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6 Using quantitative approaches to enhance construction performance through data captured from mobile devices

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This chapter presents a quantitative analysis of production data captured through mobile devices on a wide range of projects, undertaken by a multinational infrastructure and services company. Lack of primary empirical data within the architecture, engineering and construction industry has, in the past, hindered developments of academic research in the field of performance measurement in construction. This chapter presents quantitative analysis of construction production data captured through mobile information systems and provides empirical evidence that data captured through mobile devices has the potential to deliver new and enhanced methods for performance measurement and enhancement. Relational data gathered through mobile devices are used to generate metrics against which construction issue resolution performance is measured. The chapter also discusses various methods for early identification and visualisation of performance deviations. The research approach and findings can be used for the development of academic performance measurement frameworks and also as an evidence base for further development by industry in the field of performance enhancement. The chapter contributes insight regarding innovative ways to interrogate construction production data and provide stimulus to others to develop the methods and approaches taken.

6.1 Introduction

Recent reviews of construction productivity performance indicate that the industry fell short in comparison with manufacturing and services-based industry sectors. Some of the key factors hampering construction productivity include issues with quality, use of project controls and adequate levels of supervision (Merrow *et al.*, 2009). Similar observations have been made in the UK Construction Industry Performance Report (Glenigan, 2014), indicating that the majority of construction projects continue to fail timely completion. This is coupled with falling profitability and client dissatisfaction with regards to product quality, service and value for money. Although quantitative data presented in performance reports are subject to interpretation, it is obvious that there is tremendous potential for productivity growth within the construction sector.

A review of academic literature and construction industry reports highlights inadequacies in terms of forecasting project costs, duration and other issues, and the inability of construction contractors to deliver quality products and services within a resource-constrained environment. A need for process innovation to help the industry deliver greater productivity and quality has long been identified. Also, the literature identifies a need for more accurate data relating to on-site construction activities, and to develop process intelligence through better use of project data, to help improve the accuracy of project planning. The literature provides a considerable amount of existing research identifying weaknesses in current performance measurement methods, including lack of availability of empirical data.

Recent developments in information communication technologies (ICT) make available a large and detailed digital sample of production performance data to test academic/theoretical hypotheses. After a review of academic research in the field of total quality management (TQM) and its evolution from Deming's management method, Rungtusanatham *et al.* (2003) make reference to 'the power of primary data'. One of the issues they identify is the restriction on further academic progress in the field of TQM without first validating Deming's principles against a sample of good empirical data. They suggest that, until they can move beyond secondary analysis of potentially inaccurate and 'weak' data, this will continue to stifle developments in this field.

With the development of information technologies (IT), the spectrum of automatic quantitative data-capturing systems has been widening. IT-based data-capture systems minimise human intervention, bias and error in the data-collection process. One of the important automated data-collection implications in construction is the use of sensors. Sensors convert a physical parameter (e.g. temperature, distance, humidity, displacement, flow, etc.) into an electronically measurable signal. Specific technologies such as radio frequency identification, near-field communication and Bluetooth beacons (nodes) are used for the automatic identification and monitoring of construction materials, equipment, plant and personnel. A global positioning system and a geographic information system can present data related to geography and location to the researcher. By providing an accurate point cloud at a reasonable speed, 3D laser scanning applications (i.e., the LiDAR and LADAR technologies) automatically capture data on the shape/features of a surface, space or topography. The technical capabilities, IT architecture and cost and the researcher's experience in using those data-collection systems should be well defined.

The literature review identified a range of issues relating to the quality and accuracy of industry performance data and, consequently, the capability of any existing performance measurement methods reliant upon it. It identified that data relating to production issues and performance are disparate, inconsistent, often subjective and highly retrospective. There is also evidence to suggest a lack of much-needed empirical primary data relating to construction performance. The main findings from the literature review are highlighted in Table 6.1.

Table 6.1 Performance measurement issues identified from literature review

Issue identified	*Issue description*	*Supporting references*
Consistency and standardisation	A lack of standard relational data for performance measurement and organisational learning Inability to identify relationships and patterns between performance outcomes and on-site decision-making	Dissanayake and Fayek (2008); Cheng and Wu (2012)
Complexity and data quality	The subjective nature of performance measurement data; not enough detail, visibility or science surrounding performance measures A lack of detail, accuracy and scale for performance metrics	Akhavian and Behzadan (2012); Cheng and Wu (2012)
Context and communication	Poor context for causes relating to project performance failures A lack of detailed industry metrics to measure performance against benchmarks	Son *et al.* (2012)
Lagging metrics and metrics	Retrospective measurement of performance outcomes that incur extensive lag time A lack of forecasting and lead performance measures	Barber (2004)
Visualisation	A need for improved analytical reasoning through visualisation, for project performance issues	Russell *et al.* (2009)

6.2 Research approach

Before the details of the research approach are explained, the particular research philosophy, which contains important assumptions about the researchers' view of the relationship between knowledge and the process by which it is developed, should be clarified. The adopted research philosophy will indicate four important underlying assumptions (Saunders *et al.*, 2009): (1) the ontological stance as the researchers' view of reality or nature of being; (2) the epistemological stance as the researchers' view on what constitutes acceptable knowledge; (3) the axiological stance as the researchers' view of the role of values in research; and (4) the data-collection techniques as the means to obtain data to generate knowledge.

The research philosophy adopted in this particular research is positivism. Positivists believe that reality is stable and can be observed and described from an objective viewpoint (Punch, 2005) – that is, without interfering with the phenomena being studied. Therefore, ontologically, reality is external, objective and independent of social actors. To positivists, reality must be investigated through the rigorous process of scientific enquiry. The positivist philosophy calls for focusing on facts and locating causality between variables (Easterby-Smith *et al.*, 2012). Thus, epistemologically, only observable phenomena can provide credible data. As reality is external and out of researchers' control, axiologically, research is undertaken in a value-free way, independent of researchers' values (objective stance). Data-collection and -analysis methods are generally quantitative, from large samples, with highly structured data-collection approaches.

Along with the philosophical stance of a research, the nature of data accessible to researchers is also a defining parameter in research approaches. Generally, when numerical or quantifiable data, or 'hard data', are more readily accessible, as in this particular research, the quantitative research methodology is employed (Neuman, 2007). Quantitative research involves 'explaining phenomena by collecting numerical data that are analysed using mathematically based methods (in particular statistics)' (Aliaga and Gunderson, 2005). Quantitative research tends to be explanatory and generally provides 'snapshots' or instantaneous results, used to address questions such as 'what', 'how much', 'how many' (Fellows and Liu, 2015). Quantitative research allows for a study with more breadth, involving a greater number of subjects and enhancing the generalisability of the results with the capabilities of replicability and comparison with similar studies (Kruger, 2003). However, it doesn't generally yield an in-depth analysis of the studied phenomenon, as the results are limited, providing numerical descriptions rather than detailed narratives, with less-elaborate accounts of human perception (Bryman, 2012). The quantitative research approach is well suited for the deductive reasoning in which hypotheses are tested with experiments, statistical methods, observations, etc., for generalisable confirmations or rejections (top–down approach), as opposed to the inductive reasoning in which observations lead to theories (bottom–up approach; Blaikie, 2009). Quantitative researchers design studies that enable the testing of hypotheses, which are tentative explanations that account for a set of facts open to further investigation. Both the quantitative and qualitative research methodologies and data-collection methods can be simultaneously employed in the same research to take advantage of their particular strengths (multi-method research). The study outlined in this chapter, however, adopts a mono-method approach that solely exploits the quantitative research methodology and data-collection methods, as they permit inference from, and gathering of, a greater number of quantitative data elements in a relatively short time and at a relatively low cost (Balnaves and Caputi, 2001).

The research in question aims to develop an understanding of how emerging structured and detailed quantitative data, created and made possible using a plethora of mobile ICT devices, could be applied to meet the performance measurement requirements of construction operations. Key objectives included:

- assessment of whether mobile data can provide the detail, accuracy and scale for performance measurements and metrics;
- assessment of whether mobile data could reduce the lag times associated with the identification of poor performance; and
- assessment of whether mobile data could provide improved visualisation of project performance.

Those points identified in the key objectives constitute the starting point or the hypothetical stance of the quantitative deductive approach with some explorative motives.

As the quantitative research methodology generally follows a linear research path (hypothesis–data collection–analysis), speaks the language of statistics, with variables and hypotheses, and emphasises precisely measuring quantitative or 'hard' data and testing hypotheses that are linked to general causal explanations, one needs to employ a relevant quantitative data-collection method or data-collection means through which quantifiable data are obtained for further analysis and manipulation (Gray, 2004). Observations, tests/experiments, surveys (questionnaires), and archive, document and secondary-data (i.e. databases, company records, etc.) studies are the frequently used quantitative data-collection methods (Creswell, 2013). In this particular case, existing (secondary) construction production data were statistically analysed to determine their effectiveness to enhance the existing performance measurement methods. Secondary data provide researchers with a relatively quick and cost-effective data source that may otherwise not be acquired first hand. They also enable both cross-sectional (one specific point in time) and longitudinal (extending over a period of time) analysis (Vartanian, 2010). However, because secondary data were collected by another entity at some point in the past for another purpose, before the research effort, secondary analysts have no opportunity to influence the initial data-collection method in terms of data quality (completeness and consistency in the data set), bias and compatibility with their research aims (Smith and Smith, 2008). This research demonstrates a longitudinal study of a *secondary-data* source, with its specific limitations (e.g. data completeness) underlined in the discussion section.

The secondary-data source, production-data sample, used in this study for quantitative analysis contained a large number of tables and data fields. A data sample is the representative subset of the whole population, in this case all the construction productivity data. The number of records relating to key data variables used for query and analysis as part of this research has been outlined in Table 6.2. A variable is a particular characteristic of the studied phenomenon that varies or has different values. Variables are used to statistically test hypotheses or assumptions. It is obvious from Table 6.2 that there is a deficit in the number of 'date due' and 'date closed' records when compared with the total number of production issues, immediately highlighting a shortfall in the number of resolution periods available to contribute towards averages.

After obtaining the raw data sample, which requires relatively less effort with readily available secondary-data sources, the data-analysis process necessitates management and preparation of the data sample in terms of data coding, data entry and data consistency for further descriptive and inferential statistical analysis. The data-preparation and -analysis procedures for the study were largely automated to minimise human bias, error and intervention. The data sample was collated into a structured cloud database with the aid of a proprietary application that utilises mobile touch-screen tablets as the primary means for data capture (Figure 6.1). The database also has a web interface that allows the mobile data to be updated, amended and reviewed via a desktop computer. An export of the cloud data has been provided as a Microsoft Access database file. The database file is intended to be used for grouping and running calculations against large numbers of records.

Table 6.2 Count of data variables used for query and analysis

Project variables	
Total number of projects	34
Total number of project types/construction sectors	10
Geographical variables	
Total number of regions	7
Company and user variables	
Total number of companies reporting issues	716
Total number of creator roles/professions	8
Total number of users creating data	259
Total number of trade classifications	46
Issue variables	
Number of general issue types	5
Total number of production issues	149,733
Total number of date-due records	136,628
Total number of date-closed records	140,571

The detailed findings were exported to Microsoft Excel for more detailed analysis and visualisation. The approach requires the data sample to be updated via Standard Query Language (SQL) query to generate elapsed periods between the creation and resolution of issues. The resolution periods were then used to determine performance averages, standard deviations and z-scores. Averages were established by grouping issue records according to the content of geographical, trade and role variables.

The production issues contained in the sample have been recorded across multiple projects and deliberately structured to hold a number of standard data variables. The variables deemed to be of interest for this research included project type, issue classification, location, trade, dates relating to issue identification, required resolution and actual resolution, and roles and professions of the individuals capturing the issues. These variables were used as the basis for SQL queries, designed to separate records into groups, for further analysis and performance calculation.

The approach to quantitative analysis included generating a query and running it against the date entries in the database to calculate and create resolution periods, against each production issue, according to issue type, project type, creator role and trade variables. Time was employed as a standard unit (days) and used as a metric for performance measurement. Once defined, the averages were compared against their hierarchical benchmarks to establish any variance with performance averages. Further, statistical analyses were conducted to determine standard deviations for resolution periods, and, from this, z-scores were used to identify proximity to average resolution period. A z-score or a standard score indicates how many an element is from the mean. It is a standardised value that lets researchers

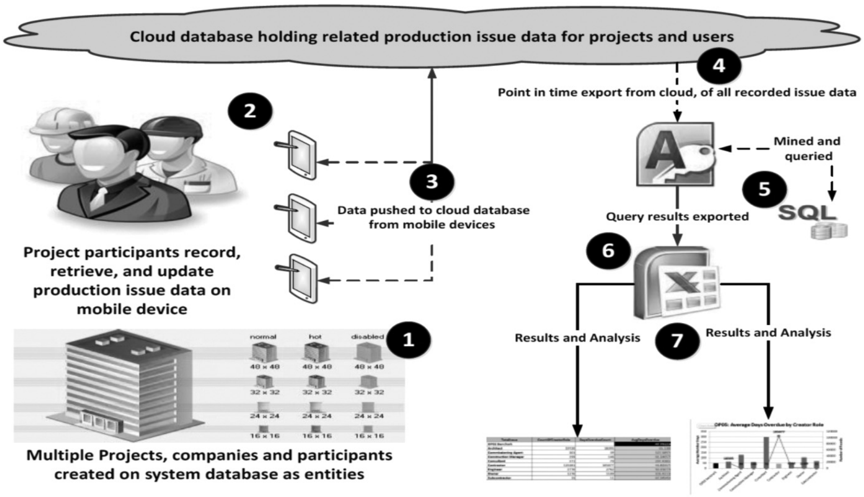

Figure 6.1 Data-collection and -analysis strategy

compare raw data values between different data sets, allowing the comparison of 'apples' and 'oranges' by the conversion of raw scores to standardised scores relative to population mean(s) (i.e. comparing one project's productivity values to another's productivity values; Field, 2009). This was identified as a proposed alternative and more robust statistical measurement for performance against a benchmark value. The following statistical analysis methods were used to undertake quantitative analysis.

Average resolution period

Determination of the average resolution period was the first step in quantitative analysis, to help evolve issue data into a standard measurement of performance. This was based on the premise that project performance is reliant on the timely resolution of production-related issues. Two averages were established for timely resolution of production issues:

1 *total resolution period*: the average time (in days) to resolve a production issue;
2 *overdue resolution period*: the average time (in days) in relation to the required resolution period.

Standard deviations for performance records

In this research, standard deviation values were used as an indication of the size of any variability, spread and distribution of resolution periods contained within the sample data. The larger the standard deviation, the more disparate and varied the sample data are assumed to be.

$$\sigma = \sqrt{\frac{\sum(X-\mu)^2}{n}}$$

Standard Deviation Formula

$$Z = \frac{x-\mu}{s}$$

Z-Scores Formula

S	Total
s	Standard Deviation (Square Root of Variance)
µ	Average resolution period
n	Number of records
x	Individual Resolution period

Figure 6.2 Formulas used and legend to support analysis of average resolution, standard deviation and z-score calculations

Z-scores reflecting performance in relation to standard deviations

The z-score was used to determine how many standard deviations from the sample norm (average) any specific resolution periods were. If successful, this was used to evidence the capability to measure performance beyond simple mean calculations. It also confirms whether results sit above or below average resolution periods, owing to their positive or negative score. The z-scores were then converted to a percentage, to show where the records sit in respect to their performance against other data in the samples: that is, the percentage of records with quicker or slower response and resolution periods.

To structure and organise the analysis process better, the data sample was divided into smaller related data tables using SQL. SQL queries were named according to query type and its intended use and the level at which it groups any data.

Data distribution

The sample was queried to count the number of records by project type and region and to establish whether data were evenly distributed or clustered within geographical areas. The results indicate that records were clustered and not uniform, with heavier concentrations in the 'NTX' and 'WDC' regions, among projects types 'Education', 'Healthcare' and 'Other ancillary facilities'. The numerical distribution and 3D column chart are shown in Figure 6.3.

Project Type	Count of Issues	FLA	GEO	HOU	HSC	MHF	NTX	WDC
EDUCATION PREK-12	38580	14277	1405				22898	
HEALTHCARE	34782						8245	26537
HIGHER EDUCATION_TRAINING	20983	20333					650	
OTHER_ANCILLARY FACILITIES	20975			16				20959
MULTI FAMILY	15687				9538	6149		
OFFICE_CORPORATE	10882	9608			974		12	288
AIRPORT	5983						5983	
PUBLIC USE_CIVIC	1051	695			182		174	
POWER_ENERGY	590							590
HOSPITALITY	220				220			

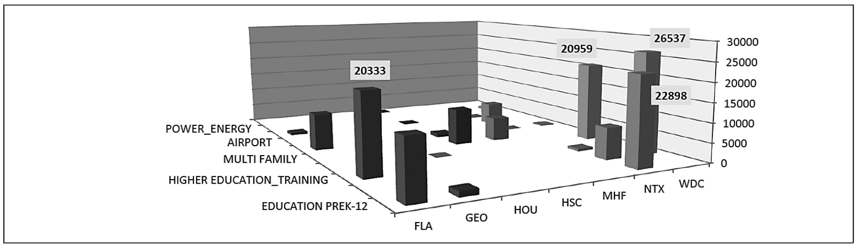

Figure 6.3 3D column chart showing distribution of issue records by project type and region

Figure 6.4 identifies a dominant record set captured by the 'Contractor' having provided 83.79 per cent of issues used to generate total resolution periods (117,787 of 140,571), and another majority related to general issues of the type 'Punch list', with 85.8 per cent of issues (120,665 of 140,571).

Figure 6.5 represents the percentage of data entries that are missing for every data field used to conduct SQL queries for analysis. This shows a generally good

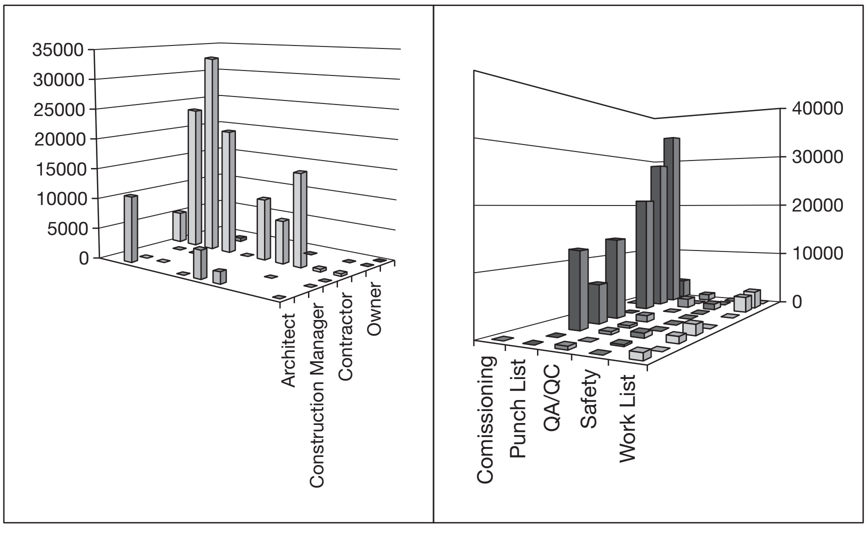

Figure 6.4 Record distribution by creator role and general issue type used to calculate total resolution periods

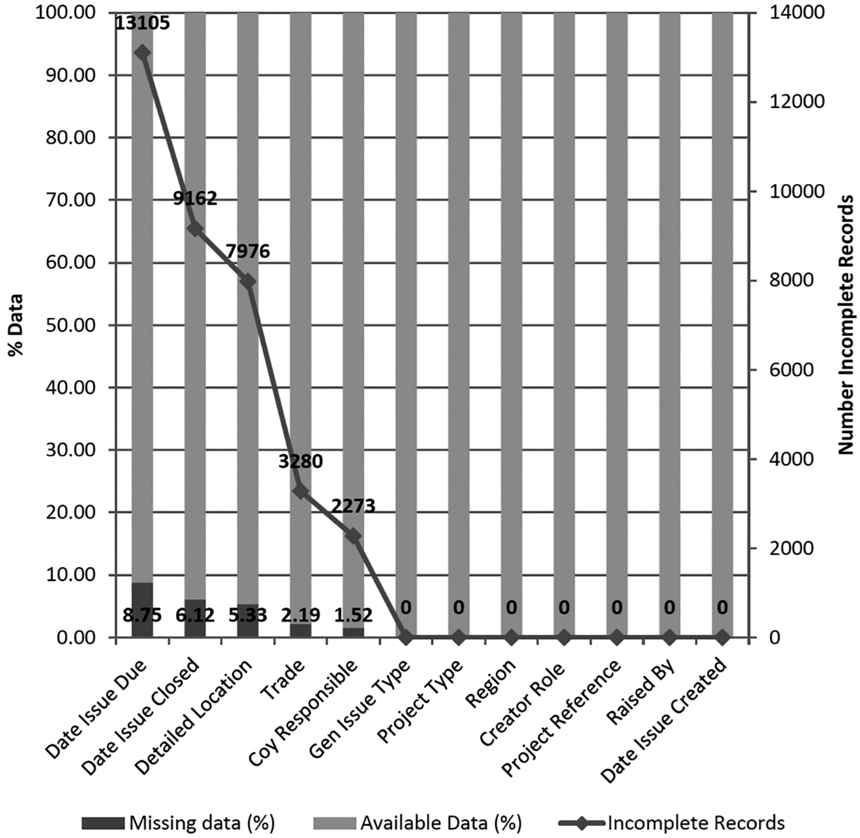

Figure 6.5 Quantity of missing entries for queried data field in the sample

level of information has been provided, with only 1.99 per cent of data fields (35,796 of a total 1,796,796) containing blank records. Most of the missing entries related to a date issue that was due or closed.

Z-score

A database query was created to establish the global organisation average and standard deviation for overdue resolution periods and total resolution periods from the data sample, to generate a metric for measurement that was statistically viable as an organisational performance standard. A further query of resolution periods for all issues was made against four projects. The data records were grouped by project, and the z-scores were then calculated for individual issue resolution periods, to establish the number of standard deviations from the data sample mean. The results were plotted into scatter graphs to help visualisation of general performance distribution. The results of the distribution of the z-scores showed that two projects (i.e. PR20 and PR06) performed relatively well in the context of organisational delivery standards, with the majority of resolution periods sitting within ±1 standard deviation. The other two projects (PR15 and PR04) did not appear to perform very well, with large volumes of records creeping up to and beyond 2 standard deviations.

6.3 Discussion

Although the quantitative analysis approach relied on a data sample of considerable size, the content was inconsistent, and the levels of available information varied, depending on what part of the sample was being analysed. The data sample used was perfectly adequate for the research, with key fields related to who, when, where and what being available and available for analysis. However, when the research process was designed, it was initially presumed to establish time-based performance as the standard unit to measure performance. However, this approach was limited, owing to the number of missing date fields within the sample.

Quantitative analysis undertaken in this research has highlighted a number of development areas. It is apparent that the quality of the sample is largely dependent on the process used to prepare the system and collate the data. The sporadic and inconsistent volumes of data within the sample suggest that the organisation is using the platform in an ad hoc capacity, rather than as a standard, systematic means to capture and communicate production issues. The user base is also significantly biased towards contracting staff. The system used to capture the data may well benefit from more controls being employed in the data-capture process, to ensure fields such as date required and trade are made mandatory. Further standardisation of automated functions would also benefit the data sample. The removal of generic defaults for data entry such as 'other' would also help prevent large portions of intelligent data becoming unwieldy, as found with issue types. The number of unsolved items in the sample, together with the considerable lengths of time elapsed before the majority of issue are closed, again suggests process issues surrounding the implementation and management of the platform. It would appear that items are raised more quickly than they are closed, and that, perhaps, there is a lack of accountability for ensuring the system is updated.

This research set out to review the potential for mobile data capture to enhance performance measurement on construction projects. The research has identified potential areas and methods for further industry development where mobile data could be used to derive new methods for future performance benchmarking. There are new opportunities emerging from technology that allow organisations to gather and record production data quickly and on site. However, the research has shown that, although these technologies can provide a great deal of clarity and insight into the nature and cause of certain performance issues, there are still considerable limitations to a purely statistical approach. Also, results highlight that getting people to use the equipment correctly is the most important and pertinent issue at present. Although increased detail and improved methods of capturing detail surrounding performance issues will be of value to many, there is still the requirement for context and perception. This is not just an issue for construction: this is an issue for most industries, as technology pushes forwards and allows us to measure things with greater degrees of accuracy.

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