Origins and Probabilities of MEP and Structural Design Clashes within a Federated BIM Model

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ABSTRACT

'Design clashes' encountered during the development of a large multi-storey educational building, awarded under a Joint Contracts Tribunal (JCT) Design and Build contract, are reported upon. The building was developed in Birmingham, UK and the contract value was circa £36 million (UK Sterling, 2015). Members of the project management team (PMT) produced designs that were subsequently integrated by the main contractor into a federated building information modelling (BIM) model; at this stage 404 error clashes were evident between the positions of the mechanical, electrical and plumbing (MEP) designer's and structural designer's building compartments. The contractor deemed that these particular clashes were 'mission critical' as previous experience suggested that project costs could spiral uncontrollably if left unabated. Participatory action research was employed to acquire a deeper understanding and knowledge of the clash incidents. Clash data accrued (in mm) was subsequently quantitatively modelled using the probability density function (PDF) and the cumulative distribution function (CDF). Two models produced were the Log Logistic Three Parameter (3P) (using all data including outliers) and Generalized Gamma distribution (excluding outliers). Both models satisfied Anderson-Darling and Kolmogorov-Smirnov goodness of fit tests at α 0.01 and 0.02 levels of significance. Model parameters could be used to forecast similar clashes occurring on future projects and will prove invaluable to PMT members when accurately estimating the time and resource needed to integrate BIM designs. The predictive modelling revealed that 92.98% of clashes reside within the 30-299 mm range while the most probable occurrence of a clash overlap resides in a discrete category of 100-199mm. Further qualitative investigation is also conducted to understand why these clashes occurred and propagate ideas about how such may be mitigated. The research concludes on two important points, namely: i) BIM is not a panacea to design related construction project rework and that innovative 21st century digital technologies are hampered by 20th century management practices; and ii) improvements in clash and error mitigation reside in a better understanding of tolerances specified to alleviate the erroneous task of resolving unnecessary clashes. Future research is proposed that seeks to: automate the clash detection management, analysis and resolution process; conduct further investigative analysis of the organizational and human resource

management influences impacting upon design clash propagation; and devise and validate new procedural methods to mitigate clash occurrence using a real-life project.

KEYWORDS

Building information modelling, clash detection, probability density function, cumulative distribution function, Generalized Gamma distribution, Log Logistic (3P) distribution.

INTRODUCTION

The digital *jacquerie* transcends the narrow confines of the information and communication technology sector and is ubiquitous throughout all industry (Edwards *et al.*, 2016). This paradigm shift in business and commerce has been enabled through the application of cloud computing (Park and Ryoo, 2013). Cloud computing is advantageous to all organizations (large and small) because utilizing internet-based services can reduce start-up costs, lower capital expenditures and increase computational power to augment business/ market intelligence (Chen and Lin, 2012). A menagerie of ‘networked’ digital devices employed within the workplace generate vast quantities of data, information and knowledge that can be further exploited via automated and intelligent analytics (Dutta and Bose, 2015). Business intelligence and concomitant data analysis have the inherent potential to uncover patterns, trends and associations related to design data, human behavior, and the interactions between the two, for improved decision making (Manyika *et al.*, 2011; Russom, 2013). Indeed, the extant literature postulates (cf. Shollo and Galliers, 2016; Seddon *et al.*, 2016) that business intelligence enables organizations to gain value from business analytics. Multitudinous benefits of digitization have similarly been promulgated within the architecture, engineering, construction and owner-operated (AECO) sector (Love *et al.*, 2015). Prominent digital technologies include: sensors (Park *et al.*, 2016); laser scanners (Oskouie *et al.*, 2016); machine vision (Teizer, 2015); and building information modelling (BIM) (Ben-Alon and Sacks, 2017). Amalgamated, these technologies have spearheaded the advancement of the digital construction *modus operandi* (Zhou *et al.*, 2012). BIM is ostensibly the most prevalent of these advanced technologies within extant literature and is gradually becoming conventional in both design and construction practice globally (Liu *et al.*, 2016). BIM provides a digital portal through which an integrated project management team (PMT) can collaboratively work upon, and share knowledge of, a construction or infrastructure development pre-, during and post-construction

(Ciribini *et al.,* 2016; Wetzel and Thabet, 2016). This innovative approach enables PMT members to enhance their inter-disciplinary interactions in order to optimize resultant decisions and afford greater whole life value for the asset (Love *et al.,* 2016).

During the design stages of pre-construction, BIM drawings and plans produced by individual designers (e.g. the architect, structural engineer and mechanical, electrical and plumbing (MEP) designer) are integrated into a federated model and tested to identify design clashes (Bagwat and Shinde, 2016). Design clashes consist of 'positioning errors' where building components overlap each other when the original individual designer models are merged. Resolving these design clashes is imperative to project performance, particularly if costly rework is to be circumvented during the construction phase. However, design clash mitigation and the utilization of deterministic modelling to enhance decision making are two areas that have been grossly overlooked within the literature (Won and Lee, 2016; Jones and Bernstein, 2014). Given scant research within this important area and the opportunity to improve construction business performance, this work reports upon the findings of participatory action research (PAR) which sought to examine design error clashes that occurred during the compilation of a federated BIM model for a multi-storey educational building development. Such work provides invaluable insight into a previously unexplored area of digital built environment research. The research objectives are to: better understand why clashes occur and engender wider academic debate; demonstrate how the probability density function (PDF) and cumulative distribution function (CDF) can accurately predict the probability of future occurrence for a specific project; formulate innovative ideas for reducing their occurrence and mitigating their impact upon construction business processes and performance; and suggest future work that seeks to maximize business intelligence through automation and apply the deterministic techniques adopted to a larger number of project developments as a means of generalizing the findings.

DESIGN ERRORS WITHIN DIGITAL CONSTRUCTION

Design errors are a prominent root cause of diminished construction project performance and manifest themselves as adverse symptoms such as: rework (Lopez *et al.*, 2010; Li and Taylor, 2014; Love, and Sing, 2013); cost overruns (Love *et al.*, 2014; Love *et al.*, 2013); schedule delays (*ibid*); and unsafe working environments (Love *et al.*, 2010). Literature proffers that the main sources of design error are inextricably linked to iterative and recurrent design cycles that result from: unanticipated changes (Lee *et al.*, 2005); poor management and communication (Arayici *et al.*, 2012); realignment of traditional/ institutionalized organizational and human resource practices (Porwal and Hewage, 2013); and interoperability between various software platforms (Merschbrock and Munkvold, 2015). These challenges have engendered frenzied research activity and resulted in the: development of system dynamics models for planning and control (Lee *et al.*, 2005); identification of critical design management factors (Whang *et al.*, 2016); and examination of causal factors (Forcada *et al.*, 2016). Despite this herculean effort, anecdotal evidence from industry reveals that design errors remain a persistent problem.

BIM offers a potential digital solution space for design error management as a collaborative and inclusive platform (Solihin *et al.*, 2016). Yet to date, limited research has investigated whether BIM in the AECO sector is effectively mitigating digital design errors. Love *et al.*, (2010) further proffer that the process of design error mitigation implies that:

> "…learning from errors is a collective capacity that can produce individual, organizational, and interorganisational error prevention practices."

Successful error mitigation should therefore nurture learning from within individual design disciplines to encapsulate the entire project team (*ibid*). BIM inherently offers this potential but as the first stage of design error mitigation, clash detection and consequential resolution between design team members has received scant academic attention. Amongst the various structural elements, MEP design errors have traditionally dogged the design process, arguably due to the confined spaces left for MEP systems (Tatum *et al.*, 1999). Recent research conducted by Peansupap and Ly (2015) examined five categories of structural and MEP related design errors, but the study was confined to schedule delays and omitted any discussion on how BIM can facilitate error mitigation at the detailed design stages. Research that has examined design clashes in a BIM environment remains anecdotal or based upon a limited scope of analysis (Al Hattab and Hamzeh, 2015; Allen *et al.*, 2005; Won and Lee, 2016).

Clash Reports and Nomenclature

When reporting upon design clashes, the main contractor produces periodic clash detection reports that contain information including: i) thematic groupings of clashes that report upon individual clashes within each compartment category (for example, and in this research ‘MEP vs building column’ and ‘MEP vs building frame’); ii) snapshots of every clash identified to aid communication with all designers throughout the PMT; iii) clash point co-ordinates (as x, y and z coordinates) to determine the exact pin-point location of the clash within the federated BIM model; iv) the date that the clash was found; v) clash status (active and unresolved or resolved); vi) a written description of the clash; and vii) a numerical value in metres (m) or millimetres (mm) that specifies the linear magnitude of the positional (clash) error. Manual data cleansing is then undertaken by the contractor’s BIM manager using industry nomenclature to define four key clash categories, namely: i) *clash errors* –fault clashes that must be identified and resolved within the federated model; ii) *pseudo clashes* – permissible fault clashes that can be tolerated within the design and do not require resolution; iii) d*eliberate clashes* – intentional clashes, for example, ducting through a floor or web of a structural steel component; iv) *duplicate clashes* – multiple versions of the same ‘singular clash’ that are repeated throughout a building (e.g. an MEP pipe that travels along the entire length of a structural column will be observed and recorded numerous times even though it actually represents one error). *Duplicate clashes* often originate from one of the three other variants of clash.

RESEARCH APPROACH

The research design employed participatory action research (PAR) (*cf.* Chevalier and Buckles, 2013; Smith *et al.*, 2010) where the lead researcher was embedded within, and worked closely with, the PMT to develop various aspects of the BIM model. The PMT included the client’s representatives (i.e. the building’s estates department) and design related disciplines (including the BIM process manager, the lead architect, contractor’s construction manager, the contractor’s BIM manager, principle designer for mechanical engineering and plumbing and the lead structural engineer). Note that the estate’s department held four fundamental roles, namely that of: client’s representative; BIM process manager; project manager; and estates department and consequently, covered all three major phases of the building’s life cycle. PAR was adopted because it offers pluralistic orientation to knowledge creation and change thus affording greater flexibility to excoriate beneath the corporate façade that can obscure truth in the interests of preserving reputation and consequential profitability. This approach to self-experimentation grounded in experience was augmented by: fact-finding, to acquire a deeper knowledge and understanding (Pain *et al.,* 2012; Mapfumo *et al.,* 2013); learning, through a recurrent process of reflection (Kornbluh *et al.,* 2015); and evidential reasoning to interpret information and knowledge characterized by varying degrees of uncertainty, ignorance and correctness (Ding *et al.,* 2012). Participatory action research is particularly beneficial because research implementation which embodies collective enquiry and experimentation (Wittmayer and Schäpke, 2014), occurs within the PMT rather than 'for it'. Consequently, PMT stakeholders are more likely to adopt emergent findings, recommendations and modify their future practices.

Data collated was analyzed using a mixed methods approach that combined predominantly quantitative probability modelling of clash data with qualitative investigation and delineation of the model federation and clash management process. Once this aforementioned process was succinctly documented in illustrative format, unstructured interviews were then conducted with members of the PMT to identify challenges that exacerbate the problem of clash propagation. The contractor was particularly insistent that error clashes between the positions of the MEP designer's and structural designer's building compartments were analyzed in greater detail. Such clashes were deemed to be 'mission critical' as previous anecdotal experience (accrued from past projects completed) suggested that project costs could spiral uncontrollably if these were left unabated.

The construction of a large multi-storey educational building located in Birmingham UK (entitled the 'Mary Seacole Building' – refer to Figure 1 for external visualization) provided the contextual setting for the research. The contract value exceeded £36 million UK Sterling and created 10,000 sq m of new teaching space. The project commenced with a client sign off on March 2015 and is currently ongoing with an expected handover to client by September 2017. A Joint Contracts Tribunal (JCT) Design and Build was employed and procurement was implemented via the Official Journal of the European Union (OJEU) tender submissions. OJEU is used for all tenders from the public sector which are valued above a certain financial threshold according to European Union legislation (Lam, 2016).

ANALYSIS

A federated BIM model was used to identify clash detections. Federated models are deployed using various BIM-related platforms including: Bentley Navigator®, Autodesk Navisworks® and Autodesk Glue®. For this research, Autodesk Glue® was used to facilitate cloud based model federation. The project employer information requirements stipulate that for the contractor:

> "Glue Coordination models will be created at different stages. They will be used for a number of reasons, some of these are, clash detection, MDM creation, 4D and 5D modeling, and used as the base model for the 'BIM 360 Field' database – these are but some of the uses."

The main contractor employed a permanent BIM manager to manage clash detection of the federated model in Navisworks® (refer to Figure 2). Spatial coordination between the various design discipline models was carried out at regular fortnightly intervals (every ten working days) throughout the design and construction stages. The BIM manager was integral within this process and facilitated regular co-ordination of team meetings, model updates, clash revisions and control. Clash detection in BIM is a global phenomenon; unlike other countries worldwide, it has been forcefully mandated in the United Kingdom (UK) (HM Gov 2012, HM Gov 2013). According to the UK Government mandated BIM Level 2 requirements, design teams must undertake weekly or fortnightly task information and clash rendition tasks to ensure designs are fully coordinated and clash free, ensuring that requests for information are minimised during construction stages (HM Government, 2012; 2013). This government intervention seeks to mitigate design error prominence within BIM implementation. The client also required that the main contractor employed a clash detection management process on a fortnightly basis. Clash detection resolution was implemented via Virtual Design and Construction (VDC) coordination meetings with the respective design teams. The BIM execution plan (as outlined by the main contractor during tender) stated that:

> "The aspiration is that beyond Stage 4, the model will be managed by the principal contractor and modifications to the model be made in house or by the design team. Throughout the project the BIM lead from each company and the soft landings champion will attend regular VDC coordination meetings. Efforts will be made to coordinate the

VDC meetings with design team meetings. During construction it will be led by the main contractor."

The main contractor and its team members adopted cloud based platforms to alleviate the number of discrepancies between the 'as-constructed' and the 'as-built' BIM model. Specifically, Autodesk's® BIM360 platform for design coordination and as-constructed validation was chosen as the cloud-based BIM tool for this task. Clash detection was also conducted via this cloud based platform enabling stakeholders to link discipline specific design models (obtained from the MEP designer, structural engineer and architect) into the main contractor's federated model (i.e Autodesk® Glue). Although open architecture was used within the federated model to reduce errors, 404 design clashes were identified between the MEP designer's model and the structural designer's model (refer to Figures 3a and 3b).

Data mining

Within this data sub-set of design clashes, 150 observations related to MEP vs building column clashes and 254 related to MEP vs building frame clashes. Summary statistical data analysis in Table 1a presents parametric and non-parametric descriptive measures of central tendency and measures of variation or dispersion within the sample data (Wheelan, 2013). Evidence of skewness was apparent given the distance between the arithmetic mean and median values (namely 212.82 mm and 166.78 mm respectively). Skewness measures the asymmetry of the probability distribution of a real-valued random variable about its mean (Schiller *et al.*, 2013). It was observed that the clash detection data was positively skewed; the majority of data fell within the 41.09 mm to circa 250 mm measurement range but a long tail extending to 550.03 mm was recorded. Because the presence of outliers was suspected an established outlier detection test was used to confirm this and subsequently remove them prior to conducting the analysis for a second time. The outlier test used was:

$$\text{Outlier} = ((Q3 - Q1) \times 1.5) + Q3) \qquad \text{[Eq. 1]}$$

Where: Q1 = is the first quartile value; Q3 is the third quartile value; and 1.5 is a constant.

The outlier limit value was noted as 440.74 mm but further data analysis revealed that two observations extended beyond this and were predominantly responsible for the long tail observed. These two values were *duplicate clashes* (457.534 mm (*frequency* = 24) and 550.031 mm (*frequency* = 36)) and accounted for 60 outliers in total. The treatment of outliers is a contentious issue within extant literature and could broadly involve either removing or transforming them using for example, square root, log10 or box-cox transformations (Cousineau and Chartier, 2010). It can be argued that removing outliers squanders important data (and hence knowledge) in the subsequent analysis but keeping them produces an uncharacteristic pattern in the trend. Given the contentious nature of outlier treatment, subsequent analysis examined both data sets – untransformed original data with and without outliers. A revised summary statistical analysis is therefore presented in Table 1b that excludes outliers and illustrates that the arithmetic mean and median are much closer together (153.69 mm and 148.64 mm) and that skewness has been reduced (although not eliminated).

The two pools of design clash data (with and without outliers) were then modelled using empirical PDF and CDF for a continuous distribution; these models were used to improve knowledge of clashes that propagate during design works. A comparative analysis between the goodness of fit tests generated for both types of probability modelling was undertaken to measure any observable differences.

Probability modelling

The PDF for a continuous distribution can be expressed in terms of an integral between two points:

$$P \int_{\alpha}^{b} f(x)dx = P(\alpha \leq X \leq b)$$ [Eq. 2]

A CDF is the probability that a variate takes on a value less than or equal to *x*. For continuous distributions, the CDF is expressed as a curve and denoted by:

$$F(x) = \int_{-\infty}^{x} f(t)dt$$ [Eq.3]

The empirical CDF is displayed as a stepped discontinuous line depending upon the number of bins and is denoted by:

$$F_n\ (x) = \frac{1}{n}.\,[Number\ of\ observations\ \le x] \qquad \text{[Eq.4]}$$

Where bins are the number of equal vertical bars contained within a CDF histogram, each representing the number of sample data values (that are contained within each corresponding interval), divided by the total number of data points.

The PDF, CDF and distribution parameters (e.g. $\alpha, \beta, \gamma, \mu, k, m, \sigma, \xi$) for 36 different continuous distributions, including *Beta*, *Exponential*, *Frechet*, *Gumbel Max/Min* and *Wakeby*, were examined using the estimation method Maximum Likelihood Estimates. The best fit distribution was then determined using two goodness of fit tests, namely the: Anderson-Darling statistic (A^2); and Kolmogorov-Smirnov statistic (D). Combined, these goodness of fit tests measure the compatibility of a random sample with a theoretical probability distribution function – or put simply, how well the distribution fits the data.

The *Anderson-Darling statistic (A^2)* is a general test to compare the fit of an observed CDF to an expected CDF. The test provides more weight to a distribution's tails than the *Kolmogorov-Smirnov* test. The Anderson-Darling statistic is defined as:

$$A^2 = -n - \frac{1}{n}\sum_{i=1}^{n}(2i-1)\cdot\left[InF(x_i) + In\left(1 - F(x_{n-i+1})\right)\right] \qquad \text{[Eq.5]}$$

The *Kolmogorov-Smirnov statistic (D)* is based on the largest vertical difference between the theoretical and empirical CDF. It is defined as:

$$D = \max_{1<i<n}\left(F(x_i) - \frac{i-1}{n}, \frac{i}{n} - f(x_i)\right) \qquad \text{[Eq.6]}$$

These goodness of fit tests were used to test the null (H_o) and alternative hypotheses (H_1) of the datasets: H_0 - follow the specified distribution; and H_1 - do not follow the specified distribution.

The hypothesis regarding the distributional form is rejected at the chosen significance level (α) if the statistic *D* and, A^2 are greater than the critical value. For the purposes of this research, 0.01, 0.02 and 0.05 significance levels were used to evaluate the null hypothesis.

The *p*-value, in contrast to fixed α values, is calculated based on the test statistic and denotes the threshold value of significance level, in the sense that H_o will be accepted for all values of α less than the *p*-value. Once the 'best fit' distribution was identified, the probabilities for a design clashes were calculated using the CDF.

Distribution Fitting: Probability of the Size of Clash – Model One (All Data)

All 404 data points were analyzed for model one. Results reported in Table 2a illustrate that the best fit probability distribution for the size of clash detections was the Log Logistic Three Parameter (3P) at α = 0.01 and 0.02 confidence intervals; notably, the fit was not achieved at α = 0.05. The three parameters are:

$\alpha = 2.2943;\ \beta = 147.33;$ and $\gamma = 23.249$

The PDF (Figure 4) and CDF (Figure 5) for the Log Logistic 3P distribution fitting are defined in equations 7 and 8 respectively as:

$$f(x) = \frac{\alpha}{\beta}\left(\frac{x-\gamma}{\beta}\right)^{\alpha-1}\left(\left(\frac{x-\gamma}{\beta}\right)^{\alpha}\right)^{-2} \quad \text{[Eq.7]}$$

$$F(x) = \left(1+\left(\frac{\beta}{x-\gamma}\right)^{\alpha}\right)^{-1} \quad \text{[Eq.8]}$$

Where: α is a continuous shape parameter with $\alpha > 0$; β is a continuous scale parameter with $\beta > 0$; and γ is a continuous location parameter where $\gamma \equiv 0$ yields the two parameter-Log Logistic distribution. The domain for this distribution is $\gamma < x < +\infty$.

Distribution Fitting: Probability of the Size of Clash – Model Two (Outliers Excluded)

For the second model, 344 observations were analyzed (excluding *duplicate clash* outliers). Results reported in Table 2b illustrate that the best fit probability distribution fitting for the size of clash detections was the three parameter Generalized Gamma at α = 0.01, 0.02 and 0.05 confidence intervals – this represented a minor improvement upon model one. The three parameters are:

$k = 0.99505;\ \alpha = 4.5101; and\ \beta = 35.997$

The PDF (Figure 6) and CDF (Figure 7) for the three parameter Generalized Gamma distribution fitting are defined in equations 9 and 10 respectively as:

$$f(x) = \frac{k x^{k\alpha - 1}}{\beta^{k\alpha}\Gamma(\alpha)} \exp(-(\frac{x}{\beta})^{k}) \qquad \text{[Eq.9]}$$

$$F(x) = \frac{\Gamma_{(x/\beta)^{k}(\alpha)}}{\Gamma(\alpha)} \qquad \text{[Eq.10]}$$

Where: k is a continuous shape parameter $k > 0$; α is a continuous shape parameter $\alpha > 0$; β is a continuous scale parameter $\beta > 0$; and γ is a continuous location parameter ($\gamma \equiv 0$ yields the three-parameter Generalized Gamma distribution).

Both distribution fitting models illustrate a good fit at the 0.01 and 0.02 confidence intervals and therefore the removal of outliers was not a prerequisite requirement to obtaining a valid result. Using the parameters contained within model two, delimiters (X1 and X2) were used to calculate the probabilities of obtaining a discrete category of clash ranging from 30-99mm, 100-199mm, 200-299mm, 300-399mm and 400-470mm (refer to Table 3). These tolerance categories were defined and delineated by the contractor for the purposes of clash detection. The research team felt that such: i) was an arbitrary decision inordinately influenced by a hired BIM consultant; and ii) lacked logic and a meaningful basis for this decision. From this discrete analysis, it was apparent that 92.98% of clashes reside within the 30-299 mm range; where this range consists of the 30-99 mm = 19.85%; 100-199 mm = 51.05%; and 200-299 mm = 22.08% discrete categories.

CLASH MANAGEMENT CHALLENGES AND CONSIDERATIONS

The quantitative analysis conducted within this research illustrates that PDF and CDF can successfully model the probability of design clashes that occur during the development of a federated BIM model. Such modelling will prove useful to the client and members of the design team who seek to better understand and mitigate future clash occurrence. However, the origins of clashes cannot be explained by quantitative analysis alone, hence further qualitative investigation of the model federation and clash management process was conducted (refer to Figure 8). A three tier process was implemented that consisted of: tier one – the design stage; tier two – cloud computing; and tier three – clash detection. During tier one, the architects, MEP designers, structural engineers and other design consultants populated *BIM semantic data* within a *discipline specific BIM* model in an iterative manner. These discipline specific models were then integrated into an *initial federated model*. Tier two involved the implementation of the contractor's *cloud computing* solution that provided a *two-way communication* portal between the designers and contractor. Within the cloud, Autodesk Glue® was used to federate the model; BIM 360 Field was used to store and upload site photographs and facilitate communication between individual PMT members; and BIM 360 Layout was used as a tool to input Cartesian coordinates (of the building and site) using a total station. In tier three, the contractor, contractor's BIM Manager and designers implemented a recurrent process of *clash detection* and resolution. The designers identified *model clashes* as a first step towards developing *resolved model clashes* that were uploaded into an initial *clash report.* The contractor's BIM Manager then used this clash report to iteratively work with designers to resolve clashes within a *final federated model* that was uploaded into the cloud for all members of the PMT to access. This clash management process was further explored using unstructured interviews with members of the PMT and highlighted several important challenges facing practitioners working within a digital construction environment. These challenges can be conveniently grouped into the following thematic groupings, namely: organizational influences; manpower and training; automation of analysis (machine learning); and cross industry knowledge transfer.

Organizational influences

BIM has been heralded as a 21st century innovation that will not only improve the efficiency of geometric modelling of a building's performance but also the management of construction projects

(Bryde *et al.,* 2013). Other researchers eulogize over BIM virtues pertaining to: energy savings and concomitant cost reductions (Guo and Wei, 2016); greater control of the design, construction and operation of an asset throughout its whole life cycle (Azhar, 2011; Wong and Zhou, 2015); and significant time savings in the production process and consistency of the product (Arayici *et al.,* 2011; Ham and Golparvar-Fard, 2015). However, the research presented here observed that a singular PMT is neither cohesive nor unified and consists of disparate teams working together to populate the federated BIM model. Moreover, the mechanistic manner via which clashes were identified and resolved afforded limited opportunity for members of the PMT to learn from mistakes made by maximizing upon readily available business intelligence. This problem is further exacerbated by software and model exchange issues when different members of the PMT work on design work sets in isolation; a member of the PMT said:

> *"For example, the structural engineer could do a lot of work and not tell the architects about it. This might happen, then both could upload their model into a centralised location and now we have multiple clashes because the architects did not update their model and the structural engineer has now done some changes to the steel frame."*

This finding concurs with earlier research conducted by Porwal and Hewage (2013) who reported that organizational and people centered issues pose the greatest challenge for BIM implementation. Other organizational issues relate to intellectual property (IP) rights particularly for architectural designs; a member of the PMT said:

> *"They [architects] are still failing to produce a coordinated design even though they are sitting next to each other [with other design members in the PMT]. This is all about intellectual property [IP] rights. Because of the IP, the architects that own the model don't want you to easily edit it, so for example when you ask them for the Revit file they will refuse to share it. This is because models are easily editable in Revit (you can design in Revit) and once they give you a Revit model you can copy it and paste it somewhere else. And they [architects] can charge you for it…"*

Cumulatively, these improvised communication, organizational and administrative arrangements make clash eradication *per se* difficult within a BIM environment particularly when a silo mentality prevails.

Manpower, Training and Competence Development

Prior research (Succar *et al.*, 2013; Murphy, 2014) advocates that professionals within the PMT must develop core BIM competencies in order to secure performance improvement. Such improvement could be achieved via organizational learning that seeks to create, retain and transfer knowledge within an organization (Duffield and Whitty, 2016). The research presented, provides an opportunity for sharing knowledge through the exploitation of business intelligence and experiential learning amongst members of the PMT (Konak *et al.*, 2014). However, organizational learning is hampered within industry by the exponential rate of software-hardware technology development and the concomitant need to continually retrain personnel to remain at the forefront of knowledge and developments (Eadie *et al.*, 2013). Evidence accrued from this research supports this assertion and suggests that some members of the PMT have deliberately created a pretense of full BIM compliance, when in fact their approach is compromised by *ad hoc* arrangements. A member of the PMT said:

> *"It's all about knowledge, how the software is used. At the moment a lot of the consultancies are running away with BIM, where they are just modelling using the CAD drawings. Rather than using a proper BIM draughtsman, they employ a Revit technician. The Revit technician receives CAD drawings and redraws these into Revit, which is not a collaborative way of working. The structural engineer is doing all the calculations and measurements in the CAD drawings in 2D and then this is being transferred into 3D with errors!"*

Evidence suggests that a huge BIM knowledge gap has developed between senior professionals (architects, MEP designers, etc.) and small to medium enterprises (SMEs) that is compounded by innate skill limitations (Harris *et al.*, 2013). SMEs are quintessentially important as their services are often used in the design, construction and/ or maintenance of buildings (Khan *et al.*, 2016). Higher education institutes (and other education providers) must collaborate more closely with these practitioners to fully embrace the concept of a ‘life-long learner for digital construction’ in order to avoid tacit knowledge redundancy within SMEs.

Automation of Analysis (Machine Learning)

Machine learning (ML) has its entomological roots grounded in artificial intelligence (AI) and embraces computer learning without explicit programming (Bottou, 2014). ML focuses on the development of computer programs that can teach themselves to grow and change when exposed to new data (Perlich *et al.*, 2014). Within the AECO sector, ML is already being used to: monitor construction progress using 4D BIM (Golparvar-Fard and Han, 2015; Son *et al.*, 2015); automate rule checking within BIM models (Solihin and Eastman, 2015); automate as-built 3D reconstruction using computer vision (Fathi *et al.*, 2015); and monitor construction performance using still images (Yang, 2015). However, despite these significant advances, clash detection remains a laborious, mechanistic, time consuming and costly exercise. Each and every clash must be manually integrated, analyzed and accessed by the BIM manager to first determine the type of clash (*i.e. clash errors, pseudo clash, deliberate clash* or *duplicate clash*) before taking suitable action and monitoring progress where a resolution is required. Automated methods are urgently required to: rapidly assimilate vast quantities of geometric data accessed from a larger range of construction and civil engineering projects to build accurate benchmark clash detection profiles that could inform future decision making; define and delineate between the various clash types to provide greater business intelligence regards which clashes require resolution thus eliminating the need for manual intervention; and eliminate the need for manual intervention and the introduction of human errors or omissions.

Cross Industry Software-Knowledge Transfer

In other more technologically advanced industries (e.g. automotive and aerospace), software exchange file formats have been standardized to aid communication between various designers and manufacturing production processes (Eastman *et al.*, 2011). Within the AECO sector the BIM authoring platforms adopted lack standardized user interfaces and file formats in an open architecture environment. Although the Industry Foundation Classes (IFCs) specification sought to alleviate these issues, anecdotal evidence from practitioners suggests that IFCs are not error free. For example, geometry and semantic information can disappear when file formats are exported from the original BIM authoring platform. A member of the PMT said:

> *"… many companies and consultancies are reluctant to give us the Revit files. That is why the IFC was invented and generated, to allow for the export from any piece of software. This was the holy grail of the BIM model, that you can export into a single format which can be opened by any company or any BIM software vendor and federated in IFC's. But obviously software vendors [vendor name removed] are failing to produce usable IFC's, so it's very hard to export correct IFC from Revit. For example, today I received some export IFC's from a vendor [vendor name removed] and they are coming out with strange geometries that are not meant to be in the model."*

Currently, there is no commercially available cloud-based BIM authoring platform that allows designers to work collaboratively. As an exemplar of contemporary industry practice, members of the project design team worked within separate BIM authoring platforms – for instance, the architect used REVIT, the structural engineer used Tekla and MEP used REVIT MEP. These various software packages, processes and procedures have been developed organically and iteratively to meet industry needs but as yet, a single system that encapsulates holistic coverage has eluded the sector. This is most likely because platform design specifications are often ill-defined, frequently complex and involve iterative processes, and user needs and specifications evolve as the temporal and recurrent 'design to user-experience' process consolidates into an optimal product solution (Chandrasegaran *et al.,* 2013). A member of the PMT said:

> *"BIM 360 Glue allows you to view and federate the models from different consultants. So for instance, I am getting uploads of the latest models to the single cloud storage to check them. But I am also coordinating them, so all the clashes which should not be there, are there to be checked by myself and my colleagues. Because the designers have been working within their own silos and then just upload the models into the cloud based platform for a clash detection."*

Working from a cloud would alleviate many of the problems and issues faced when working in a multi-disciplinary team where software and hardware requirements fail to synergize and often require frequent annual updates. Annual updates in a cloud would ensure that all team members are using the most up to date version. One common cloud-based modeling platform would provide an ideal solution but agreement between five or more software providers of alternative platforms could be problematic particularly on commercial grounds. A potential solution would be to eliminate errors within IFCs and ensure ever-greater interoperability between software vendors – transference of best practice from more technologically advanced sectors could present an ideal solution to this conundrum. A member of the PMT said:

> *"The guys [contractors] internally have got their heads around it [cloud based app] because there are a lot of changes. So over the course of the year the site team has changed slightly. Traditionally, there would be a lot of information that is stored on emails, although they were sitting next to each other and talking with one another… Because all of the issues have been raised on the iPads [on cloud] they are already there for the next site manager to find. So at least they're not completely blind when they have to come in to resolve the issues."*

CONCLUSIONS

Despite the euphoria that often surrounds digital construction within extant literature, this research has shown that BIM is not yet a panacea to mitigating design errors. Rather the nature of design error propagation has changed and evolved in parallel with 'new technologies' applied that are being managed by 'traditional management' processes and procedures. In addition, a distinct lack of organizational learning within the PMT was evident and so the opportunity to secure experiential learning is often lost. Rather than learn from clash occurrences and proactively work to mitigate them, members of the PMT take a short-term reactive approach to identifying and resolving them. Part of the problem is that clash detection software for example, currently lacks automation and requires a labour intensive (and costly) analysis and post-investigation of clash data by the BIM manager/ coordinator. For an entire project (dependent upon scope), design clashes alone could equate to several tens of thousands of observations and in the longer term, such an approach is untenable. Members of a fragmented design team were also observed to be working in isolation and with bespoke BIM authoring platforms. Although IFCs were meant to overcome this issue, errors with IFCs still doggedly persist.

PDF and CDF probability distribution models developed within this research offer invaluable insight into the size and frequency of clash occurrence – such could be used to develop probability profiles that enable BIM managers to better define and delineate tolerances prior to conducting clash detection. Such work should be extended to other building compartments (for example, architecture) and for other buildings so that a comprehensive knowledge bank of benchmark indicators can be established and used to monitor clash errors, resolution and mitigation.

In many instances reported upon in this research, a 21st century technological innovation and collaborative means of working is being managed by a 20th century management and individualistic mentality. Future work is therefore required in several key areas, namely to: i) extend the models developed to other building compartments to cover a wider range of clash detection across the entire building and multiple buildings throughout industry. Such work could form the basis of invaluable business intelligence that would inform and optimize decision making for future design projects; ii) develop machine learning processes and procedures to automate clash analysis and prognosis; iii) transfer knowledge of successful digital modelling technologies from other more advanced industrial sectors (such as mitigating interoperability issues and clash error management) into the AECO sector; and re-evaluate the training and competence development needs of SMEs working within the PMT supply chain.

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Figure 1 – Proposed Extension of Mary Seacole Building (Sheppard Robson Architects)

Figure 2 – Client Requirement Processes Adopted for Fortnightly Clash Detections.

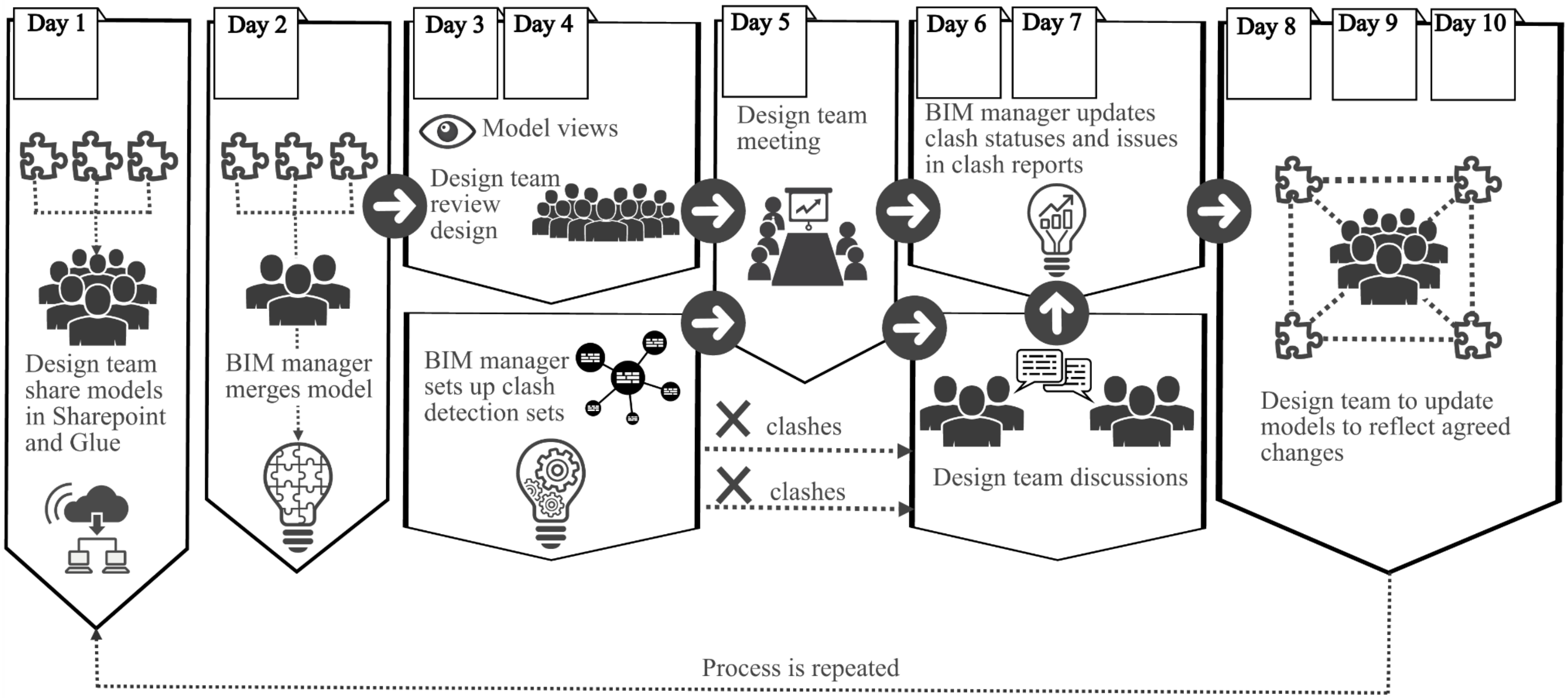


Figure 3a - Structural vs. MEP Clashes in Autodesk Navisworks (MEP service in Column)

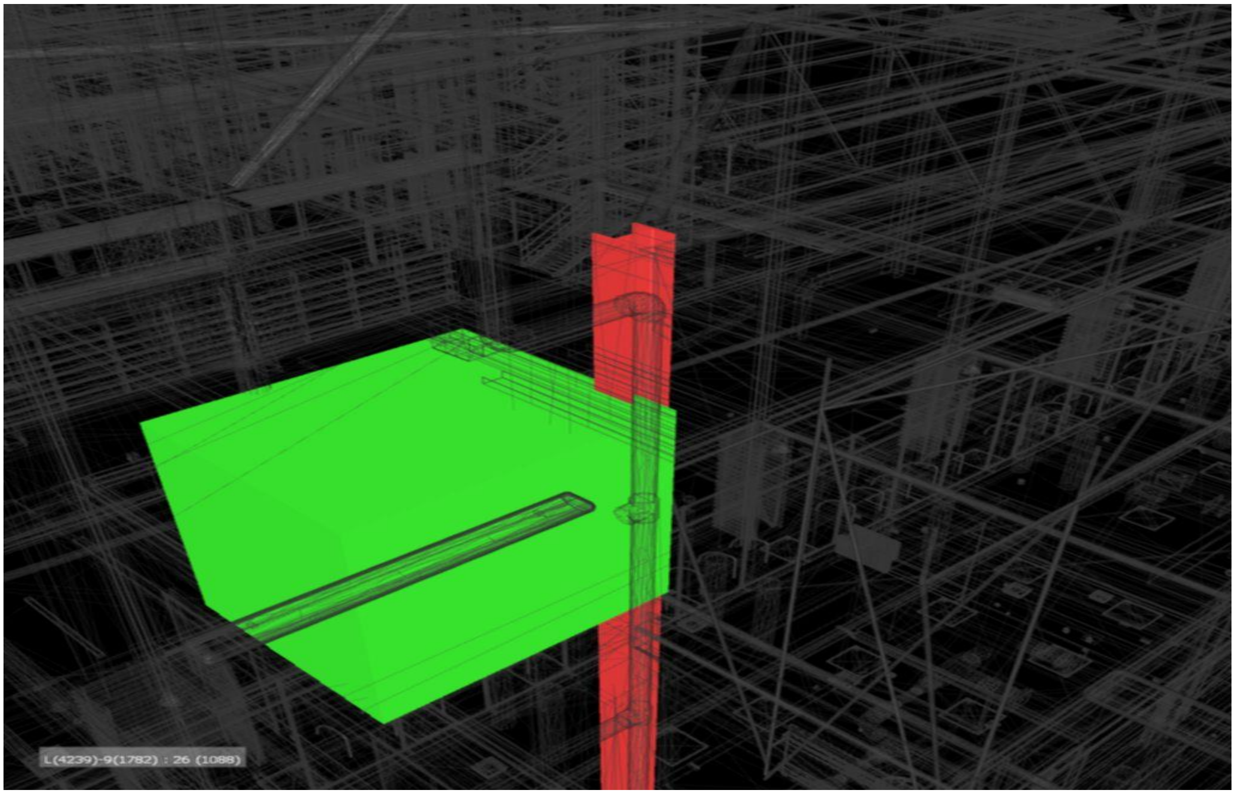


Figure 3b - Structural vs. MEP Clashes in Autodesk Navisworks (MEP Service in Beam)

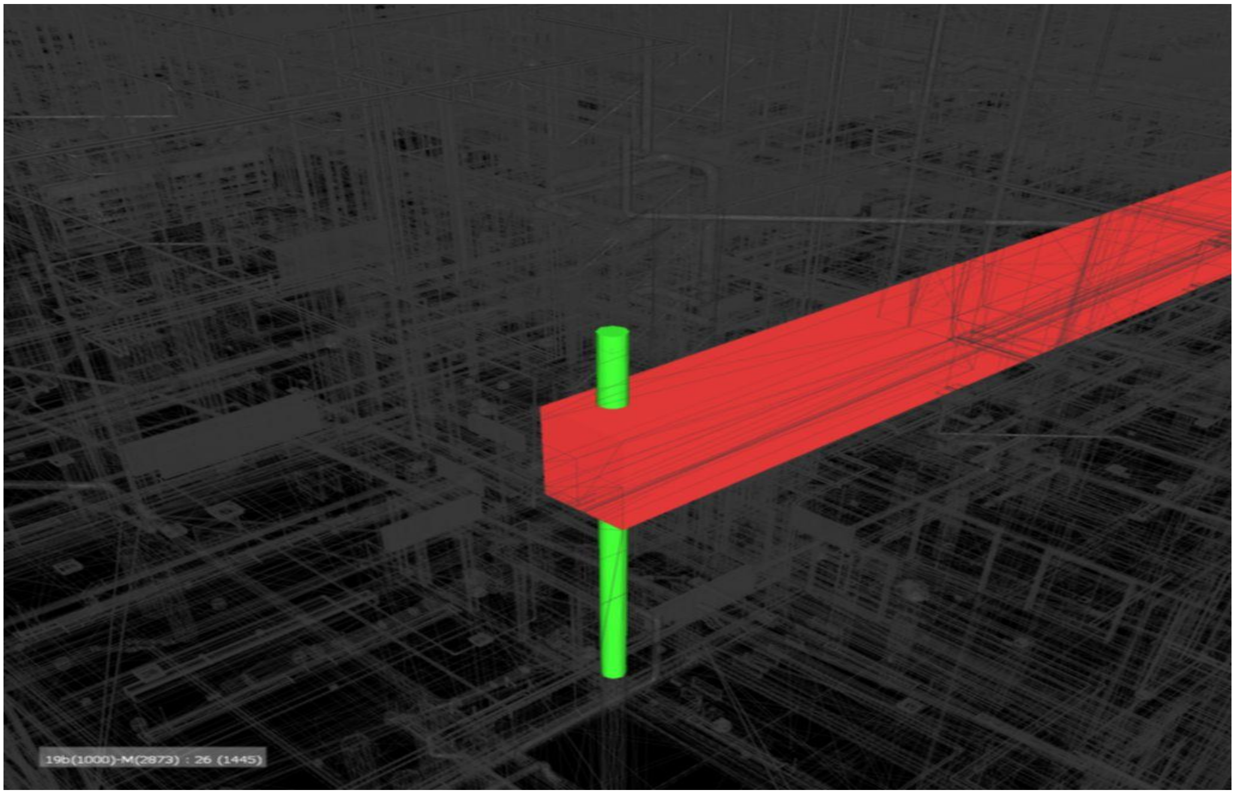


Table 1a – Summary Statistical Analysis of Error Clashes (Structural vs MEP - All Data)

Statistic	Value	Percentile	Value
Sample Size	404	Min	41.09
Range	508.94	5%	54.95
Mean	212.82	10%	74.528
Variance	19197	25% (Q1)	122.89
Std. Deviation	138.55	50% (Median)	166.78
Coef. of Variation	0.65102	75% (Q3)	250.03
Std. Error	6.8933	90%	457.53
Skewness	1.1496	95%	550.03
Excess Kurtosis	0.30751	Max	550.03

Table 1b – Summary Statistical Analysis of Error Clashes (Structural vs MEP - Outliers Excluded)

Statistic	Value	Percentile	Value
Sample Size	344	Min	41.09
Range	329.06	5%	53.811
Mean	163.69	10%	66.37
Variance	5892.2	25% (Q1)	116.77
Std. Deviation	76.761	50% (Median)	148.64
Coef. of Variation	0.46895	75% (Q3)	222.65
Std. Error	4.1387	90%	250.03
Skewness	0.75898	95%	350.11
Excess Kurtosis	0.35379	Max	370.15

Table 2a – Goodness of Fit (All Data) - Log Logistic (3P)

Kolmogorov-Smirnov	**Sample Size**	**404**		
	Statistic	0.07126		
	P-Value	0.03144		
	α	0.05	0.02	0.01
	Critical Value	0.06756	0.07552	0.08105
Anderson-Darling	**Sample Size**	404		
	Statistic	2.7754		
	α	0.05	0.02	0.01
	Critical Value	2.5018	3.2892	3.9074

Table 2b – Goodness of Fit (Outliers Excluded) – Generalized Gamma

Kolmogorov-Smirnov	**Sample Size**	**344**		
	Statistic	0.05869		
	P-Value	0.1797		
	α	0.05	0.02	0.01
	Critical Value	0.07322	0.07322	0.07322
Anderson-Darling	**Sample Size**	344		
	Statistic	1.8396		
	α	0.05	0.02	0.01
	Critical Value	2.5018	2.5018	2.5018

Figure 4 – Probability Density Function – Log Logistic (3P) All Data

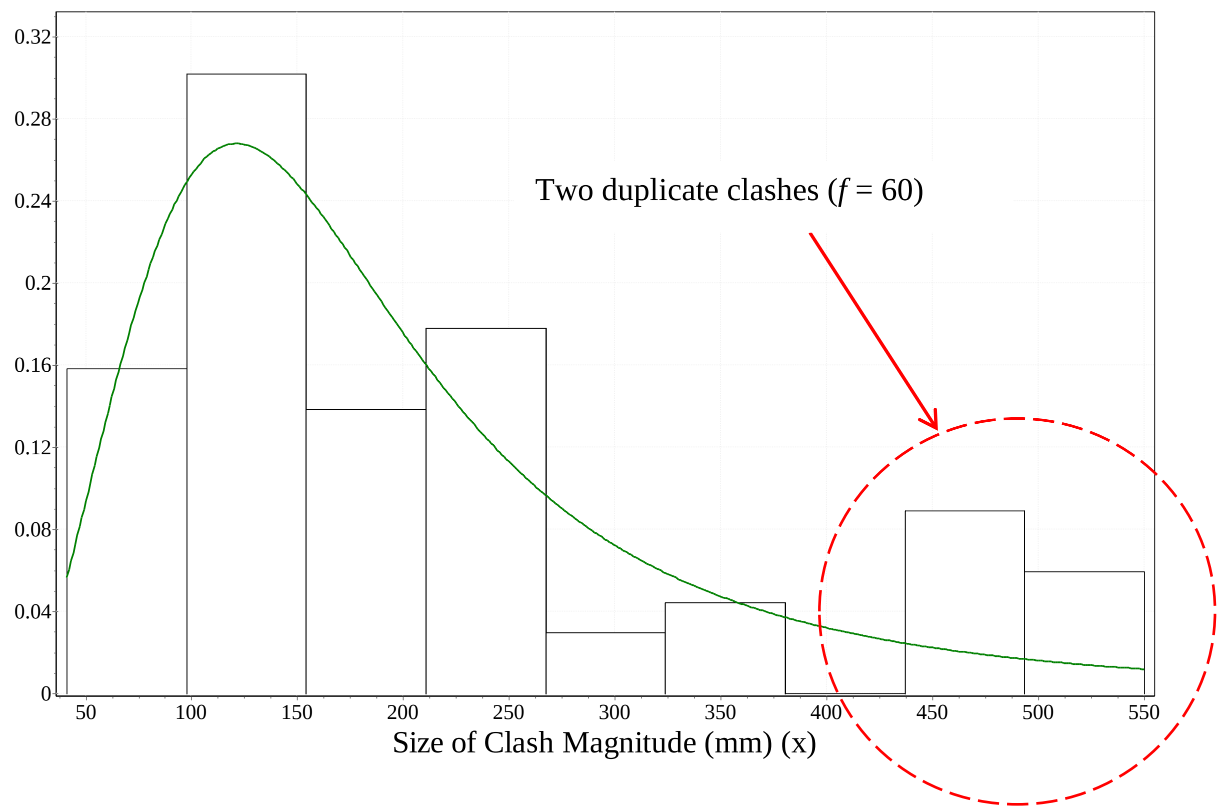


Figure 5 – Cumulative Distribution Function – Log Logistic (3P) All Data

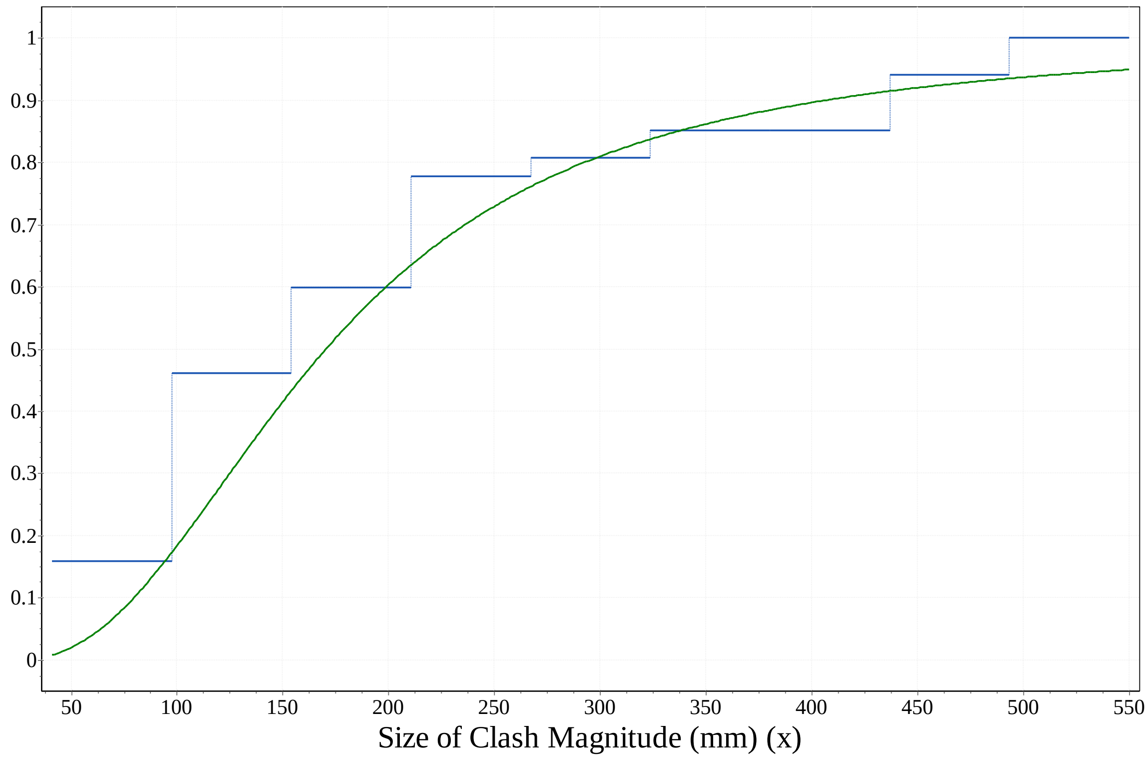


Figure 6 – Probability Density Function – Generalized Gamma Outliers Excluded

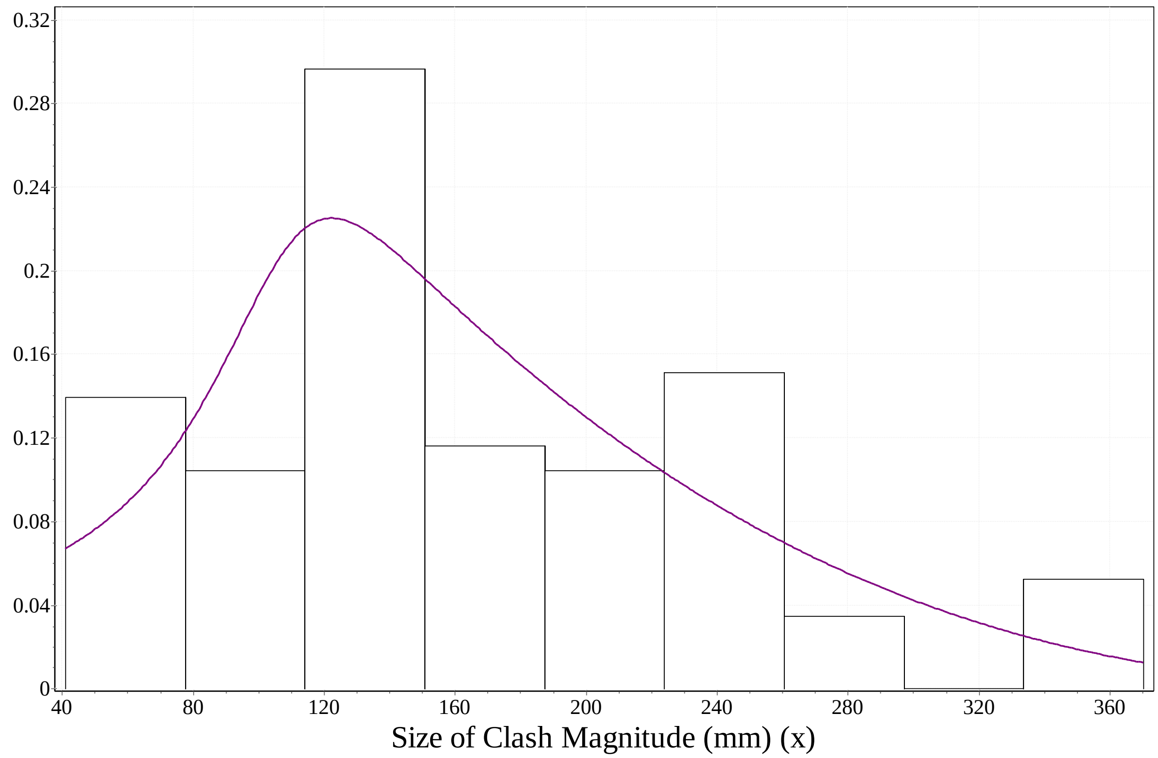


Figure 7 – Cumulative Distribution Function – Generalized Gamma Outliers Excluded

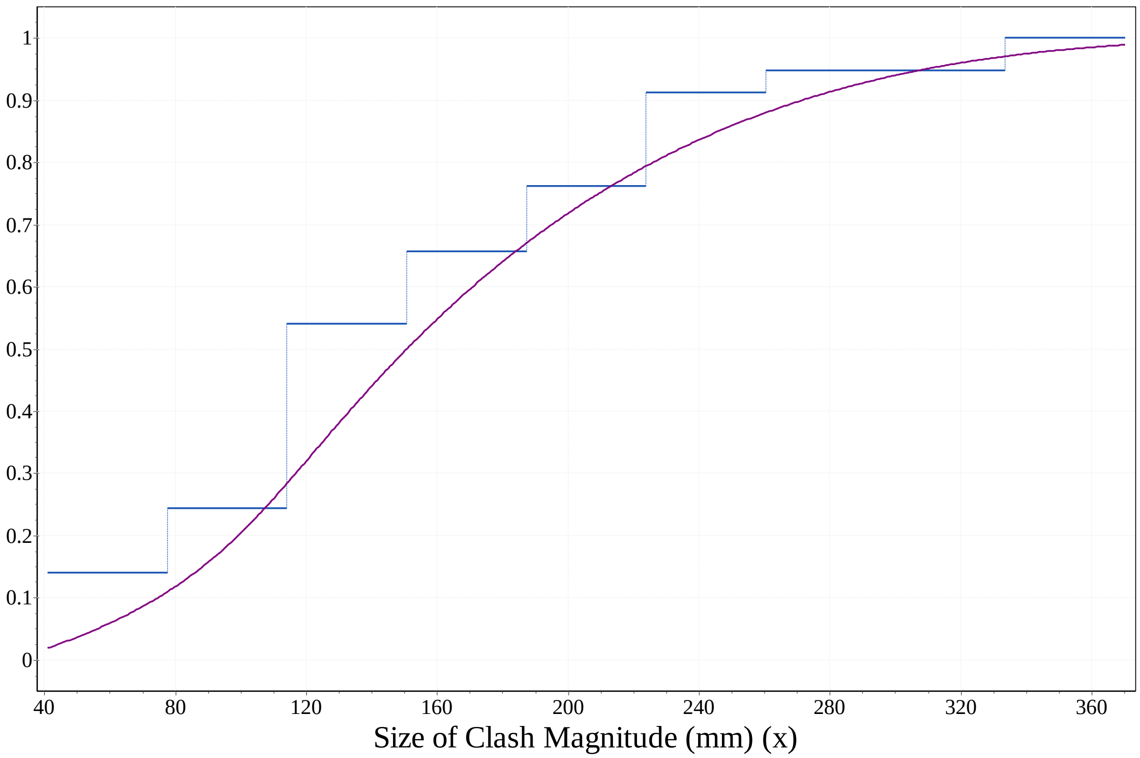
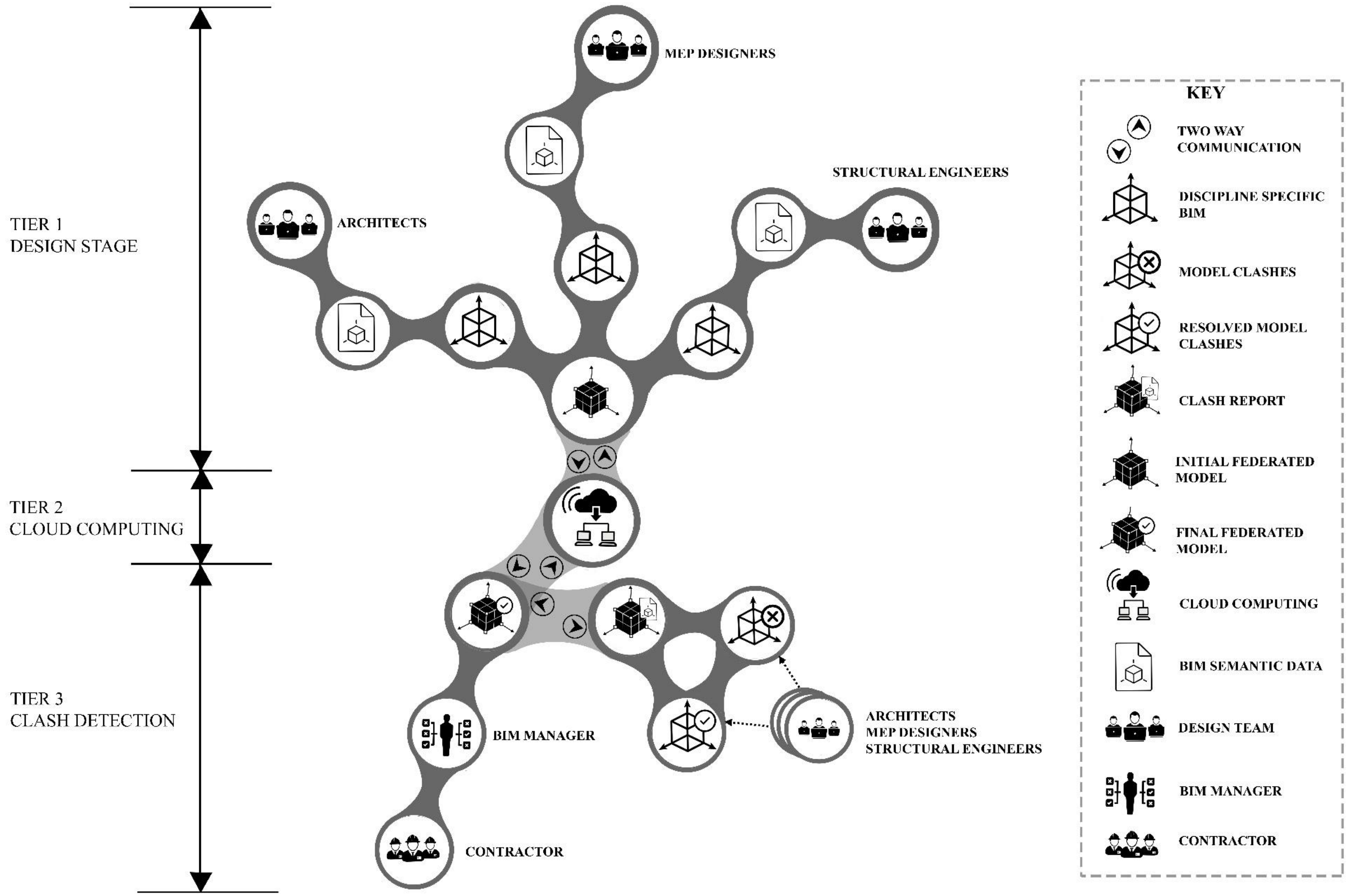


Table 3 – Probabilities of incurring a clash magnitude (range in mm)

Probability of incurring a clash magnitude (range in mm)	P(X < X1)	P(X > X1)	P(X1< X < X2)	P(X < X2)	P(X >X2)
30-99mm	1.4919E-5	0.99999	0.19852	0.19853	0.80147
100-199mm	0.20364	0.79636	0.51057	0.71421	0.28579
200-299mm	0.71779	0.28221	0.22085	0.93864	0.06136
300-399mm	0.9398	0.0602	0.05611	0.99591	0.00409
400-470mm	0.99608	0.00392	0.00385	0.99993	7.0710E-5

866 **Figure 8** – Model Federation and Clash Management



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