

# AN ANALYSIS OF ACTIVITY-LEVEL PREDICTABILITY FROM UK CONSTRUCTION PROJECTS

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Project time-predictability and performance remains low in the construction sector. Any time improvements provide opportunities to increase project efficiency, profitability and success. In project planning and programming, performance is often measured at project-level. However, this work analyses predictability accuracy at activity-level to establish trends to focus future planning efforts and make prediction improvements. To that end; an aggregation of more than 35;000 lines of activity-level programme data were collected for analysis from 27 recent UK construction projects. Analysis of the activity-level programme data was completed relative to project type; project duration; level of detail; project-level performance; and time-predictability metrics. The analysis demonstrated large disparity between activity-level predictability; with more than one-third of all predictions failing to achieve start date; finish date; or duration accuracy; and less than one-third of predictions able to accurately forecast activity start dates. Here 63% of activities were able to predict positive project outcomes; but only 24% of activities were able to achieve perfect time-predictions. Correlation between positive activity-level predictability and overall project-level time-performance is evidenced. Therefore, increased analysis of activity-level planning provides the potential to improve project-level time-performance.

Keywords: construction planning; planning effectiveness; activity programme data; time predictability; hit-rates; time performance

## INTRODUCTION

When measuring the short-term success of construction projects, the Iron Triangle of Time, Cost and Quality ('TCQ') metrics are often referenced (Tabish and Jha, 2018). Projects that achieve these metrics are deemed a short-term success and those which don't, experience an element of failure (Han *et al.*, 2012). Each unique project will rank the order of these metrics, amongst a range of other Critical Success Factors (CSFs) such as health, safety, and environment, in a hierarchy of importance, with the metrics often entwined with each other. Scholars and practitioners alike strive to attain betterment across these performance metrics with improvements providing the potential for significant efficiencies, better outcomes, repeat business, and higher

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customer satisfaction (Silva *et al.*, 2016). The focus of this research is to seek improvements of the time-performance metric, which remains one of the key pillars of short-term project success (Silva *et al.*, 2016; Musselwhite *et al.*, 2021).

### **Time-Performance in UK Contracting**

Time-performance in UK contracting is commonly measured via the high-level assessment of whether the project achieved completion on time against its planned contract completion date (Halpin *et al.*, 2017; Construction Excellence, 2018). For this, in the mid-1990s, akin to the TCQ Iron Triangle, the UK government highlighted the need to measure time-performance when it launched its Key Performance Indicator (KPI) framework, with a focus on whether projects achieved overall completion on time (i.e., project-level performance). In early UK government-led analysis it was reported that only 34% of projects were achieving completion on time in the late 1990s (Egan, 2002), a score that was recognised as wholly unacceptable. Thereafter and since the early 2000s, the centralised independent industry body - 'Construction Excellence' - has collated time-performance records annually. In their analysis they reported performance had improved to 61% of projects achieving completion on-time by 2002. However, by 2018 project-level time performance continued to be in the region of 60% of projects achieving completion on-time, showing little evidence of improvement in approximately 20-years. Considering this stagnated time performance since the early 2000s, combined with the huge potential commercial benefits, finding methods to attain time performance improvements in UK construction projects remains a primary focus for the sector and is the aim of this work via the analysis of aggregated activity-level programme data.

### **Activity-level Performance**

One such route to improving time-performance of UK projects is to alter the way in which projects are planned. Methods of planning can range from writing to-do lists, the use of line of balance diagrams, time-chainage diagrams, static unlinked lists of activities, and network linked activities (e.g., the critical path methodology) (Baldwin and Bordoli, 2014). All these methods require some form of predicting durations which can be established deterministically or probabilistically. In research by the CIOB (2008), it was found that the most common method of planning of UK construction projects was the use of network linked diagrams (applying CPM at activity-level), communicated via Gantt charts. Similar sector research by Kerzner (2017) suggested the same reliance on critical path planning at activity-level using Gantt charts. It was with this awareness that analysing the performance of construction projects at a granular activity-level was deemed relevant to determine its association with project-level time performance.

### **Planning Enhancement Opportunities**

In the consideration of construction planning, existing research has explored the application of technology to improve time-performance and prediction accuracy with the use of machine learning. In research by Flyvbjerg (2008), time-predictions were analysed and the increased use and reference of historical data from similar projects was recommended to help improve future prediction accuracy (i.e., the application of Reference Class Forecasting - RCF). The use of RCF requires a project planner use historical data to inform future predictions, recognising commonality between the previous performance and the project at-hand. Developments in machine learning, combined with a large RCF dataset, has the potential to provide planners with machine learned reference class-based predictions, removing the potential for

imperfect and bias human predictions (at both project- and activity-level). AI has been applied in a similar manner with 'big data' used to create output predictions (Ockree *et al.*, 2018; Shayboun *et al.*, 2019; Awada *et al.*, 2021). This methodology could be applied to construction planning to improve the prediction accuracy at activity-level, potentially leading to time improvements at project-level.

Time performance of UK construction projects focusses on whether the overall project achieved completion on time against the target set. Research demonstrates that said projects are planned at activity-level, yet performance at this level is seldom analysed and reported. Consequently, this provides a research gap to further examine time-performance at activity-level via an aggregation of programme data to determine whether there is a relationship between time performance at activity-level and time performance at project-level.

## LITERATURE REVIEW

In research by Dawood (2010), activity-level time-predictions were analysed from 7,028 activities across 3 projects. In his research time-performance was measured by assessing the activity-level accuracy of planned and actual start and finish date predictions. Activities were analysed across five possible outcome metrics, ranging from 1) activities that aligned planned and actual start and finish dates (i.e., a perfect prediction); 2) activities that started early and finished late; 3) activities that started early and finished early; 4) activities that started late and finished late; and 5) activities that started late and finished early. The actualised activity durations impact which of the five metrics apply. Dawood (2010) described perfect time-predictions as 'hits' and referenced the frequency of these outcomes as the 'hit rate', quantifying the 'planning efficiency' as a percentage of the activities that achieved perfect time-predictions (i.e., activities having zero planned versus actual start and finish date variance). His research then combined perfect hits with activities that also had early-start and early-finish outcomes (i.e., metrics 1 and 3 above; positive results). He sought to examine the correlation of 'hit-rates' on projects using BIM to support planning (47% perfect hit + 25% SE/FE = 72% hit-rate) and those projects planned using only traditional planning methods (55% hit-rate), with his research identifying that the application of BIM offered up to 17% time-improvements (at activity-level). His research also examined the correlation between hit-rates and activity categories (e.g., superstructure, core, glazing, fit-out) and identified that ground floor superstructure had the most inaccurate time-predictions. In contrast, cladding installations, pipework and ductwork had the most accurate time-predictions.

In subsequent work by Gledson *et al.* (2018), similar activity-level analysis was carried out across 720 activities from four recent projects. They developed the previous Dawood performance metrics, adding a further four to take into consideration fluctuating activity durations, but still achieving either start or finish dates (i.e., recognising additional degrees of time-predictability). Their research added metrics to assess activities that 1) started on time and finished early; 2) started on time and finished late; 3) started early and finished on time; and 4) started late and finished on time (a total of nine time-performance metrics). The additional 'on-time' facet of their analysis gave credence to the predictability of one metric when the others may have failed. From their research they found only 38% of activities were able to achieve perfect time-predictions against a corresponding score of 47% (perfect hits) found by Dawood (when using BIM). Gledson *et al.* (2018) concluded that time-predictions were more accurate for activity-durations than they were for predicting

activity start- and finish-dates, and that overall time-predictability at activity-level remained unsatisfactorily low. Neither Dawood (2010) or Gledson *et al.* (2018) sought to draw direct correlations between activity-level hit-rates and project-level time performance. Consequently, this work builds upon the existing research in the field of activity-level analysis, using a larger dataset as the basis for analysis and focusses on the potential relationship between activity- and project-level performance.

## METHOD

To analyse time-predictability and performance at activity-level, an aggregation of 35,915 lines of programme data were collected from a range of 27 recent UK projects. The projects ranged in value from £0.5m through to £500m and level of programme detail from 57 lines of data through to 4,378 lines of data. The projects included new build and refurbishments schemes, commercial and residential projects, high-voltage power works, Ministry of Defence (MoD) works, and rail infrastructure projects. Participating organisations granted access to the archival activity-level programme data for research purposes. The data were extracted from native project programme files in Primavera P6 (.xer), Asta PowerProject (.pp) and Microsoft Project (.mpp) file types. The programme data consisted of activity names, activity planned start and finish dates, planned durations, actual start and finish dates, and actual durations. The data was processed and cleansed, with the resulting data consisting of planned and actual date variances and planned and actual duration variances, facilitating performance analysis across a set of developed activity-level performance metrics. The data was also used to determine project-level performance for cross-referencing against the activity-level results.

### Activity-Level Performance Metrics

The activity-level time-predictability metrics described by Dawood (2010) and Gledson *et al.* (2018) were further evolved in this research to capture two additional metric outcomes. These were to distinguish between duration predictions in circumstances where activities started early and finished early or started late and finished late. The additional metrics measured whether the planned and actual durations were consistent or varied when start and finish dates were inaccurate (Dawood considered the start and finish dates but did not have a sub-set to separate outcomes that maintained or varied the activity duration). In total this facilitates a range of eleven available time-predictability outcomes (Planning Efficiency Metrics) at activity-level (5 from Dawood, 4 from Gledson *et al.*, and 2 from this work). The metrics were ranked in order of time-prediction preference in consideration of duration variance, start date variance, and finish date variance, as shown in Table 1. The 'perfect hit' (PE.1) which accurately predicted activity duration, start date, and finish date was the most preferred outcome (i.e., a perfect prediction). A failure to predict start date, finish date, or duration was deemed the least preferred outcome (PE.11).

The time-predictability metrics were also considered in relation to whether the activity-level permutation would likely result in a positive or negative project outcome. An example being an activity that started early, finished early, and had a shorter duration would be a poor time-prediction (i.e., all planned targets were missed), but because the activity was ahead of programme it would generate a positive outcome for the project. This distinction between activity-level time-predictability and positive project-level outcomes was considered during the analysis. All activity-level tasks from the programme data were assigned a performance metric (referred to

as 'PE.1', 'PE.2'... 'PE.11'). PE.1 - PE.5 were deemed positive planning outcomes (i.e., good levels of accuracy), PE.6 and PE.7 were deemed reasonable outcomes (i.e., some level of accuracy), and PE.8 - PE.11 were deemed negative planning outcomes (i.e., poor accuracy). Each project programme was also examined for its project-level performance by analysing the overall planned and actual start and finish date variances, which provided an indication as to whether the project finished early, on-time, or late. This enabled the relationship between activity- and project-level performance to be analysed.

Table 1: Activity-Level Performance Metrics

Metric	Rank	Dur. Var.	Start Var.	Fin. Var.	Project Outcome
PE.1 - Perfect Prediction.	1	=	N (0)	N (0)	Positive
PE.2 - SE, FE, Duration Maintained.	2	=	Y (-)	Y (-)	Positive
PE.3 - SOT, FE, Duration Varied.	3	X	N (0)	Y (-)	Positive
PE.4 - SL, FL, Duration Maintained.	4	=	Y (+)	Y (+)	Negative
PE.5 - SOT, FL, Duration Varied.	5	X	N (0)	Y (+)	Negative
PE.6 - SE, FOT, Duration Varied.	6	X	Y (-)	N (0)	Positive
PE.7 - SL, FOT, Duration Varied.	7	X	Y (+)	N (0)	Positive
PE.8 - SE, FE, Duration Varied.	8	X	Y (-)	Y (-)	Positive
PE.9 - SL, FE, Duration Varied.	9	X	Y (+)	Y (-)	Positive
PE.10 - SE, FL, Duration Varied.	10	X	Y (-)	Y (+)	Negative
PE.11 - SL, LF, Duration Varied.	11	X	Y (+)	Y (+)	Negative

## Programme Data Analysis

This programmed data analysis describes the aggregated results to demonstrate activity-level performance. The analysis considers the activity-level results against positive and negative project outcomes, followed by an assessment of activity-level and project-level performance to review relationships between the levels of data. The analysis explores sub-sector performance, programme durations, and the level of detail within programmes to explore performance trends for future consideration.

## Aggregated Performance

The 35,915 lines of aggregated programme data were analysed, demonstrating 24% of activities achieved a 'perfect hit' and 24% of activities failed to adhere to any of the performance metrics (planned start date, finish date, or duration). A further 21% of the activities were found to start late and finish late but maintained the planned duration (PE.4) providing a generally positive time-prediction (i.e., as a minimum the activity duration was planned correctly). A total of 18% of activities started early and finish early (regardless of activity duration - PE.2 + PE.8). The remaining activity-level prediction outcomes were spread across the available metrics, as shown in Table 2 - Activity-Level Time Performance Results.

When considering positive and negative project outcomes associated with the time-predictions, the aggregated data calculated 63% of activities had 1 or more accurate activity-level predictions combined with positive project-outcomes (PE.1 - PE.5 subtotal) and 37% of activities had inaccurate predictions (PE.7 - PE.11 subtotal) (i.e., achieved none of the performance metrics) and had negative project outcomes. Activities that achieved perfect time-predictions or started early and finished early accounted for 42% of the data (PE.1 + PE.2 + PE.8), versus the comparable 55% from Dawood (traditionally planned).

Table 2: Activity-Level Time Performance Results

Metric	Count	Percentage	Project Outcome
PE.1 - Perfect Prediction.	8,483	24%	Positive
PE.2 - SE, FE, Duration Maintained.	3,166	9%	Positive
PE.3 - SOT, FE, Duration Varied.	2,368	7%	Positive
PE.4 - SL, FL, Duration Maintained.	7,469	21%	Positive
PE.5 - SOT, FL, Duration Varied.	1,038	3%	Positive (Subtotal 63%)
PE.6 - SE, FOT, Duration Varied.	99	0%	Reasonable
PE.7 - SL, FOT, Duration Varied.	68	0%	Reasonable (Subtotal 0%)
PE.8 - SE, FE, Duration Varied.	3,327	9%	Negative
PE.9 - SL, FE, Duration Varied.	264	1%	Negative
PE.10 - SE, FL, Duration Varied.	1,112	3%	Negative
PE.11 - SL, LF, Duration Varied.	8,521	24%	Negative (Subtotal 37%)
Total	35,915	100%	

The analysis demonstrated that 54% of activities were able to predict durations accurately (PE.1, PE.2, and PE.4) versus 46% of activities that had a different activity-duration (capturing longer and shorter durations). The total percentage of activities that achieved completion on-time or early across the 11-metrics (PE.1, 2, 3, 6, 7, 8, and 9) was 50%, with an equal number of activities finishing late.

### Project-Level and Activity-Level Performance

When analysing the data by project it was possible to review correlations between activity-level predictability and overall project-level performance. This was carried out by analysing project-level finish date variance and the activity-level metric outputs. This demonstrated projects that had a project-level completion date variance of less than 30 calendar days had 58% of positive activity-level predictions (PE.1 - PE.5). In contrast, projects with a project-level completion date variance of more than 30 calendar days were found to have only 48% of positive activity-level predictions [a reduction of 10%]. This demonstrates a strong correlation between positive activity-level predictions (58%) and the net-result at project-level (i.e., improved activity-level predictions result in projects likely to finish within 30-days of the planned completion date). Similarly, the data analysis demonstrates that projects that had <30 days project-level variance had on average 16% 'perfect hit' time-predictions at activity-level (PE.1), versus projects that had >30 days project-level variance having 15% of activities with 'perfect-hits'. This reinforces the correlation between activity-level time-predictions and project-level time-performance. These two findings from the research provide critical correlations between project- and activity-level performance.

### Sub-Sector Performance

From the aggregation of 27 UK projects, 4 were categorised as 'Building - New Build', 8 as 'Cyclical Repairs', 13 as 'Power Infrastructure', and 2 as 'Rail Infrastructure'. Time-predictability was assessed against each sub-sector, and it was found that the highest performing classification was 'Power Infrastructure' achieving 66% of positive activity-level time predictions (PE.1 - PE.5), with 'Rail Infrastructure' recorded as having the lowest time-predictability achieving 49% of positive predictions. The variance between the best and worst performing sub-sectors was 17%, but with no significant outliers.

### **Programme duration and time-predictability**

The project programmes analysed ranged in duration from 2 months through to 55 months. An assessment of project programme duration and time-predictability was carried out to determine whether there was any correlation between programme duration and predictability. From the analysis it was found projects that achieved completion within 30 days of the planned date and returned 58% positive time-predictability results (PE.1 - PE.5) were on average 19 months in duration, versus those projects that finished more than 30 days later than planned and had reduced time-predictivity accuracy (48%) were on average 27 months in duration. This suggests a significant correlation between programme length and time-predictability scores. No specific assessment was carried out which examined time-predictability performance in relation to the data-date of the project (i.e., does time-predictability reduce as the activities progress through the programme akin to uncertainty curves (Winch, 2010)).

### **Level of detail and performance**

Project programmes vary in the level of detail included, ranging from activities planned to the hour through to activities planned to the nearest week or month. During the analysis the number of activities planned per-month for each project programme was assessed and cross-referenced against time-predictability. From this it was found that on average projects which had more than 50 activities per-month were more likely to achieve positive time-performance (i.e., have <30 days finish date variance). In contrast, those projects that had >30 days project-level variance (i.e., they completed more than 30 days later than planned) had on average a smaller number of activities planned per month (47 no.). This demonstrates a marginal correlation between the level of detail provided within a project programme and the likelihood of achieving positive project-level time performance, with the suggestion that programmes containing a higher number of activities are more-likely to achieve on-time completion.

## **DISCUSSION**

Time-performance is often measured at project-level with the primary metric being whether the project completed on time. Despite best efforts, project-level time performance in the construction sector has remained inadequate with a need to alter the approach to seek improvements. Dawood (2010) and Gledson *et al.* (2018) explored construction time-performance from an activity-level and found between 38% and 47% of activity-level time-predictions were able to achieve 'perfect hits'. Dawood found through the application of BIM, and by combining perfect hits with activities that started and finished early (SE/FE) this score rose to 72%, in contrast with a traditionally planned score of 55%. By comparison, this research found that 42% of 35,915 activities analysed achieved the combination of a perfect-hit or activities that started and finished early (PE.1 + PE.2 + PE.8). When the analysis was expanded to capture activities that also finished early or on-time (PE.1, PE.2, PE.3, PE.6, PE.7, PE.8 and PE.9) this score rose to 50%, lower than the score found by Dawood (traditionally planned 55%, BIM planned 72%). The number of activities that achieved perfect date and duration predictions was recorded as being just 24% (PE.1), as shown in Table 3 - Programme Data Analysis. When the data was analysed in further detail it was found that there was a correlation between positive time-predictions at an activity-level (PE.1 - PE.5) and overall project-level time performance. From the 27 projects analysed, those which finished within 30 days of

the planned completion date (15 no.) did so with higher activity-level predictability, than those which finished more than 30 days late (12 no.). There was also a positive correlation between project-level time performance and the rate of perfect-hits, with those projects with more perfect predictions correlating with a greater probability of the project achieving completion on time. There was no significant disparity of performance between the sub-sectors (infrastructure, building, power, etc), however, the analysis demonstrated that programmes with a higher number of activities per month yielded greater time-performance than those with less activities. Additionally, the data demonstrated a strong correlation between shorter duration programmes and time-prediction accuracy, with longer programmes having fewer perfect hits and fewer accurate activity-level predictions.

Table 3: Programme Data Analysis

Project Count	Completion On Time	Perfect Hits (PE.1)	Positive Outcomes (PE.1 - PE.5)	Average Project Activity Count	Average Duration Count (Months)
15	Within 30 days	16%	58%	50	19
12	More than 30 days	15%	48%	47	27

### Potential for Improvement - Technology and Big Data

Given that this analysis has demonstrated a correlation between activity-level time-predictability and project-level time-performance, it validates the value of improving focus and attention on making accurate activity-level predictions for the betterment of project-level time-performance. Establishing activity durations is a crucial aspect of project planning, alongside aspects such as constraint assessments, resource requirements and activity sequencing (Halpin *et al.*, 2017). Project teams balance the use of past experiences to help inform future duration predictions, whilst considering the unique aspects of the current project. During this planning process planners seek commonality from the historic performances but regularly suffer from the effects of Prospect Theory and set overly optimistic targets, with time-performance consequently suffering (Flyvbjerg, 2008). A reason for this could reasonably be associated with a failure to associate past experiences to the project at-hand with the planner unable to recognise commonality. It is proposed that this bias shortcoming could be addressed with the assistance of technology and the collection of activity-level 'big data' to provide a centralised reference class. Research exists for the application of 'big data' with technology offering machine learning opportunities to help generate computer-led recommendations to optimise planning (Ockree *et al.*, 2018; Shayboun *et al.*, 2019; Awada *et al.*, 2021). This provides a valid opportunity in construction planning to 'spotlight' appropriate comparable durations from an aggregation of activity-level data, with activity duration output recommendations.

### CONCLUSION

A large dataset of archival programme data was made available for analysis with the hypothesis that activity-level time-predictability improvements have the potential to lead to increased project-level time-performance. The aggregated data in this research has demonstrated correlations between positive time-predictability outputs at activity-level and project-level time performance. In this, projects that have greater time predictability accuracy at activity-level (58% as opposed to 48%) lead to improved probability that the project will reach completion on time. This demonstrates the importance of accurately detailed activity-level planning to aide teams during the delivery of construction projects. Therefore, making improvements in project

planning at activity-level would translate to improvements at project-level, potentially unlocking the stagnated time-performance of recent decades. Dawood (2010) found that with the support of BIM, time-predictability at activity-level increased to 72% versus 55% when projects were planned to use traditional methods. In his research, Dawood (2010) found 47% of activities achieved perfect predictions. Gledson *et al.* (2018) found perfect predictions in 38% of instances, and this research found perfect predictions in 24% of instances. It has been shown that attaining betterment of perfect and positive predictions at activity-level is essential for project-level time performance improvements.

In subsequent research it is proposed that machine learning provides one such route to seek activity-level prediction improvements, with a platform to process vast amounts of aggregated data to create a large reference class database to better inform future activity-level predictions. Using technology, activity-level programme data could be centralised and processed such that commonality between activities can be identified to create AI generated time predictions for planners to consider and apply in their projects. The centralised database could provide access to a range of similar historic outcomes to inform the predictions at-hand, with the potential to yield time-predictability improvements at activity-level, with an expectation that this would generate project-level time improvements. Further work is also welcomed relating to activity-level programme data analysis to consider performance correlations with project value, contract type, planning team structure, effort applied during the planning stage, and data-date proximity. Limitations are recognised in the analysis carried out in this research in the accuracy of the data from data-entry error, the stability of the planned data set (i.e., programme revisions), scope change, and delays linked to contractual relief events.

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