0	45.1	58.0	W, WIPBf
12	25	20	689	722	363.7	408	50.4	56.5	23.0	89.1	61.0	W, WIPBf
13	25	19	1,073	722	484.0	384	67.0	53.2	12.0	74.0	59.0	W, WIPBf
14	20	25	689	300	310.0	496	100.0	100.0	100.0	100.0	60.0	W, WIPBf
15	25	20	1,936	300	669.2	327	100.0	100.0	100.0	100.0	58.0	W, WIPBf
16	25	32	1,609	400	543.7	817	100.0	100.0	100.0	100.0	52.0	W, WIPBf
17	35	35	1,755	800	755.3	995	94.4	100.0	100.0	94.4	59.0	W, WIPBf
						Mean	74.7	78.4	64.7	81.6	68.7	

[a]lm = linear meter.

[b]Planned PRI is considered as 100% by project manager during the RCM implementation period.

Case Study A: Improving Planning Reliability and Project Performance

The plastering activity of the P_6 project shown in Table 3 was selected as Case Study A to analyze the effect of using the RCM on project performance. It is interesting to note that the project manager was initially reluctant to make operational decision based on the RCM. Table 4 and Fig. 3 show the data and evolution of RCM application in Case Study A during 17 weeks.

Table 4 shows the main production parameters used by the RCM, and the MLR models specified as a combination of W and WIPBf variables. Fig. 3 shows the evolution of the RCM application. Three different periods can be distinguished in Table 4, by the dashed lines, and in Fig. 3: the no-predictions period (1st and 2nd weeks), where data are collected for the RCM; the predictions/no-decisions period (3rd–13th weeks), where planning predictions were performed to test the RCM, but were not

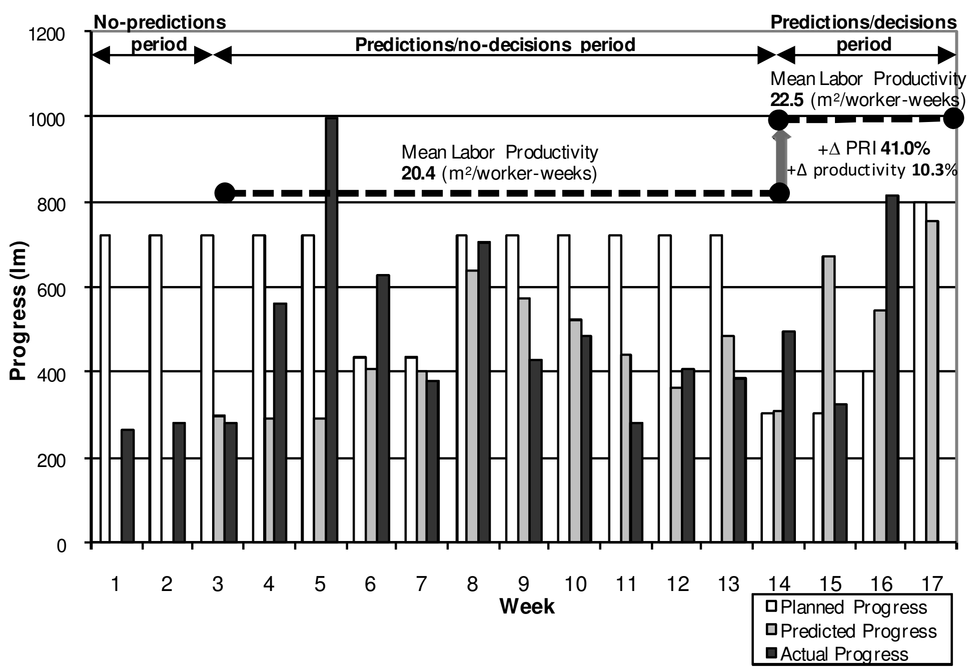

Fig. 3. RCM application evolution: Case Study A

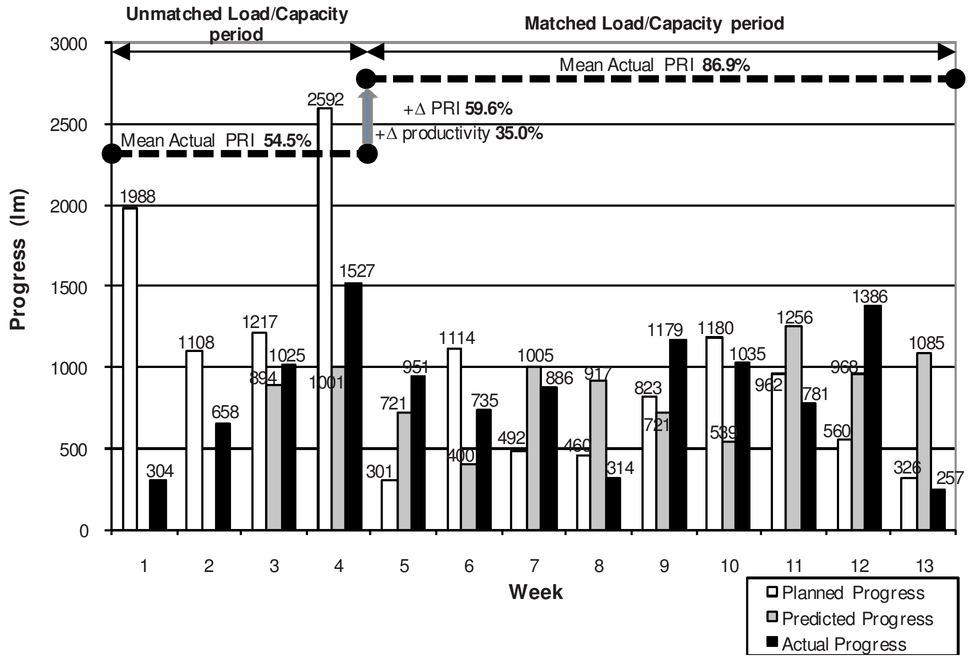

Fig. 4. RCM application evolution: Case Study B

used by the manager to make decisions; and the predictions/decisions period (14th–17th weeks), where the manager relied on the RCM outputs to make planning decisions. The analysis focuses on the last two periods.

An active intervention on the W and WIPBf variables was decided starting from the 11th week. From the beginning of the 14th week, the RCM was used to study the effect of WIPBf over W in the following weeks. Based on this analysis, the manager decided to slow down the activity not involving a higher number of W during the 14th and 15th weeks. During these weeks, a larger WIPBf was deliberately generated maintaining a low W level. It was determined that a WIPBf size closer to $2,000\ \text{m}^2$ could maximize labor productivity in order to achieve PP levels of $800\ \text{m}^2$ with W levels closer to 31 worker weeks. During the 16th and 17th weeks the numbers of W was increased to take advantage of a higher buffer size.

A rough analysis of the data from Table 4 and Fig. 3 shows that the mean actual PRI for the predictions/no-decisions period and the Predictions/decisions period is 70.55 and 100%, respectively. The effect over labor productivity for the same period was estimated as the ratio between actual progress and worker weeks. Mean labor productivity for the predictions/no-decisions period and predictions/decisions period was 20.4 $(\text{m}^2/\text{worker week})$ and 22.5 $(\text{m}^2/\text{worker week})$, respectively. In other words, planning reliability was increased by 41.0% and productivity by 10.3% (see Fig. 3). Table 4 shows that a larger WIPBf size during the 14th and 15th weeks, results in improved productivity for the following weeks. The mean actual PRI for the 3rd–15th weeks is 72.49% and for the 16th–17th weeks is 100%, improving planning reliability by 38.0%. Similarly, the mean labor productivity for the 3rd–15th weeks is 20.6 $(\text{m}^2/\text{worker week})$ and for the 16th–17th weeks is 27.0 $(\text{m}^2/\text{worker week})$, with a productivity improvement of 31.0%. The improvement in labor productivity is explained by a better planning reliability and a direct action over production variables such as W and WIPBf using the RCM. There is also an unexpected increase in labor productivity explained by the psychological effect of higher WIPBf levels over subcontractor' crews, which given better production conditions improved their performance to increase their profitability (González et al. 2009; Sacks and Harel 2006).

Note that the predicted progress by RCM is more accurate than the manager's estimates given the mean predicted and planned CCL shown in Table 4 (81.6 and 64.7%, respectively). Fig. 3 shows that the planned progress from the 3rd to 13th weeks generally overestimated actual progress. When the manager started relying on the RCM predictions, from the 14th week, planning reliability significantly improved (see Table 4). During the last four weeks predicted and planned CCLs were similar.

However, it should be noted that RCM predictions can sometimes be less accurate. We believe that this may be due to the nature and variation of the RCM inputs specifically selected by decision makers such as planned worker weeks (see methodology in Fig. 2). For instance, the 15th week has an actual progress lower than predicted progress, which was probably due to the overestimation of the planned worker weeks by the manager. In contrast, during 16th week, actual progress is higher than predicted progress due to the underestimation of planned workers. The 17th week shows that similar predicted and planned progresses are obtained if planned (inputs) and actual worker weeks have similar levels.

Case Study B: Matching Load with Capacity

The north formwork activity of the C_2 project shown in Table 3 was selected as Case Study B to determine the influence of the RCM in the load-capacity matching problem. Fig. 4 shows a summary of the RCM implementation results of this case study. The RCM was implemented within 13 weeks. The project manager began making planning decisions based on the RCM from the 5th week. MLR models during the implementation period were mostly a function of W, WIPBf, and PP.

Fig. 4 shows the planned progress, predicted progress, and actual progress for each week. Two periods were identified: the unmatched load/capacity period, where there is no a clear balance between planned and actual progress, and the matched load/capacity period, where there is more balanced planned and actual progresses. In theory, a perfect matching between load and capacity should imply equal planned and actual progress levels, i.e., actual PRI levels of 100%, and a balanced used of labor resources according to planned progress.

Fig. 4 shows that during the unmatched load/capacity period (from the 1st to 4th weeks) planned progress is overestimated. In the matched load/capacity period (from the 5th to 13th weeks), planned and actual progresses were more balanced, showing that previous planning commitments were largely overestimated. Thus, the manager used RCM outputs to perform a sensitive analysis to determine planned progress according to real production conditions (pull approach). Fig. 4 shows that the mean actual PRI for the unmatched load/capacity period and the matched load/capacity period were 54.5 and 86.9%, respectively, which is not only an improvement of 59.6% in planning reliability, but also an increased balance between load and capacity during the period in which RCM is used (a similar load/capacity matching behavior can be seen in the last period in Fig. 4).

Case Study B also showed an improved labor performance promoted by the RCM (for the sake of simplicity only mean labor productivity is addressed). The mean labor productivity for the unmatched load/capacity and matched load/capacity periods were 18.9 (m^2/worker week) and 25.6 (m^2/worker week), respectively. In other words, the planning reliability improvement of 59.6% promoted a labor productivity increment of 35.0%.

In brief, RCM allows effectively matching load with capacity by explicitly using its predictions based on historical data and statistical models, promoting a pull mechanism. Planned estimates are defined and appropriate to available resources that should be balanced during the construction phase.

Summary and Conclusions

A decision-making tool for planning decisions at operational level and capable of supporting and improving planning reliability and project performance and the matching load/capacity issue, we call RCM, is proposed in this paper. RCM is based on lean production principles and uses statistical models to predict commitment planning using production information such as workers, buffers, and planned/actual progresses. A reasonable amount of site evidence was provided to demonstrate the theoretical and practical validity of the RCM. Historical information from three projects and eight activities, ranging from 6 to 9 weeks, were used for a preliminary validation of the RCM, while historical information from six projects and 15 activities, ranging from 8 to 17 weeks, were obtained from the implementing RCM using a computer prototype. In summary, nine projects, 23 activities, and a total of 260 weeks were analyzed and used in the RCM validation and implementation processes, with a confidence level of commitment planning predictions close to 77%.

Basically, two aspects of the RCM were tested in this research: its capability to improve planning reliability and project performance and its capability to support matching load and capacity decisions. Preliminary evidence supports the claim that RCM has both capabilities. In particular, the RCM showed it could improve planning reliability and project performance; the latter measured as labor productivity. Although the number of activities analyzed in each project did not allow analyzing the overall performance impact of improving planning reliability at the project level (i.e., the improvement of the general project productivity), the research provides significant evidence that the RCM has an important effect on project performance. The RCM effectiveness to match load with capacity rests on its pull mechanism that allows defining the load as planned progress according to production system condition, e.g., the labor level which yields a determined capacity as actual progress. This mechanism is based on the RCM ability to support an accurate and transparent decision-making process for the contractor, as well as for the subcontractor personnel, where several productions variables can be simultaneously analyzed to improve reliability of commitments planning.

The RCM can also serve as a practical and simple tool to support planning decision making. The RCM does not require, for instance, input data other than that usually gathered in construction projects, simplifying the data collection process. The use of multivariate linear regression models is also common in engineering.

However, several limitations and questions should be solved to improve, not only the mathematical specification of the RCM, but also practical issues of its on-site implementation. Some of these are the following: (1) involve additional production variables in the RCM to increase its predictive capability, (2) develop complementary quality indicators of predictions related to net progress (not only planning reliability), (3) study more activities and different kinds of projects in order to effectively analyze the impact of improvements of planning reliability and project performance of using the RCM, (4) systematize the development and use of a computer application to facilitate and speed up data processing and visualization, (5) state negotiation frameworks based on the RCM to improve the relationship between contractors and subcontractors, and consequently, their performance, and (6) compare the RCM performance to other methods for construction predictions. Several of these topics are part of ongoing research currently carried out by the writers.

Finally, this research provides evidence that better decisions are possible with the aid of an analytical-statistical tool, which can achieve a more reliable and accurate planning process with meaningful and positive impacts over project performance. Also, the RCM might assist the LPS implementation as a complementary tool. On the other hand, intuition and experience will always be an important part of the decision-making process in construction. However, tools as the RCM can help to improve the "intuition" and "experience" abilities of construction decision makers for the construction industry business.

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