AN INTEGRATED APPLICATION OF BUILDING INFORMATION MODELING, COMPUTER-AIDED MANUFACTURING, MACHINE LEARNING, AND THE INTERNET OF THINGS

A Hybrid Stadium as a Case Study

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Abstract Using building information modeling (BIM), design teams can maximize decision-making efficiency by using one data-sharing platform and one integrated digital model. We present a novel built-project that integrates computer-aided manufacturing (CAM), machine learning, and internet of things (IoT) with a BIM process. The goal is to solve design and manufacturing problems and tightly connect virtual design data with the real-world construction process. Introducing CAM in the early phase reduces the cost of reverse engineering and optimizes material and construction costs. Machine learning has been used for curtain wall panel standardization and to solve manufacturing problems. The IoT concept focuses on directing the data stream onto real-world objects and updating the digital model using feedback from real-world monitoring. Using the integrated application in this project, a hybrid Olympic stadium, helped to accelerate the process of design and reduced the time and cost for manufacturing and construction.

Keywords Building Information Modeling (BIM), Computer Aided Manufacturing (CAM), Machine Learning, Internet of Things (IoT), Panel Standardization.

1. Introduction

In recent years, building information modeling (BIM) has become the most powerful tool for increasing efficiency and accuracy within AEC (Architecture, Engineering, and Construction) industries. By integrating different disciplines into one data-sharing platform during the design phase, a much more accurate digital representation, or model, can be created, significantly decreasing data loss during the transitions between project phases (Borrmann et al., 2018). Many data-based advanced technologies can be integrated with the BIM data stream to address specific problems. Recent work in the BIM field has focused on BIM-enabled AR for construction (Chernick et al., 2021), data transmission for cloud-based BIM (Kereshmeh et al., 2016), BIM vocabulary and syntactical study (Al-Assaf & Clayton, 2017), diagram-aided design in BIM (Al-Assaf & Clayton, 2021), and machine learning-aided fire code classification in BIM (Albassel & Waly, 2021). These studies expanded the scope of BIM application.

1.1. MACHINE LEARNING AND DATA CLUSTERING

Over the past decade, machine learning has proven to be a very powerful tool in many fields, including architecture. Clustering is a basic but important machine-learning method. Clustering is the task of dividing data into several groups based on similarity. It has been widely applied in many fields, e.g., in marketing to characterize different customers, in biology for species classification, and in business for fraud detection. In architecture, clustering has been used for architecture type classification (Abdulrahman et al., 2020), urban features recognition (Chaszar & Beirã, 2013), and data visualization in building space (Meng et al., 2020). The potential for applications of clustering related to design construction is substantial, not least because it could help rationalize the application of non-linear parametrical design to buildable segments. In this paper, we refer to the Soumaya Museum project conducted by FR-EE in 2011, which applied a clustering technique to rationalize the hexagon panels on its façade.

1.2. CONSTRUCTION AND USER MANUAL

Among the AEC industries, architecture and engineering are the most digitized and can smoothly embrace BIM, achieving a significant reduction in lost information. However, the use of BIM in construction is lagging. Traditional drawings from the design team continue to be the primary output for the contractor or manufacturer, even in BIM projects. Previous study has proposed an AR-aided method based on real-world alignment (Chernick et al., 2019), but this promise to complement the drawing set rather than replace it. Construction is a dynamic process that combines raw materials based on the contractor's experience and the detailed user manual. Designs focus more on the product than the process. An analogy can be made to assembling an Ikea cabinet after seeing only a model of the final product; unless you are an expert in Ikea products, you may also require a step-by-step manual. In most cases, the modern practice in BIM is not to focus on creating the step-by-step manual but rather on the design result.

Moreover, the processing technology required for complex structures may not fully satisfy the requirements of the engineered structure. In conclusion, there remains a gap between the design goal and the resulting construction that is not being filled by BIM.

1.3. PROJECT BACKGROUND

Designed by Archi-Tectonics, the table tennis stadium project is part of a larger master plan for the 2022 Asian Games. It is a 116-acre sustainable landscape with two Olympic stadiums, a shopping mall, an exhibition center, a fitness center, and two underground parking garages. The table tennis stadium itself was inspired by an ancient Chinese object called a Cong, which is an intersection of two different geometries—a cylinder and a square. The shape of the table tennis stadium is two intersecting ellipses which are completely asymmetrical and non-linear.

This complex project involves many stakeholders from different fields of expertise, which poses many challenges in coordinating the massive amount of information. In addition, as the project is being built for the 2022 Asian Games, which will be held in the autumn of 2023, it is extremely time sensitive.

1.4. PROJECT GOAL

As described above, in the traditional BIM process, information continues to be lost throughout the process, especially when transferring data from design entities to manufacturers and construction workers. This paper aims to discover how to create a workflow that can carry information from the digital design to the construction site with much less information loss.

The goals are as follows: to establish a continuous flow of information on a shared platform for all stakeholders throughout the project, including the manufacturers and construction entities; to build a central digital model that contains data from all the disciplines; to apply advanced, data-driven technologies to solve specific problems during a stage when information usually tends to be lost; and to improve accuracy and efficiency and minimize costs and losses by all teams. This paper consists of two parts: the first describes the overall BIM strategy, and the second uses the curtain wall system as an example to show how machine learning, the internet of things, and other techniques have been used to deliver data from design to build.

2. Methodology

2.1. GENERAL METHODOLOGIES

To manipulate data as smoothly as possible, this project fully adopted the BIM process in the second stage, which is when most stakeholders in other disciplines, we included the main manufacturers and contractors early in this stage.

We based our BIM pipeline on the classic method using one software system for cloud data sharing and one central software model by Revit. Rather than using only the central software, we chose to adopt the "open BIM" approach, which allows all stakeholders to use different data media, with certain restrictions, on a shared platform. This approach will be clarified in the next section. We will then show how we applied machine learning and the IoT to the manufacturing of the curtain wall system.

2.2. . WORKFLOW FOR DATA

We assembled a large multi-disciplinary stakeholder team. First, working with the code consultants, we developed a unique set of BIM standards for this project, based on local codes and regulations as well as the actual situation of each participant. Next, a mutual data-sharing cloud-based platform was established. We chose ProjectWise to serve as the main file exchange platform. We choose to use open BIM, which allows different file formats to be coordinated. There are two reasons that open BIM was the preferred choice. First, there is no single software product that could provide the best solution for all disciplines. Second, every industry already has its own preferred software, so open BIM would serve best for interdisciplinary coordination. We set up the Revit model as the central integrated model to be used by the architect, landscape designer, and the structural and MEP engineers. This central model focuses on the result of the building.

Different software systems were used for different purposes (Figure 1). For example, the structural analysis took place on SAP2000, which is a mature finite element analysis software based on mesh.

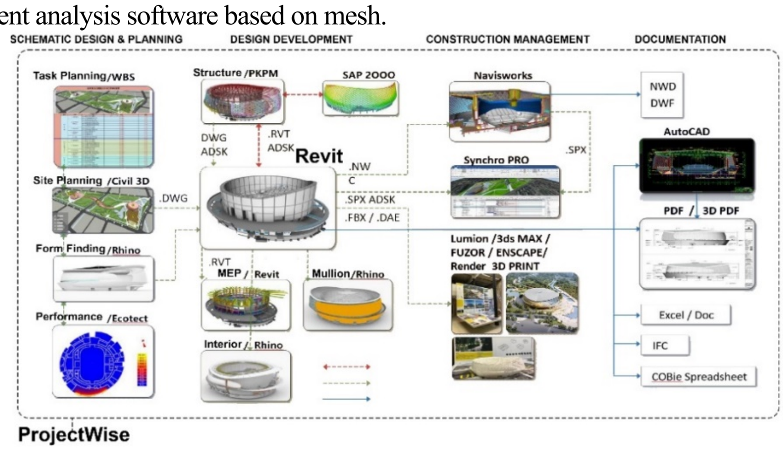


Figure 1. Revit-centered BIM software on ProjectWise platform

At this stage, the goal was to detail the design of every part of the building, which means the output model of this stage would be the same as the built project—a fully integrated digital model. All engineering systems would be simulated and proved to work. The BIM was broken down into eight systems (Figure 2), depending on professions and location.

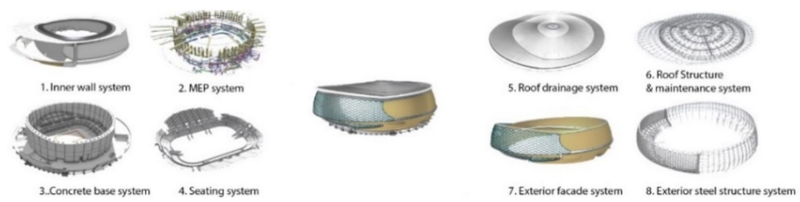


Figure 2. Eight systems for the hybrid building

2.3. EXTERIOR CURTAIN WALL

Among the eight systems, two of them— the façade steel structure and the curtain wall system attached to it—together form the exterior envelope, which was designed as the intersection of several freeform surfaces. Half of the surfaces is covered in brass shingle panels; the other half is covered by tilted rhombus shapes. Figure 3 shows the detailed sub-layers of the glass and metal curtain wall systems. This stage could present challenges in terms of translating the design information into built objects, considering the gap between design and manufacturing in a traditional workflow. However, manufacturing stakeholders—including local suppliers and the procurement team—

were involved in the design development phase of the BIM process, which facilitated effective problem-solving. Our design team understood the requirements of the manufacturing method and thus set up a workflow from design to manufacture.

Figure 3. Exterior curtain wall system of the stadium

2.4. RATIONALIZATION OF STEEL STRUCTURE

The geometrical logic of the twisted diagrid structure is based on the freeform control surface and control grid curves (Figure 4). The challenge was that the tilted glass panels and the structure underneath are integrated, which means the design had to balance structural performance and aesthetic values in ways that were difficult to manufacture.

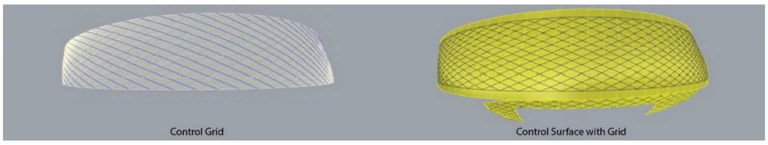


Figure 4. Control surface and control grid

In the original design, we established an equal-thickness shell model by offsetting the control surface in the direction of the surface normal. We then hollowed out the shell according to the control grid. The resulting model has two freeform surfaces: front and bottom. These cannot be flattened to a planar surface. The processing technique could not manufacture the freeform 3D geometry.

The manufacturing method is based on metal bending in which planar steel panels are bent to developable spatial surfaces. Based on this method, we rationalized the model to meet the manufacturing requirements. The mathematical detail has been explained in another paper (Wu et al., 2021). The final model was modified to sweep surfaces with rectangular section frames on the control grid based on arc length so that all surfaces would be developable (Figure 5). During manufacturing, the suppliers can CNC-cut the planar metal sheets, bend them separately to form the four surfaces of the structure, and assemble them onto structural tubes, which will be delivered to site for final assembly.

The rationalization process was conducted using Rhino and Grasshopper. We exported the design model to match the data format used by the CNC-cutting and bending machines, giving the supplier access to the file via ProjectWise.

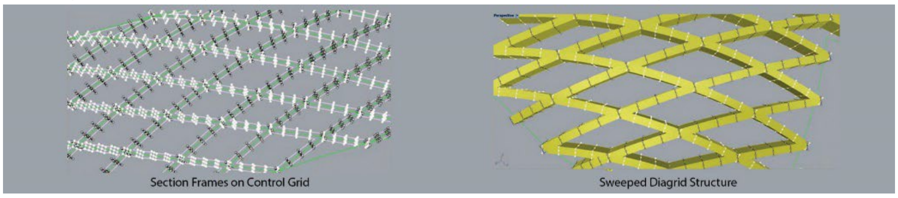


Figure 5. Section frame and diagrid structure by sweep

2.5. MACHINE LEARNING-AIDED PANEL STANDARDIZATION

Unlike the glass façade, the structure and appearance of the brass shingle façade are separate. The challenge here is that there are 6,435 panels, each of which has an identical spatial surface (Figure 6). It was impossible to manufacture each one locally.

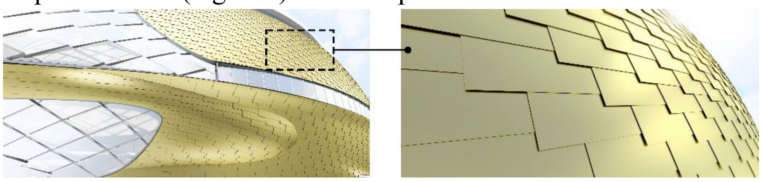


Figure 6. Original parametrical brass shingle panels

The goal was to standardize the panels to an acceptable number of groups and to simplify the spatial panels to planar panels, in response to the manufacturing requirement, the design team applied new techniques to optimize the design, aiming to avoid any reverse engineering and reduce information lost. We conducted a three-step method, aided by the machine-learning clustering technique, to achieve this level of rationalization.

First, we divided the panels into two groups: edge panels and center panels. The edge panels were more irregular and had to be processed separately. Regarding the central panels, the vital challenge was to find a way to divide them into a certain number of groups of similar panels so that they could be standardized to type. An unsupervised machine-learning model was used for this task. Lastly, one standardized panel was generated for each group of panels, based on the average features of all the panels in that group.

2.5.1. Pre-training preparation and features engineering

Features engineering is crucial for machine-learning training. Before applying the machine-learning method, the panels needed to be flattened to planar surfaces to reduce the number of features during training. This is because a planar quadrilateral can be defined only by the length of its four sides and the angles of its four corners, and it is much harder to define an undevelopable quadrilateral. To obtain a sufficiently accurate flattened surface, we extracted the four corner points of each panel, obtained a fitted plane using the PlaneFit battery in Grasshopper, and projected the panel to the fitted plane to generate the flattened surface. During the flattening process, we obtained the first feature for future training—the deviation between the fitted and original surfaces.

After flattening, twelve features were selected: one panel deviation rate (1); the lengths of four sides (4); the angles of three corners (the fourth was not needed mathematically) (3); the area of the panel (1); and the coordinates x, y, and z of the center point (3).

The first eight features are fundamental; the ninth feature, area, can be used as an estimate feature to stand in for lengths and angles features. The location features are not related to the shape of the panels, but the clustering of neighboring panels made the numbering process easier and improved efficiency during site assembly.

Feature normalization was conducted after feature selection. This process is necessary because the above-mentioned features were in varying scales. The scaling technique shifted and rescaled features to the same or a similar range (usually 0 and 1). This helped to speed up the model training and ensured that every feature was training proportionately. The features used in training were determined after multiple iterations of training, more details will be explained in the next paragraph.

2.5.2. Model training and comparison of results

We used two clustering methods for training: the K-mean model and the Gaussian Mixture Model (GMM). After comparing results and feature selection, we determined the best method for clustering.

We used three groups of features for training with both models: Group A contained deviation and area features; Group B contained the side lengths, the corner angles, and the deviation feature; Group C contained all features other than the area feature.

We set the K number for both models and determined the number of groups from 10 to 50. Figure 7 shows the visualized results for different K and feature groups. Each color in one single training result represents one cluster. The training results were very similar for both models in Group A, while the training speed of the K-mean was faster.

The training results in Group C for both models were similar as well; however, the location feature was too dominant and unnecessary. The K-mean algorithm is based on the Euclidean distance of features, while the GMM is based on probability and an assumption that each feature would fit a Gaussian distribution. Without going into detail on the mathematics involved, the conclusion is that when data distribution is more irregular, the GMM is more accurate, and when data distribution is more homogeneous, the K-mean model is accurate enough but faster.

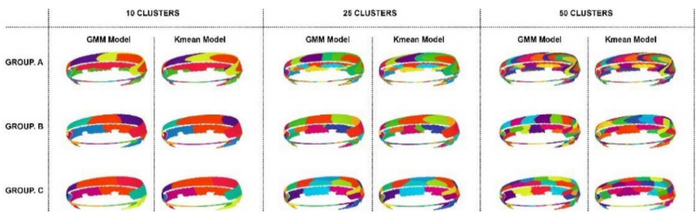
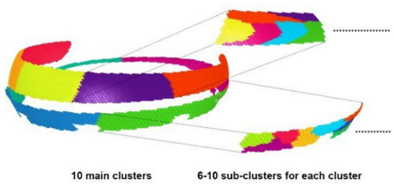


Figure 7. Training results for all three groups

Another way to reduce the training time and increase accuracy is to conduct multi-step clustering. Considering the training result in Figure 7, we conducted a two-step clustering process. First, we clustered the panels into 10 groups by K-mean with area feature; then, we trained each of the ten groups into 85 smaller groups by GMM with Group B features (Figure 8).



B-3	B-rec03	1850	1000	30	1.91	26	49.54	455	907.30
	B-rec04	1900	1000	30	1.96	118	230.93		
	B-rec05	1950	1000	30	2.01	165	331.40		
	B-rec06	2000	1000	30	2.06	124	255.44		
	B-rec17	1850	950	30	1.81	20	36.26		
	B-rec18	1900	950	30	1.86	2	3.72		
B-6	B-rec04	1900	1000	30	1.96	32	62.62	363	716.36
	B-rec05	1950	1000	30	2.01	94	188.80		
	B-rec06	2000	1000	30	2.06	135	278.10		
	B-rec15	1750	950	30	1.72	2	3.43		
	B-rec16	1800	950	30	1.76	26	45.86		
	B-rec17	1850	950	30	1.81	28	50.76		
	B-rec18	1900	950	30	1.86	23	42.83		
	B-rec19	1950	950	30	1.91	23	43.95		

Left: Figure 8. Final clustering method. Right: Figure 9. Sample spreadsheet for each panel

2.5.3. Panel standardization and deliverables

The previous step successfully decreased the number of panels to 85 groups. The last step was to generate a standardized panel in each group and then to number all the panels for manufacturing and later construction.

The method was straightforward; all panels in each group were oriented to overlay each other, then the average corner points of the four corners were calculated. Finally, a planar quadrilateral was created by connecting the four generated points by lines. The optimized model was created to the manufacturer's requirements with a label on each panel (Figure 9). These, combined with Excel spreadsheets providing detailed dimensions of all the panels, were saved on the ProjectWise platform for easy access by the manufacturers.

2.6. IOT-AIDED CONSTRUCTION

Figure 10. QR code "sensor" and user interface of the app

One major challenge was to use the BIM model to create a user manual, to replace the traditional hard-copy drawing output, so that the work of the designers and engineers could be clearly grasped by the on-site workers, thus reducing possible misunderstandings and the loss of data in the transition to construction. We attempted to introduce IoT into the BIM, using mobile applications, to create a basic user manual of the steel structures for each worker. IoT is focused on connecting physical objects in the real world with devices through data. The idea was to track each structural component in the real world, connect each component to its digital representation in BIM, and then create an assembly simulation, allowing each worker on the site to track and understand the process of certain components.

To connect the components, first, we created a unique identifier (UID) for each structural component and connected each UID to the digital model. Then, we created a QR code for each UID, which acted as our "sensor." Those QR codes were sent to the factory via the BIM platform. Immediately after each component was produced, the corresponding QR code was attached to it (Figure 10). These sensors did not continuously send and receive data over a wireless network; instead, they were passive sensors to which location and historical data were updated each time it was scanned.

A mobile application was created that could review a partial BIM model of the exterior steel structure. When the user selected a component in the model, the app would send them the information for that component—the properties of the component, the tracking data from the UID, the physical location of the object, and its estimated time of arrival. Conversely, scanning the QR code in this application gave the user a digital representation of the corresponding physical component, so that the user could identify its relative position in the overall model and would understand when it needed to be assembled. We also created assembly simulations showing how each component should be assembled into the integrated structural system. The simulation was embedded inside the application.

3. Achievement and conclusion

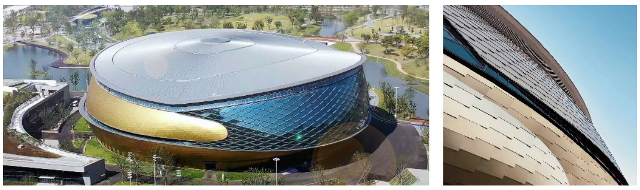


Figure 11. Completion of the table tennis stadium

This paper presents a practical application of BIM to answer the question: how to conduct a workflow that could carry information from the design to the construction with much less information loss? A complete methodology was developed for data sharing by stakeholders throughout the BIM process. Data-based technologies were integrated into this workflow. In this paper, we show that machine learning, IoT, and CAM were practical applications for the design, manufacturing, and construction of the exterior envelope of the project. The final project shows very little deviation from the initial design. Information was shared seamlessly and efficiently through the BIM process from design to construction. Integrating the different data-based technologies led to significant savings in costs, labor, and time. Using the machine-learning application on the brass panels saved approximately 1.2 million dollars by standardizing the panels to 85 types from more than 5,000 center panels. (Figure 11). Using an IoT system along with other technologies for construction site management and human resources management aided the transportation and installation of the steel structures. The final construction period was reduced from ten months to eight months.

The project has limitations. For example, the IoT application sensor could not update the information about objects continuously, and the IoT app eventually served as a supplement to the drawings, even though it had been designed to replace those. There are benefits and drawbacks, but it remains a very innovative project and a bold approach to demonstrate the strengths of the BIM process. This project serves as a good reference for future practitioners and researchers seeking to conduct data-based BIM studies on real-world projects and a valuable case study for BIM education.

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