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Application of Bayesian models in building information modeling of residential buildings



Abstract: - This paper lays forth a process for continuing Bayesian calibration of full-scale building energy simulation (BES) models by making use of data obtained from building information modeling (BIM) and building energy management systems (BEMS). According to a survey taken in China, it is possible that importing data from BIM and BEMS will dramatically cut down on the amount of time and effort required for the continuing calibration of BES models. After that, the continuous calibration approach that had been developed was examined with the use of a case study that was based on the actual calibration of a building. In China, Building Information Modeling (BIM) and data on the amount of electricity used each month over the course of the preceding three years were both incorporated into the case study. According to the findings, a non-continuous technique on the test dataset fared worse than a continuous Bayesian calibration method in terms of prediction accuracy and reduced uncertainty. The normalized mean biased error (NMBE) and the coefficient of variation of the root mean square error (CVRMSE) are both discussed in this research, and comparisons are drawn between the two.

Keywords: Bayesian models, Residential Buildings Model, Building Information, Design.

Introduction

Building information modeling, often known as BIM, is a type of digitized technology that can be defined or characterized as the process of creating, arranging, supervising, trading, and sharing building-related information in a way that is both reusable and interoperable. BIM is also referred to by its acronym, which stands for "building information modeling." BIM is made up of a large number of vital capabilities for doing building conduct analysis, which makes it easier to explore how environmentally friendly building design can be. While more recent BIM enhancements have enabled interoperability with energy performance simulation (EPS) devices, which in turn enable appraisal of operational energy, the existing BIM software, for the most part, requires interoperability with classic LCA devices, which are the primary means for measuring embodied energy(1). While this is true, more recent BIM enhancements have enabled interoperability with energy performance simulation (EPS) devices, which in turn enable appraisal of operational energy. Evaluation of operating energy is made possible by EPS devices. When the design is either done or constructed to a small degree of detail, which is when there is less extension to examine distinctive design alternatives for decreasing the building's overall energy consumption, embodied energy evaluation is typically accomplished. This is because there is less time available to investigate these distinctive design alternatives. This is as a result of the limited number of options available to do so at this moment(2). BIM systems have the potential to achieve the following objectives: (i) an improvement in productivity, efficiency, infrastructure value, quality, and sustainability; (ii) a decrease in lifetime costs, lead times, and duplications; (iii) a restriction on waste; and (iv) greater cooperation between design disciplines.

In the construction sector (3), legislation that makes it mandatory to use the green building approach was recently enacted. This was done in response to growing concerns about issues such as energy dependence on fossil fuels and carbon output. In addition, it is common for projects in the private and public sectors, as well as those located in a diverse range of countries, to exceed their allocated budgets and miss their target completion dates. The manufacturing of buildings and their upkeep are responsible for over forty percent of the world's total carbon emissions. The low worker productivity that contributes to the construction industry's inadequate production is a source of concern for construction industry experts as well as researchers in the sector. Productivity is of the utmost importance in the construction business because of the massive cost and time overruns that are experienced by building projects all over the world (4). BIM allows for the simulation of a wide variety of sustainability measures, including energy use, thermal flows, and lighting patterns, among other things. During the construction phase of a building's life cycle analysis, which also includes the phases of embodied energy and operational energy

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use, the various structural substitutes are compared with one another. The decision-making process regarding the design provision in structures to reduce the amount of energy consumption and greenhouse gases would be considerably improved by sharing information from designers. In order to direct the investigation, you will need a building information system that is both highly efficient and open to collaboration. Utilizing BIM in the construction business leads to greater quality assurance standards, which is one of the most essential benefits of doing so. Participants in Construction have the ability to inspect their works at regular intervals in order to identify any flaws that may have developed as a result of the construction process. The implementation of BIM in the construction industry has had very little impact on the safety of construction workers. Even though there are ways that BIM can be used to promote safety, many participants in the construction sector are still unable to use BIM in this way (5). This is despite the fact that there are methods that BIM can increase safety.

When making a decision based on a number of different criteria, one of the most important parts is selecting the most appropriate course of action among a number of different options that are differentiated by a number of characteristics that frequently compete with one another. As a result of its adaptability, it is capable of incorporating not only quantitative but also qualitative data. Many authors have contributed to the body of knowledge (6) on the subject of sustainable development and energy efficiency in building construction by writing about it from a variety of perspectives. Probability theory, fuzzy logic, and utility functions are three of the most popular types of analytical tools that are used to facilitate decision-making. There are a large number of different criteria that may be utilized to establish which tactic is the most effective, and each of these choices offers a one-of-a-kind way for carrying out this task. Research (7) was carried out with the help of the established model, and the findings shown that either approach may be utilized to arrive at the same overall grade for low carbon building measures. Because of the dependability of the conclusions it draws Building Information Modeling (BIM) software that makes decisions uses a Bayesian Network (BN). BIM stands for Building Information Modeling.

Both the estimate of model techniques and the quantitative analysis of uncertainty are included in Bayesian approaches(8). A number of different Bayesian approaches can be used to accomplish the task of estimating subsequent parameter divisions for a specific model given the associated data. In particular, one of the most important aspects of Bayesian deep learning (BDL) is its capacity to accurately express uncertainty while also producing accurate predictions. This, in turn, makes deep neural networks more interpretable within the framework of probability theory. The ability of Bayesian deep learning neural networks (BDL NN) to incorporate both aleatoric and epistemic uncertainty in the energy performance of buildings enables them to excel at probabilistic load analysis (9). Bayesian deep learning neural networks (BDL NN).

The process of quantifying uncertainty can be made easier by using Bayesian deep learning, which simplifies the effort by generating estimates based on sampling model techniques rather than mandating the use of a number of different input situations. As a result of this, you won't be required to go with the second choice. Because of the prior division that is applied to all of the model techniques, Bayesian deep learning methods have a stronger generalization power even when they are dealing with a smaller number of datasets. Despite the growing interest in uncertainty quantification via the use of Bayesian deep learning algorithms in a variety of domains (such as image processing, medical applications, etc.), very few research groups (10) have developed BDL approaches for the forecasting of electric load or electricity generation. This is the case despite the fact that BDL approaches have been developed for the forecasting of electric load or electricity generation. Despite the fact that Bayesian deep learning algorithms are becoming increasingly popular in a variety of fields (such as image processing, medical applications, and so on), this remains the case. This is the case despite the fact that BDL approaches have been developed for the forecasting of electric load or electricity generation. Throughout the course of the investigation, Bayesian neural networks and Gaussian process models are utilized to make forecasts regarding a number of potential yearly construction power presentation outcomes (11). These outcomes are in part due to the contributions made by the building's HVAC system, solar power generation, building fixtures, and other internal systems. In order to create forecast forms for electric freights an hour and a day in advance that take into account both aleatoric doubt, a variety of deep learning algorithms (such as concrete dropouts, deep ensembles, Bayesian neural networks, deep Gaussian processes, and functional neural processes) are being developed. These algorithms include some realistic representations of processes that occur in the brain. In order to estimate daily shifts in electric demand and to evaluate epistemic and aleatoric uncertainty, three separate forms of deep neural networks are used. A few examples of these kinds of networks include the long-term short-term memory network, the gated

recurrent unit, and the recurrent neural network (12). The aforementioned studies either establish BDL approaches to capture aleatoric or epistemic uncertainty or they focus on electric freight estimation devoid of expanding their study to the plethora of unit power renovation schemes that are often established in buildings. Both of these categories of work can be categorized as uncertainty modeling. To put it another way, the research either concentrates on electric load forecasting or it develops BDL techniques to capture either aleatoric or epistemic uncertainty. This demonstrates how important it is to develop individualized probabilistic models at the level of specific energy systems. These models will make it possible to evaluate the energy performance of a building even when there is uncertainty present, and they will also make it possible to use the flexibility associated with that evaluation from the perspective of an entire system. In each of this research, Bayesian deep learning neural networks were utilized to make projections regarding the buildings' future energy consumption(13). They have not, however, extended the scope of their research to include a prediction of the adaptability of a building. By taking into consideration forecasts for the future, the method that has been provided is able to evaluate the epistemic as well as the aleatoric uncertainty that is linked with the operational flexibility of structures. We make use of models that are routinely updated, a technique called sliding windows, and Bayesian deep learning neural networks in order to make predictions regarding a wide range of objective factors associated with completely realizing a building's DR potential. In order to accomplish this, we apply the sliding window technique. A few examples of such elements include the load on the HVAC system, the temperature in the various zones, unpredictable loads, and the electricity generation from PV. The created data-driven models take as input components those that can actually be acquired by a home energy management system (such as data pertaining to weather forecasts and historical data pertaining to the targeted variables). The Spearman correlation coefficient is used to guide the decision-making process when selecting the input variables. After that (14), a Bayesian feed forward convolutional neural network is constructed for each target variable by utilizing the Keras Tensorflow framework. The effectiveness of the machine-learning models that were built is tested over a diverse set of scenarios, such as projections for one hour and one day ahead that can be used to plan DR actions in reaction to grid signals. In order to evaluate the usefulness of various forecasting approaches for certain DR programs like day-ahead scheduling and secondary reserve time resolution, a comparison of deterministic and probabilistic performance is employed. The accuracy with which these systems can forecast what will happen next is a critical factor in determining the degree to which they are useful. It is now possible to compare the many different flexibility possibilities that are offered by residential constructions thanks to the Bayesian deep learning framework that has been supplied. This is achieved by taking into account the inherent unpredictability, as well as the lack of knowledge regarding the demand of the building and the onsite generation of electricity (15). This allows for the achievement of the desired result. Additionally, it enables the development of prediction models that may be adapted to the energy systems and climate zones of specific locations. This makes it possible to conduct an analysis of the adaptability of the building as well as any potential implications on the thermal comfort of the occupants. As a result of the fact that they are not dependent on any particular control strategies or market structures, the proposed KPIs are ideally suited for use in dynamic situations such as those that are presented by DR applications. As a result of this, they are helpful in a wide variety of settings. This methodology can be utilized by electricity aggregators in order to evaluate building portfolios along with the related uncertainty. Because of this, it will be feasible to make more precise predictions regarding the adaptability potential of a building. In addition to providing a framework for capturing the relevant uncertainties, the method that has been developed may also quantify energy shifting capabilities and potential variances in thermal comfort. This only touches on a couple of the many functions that come standard with the system. This was but one of the numerous potential advantages that may be gained from using the strategy. These are merely two illustrations of the kinds of outcomes that are conceivable when the method is put into action. Building portfolios are able to be assessed or optimized within appropriate prediction intervals when using this technology and this capability extends all the way through the end-user prequalification process and beyond. In one of those situations, one could carry out this action (16). This might take place during the prequalification of the end user or it might take place at any point throughout the operation of the facility. It can be used to optimize the exploitation of flexibility potential in various energy systems by shifting demand to off-peak periods or periods of excess onsite electricity generation. In addition to increasing the proportion of renewable energy and mitigating potential issues with electricity generation and division capacity, it can also be used to maximize the potential for increasing the proportion of renewable energy. You will be able to accomplish all of your objectives by utilizing it. You will be able to check everything off your

list if you put this information to good use. The fact that making use of this technology enables you to obtain the full benefit of all of these qualities is one of the reasons why it is so appealing.

Literature Review

This work addresses the difficult problem of measuring improbability in energy elasticity estimations, which is a major challenge. This paper attempts to provide a solution to this challenge in order to solve a large research gap in the field of energy flexibility evaluation. Experts came up with a solution to this issue in the form of a tactic that assesses the adaptability of various thermal and electrical schemes (17). This is done by monitoring the appropriate indications and taking into account the many different kinds of uncertainty that are associated with the utilization of building energy. In order to take into consideration the stochastic and epistemic uncertainty that is associated with the operation of energy conversion devices as well as temperature changes that are the result of exploiting building flexibility, a Bayesian convolutional neural network is currently being created(18). The standard models that are used for creating forecasts are routinely updated, and they make use of household occupancy patterns in addition to a method that is known as sliding window. There were a number of potential sources of power, including a heat pump, a solar array, and a immobile series. In order to develop synthetic datasets for these energy systems, we use two different occupancy profiles in conjunction with a physics-based model that has been calibrated to represent an all-electric residential building(19). Using the model, the requirements for the amount of energy that the building requires for the two distinct occupancy profiles were estimated. The findings of the simulation imply that the behaviors of the building's inhabitants and the surrounding conditions both have an influence on the potential predictability of the building's flexibility (20).

Because of the numerous advantages they offer over the entirety of a building's life cycle, building information modeling (BIM) and multi-criteria decision-making (MCDM) are receiving an increasing amount of attention in the form of research and conversation(21). The purpose of this article is to educate experts on how to apply BIM and MCDM to reduce the amount of wasted energy in their buildings in order to make them more environmentally friendly and sustainable. This methodology intended to find the most relevant aspects in sustainable construction by minimizing embodied energy consumption as well as operational energy consumption and carbon emissions(22). The results of the survey were studied via the lens of descriptive statistics. The model that was created contained a total of six nodes and three clusters, and pair wise comparisons of relevance levels were done between each cluster and the others. According to the findings, the BIM tool ought to place a higher priority on optimizing the design and cutting down on the amount of material needed as essential aspects of sustainable building.

The utilization of building information modeling (BIM) for the purpose of collision detection has proven to be rather fruitful in a variety of construction-related disciplines in terms of improving the coordination of their activities(23). The procedure's dependability, on the other hand, has been called into question due to the extremely high number of insignificant collisions that are counted as part of the total when collision detection is performed. This research makes use of Bayesian statistics to classify collisions as either beneficial or useless in an effort to enhance the collision detection capabilities of BIM. This research evaluates the efficacy of three different Bayesian statistical methods: the naïve Bayesian, the Bayesian network, and the Bayesian probit regression (24). The evaluation is accomplished through a series of comparisons and parallels. In addition to this, the research investigates whether or not the accuracy of predictions could be improved by combining the three approaches using the majority rule. Using Bayesian statistics, which gives a mechanism for mining knowledge from prior data, it is possible to build conflict management procedures that are less reliant on the competence of BIM organizers. This can be accomplished by using Bayesian statistics. The application of Bayesian statistics allows for the possibility of information extraction from spatial data as well(25).

The nature of the work environment on construction sites, which is characterized by high levels of complexity and is subject to rapid change, is a major contributor to the construction industry's dismal safety record. The aforementioned factors are taken into consideration only infrequently and even fewer of the approaches now available for evaluating control measures deal with them in an appropriate manner(26). The authors of this paper propose a hierarchical Bayesian model that accounts for workers' reactions to proximity signals about potential safety threats. This model addresses the issue by having three levels (i.e., individual hazards, hazard types, and

generic hazards), and it accounts for workers' reactions to proximity alerts about potential safety dangers. In order to generate estimated response rates (ERRs), the model in question takes observational response rates as an input, takes into consideration past information about workers' responses to comparable dangers, and does so. There are two different types of proximity warnings, which are known as main control measures and secondary control measures. These event report rates (ERRs) are the key evidence for either the effectiveness of a certain control method or the authenticity of a suspected safety issue(27). These ERRs are also utilized in the process of authenticating a potential threat to safety in order to protect the public. As part of a field experiment that tested the proposed technique by utilizing a location-based proximity warning system, workers were notified of potential risks over a period of seventeen days, and their responses were recorded. This was done as part of the experiment.

Methodology

The Bayesian technique is superior to other methods in terms of providing an accurate estimate of the parameter values because it takes into consideration the possibility of error and continually revises its assumptions in light of fresh evidence. In addition to this, it offers a methodical framework for the selection of models and is capable of dealing with complex and nonlinear models. In order to feed the models that need to be updated, therefore, essential experimental knowledge is required. The experimental measurement of attributes and the estimation of unknown or unobservable model techniques by minimizing an error function are at the core of the majority of structural identification techniques that take a deterministic method of attack. It is not a mystery that determinism has been utilized for a considerable amount of time. A deterministic technique is one that can only provide information on the measurements that were collected and the quality of those measurements when conducting tests; it ignores any ambiguity or variability in the data. On the other hand, the doubt in the model limitations and the incorporation of former information via possible techniques such as Bayesian updating may result in more exact and resilient parameter evaluations. Bayesian updating is an example of such an approach. Bayesian updating is an example of one of these probabilistic methods. By observing how a structure reacts when subjected to vibration from the environment, modal techniques can be determined in a manner that is helpful. This technique allows for the quantification of the reactive potential of a structure. The Bayesian Inference (BI) strategy puts out a method for quantifying the unpredictability of the model and the techniques that it uses as input. In order to enhance the knowledge obtained from experimental testing, Bayesian models are employed to evaluate the level of uncertainty present in the statistics. On the other hand, including Bayesian model reform into FE models remains a difficult task to accomplish. When working with large FE models, using a Bayesian strategy to update the model techniques is required because it involves constantly evaluating functions, which can be a computationally intensive process. In spite of this, the development of Bayesian model updating is being driven by increasingly efficient computational approaches and algorithms in the field of structural engineering. The objective of this research took place in the construction sector of China in supervision of professionals is to adapt a finite element (FE) model of a structure by making use of the BI framework and basing the adjustments on experimental modal property data. As stipulated by this methodology, a multivariate normal likelihood function will be utilized in order to conduct an analysis on the degree of uncertainty inherent in the model. The utilization of specialized software is necessary in order to do Bayesian updating on a complex model. It is now possible to update this computationally intensive model, which is a prospect that is both realistic and worthwhile thanks to the program's support for cloud-based computing solutions and other ways. Figure 1 illustrates the whole process that must be followed for the purpose of carrying out the Bayesian update of the parametric data for the five-story model. The phases shown in this image will be discussed in greater detail in the next sections of this publication, with an emphasis placed on the most significant facets of the method.

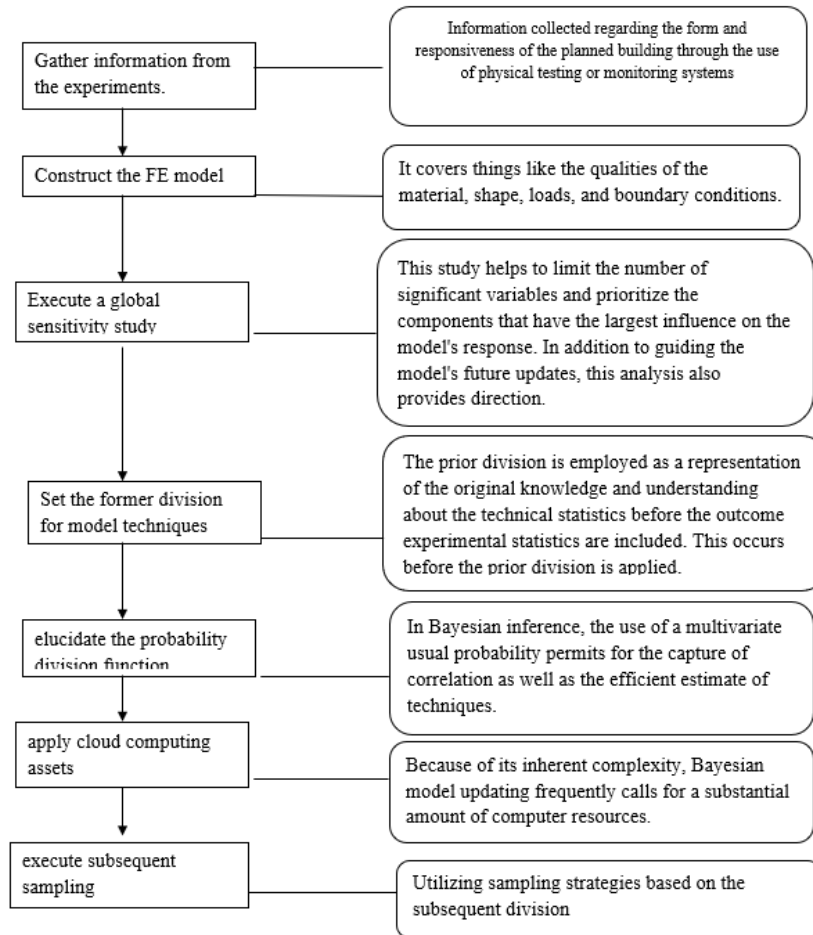


Figure 1: The process of the methodology that was developed so that a Bayesian parametric update could be performed on the model of the building.

The Markov chain affine invariant sampled by Emcee is a product of the work of Goodman and Weare. Estimation of techniques can be performed with the help of Bilby while utilizing BI. Plotting is accomplished with the help of Matplotlib. Scipy is a statistical package that can be utilized (it can do things like probability divisions, correlation functions, and so on). Data manipulation and analysis are two of Pandas' primary uses. An Opensees interpreter is provided by the program Openseespy.

In order to conserve resources within the system that is currently under construction while the data is being transmitted, the programming code for the numerical model has been included into the programming code for the principal Bayesian update. The calculations are carried out with the assistance of a Markov chain Monte Carlo (MCMC) ensemble sampler that has a sum of 143,000 samples and uses LogNormal divisions as priors for each and every parameter (Table 1).

| Techniques | Types of Division | Mean | Std.Dev.(MPa) |
|------------|-------------------|-------|---------------|
| Ebeam 1 | LogNormal | 36000 | 9800 |
| Ebeam 2 | LogNormal | 36000 | 9800 |
| Ecol 1 | LogNormal | 36000 | 9800 |
| Ecol 2 | LogNormal | 36000 | 9800 |
| Eslab 1 | LogNormal | 36000 | 9800 |
| Ewall 1 | LogNormal | 36000 | 9800 |
| Ewall 2 | LogNormal | 36000 | 9800 |

Table 1: Prior divisions for model updating

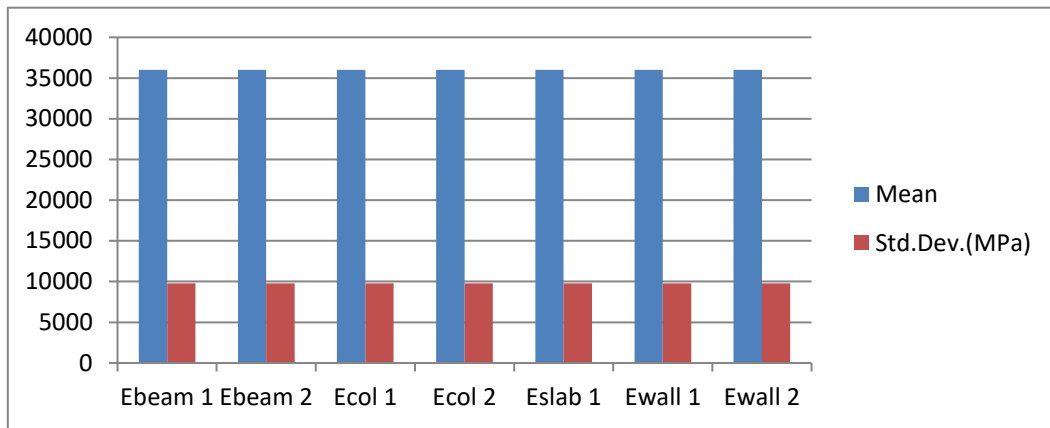


Figure 2: Graphical representation of prior division

Results and Discussion

In the following explanation, "calculating the covariance matrix at each monotony" and "using an identity matrix as the covariance matrix" will be referred to as "the iteration-approach" and the "identity-approach," respectively. Both of these methods involve the same step: "calculating the covariance matrix". This nomenclature change will take effect immediately. In this subsection, we will show the results of the likelihood function's covariance matrix using the two different methods, and then compare those results. One option for the covariance matrix is to employ an identity matrix; another is to generate it manually after each iteration.

When the findings of the two methods are compared to one another, it is possible to evaluate the relative benefits and drawbacks of each approach in terms of the precision, computational efficiency, and robustness of the results. The findings of such an analysis in Chinese building construction sector might be used to guide the planning of future research that integrates the Bayesian update of structural models, in addition to assisting in the selection of the method that is most appropriate for a given subject area. This could be done by using the findings as a basis for planning that incorporates the Bayesian update of structural models.

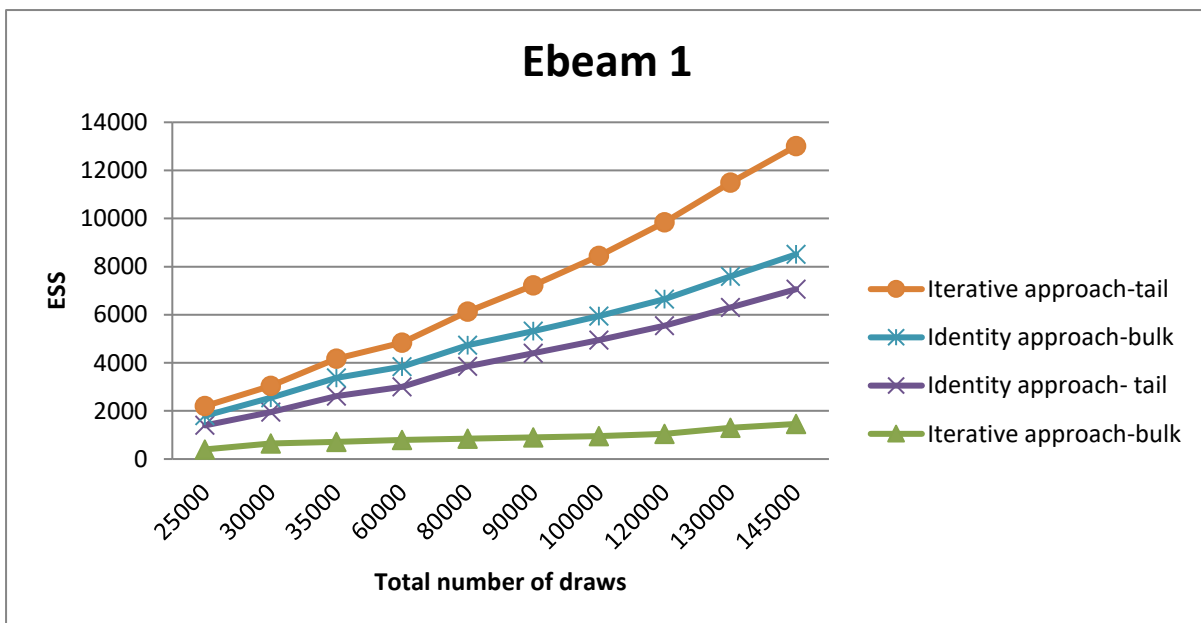


Figure 3

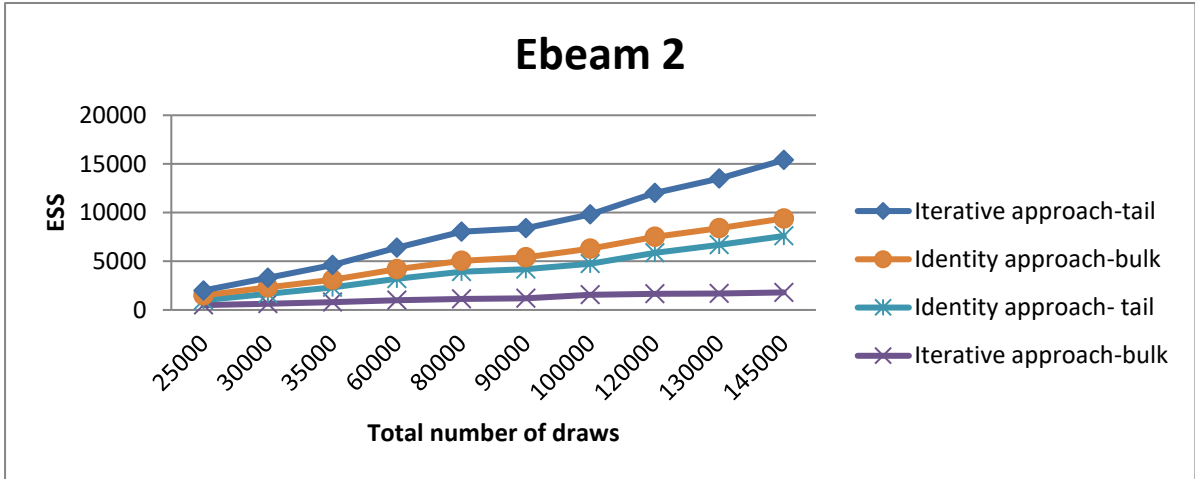


Figure 4

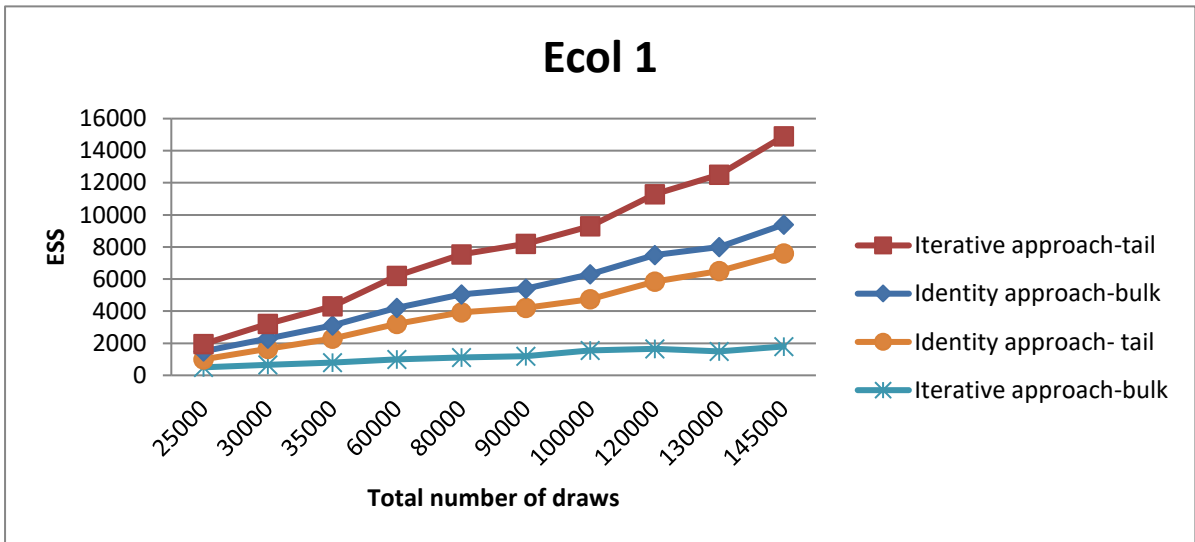


Figure 5

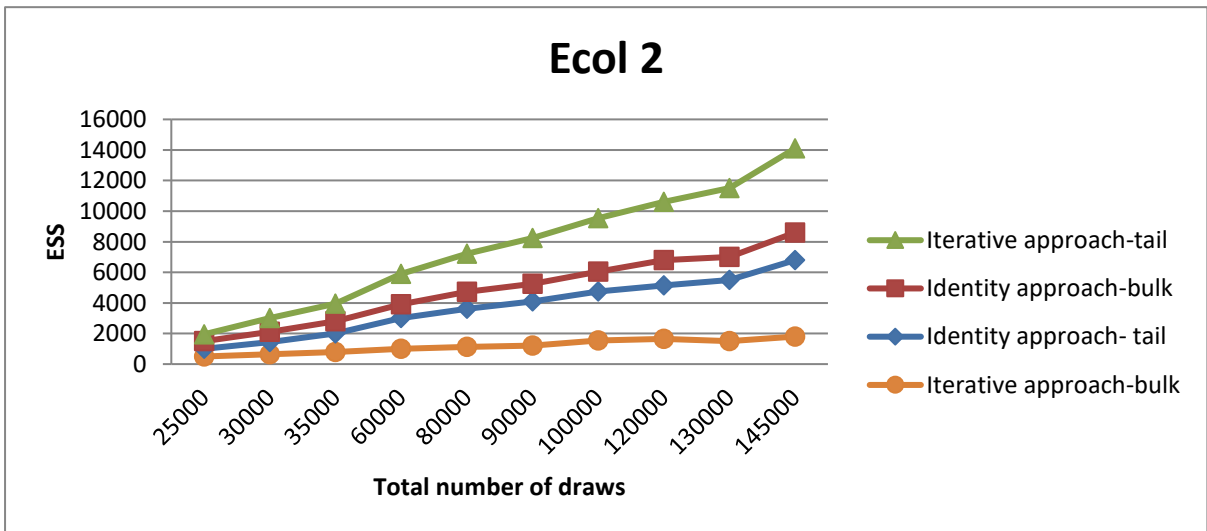


Figure 6

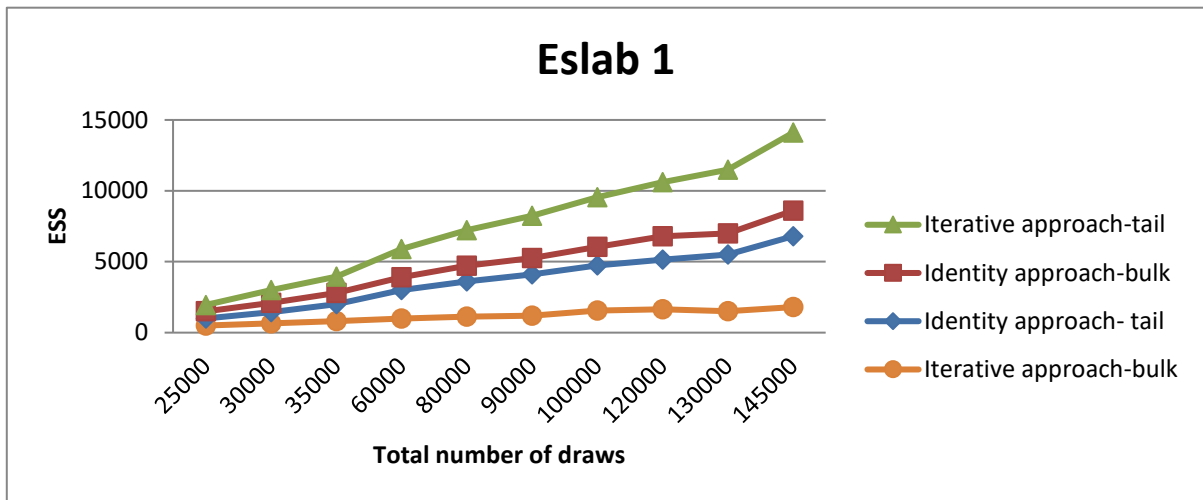


Figure 7

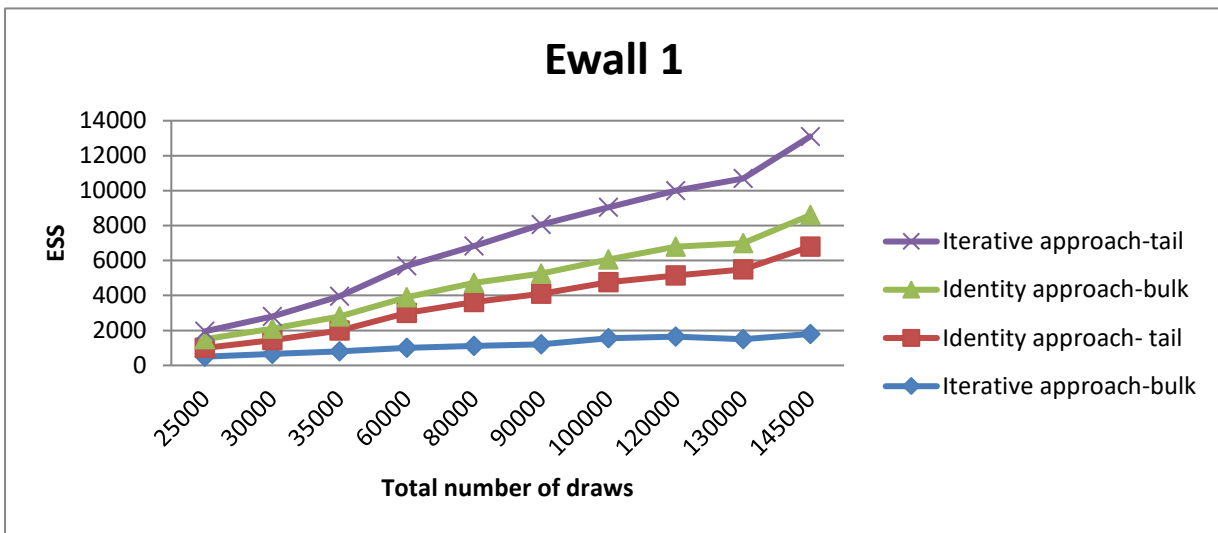


Figure 8

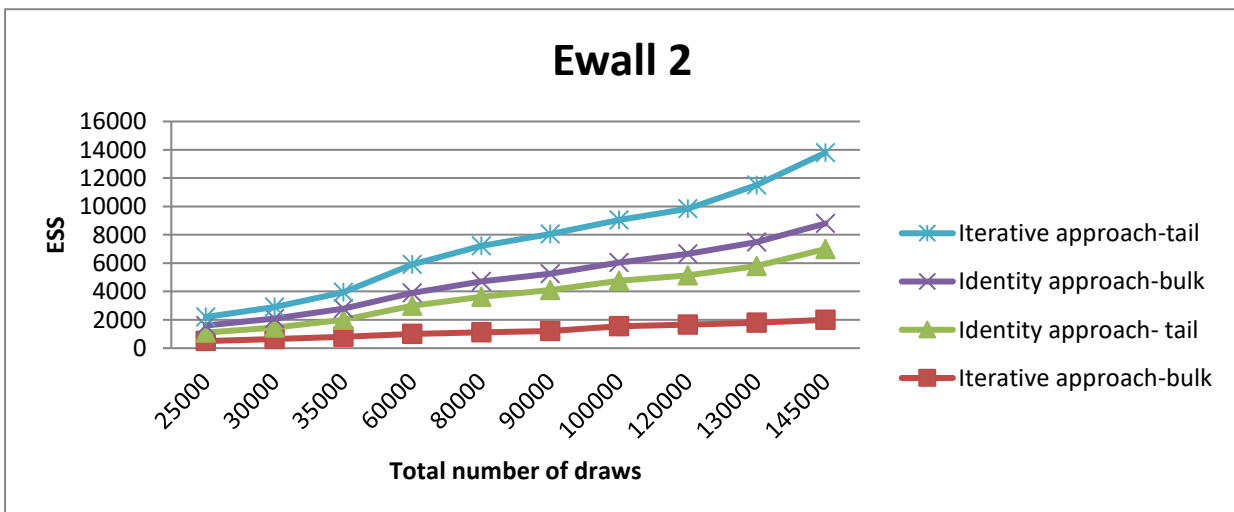


Figure 9

Figure 3-9: The development of an effective sample size, also known as an ESS, for use in subsequent sampling.

A comprehensive analysis of the model's techniques is made possible thanks to the subsequent probability density. From such an analysis, one can infer the most likely values for the techniques, in addition to the level of correlation that exists between the techniques and the degree to which there is a degree of ambiguity. The following table provides high-density intervals as well as trend lines for each of the techniques, and they reveal that the module of elasticity of Ebeam1, Ebeam2, Ecol1, and Ecol2 are all significantly bigger than those of Eslab1, Ewall1, and Ewall2, respectively. These graphs may be helpful in locating data points that significantly deviate from the norm and can be used to identify outliers. Both of these approaches produce subsequent divisions of the model techniques that are extremely comparable to one another, which suggest that the resulting subsequent division estimates are also extremely comparable to one another in terms of precision.

| | Mean [Gpa] | SD [GPa] | HDI 3% [GPa] | HDI 97% [GPa] |
|---------|------------|----------|--------------|---------------|
| Ebeam 1 | 48.94 | 4.88 | 39.76 | 58 |
| Ebeam 2 | 48.17 | 5.28 | 38.4 | 58.19 |
| Ecol 1 | 48.15 | 4.89 | 38.91 | 57.24 |
| Ecol 2 | 47.93 | 5.04 | 38.61 | 57.69 |
| Eslab 1 | 38.2 | 5.01 | 28.76 | 47.49 |
| Ewall 1 | 36.24 | 5.04 | 26.75 | 45.67 |
| Ewall 2 | 37.26 | 4.05 | 29.51 | 44.73 |

Table 2: A summary of the subsequent division of the techniques of the model. Method based on iteration

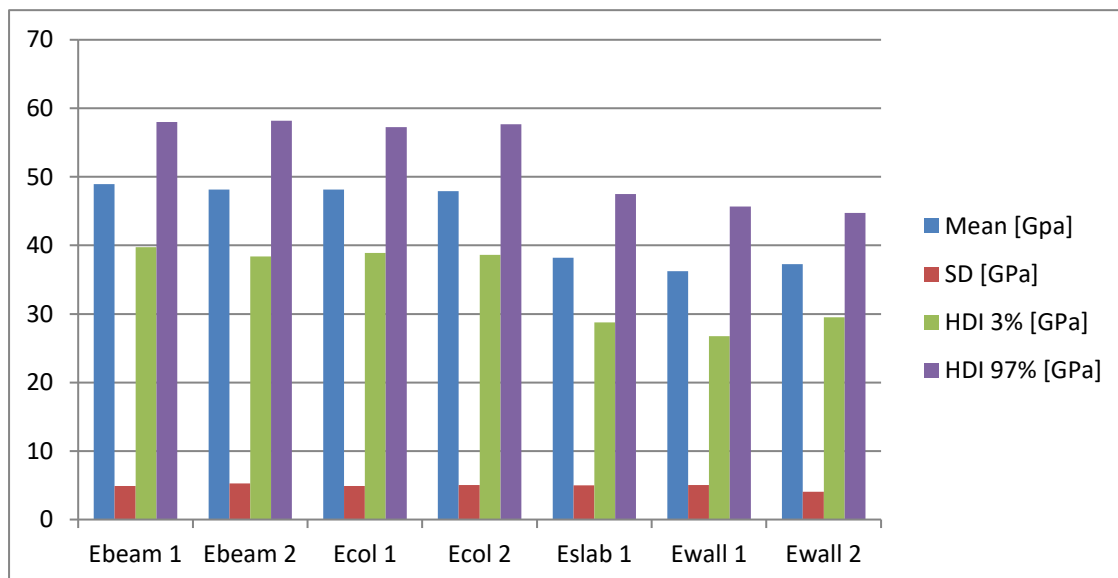


Figure 10: Graphical presentation of summary of the subsequent division of the techniques of the model. Method based on iteration

| | Mean [GPa] | SD [GPa] | HDI 3% [GPa] | HDI 97% [GPa] |
|---------|------------|----------|--------------|---------------|
| Ebeam 1 | 49.23 | 4.87 | 40.02 | 58.26 |
| Ebeam 2 | 48.3 | 5.16 | 38.43 | 57.8 |
| Ecol 1 | 48.55 | 4.86 | 39.28 | 57.55 |
| Ecol 2 | 48.77 | 4.97 | 38.6 | 57.26 |
| Eslab 1 | 38.39 | 5.05 | 28.64 | 47.51 |
| Ewall 1 | 35.56 | 5.18 | 25.84 | 45.35 |
| Ewall 2 | 37.09 | 4.16 | 29.21 | 44.78 |

Table 3: A summary of the subsequent division of the techniques of the model. Method based on identity

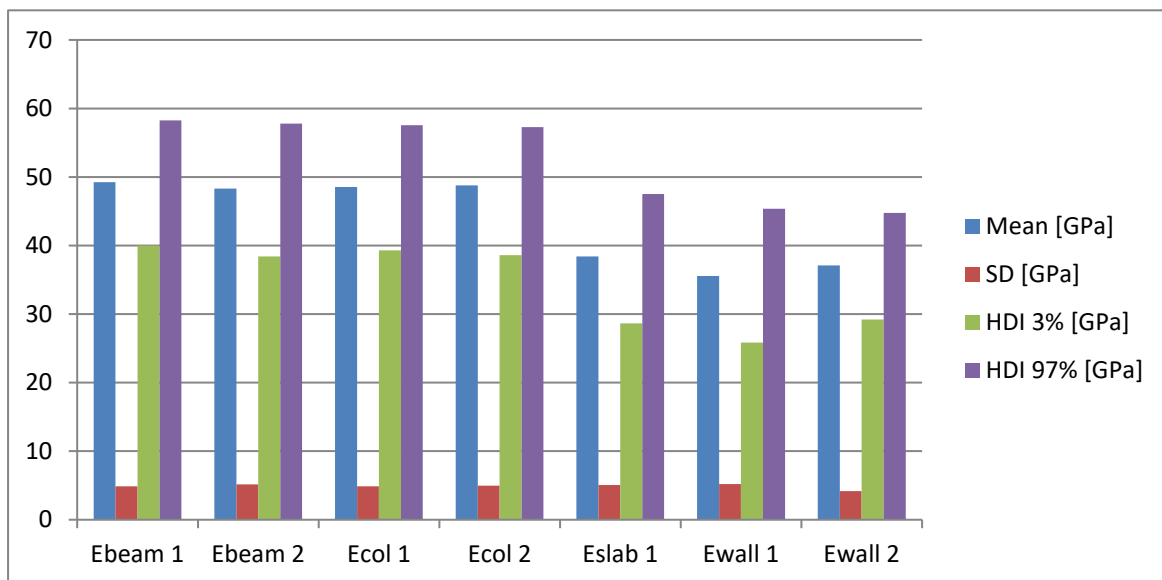


Figure 11: Graphical representation of summary of the subsequent division of the techniques of the model. Method based on identity

Following the incorporation of the Bayesian updating procedure's predictable principles for the modal statistics the subsequent values have been brought into alignment with the subsequent division of the modal coordinates. This is the case as a result of the fact that the subsequent values are a component of the subsequent division of the modal coordinates. The Bayesian model is being updated to account for the findings of the experiments, as shown by the excellent presentation in the MAC fit.

Conclusion

This research in construction sector of residential buildings in China presents a method for modifying the techniques of a structural model by making use of business intelligence (BI). In order to improve the FE model, modal characteristics of a full-scale, five-story RC building were employed as a source of information. This was done in order to ensure that the update contains the most accurate information possible. The approach that was proposed was used to document the procedures that were taken to quantify the parametric uncertainty as well as

the results of those steps. After computing the covariance matrix of the data and comparing it to the various model realizations, the updating technique arrived at a subsequent probability for the FE model's techniques. This was accomplished by comparing the covariance matrix. A comparison of the covariance matrix and the FE model was used to accomplish this goal. This was accomplished by comparing the covariance matrix to the FE model. We were able to zero in on the source of the mistake that was being produced by the multivariate normal likelihood function thanks to the covariance matrix that we developed between the data and the adjusted model.

Comparable subsequent divisions and convergence rates were generated by utilizing either the same method or an iterative approach to add the covariance matrix into the framework for Bayesian model update. This was the instance despite the fact that the iterative approach enabled a more in-depth comprehension of the way the system operated. The iterative calculation of the covariance matrix did not result in the comprehensive picture of the system's behavior that could have been obtained from doing so; despite this possibility, it did not materialize. Due to the fact that this is the situation, each method can be substituted for the other without having an adverse effect on the dependability or precision of the results. This discovery has important implications for practice since it makes computational techniques more efficient when they are applied to large sample numbers.

It is possible to think of the subsequent update that was accomplished for the FE model's input techniques as being fundamentally symmetric. This is because it is akin to divisions that have normal forms, and there are no visible biases. When compared to the standard deviation of the prior divisions, the subsequent divisions invariably have a lesser typical divergence. This is the case in each and every possible circumstance. This demonstrates that the degree of error connected with the model and the values of the techniques is significantly lower than what was previously thought to be the case. In addition to this, the process that was used to figure out the MAC function provides some insight on the mode shape dependability of the model update. In light of this, it is absolutely necessary to contrast the findings of the PPC with the data obtained from experiments in order to evaluate the degree of uncertainty present in both the related frequency and the associated frequency. The construction methodology of residential buildings in **China** has the ability to assist in making decisions pertaining to design and evaluation, as well as increase the correctness of structural models.

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