

COMPLETION ASSESSMENT FOR MULTIPLE PRODUCTION SYSTEMS USING MARKOV CHAIN ANALYSIS

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ABSTRACT

This research introduces a novel method for predicting project completion in construction by simulating and analyzing historical progress performance data through Markov Chain Analysis (MCA). This approach diverges from conventional regression analysis and quantitative risk analysis (QRA) via Monte Carlo simulation, which primarily emphasize modeling activity durations. Instead, the study evaluates progress by focusing on deliverables rather than activities, defining completion states instead of durations. The mutually exclusive states utilized are not-started (NS), work-in-process (WIP), and complete (OK). The method enables the application of MCA to determine when all deliverables achieve the absorbing state of completion, integrating confidence intervals and data discrimination criteria, while exhibiting satisfactory consistency in forecasting completion ranges.

KEYWORDS

WIP, completion, Markov chain analysis, machine learning.

INTRODUCTION

Project delays in construction are common. Studies conducted in various countries, including Saudi Arabia, have concluded that more than 70% of projects experienced unplanned delays (Al-Kharashi & Skitmore, 2009); similarly, Changali et al. (2015) estimates that over 98% of projects face cost and/or schedule overruns. Current practice for assessing completion typically relies on Monte Carlo simulation, which, together with the Earned Value Method (EVM), provides forecasts based on different scenarios. However, this approach presents limitations related to the selection of activity statistical distributions and the historical data supporting such selection (Avlijaš, 2018). Furthermore, the range of available distributions varies across different software solutions, while activity behavior may change during project execution—requiring updates to simulation inputs. For mega-projects involving massive datasets, conducting granular activity-level distribution behavior follow-up can become impractical. Eventually, project extension follows a pattern called the 90% Syndrome—a phenomenon modeled by Ford & Sterman (2003) in “Overcoming the 90% Syndrome: Iteration Management in Concurrent Development Projects”—using system dynamics to obtain a completion curve for the entire project scope, which, although insightful, does not incorporate common elements in construction management such as physical deliverables and the associated technical information needed for completion traceability and further modeling. The Last Planner® System (LPS) typically relies on conventional progress curves such as those derived from EVM and is not intended to monitor project extensions. However, Alarcón et al. (2014) demonstrated that

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LPS indicators can provide early signs of project performance without directly relying on progress curve representation. More recently, Samaniego (2025) introduced an approach based on the Completion State Leaps Rule (CSLR), where each deliverable transitions through three aforementioned mutually exclusive states: NS may remain NS or leap to WIP; WIP may remain WIP or leap to OK upon requirement compliance; and OK, as an absorbing state, remains OK. In this approach, Samaniego (2025) demonstrates that progress is not equal to completion. Thus, this framework defines upper and lower bounds—Q6' and Q6, respectively—within which the progress curve is always found, and the expected convergence of these bounds establishes the completion time—thereby setting the foundation for further assessment of how this convergence can be modeled. In light of this, the question arises as to how convergence can be better assessed. Accordingly, the present theoretical study proposes a method for estimating completion in Multiple Production Systems (MPS) using MCA to model completion convergence, which functions as an early warning mechanism for preventing unexpected project delays at different stages, including later stages that denote the existence of the 90% Syndrome in project completion. This study also aims to serve as a foundation for future research.

LITERATURE REVIEW AND FOUNDATIONS

Uncertainty modeling has been developed in a limited way within the LPS, some approaches to this include constraint modeling related to PPC so that plan reliability increases (Javanmardi et al., 2018). Yang (2002) proposes a Repetitive Scheduling Method (RSM) to ensure the continuous utilization of resources from unit to unit, which meets the goal of eliminating waste in Lean Construction; a probabilistic model is simulated to compare the impact of the RSM and Critical Path Method schedules on the project duration. Torp et al. (2018) proposed a qualitative approach to integrate uncertainty management to LPS through different planning phases. WIP is a core element within production system analysis, focused on strategically managing constraints to accelerate task finalization. In manufacturing, WIP constitutes inventory, categorized as waste in lean principles (Ohno, 1988). In construction, Gharaie et al. (2012) characterized WIP as projects currently being built, using average house completion time (AHCT) to quantify processing duration. While their definition emphasizes WIP as a component of a production system, it inherently treats WIP as a state—specifically, the condition of an unfinished deliverable. Concerning WIP control, Hopp and Spearman (2000) introduced the CONWIP (constant WIP) concept, a pull-based production system designed to maintain fixed WIP levels throughout entire production lines. Further advancing systematic WIP management, Jang and Kim (2007) developed the Percent of Constraint Removal (PCR) method, which focuses on identifying and eliminating obstacles that hinder workflow progression. Emdanat et al. (2016) presented Percent Required Completed or Ongoing (PRCO), a metric that measures the proportion of necessary activities completed by scheduled dates, while also accounting for ongoing work projected to be finished. They further introduced Milestone Variance (MV), which quantifies the discrepancy between expected finish dates for outstanding tasks and established milestone deadlines. Although this approach does not strictly differentiate between remaining and ongoing activities, it effectively underscores the significance of activities in the not-started state. For overall project completion assessment, traditional metrics from the EVM—such as the Cost Performance Index (CPI) and Schedule Performance Index (SPI)—can serve as supplementary indicators. However, EVM aggregates the entire scope of work, combining both WIP and completed deliverables into a single measure, which prevents it from providing an isolated evaluation of completion for individual deliverables. Kim and Reinschmidt (2009) propose a Bayesian beta-curve method that fits S-curves to cumulative progress data, updating predictions using optimistic, most likely, and pessimistic duration assumptions, making no distinction between progress and completion. This

limitation underscores the need for practical constraint assessment approaches that promote timely completion by focusing on requirement (specification) fulfillment and the specific characteristics of each deliverable, moving beyond purely quantitative progress estimates and based on the concept that the progress is not equal to completion.

METHODOLOGY

The methodology for this study follows a structured approach: **observation and hypothesis** development regarding project production management practitioners' understanding of key concepts on Lean Construction principles and completion; **assessment of key concepts understanding** through directed polls on theoretical completion, and practical WIP understanding; **analysis and development** of the completion forecast estimate model; **simulation** defining data inputs parameters; **result** assessment, and **discussion**.

OBSERVATION AND HYPOTHESIS

In Peru, completion assessment is biased by the erroneous conception of equating completion with progress; thus, it establishes an inherent bias in the completion date estimate (CDE) as it is assessed from a progress-equals-completion perspective (PECP). Available LPS tools lack a tailored forecasting framework and solely present planned and executed activities, omitting WIP representation. Common CDE—biased by PECP—typically relies on ordinary basic regression estimates or Monte Carlo quantitative risk analysis, where the inputs are activities listed in Gantt charts. In this scenario, a framework based on a real completion conception, using deliverables instead of activities and mutually exclusive completion state leaps, is an alternative for completion date forecasting.

ASSESSMENT OF KEY CONCEPTS UNDERSTANDING

Poll Results on Completion Understanding and WIP

There is a disconnect between the expected results of applying LPS and completion, as the former is not properly understood as do-it-right-the-first-time (DIRFT), and the latter is wrongly understood as coexisting with WIP. This will be shown in the poll results. Figure 1 shows the answer to the following question: *In a 24-month building construction project, where all Lean Construction principles are consistently applied and the tools provided by the Last Planner® System (LPS) are adequately implemented, what is the typical timeline you would expect due to work such as patching, repairs, or similar activities? Please note that this does not necessarily imply an extension of the timeline, as these tasks can be carried out in parallel without affecting, for example, concrete pouring dates according to the LPS Activity Train.* In this sample, 42.5% responded that the typical timeline overrun is 1 to 2 months; this shows that among LPS practitioners there is a misalignment between DIRFT and Lean Construction principles.

Table 1: Survey on LPS and completion relation understanding

Location	Peru	% Peru responders	73.6%
Size	87	Avg LPS experience	5.6 years
Mean	Online poll	Dates	Dec 2025; April 2026
Tool	Google Forms	Source	Database built in Peru
Type	LPS social media & Emailing	Target	Construction Mgmt Practitioners

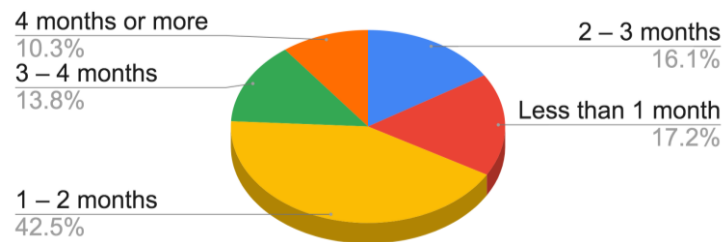


Figure 1: Answers to poll on timeline extension in LPS based projects

On the other hand, regarding the coexistence of WIP with completion, Figure 2 shows the answers to one relevant question: A crew begins its work in week "n," strictly adhering to the planning according to the Last Planner® System activity train, resulting in the pouring of all planned concrete elements. If this scenario repeats such that 100 planned concrete elements are successfully poured by the end of the month, and the Activity Train records that all planned activities for the month were completed, in your opinion, what minimum percentage of minor rework would you expect for the aforementioned poured elements (e.g., patching of honeycombing, localized chipping, leveling)? Only 10.3% of respondents selected the correct answer, corresponding to 0% rework, as completion is logically and factually mutually exclusive with WIP.

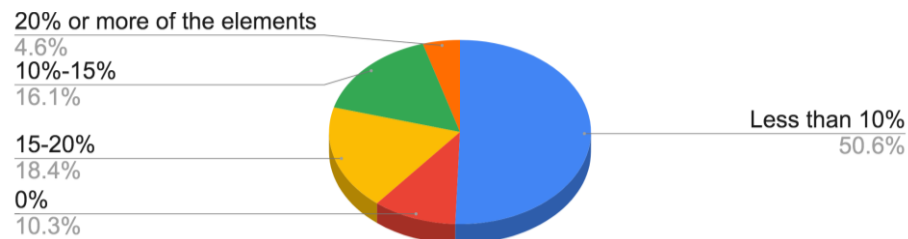


Figure 2: Answers to poll on understanding LPS and WIP as rework

Although the sample size is not statistically representative and needs to be increased, these results are very consistent with the hypothesis that, in Peru, there is a disconnect between the expected results of applying LPS and the understanding of completion, taking the latter as capable of coexisting with WIP, which is not possible. A larger survey showing similar patterns would indicate that most practitioners fail to properly analyze activity results, leading to incorrect assumptions about completion and WIP.

ANALYSIS OF COMPLETION FORECAST ESTIMATE MODELING

MCA for Multiple Production System

The Single Production System is Takt Time Planning (TTP) based, using, for example, the Activity Train (Brioso et al., 2016), which shows the sequence of trades and sectors. However, it provides no representation of WIP state (see Figure 3), which is needed for identifying the CSLR among deliverable states. In this study, completion is based on deliverable requirements being fully defined in advance, with no engineering changes applied after completion is achieved.

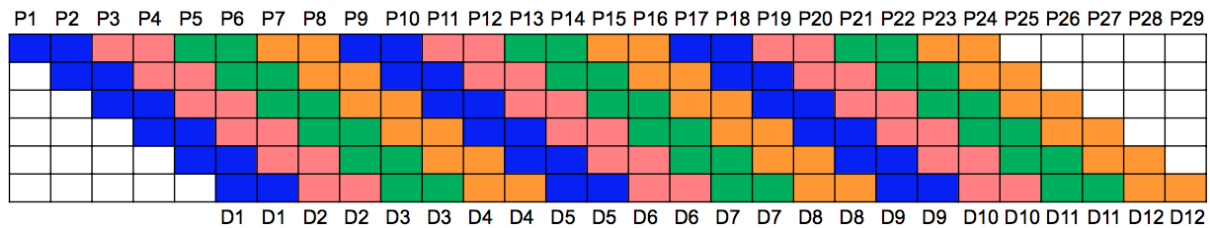


Figure 3: Activity train based on TTP

This is why there is a need for an Activity Modelling Grid (AMG) showing the three Completion State Leaps (CSL). This grid representation helps to identify patterns necessary for MCA. The use of grid-based representations is not uncommon in MCA, as illustrated by Gustavsson et al. (2018), who employed a grid to map engineering change request leaps from created to solved state. In this sense, Last Planner® System activity train and sector (LPSAT) elements are reorganized into this AMG where one sector is treated as a single deliverable for the purpose of simplification; thus, this deliverable is to be finished in a given timeframe. The method restructures the LPSAT configuration into a General Activity Modeling Grid (GAMG) as a representation of MPS (see Figure 4). For example, in the Single Production System (SPS) described in Figure 4.a, D1 started its formation from P1 to P6. In this way, D1 remains in a WIP state until P6 and leaps to OK in P7 based on requirements fulfillment rather than finished activities. Figure 4.b represents another SPS starting at a later time, so that its 'P1' period coincides with the 'P2' period of the first SPS; a similar pattern happens in Figure 4.c. Eventually, all overlapping SPSs show a mixed pattern as shown in Figure 4.d, which is a sectional representation of the GAMG.

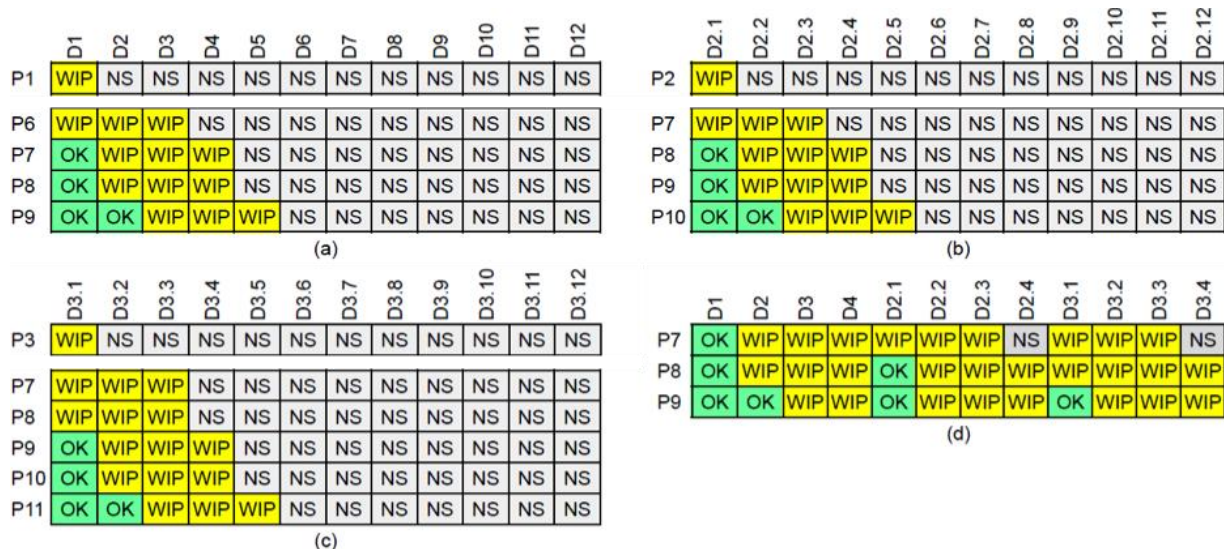


Figure 4: AMG for activity train and overlapping SPS representation

For modeling purposes, the GAMG was programmed so that each deliverable—represented in every cell—advances vertically and stochastically between periods (P_w to P_w+1) according to the CSLR, as illustrated in Figure 5. The state transition frequencies recorded from P_0 to P_n form the Data Feed Range (DFR), to be used as input for MCA (see Figure 5). Thus, the cumulative configuration of cell states represents one of many possible combinations until completion is achieved—when all cells turn green in a certain measurement period, here labeled as actual completion period (P_x).

Given the need for a minimum number of CSL records for a reliable MCA, it can be expected that for a given DFR there is a confidence period (P_c), greater than P_n , from which onward the expected completion date can be consistently estimated, given the associated

transition matrix (TM). There is also an unlikely constant transition matrix (UTM) where the probability of each state leap equals 50%. In general, any kind of constant matrix represents stationary transitional probabilities where Markov Chain is homogenous (Gantar, 2009). This extremely rare value represents the ideal—yet unattainable—scenario for completion state leaps. The results from operating the MCA using the UTM and the associated TM will provide the lower time boundary (Pl) and the upper one (Pu) within which Px is expected to be found. Consequently, a Completion Date Estimate Range (CDER) is defined based on an empirical and statistical approach.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	D15	D16	D17	D18	D19	D20
P1	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS
P2	WIP	NS	NS	WIP	WIP	NS	NS	NS	WIP	WIP	WIP	WIP	NS	NS	WIP	WIP	WIP	NS	NS	WIP
P3	WIP	NS	NS	WIP	WIP	NS	NS	NS	WIP	OK	WIP	WIP	WIP	NS	WIP	WIP	WIP	WIP	WIP	WIP
P4	WIP	WIP	WIP	WIP	WIP	NS	NS	WIP	WIP	OK	WIP	OK	WIP	NS	OK	WIP	OK	OK	WIP	OK
P5	WIP	OK	WIP	OK	OK	WIP	WIP	OK	WIP	OK	WIP	OK	WIP	WIP	OK	WIP	OK	OK	WIP	OK
P6	WIP	OK	WIP	OK	OK	WIP	OK	OK	WIP	OK	OK	OK	OK	OK	OK	WIP	OK	OK	WIP	OK
P7	OK	OK	WIP	OK	OK	WIP	OK	OK	OK	OK	OK	OK	OK	OK	OK	WIP	OK	OK	WIP	OK
P8	OK	OK	WIP	OK	OK	WIP	OK	OK	OK	OK	OK	OK	OK	OK	OK	WIP	OK	OK	WIP	OK
P9	OK	OK	WIP	OK	OK	WIP	OK	OK	OK	OK	OK	OK	OK	OK	OK	WIP	OK	OK	WIP	OK
P10	OK	OK	OK	OK	OK	WIP	OK	OK	OK	OK	OK	OK	OK	OK	OK	WIP	OK	OK	WIP	OK
P11	OK	OK	OK	OK	OK	WIP	OK	OK	OK	OK	OK	OK	OK	OK	OK	WIP	OK	OK	OK	OK
P12	OK	OK	OK	OK	OK	WIP	OK	OK	OK	OK	OK	OK	OK	OK	OK	WIP	OK	OK	OK	OK
P13	OK	OK	OK	OK	OK	WIP	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
P22	OK	OK	OK	OK	OK	WIP	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK
P23	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK	OK

Figure 5: Single simulation showing stochastic completion state leaps

Building the MCA Model for Completion Date Forecast

To build the MCA model, the DFR must first be defined. Therefore, and in accordance with the aforementioned method, in this example, Pn equals P10 as shown in Figure 5. By implementing this, the number of completion states is recorded in Table 2. For instance, the number of NS states in Figure 5 decreases from 3 to 0 between P4 and P5, as documented in the table.

Table 2: Individual state leaps counting for a given DFR10

Period	NS	WIP	OK
P1	20	0	0
P2	9	11	0
P3	6	13	1
P4	3	11	6
P5	0	10	10
--	--	--	--
P10	0	3	17

In Table 3, the existing CSL counts across DFR10 are represented. For example, from P4 to P5, the NS-NS count decreased by 3, and correspondingly, the NS-WIP leap count increased by 3. This indicates that in P5, the number of NS-NS states is 0, while 3 new NS-WIP states are recorded. The data for all leaps is subsequently normalized.

Table 3: CSL recording for a given DFR10

Period	NS-NS	NS-WIP	NS-OK	WIP-NS	WIP-WIP	WIP-OK	OK-NS	OK-WIP	OK-OK	SUM
P1	20	0	0	0	0	0	0	0	0	20
P2	9	11	0	0	0	0	0	0	0	20
P3	6	3	0	0	10	1	0	0	0	20
P4	3	3	0	0	8	5	0	0	1	20
P5	0	3	0	0	7	4	0	0	6	20
--	--	--	--	--	--	--	--	--	--	--
P10	0	0	0	0	3	1	0	0	16	20
Sum	38	20	0	0	46	17	0	0	79	
Norm.	0.66	0.34	0.00	0.00	0.73	0.27	0.00	0.00	1.00	

By doing this, it is possible to obtain the TM, which, in alignment with the aforementioned example, is described in Table 4. This table also describes the UTM.

Table 4: TM (a) and UTM (b)

	NS	WIP	OK		NS	WIP	OK
NS	0.66	0.00	0.00	NS	0.50	0.00	0.00
WIP	0.34	0.73	0.00	WIP	0.50	0.50	0.00
OK	0.00	0.27	1.00	OK	0.00	0.50	1.00
	1.00	1.00	1.00		1.00	1.00	1.00
(a)				(b)			

In one simulation, the TM is multiplied by a three-element vector representing the counts of elements in each completion state (NS, WIP, OK) in the last recorded period (P_{x-m}). The multiplication yields three new expected state counts for period P_{x-m+1} . These values are then multiplied again by the same transition matrix to produce predictions for P_{x-m+2} . The process repeats iteratively until the proportion of OK elements—labeled Q_6 —approaches 100%, as an asymptotic limit where Q_6' also converges. Here, Q_6 values conforms the Completion Curve, and Q_6' is the maximum completion presented as $Q_6' = Q_6 + WIP$ (Samaniego, 2025). The same process separately applies to UTM; in both cases, mathematically, true Q_6 equals to 100% is only reached at infinity, but practical convergence is evident. Therefore, a practical 100% threshold must be empirically defined, using the simulation output data. The limits for the results derived from the UTM and the TM are labeled as P_l and P_u , respectively, and together they define the CDER.

RESULTS

MCA IN MULTIPLE PRODUCTION SYSTEMS

The results were obtained by applying the boundary of confidence for completion (P_c) defined from P_{14} onward. In this case, as DFR10 is defined only until P_{10} , there is a ratio of 1.4 between these parameters, we call this as ratio of feed parameter (R_{fp}). Consequently, every simulated P_x falling below P_{14} was considered "out of range" for MCA completion forecast estimates. Tables 5 and 6 represent the results of one simulation based on the UTM and the associated TM, with the practical completion thresholds P_l and P_u set at 99.0% and 99.9%, respectively, and therefore equals to P_{14} and P_{26} . It is worth noting that, in contrast to Monte Carlo simulation and the approach proposed by Kim and Reinschmidt (2009)—where the forecasting dataset relies on conventional assumptions regarding optimistic, most likely, and pessimistic durations—the criteria for defining the 99.0% to 99.9% range are derived from empirical

assessment of the simulation outcomes, thereby grounding the forecast limits in observed performance patterns rather than predetermined probabilistic assumptions.

Table 5: Sampled simulation results for DFR10 and UTM

	Historic Values							MCA Values			
	P1	P2	P3	--	P8	P9	P10	P11	P12	P13	P14
NS	20	9	6	--	0	0	0	0.0	0.0	0.0	0.0
WIP	0	11	13	--	4	4	3	1.5	0.8	0.4	0.2
OK	0	0	1	--	16	16	17	18.5	19.3	19.6	19.8
SUM	20	20	20	--	20	20	20	20.0	20.0	20.0	20.0
Q6	0%	0%	5%	--	80%	80%	85%	92.50%	96.25%	98.13%	99.06%
Q6'	0%	55%	70%	--	100%	100%	100%	100%	100%	100%	100%

Table 6: Sampled simulation results for DFR10 and TM

	Historic Values						MCA Values				
	P1	P2	P3	--	P9	P10	P11	--	P25	P26	P27
NS	20	9	6	--	0	0	0.0	--	0.0	0.0	0.0
WIP	0	11	13	--	4	3	2.2	--	0.0	0.0	0.0
OK	0	0	1	--	16	17	17.8	--	20.0	20.0	20.0
SUM	20	20	20	--	20	20	20.0	--	20.0	20.0	20.0
Q6	0%	0%	5%	--	80%	85%	89.05%	--	99.87%	99.90%	99.93%
Q6'	0%	55%	70%	--	100%	100%	100%	--	100%	100%	100%

Table 7 presents the cumulative simulation results, with each row corresponding to one simulated completion scenario. The table provides a sample illustrating the normalized P_x location (NPXL) within the CDER based on the parameters P_l , P_x , and P_u . For the set of 147 simulations executed for the given DFR10, the CDER achieves a more than 90% match rate. All results shown satisfy the scope equation $NS + WIP + Q6 = 1$ (Samaniego, 2025), confirming correct simulation behavior. “Out-of-Range” cases—where P_x falls below P_c —were not included in the aforementioned number of simulations.

Table 7: Sample of cumulated simulation results for DFR10

PI	Px	Pu	RANGE	NS	WIP	Q6	NPXL
14	15	26	MATCH	0	0	1	0.08
13	14	16	MATCH	0	0	1	0.33
16	17	25	MATCH	0	0	1	0.11
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Figure 6 and 7 show the $Q6$ and $Q6'$ evolution until completion for a single simulation based on UTM and TM

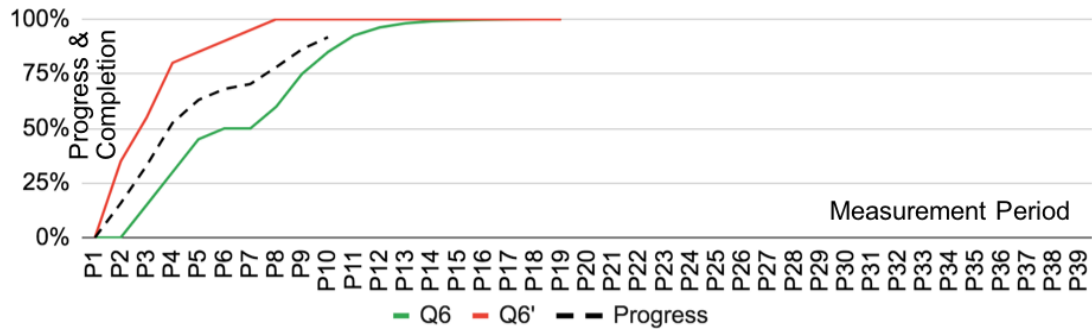


Figure 6: MPS completion curves defining lower limit (Pl) per UTM for one simulation

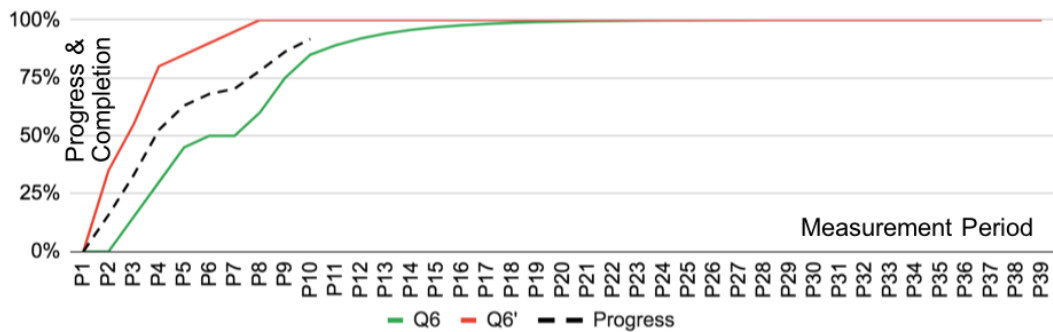


Figure 7: MPS completion curves defining upper limit (Pu) per TM for one simulation

Table 8 presents a sensitivity analysis across different DFR values, showing a decrease in the match rate as DFR approaches P_c . Moreover, when extending the CDER from P_l-1 to P_u+1 —which implies allowing one less day for P_l and one more day for P_u within a new normalized range—the match percentage increases to 97.96% for DFR10. Sabillon et al. (2018) reported a comparable 90% correspondence between predicted and observed outcomes by integrating a Markov Chain model for activity transitions within a Bayesian approach to construction cyclic operations. The decay in CDER Match % as DFR approaches $P_c=14$ does not affect DFR10 selection. Likewise, the extended CDER Match' % includes $P_c=14$ within "out of range," producing a smoother decay and confirming that DFR10 remains robust with acceptable range—offering a more inclusive yet equally valid completion estimate.

Table 8: Statistics for DFR including extended CDER

DFR	CDER Match %	CDER Match' %	NPXL Mean	NPXL Median	NPXL Mode	NPXL 80 th Percentile	NPXL Std. Deviation	CDER type
13	43.54%	65.31%	0.22	0.17	0.00	0.33	0.23	Regular
13	62.59%	93.88%	0.19	0.14	0.00	0.33	0.20	Extended
12	58.50%	89.58%	0.20	0.13	0.00	0.38	0.24	Regular
12	90.48%	95.83%	0.18	0.14	0.00	0.32	0.21	Extended
10	91.16%	91.26%	0.29	0.22	0.00	0.50	0.26	Regular
10	97.96%	97.09%	0.34	0.29	0.33	0.54	0.24	Extended
9	88.44%	88.99%	0.39	0.33	0.50	0.60	0.26	Regular
9	93.88%	91.74%	0.40	0.37	0.33	0.60	0.23	Extended
8	82.99%	77.88%	0.40	0.33	1.00	0.66	0.28	Regular
8	91.84	89.42%	0.47	0.40	1.00	0.71	0.27	Extended

Table 9 presents the sensitivity analysis for match percentage across different numbers of deliverables (DQTY) for a given DFR10. It shows that the match percentage increases as DQTY increases.

Table 9: Statistics for DFR10 applied to different numbers of deliverables

DQTY	CDER Match %	NPXL Mean	NPXL Median	NPXL Mode	NPXL 80 th Percentile	NPXL Std. Deviation	CDER type
15	81.63%	0.26	0.17	0.00	0.41	0.25	Regular
15	93.20%	0.31	0.25	0.00	0.44	0.25	Extended
18	85.03%	0.32	0.22	0.00	0.50	0.27	Regular
18	93.88%	0.36	0.29	0.29	0.57	0.26	Extended
20	91.16%	0.29	0.22	0.00	0.50	0.26	Regular
20	97.96%	0.34	0.29	0.33	0.54	0.24	Extended

DISCUSSION

In MPS, completion estimates can be assessed using MCA, which evaluates mutually exclusive physical deliverable completion status "leaps." This contrasts with traditional progress estimation methods based primarily on quantities or activity status. The MCA approach focuses on completion as the achievement of requirements, addressing the common misconception that progress and completion are equivalent. To execute the MCA, a DFR is required. The DFR presents sample patterns of deliverable completion states—NS, WIP, and OK. This framework challenges existing biases that rely solely on activity tracking to determine completion, emphasizing instead the requirement fulfillment process inherent to a deliverable's physical conformation as the driver for completion evolution. The modeling relies on randomized completion status patterns, which typically do not appear in SPS due to its TTP approach. However, the modeling transforms a standard TTP scheme—which lacks representations of WIP deliverables—into a structure analogous to MPS. This transformation enables the simulation of completion status leaps, representing WIP applied to deliverables that have not yet fulfilled requirements, which then includes deliverables needing rework, even though their corresponding quantities might be achieved. These leaps are necessary for advancing to the completed state, yet they are rarely represented in current LPS tools used by practitioners. Although MCA mathematically expresses completion status as an asymptotic value, which may appear as a limitation, a practical completion estimate can still be defined. In MPS, the estimate was empirically defined based on the highest number of consistent outcomes. Additionally, a sensitivity analysis was conducted to serve as parameter selection calibration for the DFR. In this regard, a finding is that a ratio of 1.4 between DFR10 and P14 yields the highest number of matches in the simulations. Additional criteria—together with the DFR—are used to define a confidence range for modeling applicability. The results demonstrate high consistency with actual completion dates obtained from stochastic simulation.

It is worth noting that, although each of the 147 simulations derives a TM from a specific DFR, the ensemble of TM generated across simulations—incorporating different DFRs, Pc values, and practical completion sets (not limited to a single 99.0% and 99.9% thresholds)—constitutes a learning dataset. This dataset can be integrated with Building Information Modeling (BIM), as every BIM element follows the CSLR and can therefore be leveraged by machine learning (ML) models to identify higher-order completion patterns, thereby opening a clear pathway for BIM analytics that operates in parallel with the MCA. Bassier et al. (2019) also present an approach for assessing completion using ML on point-cloud data; however, their method relies primarily on geometric parameters, whereas the present MCA approach determines completion based on full deliverable requirement achievement.

CONCLUSIONS

This study introduces a novel application of MCA for forecasting project completion by modeling the stochastic evolution of deliverables through three mutually exclusive states: NS, WIP, and OK. This concept approach shifts the focus from deterministic activity durations to

probabilistic state transitions governed by requirement fulfillment, the method addresses the common bias of equating progress with completion. The proposed framework, utilizing a GAMG and defined CSLR, successfully transforms LPS activity data into a format suitable for MCA, enabling the estimation of a CDER. The results demonstrate that a practical completion forecast can be derived from a DFR of historical state transitions. By applying both a UTM and a TM, the model establishes lower and upper bounds for the completion period. Simulations show a high consistency (over 90% match) in locating the actual completion date within the predicted range, validating the model's robustness for multiple, overlapping production systems. This research provides a foundational, statistically-grounded alternative to traditional regression and Monte Carlo-based completion forecasts. By treating completion as an absorbing state within a Markov process, it offers a proactive tool for identifying the "90% Syndrome" and managing schedule risks. The study sets the stage for further empirical validation and refinement of MCA parameters in real-world construction projects, which will allow ground generalization and assessment of real impact. All of this can be facilitated by using BIM to easily track and compute deliverable states. In this aim, extended research could strengthen these observations by: (1) conducting broader surveys on the concepts presented; (2) organizing focus groups with both senior and junior LPS practitioners; and (3) reviewing WIP records in active projects. Regarding the proposed MCA for estimating completion, site validation experiments should consider the following: (1) conducting experiments in ten building projects (towers); (2) involving senior LPS practitioners in the selected projects; and (3) assessing actual completion achievement and completion date estimates as defined in this study.

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