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Optimising existing digital workflow for structural engineering organisations through the partnering of BIM and Lean processes

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Optimising existing digital workflow for structural engineering organisations through the partnering of BIM and Lean processes.

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ABSTRACT: Building Information Modelling (BIM) is now seen as one of the leading transformative processes within the Architectural, Engineering and Construction (AEC) sector and has the potential to assist in streamlining the structural design process. However, its practical implementation can often add another layer to the existing workflow and can result, to its detriment, in the primary objective of optimising structural workflows being hindered. This can lead to structural organisations producing 3D models in tandem with traditional drawings, a lack of human intervention regarding software interoperability, and a reluctance to move away from conventional work methods. This paper will explore how a lean approach to BIM adoption can optimise the digital structural workflow, thereby enhancing BIM adoption. Although much research has been conducted on BIM as an enabler of Lean, there remains a gap regarding the synergies in how Lean tools can advance BIM adoption within the structural discipline. The closing of this knowledge gap will be advanced by comparing existing digital workflows within a structural organisation against a proposed integrated BIM workflow underpinned through Lean. The findings highlight that while BIM and Lean offer enhanced digital solutions to modernise structural design office workflows, the true capability of these tools will not be realised without a cultural change.

KEYWORDS: Building Information Modelling; BIM and Lean; Robot; RC; Value Stream Mapping.

1 INTRODUCTION

Engineering is constantly evolving and, through its very nature, embraces innovation. An innovation currently shaping the construction industry's future is Building Information Modelling (BIM). BIM can be viewed as a disruptive innovation; it requires a fundamental shift from traditional work practices. It is not a software but a process underpinned by technology and collaboration, requiring cultural change within organisations to leverage its benefits fully. BIM adds value to the construction design process, but that is dependent on human interaction with it.

The authors' anecdotal experience within the structural engineering sector suggests that BIM is used primarily due to project or client requirements. The organisational structure, in many cases, is set up to react to this requirement, not embrace it. BIM can often be viewed as a draughting software and when introduced alongside traditional work practices can sometimes add to existing workflows and create a more inefficient structural design process. BIM in isolation has not resulted in a complete cultural change within the sector; a shift in mindset is also required to facilitate this. Lean thinking, a philosophy driven by eliminating waste and creating better value, helps accelerate this cultural change.

This paper highlights how lean thinking can aid effective BIM implementation within the structural engineering sector, removing wastes, adding value, and optimising design office workflows.

2 LITERATURE REVIEW

Structural engineering is a sub-discipline of civil engineering that deals primarily with analysing, designing, and constructing structures. Structural engineers apply the laws of mathematics, physics, and empirical knowledge to safely design the internal skeleton and foundation of a structure [1]. The field has advanced by necessity to support the growing size and complexity of buildings and other structures through the ages. As human knowledge has progressed, it has introduced new ideas and technologies that continue to evolve the industry, such as the use of cast iron and cement in built structures and the introduction of AutoCAD, one of the most widely utilised CAD programs in the structural engineering sector today [2]. One of the more recent advances with the potential to transform the industry is Lean construction, a philosophy based on lean manufacturing concepts.

2.1 Lean

Toyota developed the 'Lean' manufacturing process in its car manufacturing plants in Japan in the decades after the Second World War, which at its core was eradicating waste and non-value-adding methods [3]. Toyota achieved this by developing the 5S (sort, set in order, sweep, standardise, sustain) process and empowering employees [4].

The success of Toyota's lean approach led to the realisation that the same principles, extrapolated from the specific environment of car manufacturing, have the potential for a universal application in other areas of manufacture and production. Adopting Lean principles such as defining value; mapping the value stream; creating flow; using a pull system, and pursuing perfection would significantly reduce waste from the supply chain. Many studies have explored its context within the construction industry, where adopting this new philosophy would create a paradigm shift within the sector [5,6].

Lean implementation is mainly focused on eliminating Muda (waste) in the process. Lean tools, including Value Stream Mapping (VSM), Last Planner, and Just-in-Time, help identify these wastes, allowing the sector to improve efficiency, and enabling lean thinking to be applied in practice [5].

Despite increased awareness and the clear advantages offered by implementing Lean thinking, tools, and principles in the construction sector, the actual implementation of Lean construction practices has been anything but universal in the industry. Many structural and cultural factors feed into the failure to embrace Lean construction principles fully, including:-

- Traditional management structures within the sector that do not allow for the 'flattening of the management structure' and 'closing the loop';
- The existing disconnection between design and design implementation leads to costly conflicts;
- The adoption of Lean-thinking principles from the manufacturing industry without the necessary modification for the construction sector;
- A lack of knowledge or understanding of the fundamental concepts and application of Lean;
- The disparate and fragmented nature of the construction industry;
- The financial cost of providing the necessary education, skills, and resources required to implement Lean [6].

This has seen the argument for the partnering of Lean and BIM due to their substantial synergies as a potential vehicle to advance the sector.

2.2 BIM

Traditional non-BIM methodologies see professionals develop their design in silos before exchanging information with the rest of the project team. As a result, this data may have already become obsolete by the time it is shared. In contrast, BIM, which can be defined as using a shared digital representation of a built asset to facilitate design, construction, and operation processes to form a reliable basis for decisions, can enable a more integrated approach [7,9].

The information produced through the BIM model can be shared with partners through a common data environment (CDE), which encourages collaboration and enables the structural engineer to connect with the workflows and data of all project team members, offering a real-time view of the design development [11].

BIM is becoming an integral part of the structural engineering workflow. The interoperability of programs within BIM allows for a quicker and more accurate structural design. The structural engineer's ability to collect a vast amount of information from these data-rich models has resulted in a more precise assessment of developments allowing them to incorporate as lean and as sustainable a design as possible [8].

If BIM implementation is successful, companies need to ensure that their adoption processes result in a leaner and more efficient workflow [9]. Suppose BIM is operated in tandem with traditional methods. In that case, the company does not benefit from BIM's potential for streamlining the construction process, enhancing efficiency, and waste reduction, but it can add to workflows and costs. This, in turn, can lead to a negative view of new technologies and a reluctance to introduce them into the sector [10].

2.3 Lean and BIM

BIM facilitates lean measures through design to construction to occupancy and, at the same time, contributes directly to lean goals of waste reduction, improved flow, reduction in overall time, and improved quality by utilising clash detection, visualisation, and collaborative planning [15]. According to Sacks *et al.,* there are 56 synergies between BIM and Lean construction. A survey of experimental and practical literature found that 48 of the 56 interactions were seen as beneficial in optimising the flow of information and materials [11].

The Construction Industry Research and Information Association (CIRA) put forward four main mechanisms for how Lean and BIM interact. These mechanisms include;

- *BIM contributes directly to Lean goals* - BIM offers the ability to visualise the project and analyse the building design, greatly benefiting the client, designers, and contractors. This results in reduced variations at the planning and design stage.
- *BIM contributes indirectly to Lean goals by enabling Lean processes* - Utilising BIM tools such as 4D planning to simulate and demonstrate how a task can be best-performed offers a much greater understanding than the traditional methods at the planning stage.
- *The auxiliary information systems of the design team can, when enabled by BIM, contribute directly and indirectly to Lean goals* - The analysis model for the structural engineer is an example of this, whereby the interoperability of BIM programs has enabled a smoother iteration between the design and analysis programs than more traditional methods.
- *Lean processes facilitate the introduction of BIM* - Lean construction's emphasis not only on collaboration, predictability, and discipline but also on experimentation facilitates BIM implementation [12].

Team working skills, critical thinking, leadership, communication skills, work ethics, knowledge, and positive attitudes help enable lean and provide the foundation to facilitate the full potential of BIM within the sector [13]. A willingness to transition from traditional working methods and embrace Lean thinking and new technologies could positively impact structural engineering organisations. An example of this is in modelling reinforced concrete (RC) components in structural concrete models. RC can account for up to 15% of an overall construction build, so a significant opportunity exists to leverage BIM for RC design within the sector to minimise waste and visualise complicated junctions to solve clashes before they reach the site, ultimately saving considerable time and money on a project [14].

3 METHODOLOGY

This paper aims to understand to what extent Lean thinking and its culture can enhance BIM processes and facilitate its adoption within a structural engineering organisation. Focusing on an existing BIM project, an action research study is applied to discover and compare the current workflow used on BIM projects against a leaner BIM workflow. The subject of the action research study is a large mixed-use development spread over multiple blocks comprising of apartments, commercial and amenity spaces. Due to the scale of the development, the fact that it is still under construction, and the time constraints of this study, the authors focused solely on one aspect of the structural design office workflow, namely the current RC element of the project, from the initial design to publishing the drawings and schedules on the project's CDE. The potential benefits of utilising the interoperability of the company's analysis software and integrating project reinforcement elements into the BIM environment will be explored.

Design engineers built the initial analysis model, and a survey was issued to help gather an accurate indication of the data for this element. The results found that the engineers did not complete an overall analysis model containing the complete design analysis for the development; instead, a series of individual models were built up based on the most urgent RC requirement on site. The process involved in building these models, how long it took, and the advantages and disadvantages of this method were investigated. The information gathered helped to assign a time to this research element.

To provide data for building the proposed future state analysis model, the authors used the structural model to set up the analytical model in Revit before using the bi-directional link to send this information to Robot. The design engineers then checked the model to ensure it was fit for purpose. The time taken to undertake this process was recorded.

The time constraints of this study meant it was not possible to re-do the entire reinforcement drawings and schedules for the project in 3D. Instead, the authors completed an area within the BIM environment utilising CADS RC3D, and the time taken to undertake this task was recorded.

The Lean tool Value Stream Mapping (VSM) was chosen to provide a structured visualisation of the critical steps and associated data to help understand and optimise the entire process. VSM, one of the most widely adopted Lean tools for construction, is designed to eliminate waste and all activities that do not add value throughout the construction processes, thereby providing a clear view of the best way to maximise customer value.

4 PRIMARY RESEARCH

4.1 The current workflow for reinforcement on BIM projects

To evaluate if Lean and BIM synergies could enhance RC workflows within the structural engineering sector, it is essential to understand the organisation's current process. The action research was conducted on a BIM project set to ISO 19650 standards. The concrete elements were modelled within the BIM environment; however, the reinforcement input sat unconnected alongside this process. As discussed earlier in this paper, BIM is not widely leveraged by structural engineering organisations for reinforcement design, a more traditional workflow is often used.

Revit and Robot Structural Analysis Professional software was used to create draughting and analysis models on structural projects within the organisation. Revit supports the BIM process by providing a physical model for documentation and an associated analytical model for structural analysis and design. The bidirectional link between these programs enables users to send a model directly from Revit to Robot for structural analysis and design.

Similar to traditional non-BIM methodologies, software-dependent silos developed within the organisation, as illustrated in Figure 1. Each professional developed the design before exchanging this information with the rest of the structural team. As a result, this data can become obsolete by the time it is shared.

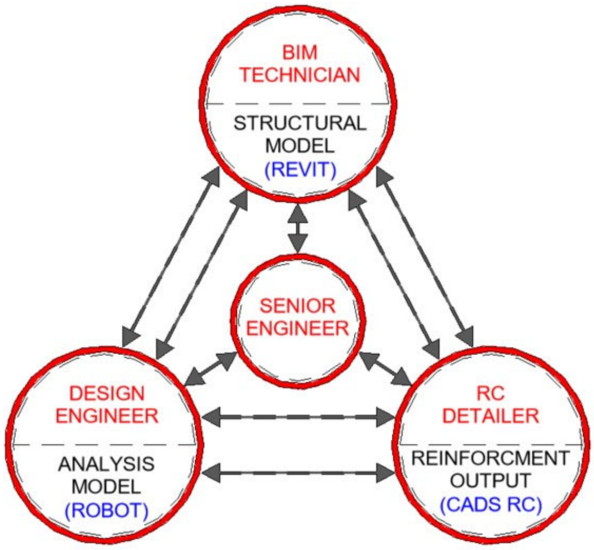

Figure 1. Current RC Workflow

The current organisational workflow for project reinforcement design and the production of RC construction documentation is detailed below:

- A structural model is created from the existing architectural information;
- 2D dwg format plans are extracted from the model by the BIM technician and sent to the design engineer;
- The design engineer inputs connection point locations into these drawings and links this information into Robot Structural Analysis;
- The design engineer creates an initial independent analysis model from 2D information;
- The design engineer runs calculations within Robot and informs the BIM technician of the required changes;
- As neither model is linked, the BIM technician updates the Revit model accordingly, i.e., incorporate beam loads and changes, column or foundation sizes, etc.;
- Multiple plans, sections, and elevation sheets are created and cut from the Structural model by the BIM technician, providing this information to the RC detailer;
- After extraction to dwg format, this information is deleted from the model to ensure no reinforcement-specific section marks, plans, or elevations are shown on the general arrangement (GA) drawing sheets within the model;
- In AutoCAD, the extracted sheets are cleaned up by the RC detailer to align with all company draughting standards, including line type and text styles;
- The RC detailer undertakes the reinforcement in CADS RC 2D; and
- The RC detailer then publishes the reinforcement drawings and schedules to the project CDE.

As the project design develops, the structural and analysis models and reinforcement drawings are updated independently, requiring the above steps to be repeated after every design change.

4.2 VSM – The Current State

A value stream map was created to help record and reflect on this workflow. Each step was mapped, with a data box included in each process containing information on the cycle time (C/T) or person-hours to undertake the task.

As illustrated in Figure 2, the information flows left to right across the page from the project CDE before being pushed back into the CDE once the design and analysis processes are completed. Due to the siloed nature of the current workflow, mapping of three independent design engineers, BIM technicians, and RC detailer workflows was required, placed from top to bottom respectively, on the diagram. Points, where these workflows interact, were added before two timelines were created, one for the reinforcement design and the second for the drawing and schedule production process. The timelines have two levels of information taken from the data boxes. On the top are the value-added processes' times, and on the bottom, the non-value-added actions or lead times. Added together, this provides the total C/T to complete each workflow.

The current state had excessive waste in the process, with considerable time, effort, and re-work expelled on the project. A significant finding of the mapping exercise was that the total contribution of the BIM technician to the current RC workflow consisted solely of waste or necessary non-value-adding activity. In essence, the current way of working with reinforcement was not only outside the BIM workflow but it also required much additional work to extract information.

4.3 Embedding reinforcement drawings and schedules within the BIM workflow

Mapping the current process enabled the authors to identify the areas of overproduction and waste, and this information was used as the basis for the future state map. The authors identified some typical lean opportunities within this design environment to eliminate this waste to improve efficiency and the overall quality of the process. One of these opportunities involved leveraging the power of the software packages and utilising the interoperability of the organisation's structural design and analysis software to reduce the person-hours within the workflow.

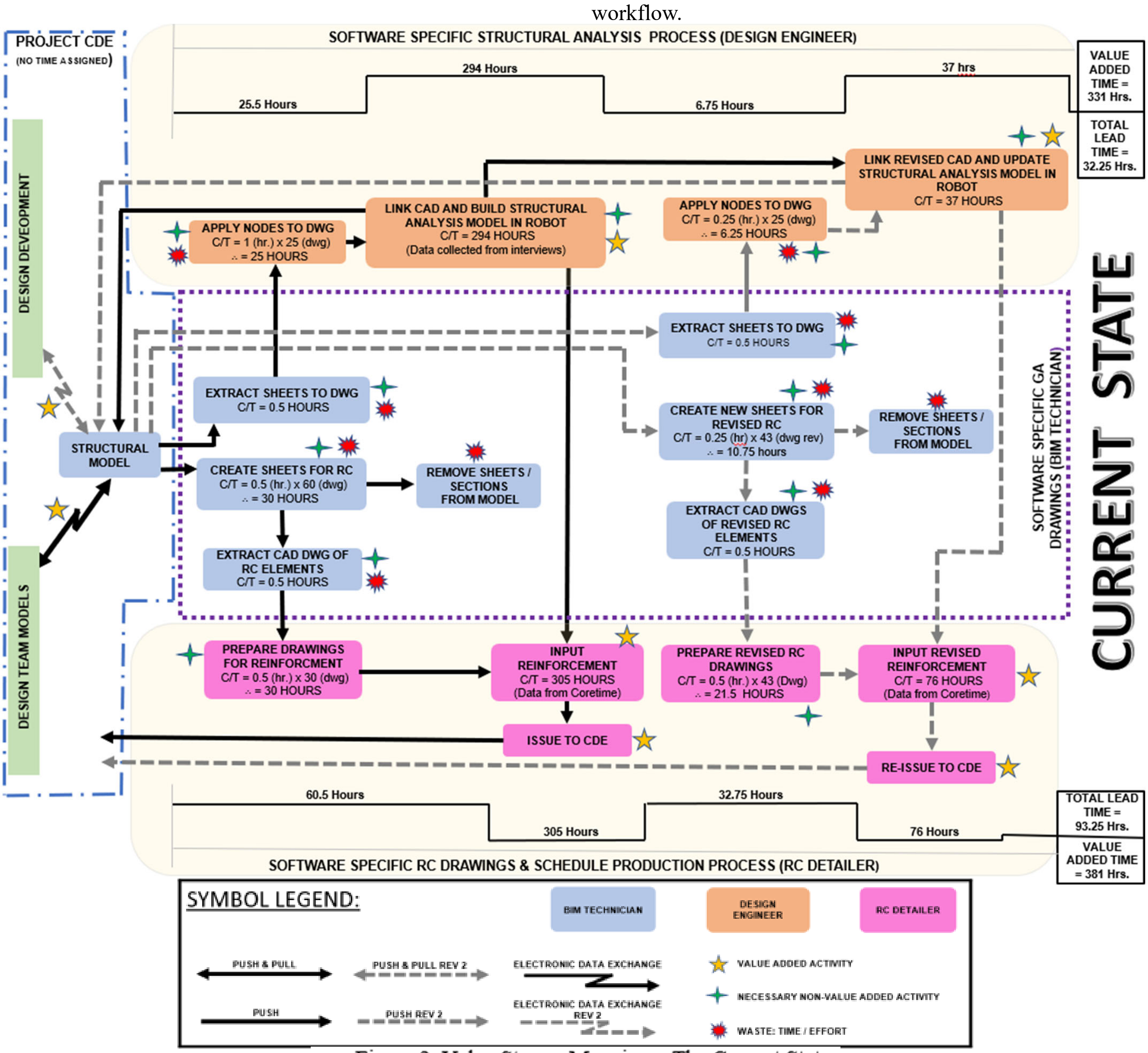

Figure 2. Value Stream Mapping – The Current State

The current software used to detail reinforced concrete within the organisation is CADS RC2D. In recent years a Revit add-on CADS RC3D., has been developed to enhance reinforcement detailing and scheduling within Revit. This has made the transition from 2D detailing more straightforward, offering increased productivity through its enhanced functionality. The authors explored the functionality of this software by detailing sections of the project previously completed in 2D and testing the viability of introducing it into the company's reinforcement workflow.

There were significant advantages that contributed to lean goals. The ability to produce the reinforcement within the structural model provided the opportunity to streamline the office workflow significantly by removing the excessive non-value added activities. In addition, as the design develops, less re-work is required. Initial parameters, such as reinforcement cover and centres of bars, are set, and Revit retains this information. If a pile cap, column, or beam size, for example, is changed, then the reinforcement for these elements will automatically update. The detailing process is also enhanced by visualising this information in 3D. A complete view of complicated areas is provided, ensuring all factors are considered and offering greater clarity.

The reinforcement now embedded in the BIM workflow enables the project team to utilise clash detection tools. The entire project team can track the progress of this clash resolution, ultimately eliminating the risk of costly errors and re-work on site.

4.4 VSM – The Future State

A VSM was created to focus on what the workflow ideally looks like after the process improvements outlined in the previous sections of this paper have taken place in the value stream. This future state workflow, illustrated in Figure 3, shows considerably less waste in the process. The fragmented nature of the current workflow is replaced by a more collaborative approach achieved through integrating the RC deliverables into the BIM workflow. The ability to push and pull information electronically from the structural and analysis model, as illustrated in Figure 4, enriching the central structural model hosted on the project CDE helps avoid potential errors resulting from manual coordination of construction documentation. The structural model is enriched with the RC analysis and draughting information, ensuring that the organisation's design team, the project design team, and all other professionals involved in the project have access to the most up-to-date and reliable information.

While the data illustrated demonstrates the considerable gains in design efficiency in bringing the development to its current stage on-site utilising this workflow, it also indicates the potential of exponential advantages as the project develops. Design changes naturally occur on projects; the dashed arrows shown on the future state map represent such changes undertaken on the project to date. With the link already created between the RC elements and the structural model, the time

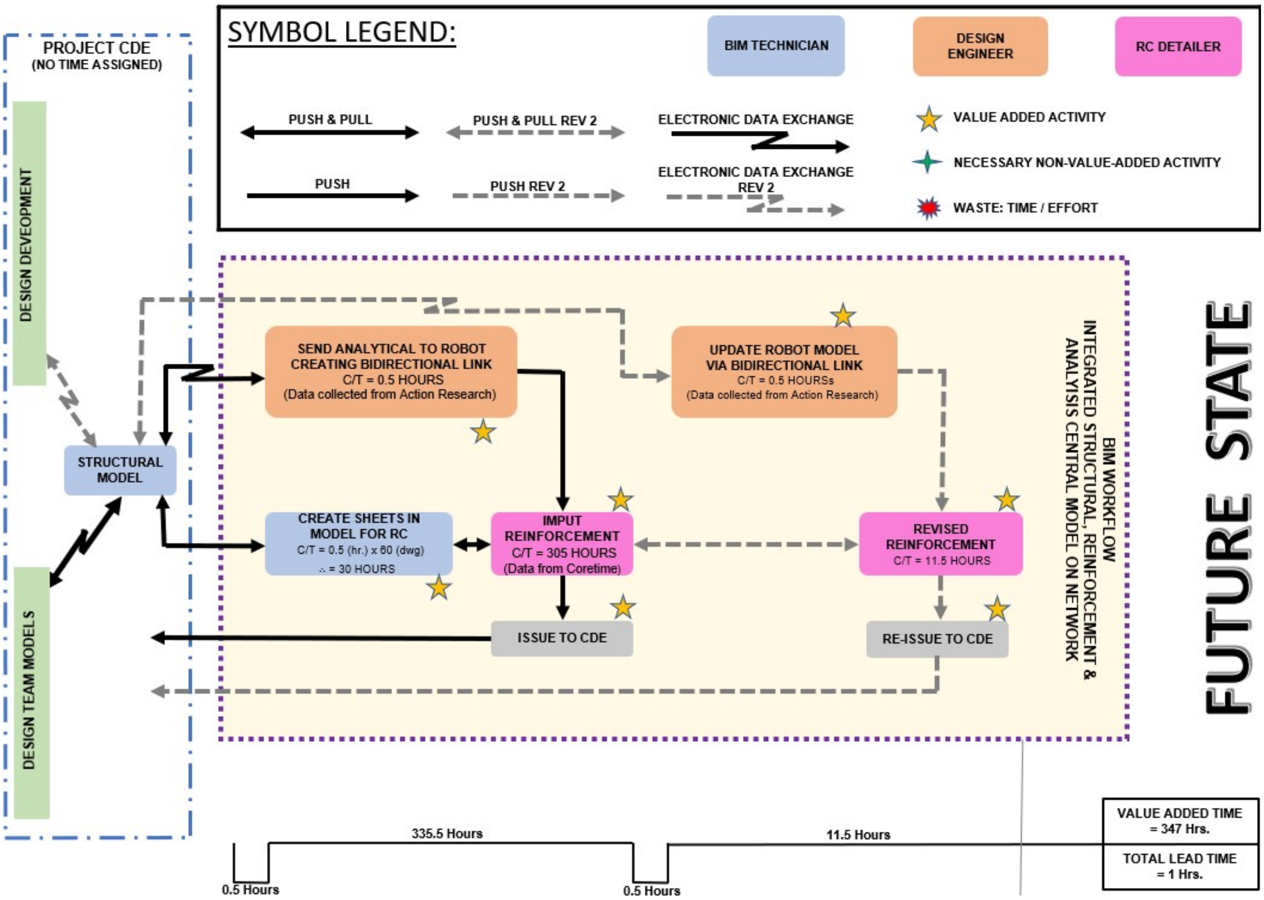

Figure 3. Value Stream Mapping – The Future State

required to undertake these revisions would be reduced up to the project completion stage.

From conducting the VSM exercise on both the current and future state workflows, the importance of integrating the reinforcement elements of projects into the BIM environment is evident.

4.5 Enhanced BIM and Lean workflow

Throughout their research on the project, the authors found that embedding the reinforcement design and draughting processes can bring the whole structural design team together, offering a more collaborative workflow that eliminates non-value-added activity.

The central model stored on the organisation's network, hosting the integrated structural, reinforcement and analysis models, essentially acts as a CDE for the project. Creating local files from this data-rich central model, which serves as `the single source of truth` for the structural information, allows each collaborator to proceed with their specific design or detailing before syncing this information back to the central model and updating it. The enhanced workflow, illustrated in Figure 4, removes the current design silos, ensuring that the most up-to-date information is accessible to all stakeholders within the process.

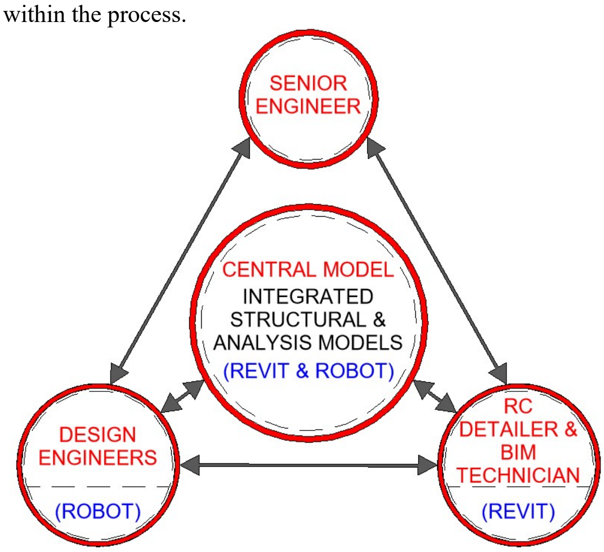

Figure 4. Enhanced RC BIM Workflow

The findings of the mapping exercise highlighted a marked increase in efficiency, with the future state workflow reducing cycle times by 60%, as shown in Table 1.

Table 1: Cycle Time Reduction

	Current State (hrs)	Future State (hrs)
Value Added Time	712	347
Lead Time	168.25	1
Cycle Time	880.25	348

Percentage Improvement in Process Time =
(Future State–Current State)/Current State x 100%

∴ (348-880.25) / 880.25 x 100%
∴-532.25 / 880.25 x 100%
∴ = -60.46%

5 CONCLUSIONS

One of the most significant obstacles to the advancement of BIM within structural engineering organisations is that it is often presented as a stand-alone initiative. As highlighted in this paper, BIM can be applied without Lean; however, the efficiencies inherent in BIM are not often realised when implemented in this way. Introduced in this manner, BIM can, in many cases, add another layer to the traditional structural design workflows without the proper organisational structure in place. Thus, the successful alignment of BIM with work processes is critical for successful BIM adoption. Lean thinking fosters a culture of continuous improvement, enabling organisations to adapt and embrace this new way of working. The synergies between Lean and BIM mean combining both achieves more significant benefits than introducing BIM in isolation.

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An advanced binary slime mould algorithm for feature subset selection in structural health monitoring data

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ABSTRACT: Feature selection is an important task for data analysis, pattern classification systems, and data mining applications. In this paper, an advanced version of binary slime mould algorithm (ABSMA) is introduced for feature subset selection to enhance the capability of the original SMA for processing of measured data collected from monitoring sensors installed on structures. In the first step, structural response signals under ambient vibration are pre-processed according to statistical characteristics for feature extraction. In the second step, extracted features of a structure are reduced using an optimization algorithm to find a minimal subset of salient features by removing noisy, irrelevant and redundant data. Finally, the optimized feature vectors are used as inputs to the surrogate models based on radial basis function neural network (RBFNN). A benchmark dataset of a wooden bridge model is considered as a test example. The results indicate that the proposed ABSMA shows better performance and convergence rate in comparison with four well-known metaheuristic optimizations. Furthermore, it can be concluded that the proposed feature subset selection method has the capability of more than 80% data reduction.

KEY WORDS: Feature selection; Binary slime mould algorithm; Surrogate model, Data reduction.

1 INTRODUCTION

Vibration-based structural health monitoring has been widely explored over the past decades. Avci et al. [1] and Das et al. [2] presented a comprehensive review of various vibration-based damage detection methods and their applications to civil structures and infrastructures. Recently, with the fast development in sensing technologies [3], [4], signal processing techniques [5], [6], and machine learning [7], [8], a number of advanced methods have been proposed [10,11]. Gharehbaghi al. [9] recently reviewed the new development of structural health monitoring for civil engineering structures.

In vibration-based SHM, damage identification is performed from vibration signals measured simultaneously at different locations of the structure [10]. Damage detection can be performed in the time domain from the raw sensor data or in the feature domain, in which damage-sensitive features are first extracted from the time series, This process is referred to as feature extraction [11].

Another importing step in extracting the useful information and signal processing is Feature Selection (FS) [12], [13]. FS is generally used in machine learning, especially when the learning task involves high-dimensional datasets. The primary purpose of feature selection is to choose a subset of available features, by eliminating features with little or no predictive information and also redundant features that are strongly correlated [12]–[14]. The availability of large amounts of data represents a challenge to classification analysis. For example, the use of many features may require the estimation of a considerable number of parameters during the classification process. Ideally, each feature used in the classification process should add an independent set of information. Often, however, features are highly correlated, and this can suggest a degree of redundancy in the available information which may have a negative impact on classification accuracy [12]. Thus, the FS approaches is needed to tackle these problems.

For a large number of features, evaluating all states is computationally non-feasible and therefore metaheuristic search methods are required. Due to the inefficiency of traditional search approaches in solving complex combinatorial optimization problems various metaheuristics have been proposed, such as Particle Swarm Optimization (PSO)[15], Genetic Algorithm (GA)-based attribute reduction [16], Gravitational Search Algorithm (GSA) [17].

The metaheuristic algorithms above-mentioned strengths motivated us to present a metaheuristic-based method for FS in SHM. Slime mould algorithm (SMA) [18] is a novel and robust metaheuristic algorithm proposed to solve continuous problem and it's inspired by the propagation and foraging of the slime mould and includes a unique mathematical model. However, considering that the FS is a combinatorial optimization problem, a binary version of SMA is used [19], and its performance is improved by incorporating two new operators in algorithm: mutation and crossover.

The main focus of this research is facilitating the processing of large data set in SHM [20]. Accordingly, the integrated system consists of three blocks is used in this paper. Firstly, statistical characteristics of structural response signals under ambient vibration are extracted, and feature vectors are obtained. Subsequently, the best feature subset is selected by the ABSMA algorithm based on desirability index using F-score [21]. In the final step, selected feature is employed for training the surrogate model based on radial basis function neural network (RBFNN).

The proposed method's performance is evaluated statistically on benchmark dataset of wooden bridge model [22]. Furthermore, the efficacy of using ABSMA as the main algorithm for feature selection is compared to Binary Particle

Swarm Optimization (BPSO) [15], binary Harris hawks optimization(BHHO) [23], binary whale optimization algorithm (BWOA) [24] and binary farmland fertility optimization algorithm (BFFA) [25]. Moreover, the impact of various transfer functions on accuracy of ABSMA is also accessed

2 DAMAGE DETECTION PROCEDURE BASED ON THE PROPOSED ALGORITHM

Fig. 1 presents a summary of the method employed in this paper for an optimal feature subset selection and health monitoring of structures. The method consists of three main blocks:
(A) The Feature Extraction Block, (B) The Feature Selection Block and (C) The Feature Classification Block.

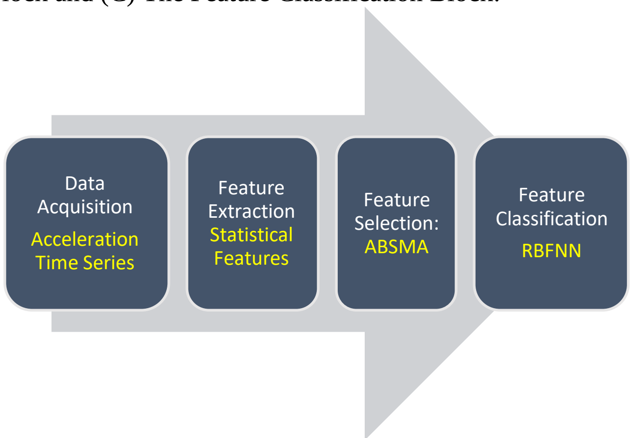


Figure 1. Summary of damage detection approach

2.1 *Feature Extraction block: Statistical Features (SF)*

Time-domain vibrational signals collected from sensors can be pre-processed to form feature vectors using the functions shown in Table 1. The features of each sensor are: root mean square, variance, skewness, kurtosis, crest factor, the maximum and range of acceleration response signal of each sensor [26].

Table 1 Time-domain features

Feature	Function
Root mean square	$rms = \sqrt{\frac{\sum_{n=1}^{N}(x(n))^2}{N}}$
Variance	$var = \sigma^2 = \frac{\sum_{n=1}^{N}(x(n) - mean(x))^2}{(N-1)}$
Skewness	$skewness = \frac{\sum_{n=1}^{N}(x(n) - mean(x))^3}{(N-1)\sigma^3}$
Kurtosis	$kurtosis = \frac{\sum_{n=1}^{N}(x(n) - mean(x))^4}{(N-1)\sigma^4}$
Crest factor	$crest = \frac{\max \lvert x(n) \rvert}{rms}$
Maximum value	$max = \max \lvert x(n) \rvert$
Range	$range = \max\lvert x(n)\rvert - \min\lvert x(n)\rvert$

These features represent the energy, the vibration amplitude and the time series distribution of the signal in time-domain [26].

2.2 *Feature Selection Block: Slime mould algorithm*

In second block, the best subset of extracted features will be selected using ABSMA based on the objective function that will describe in next subsection.Slime mould algorithm (SMA) is proposed by [18] based on the oscillation mode of slime mould in nature. The proposed SMA has several features with a unique mathematical model that uses adaptive weights to simulate the process of producing positive and negative feedback of the propagation wave of slime mould based on bio-oscillator and to form the optimal path for connecting food with excellent exploratory ability and exploitation propensity. For complete details, please refer to main paper by Li et al. [18]. The logic of SMA is shown in Fig. 2.

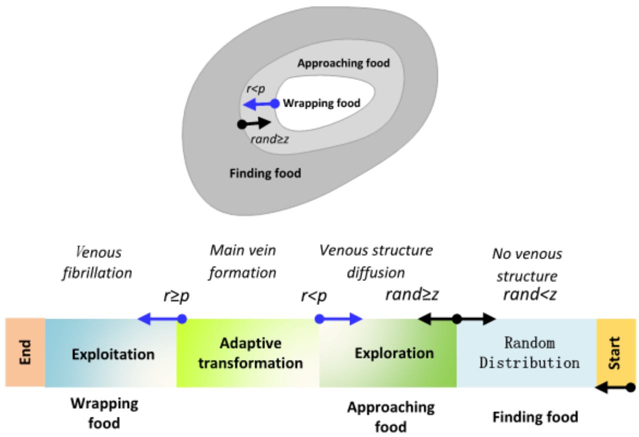


Figure 2. The overall steps of SMA [18].

2.2.1 Binary Slime mould algorithm

All meta-heuristics start with the initialization step to spread the solutions within the search space of the optimization problem. Accordingly, the proposed algorithm is initialized by creating a population of n moulds. Each mould which represents a solution to the optimization process that has d dimensions equal to the number of features in the used dataset. The FS problem is considered a discrete problem as it is based on choosing a number of features that provides the machine learning methods with better classification accuracy. Therefore, for each dimension, the proposed algorithm is randomly initialized with a value of 1 for the accepted feature or 0 as the rejected one as shown in Fig. 3. This provides the representation of an initial solution for the FS. Then, at the end of each iteration, each mould has a solution in the form of a binary vector with the same length as the number of the features, where 1 means selecting and 0 means deselecting the corresponding feature. This process continues for all iterations and at last, the best feature subset with the least classification error of the classifier is suggested as the best result.

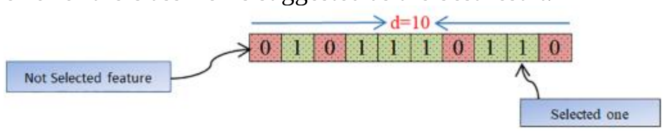


Figure 3. An initial solution to the FS.

It should be noted that, the values generated by the standard SMA are continuous, but the features in FS problems are binary: 0 (selected feature) and 1 (not selected) values. Therefore, a wide range of transfer functions belonging to the family of the V-Shaped and S-Shaped functions [19] has been supposed to convert continuous values into binary.
Selected V-Shaped and S-shaped transfer functions are listed in Table 2. A transfer function receives a real value from the standard SMA as an input and then normalizes this value between 0 and 1 using one of the formulas in Table 2. The normalized value is then converted to a binary value using Eq. (2) [19] .

$$S_{binary} = f(x)\begin{cases}1, & if\ S(a) > 0.5\\ 0, & otherwise\end{cases} \tag{1}$$

Table 2: V-Shaped and S-shaped transfer function.

V-Shaped	S-Shaped
V1, $F(a) = \left\lvert\frac{2}{\pi}\tan^{-1}(\frac{\pi}{2}a)\right\rvert$	S1, $F(a) = \frac{1}{1+e^{-a}}$
V2, $F(a) = \lvert\tanh(a)\rvert$	S2, $F(a) = \frac{1}{1+e^{-2a}}$
V3, $F(a) = \left\lvert\frac{a}{\sqrt{1+a^2}}\right\rvert$	S3, $F(a) = \frac{1}{1+e^{-\frac{a}{2}}}$
V4, $F(a) = \left\lvert\mathrm{erf}(\frac{\sqrt{\pi}}{2}a)\right\rvert$	S4, $F(a) = \frac{1}{1+e^{-\frac{a}{3}}}$

2.2.2 Fitness Function

The fitness function (FF) is an important factor for the speed and the efficiency of ABSMA algorithm. In this study, the fitness function of ABSMA is developed based on the surrogate model accuracy and the efficiency of selected subset of features. The surrogate model (RBFNN) accuracy is obtained by the evaluation of the test data classification using the trained model. In addition, efficiency of the selected subset of features are evaluated using the F-score to measure desirability of the features. ABSMA selects the vector with the smallest fitness value when the completion conditions are satisfied. The fitness function of ABSMA is formed as follows:

$$FF = 1 - \left[W \times (Classification\ Accuracy) + (1-W) \times \left(\frac{1}{\mathrm{n}}\sum_{i=1}^{n} F_{score_i}\right)\right] \tag{2}$$

where W is weighting factor between 0 to 1 and n is the total number of features.

2.2.3 Measure the desirability of features: F-score

A desirability value, for each feature generally represents the attractiveness of the features, and can be any subset evaluation function like an entropy-based measure or rough set dependency measure [27]. In this paper, F-score will be used as index for measuring the desirability of the features. The F-score is a measurement to evaluate the discrimination ability of the feature $\boldsymbol{i}$. Eq. (3) defines the F-score of the $\boldsymbol{i^{th}}$ feature. The numerator specifies the discrimination among the categories of the target variable, and the denominator indicates the discrimination within each category. A larger F-score implies to a greater likelihood that this feature is discriminative [21].

$$F_{score_i} = \frac{\sum_{k=1}^{c}\left(\bar{x}_i^k - \bar{x}_i\right)^2}{\sum_{k=1}^{c}\left[\frac{1}{N_i^k - 1}\sum_{j=1}^{N_i^k}\left(x_{ij}^k - \bar{x}_i^k\right)^2\right]} \tag{3}$$

where c is the number of classes and $\mathbf{n}$ is the number of features; N_i^k is the number of samples of the feature i in class k, ($\boldsymbol{k} = \mathbf{1}, \mathbf{2}, \dots, \boldsymbol{c}$; $\boldsymbol{i} = \mathbf{1}, \mathbf{2}, \dots, \boldsymbol{n}$), x_{ij}^k is the $\boldsymbol{j}$-th training sample for the feature $\boldsymbol{i}$ in class k, ($j = 1,2,\dots,\boldsymbol{N_i^k}$), $\boldsymbol{x_i}$ is the mean value of feature $\boldsymbol{i}$ of all classes and x_{ik} is the mean value of feature $\boldsymbol{i}$ of the samples in class $\boldsymbol{k}$ [21].

It should be mentioned that the features selected by the proposed algorithms are evaluated with the well-known metrics precision, recall, accuracy, F1- score and Feature-Reduction index (F_r). In this paper, the classification accuracy (CA) is used to define the quality function of a solution, which is the percentage of samples correctly classified and evaluated as Eq. (4):

$$Accuracy = \frac{Number\ of\ samples\ correctly\ classified}{Total\ number\ of\ samples\ taken\ for\ exprimentation} \tag{4}$$

Another parameter which is used for comparison is the average feature reduction F_r, to investigate the rate of feature reduction:

$$F_r = \frac{n-p}{n} \tag{5}$$

where n is the total number of features and p is the number of selected features by the FS algorithm F_r is the average feature reduction. The more it is close to 1, the more features are reduced, and the classifier complexity is less.

2.2.4 Advanced version of binary slime mould algorithm

In the proposed BSMA, two ideas from genetic algorithm [28] are implement on the BSMA to enhances its capability for the FS and solve low population diversity. The new solutions in GA are created by the two operators: crossover and mutation. In the crossover operator, two solution sets are selected randomly and some portions are exchanged, thereby creating two new solutions. In the mutation operator, a randomly selected bit of a particular solution is mutated; means the 1 is changed to 0 and 0 is changed to 1. Therefore, in the first step of proposed method, a random solution is generated, and then a crossover operation is applied to the randomly generated solution and the best solution. Next, the solution obtained from the crossover operation is given as inputs to the mutation operation. The main intention of these operations is increase population diversity and escapes from local optimal points and improve solutions' quality.

2.3 Feature Classification Block: radial basis function neural network

In the final block of the employed framework, a well-trained surrogate model is applied to classify various condition of the structure. In these models, the input matrix will include the selected features and the outputs are the corresponding damage conditions. In recent years, many neural network models have been proposed or employed for various components of structural health monitoring in order to perform pattern classification, function approximation, and regression [29],

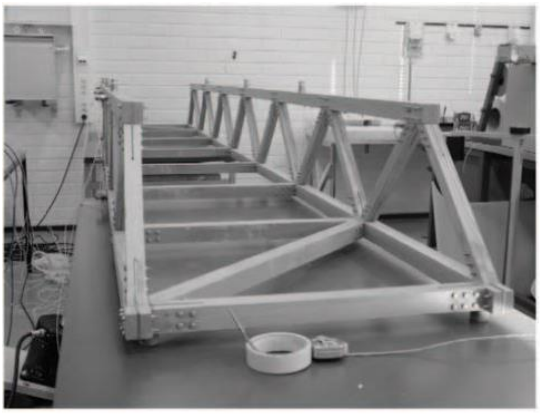
[30]. Among them, the RBF network is a type of feed forward neural networks that learns using a supervised training technique. Lowe and Broomhead [31] were the first researchers that exploited the use of the RBF for designing neural networks. Radial functions are a type of function in which the response reduces or grows monotonically with the distance from the center point. It has been shown that the RBF networks are able to approximate any reasonable continuous function mapping with a satisfactory level of accuracy [32].

3 EXPRIMENTAL RESULTS

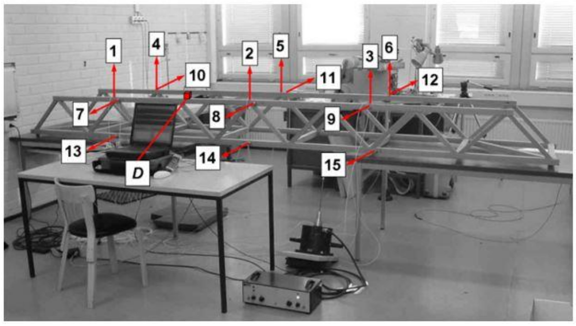
In this section, a benchmark data set is used to show the effectiveness of the proposed feature selection algorithm. The data set collected in the laboratory of Helsinki Polytechnic Stadia [22], [33] is employed in this paper. The structure was a timber bridge model as shown in Fig. 4. In order to excite the lowest modes, a random excitation was generated with an electrodynamic shaker to activate the vertical, transverse, and torsional modes. The response was measured at three different longitudinal positions by 15 accelerometers. The frequency of sampling was 256 Hz and the measurement period was 32 s. The data were filtered below 64 Hz and re-sampled for sufficient redundancy. The measurements were repeated several times and it was noticed that the dynamic properties of the structure vary due to the environmental changes. The main influencing factors were assumed to be the changes in the temperature and humidity.

In the SHM community, there are various schemes for modelling of damage scenarios, mainly damage modelled as decreasing in the module of elasticity or in the stiffness parameter of elements [8]. Moreover, some researchers used additional mass as an indicator of damage [34]. In this benchmark data set, five artificial damage scenarios were then introduced by adding small point masses of different size on the structure. The mass sizes were 23.5, 47.0, 70.5, 123.2 and 193.7 gr. The point masses were attached on the top flange, 600 mm left from the midspan (Fig. 4). The added masses were relatively small compared to the total mass of the bridge (36 kg), where the highest mass increase was only 0.5 %.

The total number of experiments were carried out on the structure was 273. The 190 measurements were selected as the training data. The test data consisted of both healthy and abnormal systems measurements. It is worth mentioning that the total number of extracted features for each experiment based on Table 1 is: 15 sensors ×7 features=105 features.



(a) Wooden bridge model



(b) Wooden bridge with the locations of sensors and damage (D) are indicated [22].

Figure 4. Wooden bridge

3.1 *Impact of transfer functions on the ABSMA*

In this subsection, the impact of the transfer functions on the ABSMA's performance is investigated. For providing the stochastic behaviour of metaheuristic algorithms, the performance of the algorithms is compared using the best, worst, average and standard deviation (SD) of the obtained fitness values over 20 independent runs in Table 3. Columns BSMAS1, BSMAS2, BSMAS3, BSMAS4, BSMAV1, BSMAV2, BSMAV3, and BSMAV4 gives the results of the transfer functions S1, S2, S3, S4, V1, V2, V3, and V4, respectively. According to the results of Table 3, the ABSMA algorithm has performed the best using V2. Moreover, according to the SD, the best performance is related to BSMAV2. Therefore, V2 is selected as the transfer function in this study.

Table 3: The best fitness values under eight different transfer functions

	ABSMA-V1	ABSMA-V2	ABSMA-V3	ABSMA-V4
Best	0.07	0.04	0.09	0.1
Avg	0.11	0.07	0.11	0.13
Worst	0.14	0.12	0.13	0.15
SD	0.02	0.02	0.01	0.02
	ABSMA-S1	ABSMA-S2	ABSMA-S3	ABSMA-S4
Best	0.11	0.1	0.07	0.05
Avg	0.13	0.12	0.09	0.07
Worst	0.14	0.14	0.11	0.1
SD	0.01	0.01	0.01	0.01

3.2 *Classification accuracy of metaheuristic optimization algorithms*

In this section, the accuracy and effectiveness of the proposed framework for feature extraction/selection in SHM domain is evaluated. Furthermore, the results obtained by the proposed ABSMA algorithm are compared to BPSO [15], BHHO [23], BWOA [24], and BFFA [25] which are reported to be good algorithms in FS [19]. The parameters need to be set in these algorithms are set to the best values are reported in the original papers. The population size for all the algorithms is 50 and the maximum iterations is set to be 200. The weighting factor W in the fitness function is varied from 0.6 to 0.9 to get the different sets of features. The results are averaged over 20 independent runs in each data set and by every algorithm.

Table 4 gives the mean of the CA, best, worst, average and SD of the results for each algorithm. The number in the brackets in each table slot shows the ranking of each algorithm. A comparison of the average precision, recall, F1 score and the amount of F_r for other algorithms are given in Table 5. It can concluded from these tables that the proposed ABSMA algorithm can obtain, in most of cases, better classification accuracy using a smaller feature set, compared to other algorithms

Table 4: Classification accuracy of each algorithm for the tested datasets of Wooden bridge

	ABSMA	BHHO	BPSO	BWOA	BFFA
Mean of CA (Rank)	**0.94** (1)	0.87 (2)	0.81 (4)	0.86 (3)	0.8 (5)
Best	0.04	0.09	0.12	0.09	0.13
Avg	0.07	0.13	0.17	0.13	0.19
Worst	0.12	0.16	0.22	0.16	0.23
SD	0.02	0.02	0.03	0.02	0.03

Table 5: Comparison of the performance (precision, recall, F1-score and Fr) of the algorithms on Wooden bridge

Metrics	ABSMA	BHHO	BPSO	BWOA	BFFA
Precision	0.94	0.88	0.83	0.87	0.81
Recall	0.96	0.92	0.87	0.91	0.86
F1-score	0.95	0.90	0.85	0.89	0.83
Fr	0.81	0.714	0.667	0.743	0.619

The extended results are also shown in Figures 5-6. From these figures, one may admit that ABSMA not only finds smaller feature subsets than the other algorithms, but also the number of selected features also decreases much faster.

It can be concluded that the ABSMA provides a higher degree of exploration than the other algorithms, which enables it to explore the search space to find a solution that selects a smaller number of features and better performance.

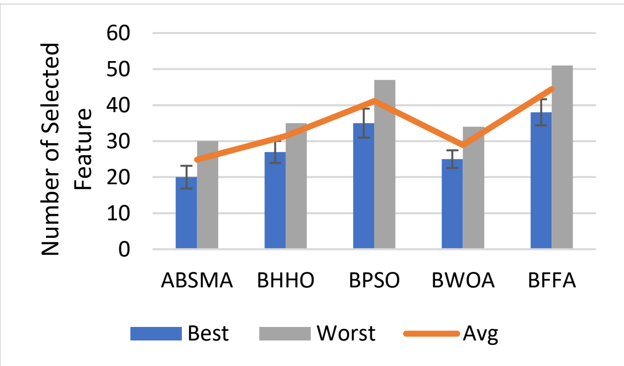


Fig. 5 Number of selected features of each optimization algorithms

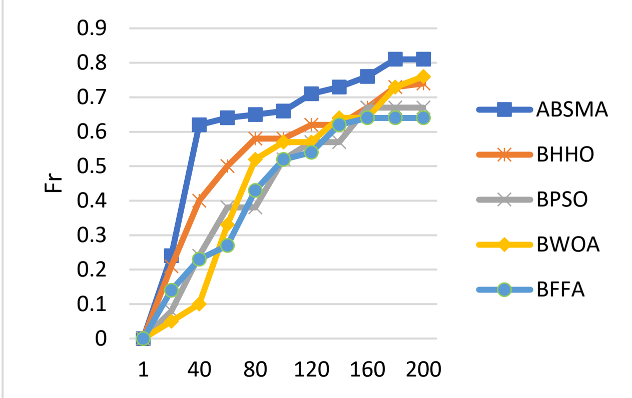


Fig. 6 Average of Fr for each optimization algorithms with respect to number of iteration

It is worth to note that, the FS method proposed in this study is a supervised wrapper-based feature selection method [13]. Generally, in comparison with the filter model, the wrapper model could achieve a higher classification accuracy and tend to have a smaller subset size; however, it has high time complexity [12].

Finally, according to the results shown, adding desirability index, mutation and crossover operators to the BSMA increases the exploration of the search and guide the algorithm to more salient features.

4 CONCLUSIONS

In this paper, a new framework is presented for the feature selection for SHM problems. Furthermore, an ABSMA is presented for enhance capability of SMA in this domain. The mutation and crossover operators are employed in the original BSMA to the proposed ABSMA which could increase diversity and prevent excessive convergence during the optimization process, and local optimal trap escape. A data set collected from a timber bridge is employed in this paper. The ABSMA is initially evaluated using eight transfer functions that convert continuous solutions to binary ones, in which the best transfer function (transfer function V2) is selected. The results obtained from the proposed algorithm were compared with 4 state-of-the-art metaheuristic-based algorithms including BHHO, BPSO, BWOA and BFFA. The results of the experiments indicate that a significant improvement in the proposed algorithm compared to other ones. Moreover, the proposed framework can remove the irrelevant and redundant information by choosing useful features as the input of the surrogate model. It is shown that the proposed FS approach based on the ABSMA optimization algorithm reaches a better feature set in terms of classification accuracy and the number of selected features.

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