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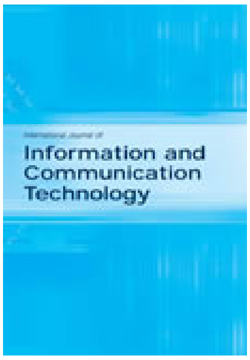

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A furniture design assistance method based on spatiotemporal graph neural networks and multi-objective optimisation

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Abstract: This paper suggests a furniture design assistance method (FD-STGMO) based on spatial-temporal graph neural network (ST-GNN) and multi-objective optimisation to help with the problem of balancing the structural complexity and multi-objective optimisation needs in the furniture design process. The technique first employs ST-GNN to find structural change features. Then, it uses multi-objective optimisation algorithms to come up with design solutions. Finally, it builds a collaborative end-to-end design support system. The performance comparison tests done on the simulation dataset all show that the new FD-STGMO method is better than the old one in four areas: structural stability (0.84), material utilisation (0.88), functional adaptability (0.80), and aesthetics score (0.85). The findings of the modular contribution analysis experiments show that FD-STGMO has good potential for use in engineering and business.

Keywords: furniture design; spatial-temporal graph neural network; ST-GNN; multi-objective optimisation; intelligent aided design.

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1 Introduction

1.1 Background of study

Furniture design is a big part of industrial design, and it is mostly about combining function and style. In the traditional design process, designers mostly use their own experiences and opinions to choose the structure, materials, and practical layout of furniture (Prabhakaran et al., 2021). This human-centred design method does have some benefits when it comes to meeting individual needs, but it also has some problems that come up over time. For example, the design process is slow, it is hard to keep the quality of the solution consistent, and it is hard to balance the design goals when there are a lot of different product design needs. Personalised customisation is becoming more and more common in the furniture industry, especially in the context of intelligent manufacturing. One of the main problems that needs to be solved in the process of digital transformation of furniture design is how to use computer technology to make the design process smarter, standardise capabilities, and balance multiple objectives.

Furniture items have a natural intricacy in their structure. A full set of furniture usually has several functioning parts that are connected, nested, or combined in other ways. There is a clear structural relationship between the parts, and they depend on each other in space. Because the total product is made up of local parts, this property means that furniture design exhibits typical graph structure properties. Graph neural network (GNN) has become very popular in recent years for modelling complex structured data. It has shown great ability to learn representations and model relationships, especially in the areas of molecular structure analysis, traffic flow prediction, and social network modelling. Using GNN in furniture design should help find the structural relationships and local dependencies between furniture parts, which will help create design solutions that are both structurally sound and fully functional (Zhan et al., 2020). But traditional GNNs mainly employ static graph modelling, which only looks at the spatial dimension of the product structure and does not take into account how the design solutions change over time at each stage of the design process. Furniture design is actually a dynamic process that goes through many iterations and local alterations. The design solutions are always being improved based on changes in material limits, functional needs, and aesthetic preferences. So, GNNs that are only based on static structures cannot accurately show how the design process develops over time and how it depends on time. This makes the model less flexible when it comes to real design situations.

ST-GNN was made to deal with the changing nature of the design process. It builds on traditional GNN by adding a time dimension. It treats design solutions at different stages of the furniture design process as a series of time diagrams. It also uses the time modelling mechanism to capture the changing patterns of the design solutions over time and how small changes affect the overall structure. This way, the design process can continue, and the changing patterns can be accurately captured. ST-GNN opens up a new technical path for making furniture design models that can change and grow over time. This is expected to get around the problems with traditional structural static modelling methods and give intelligent design assistance more timely and flexible support.

At the same time, furniture design aims are often several and limit each other. For instance, trying to make the structure more stable and stronger will mean using more materials, which goes against the purpose of saving money. Using too many materials may also make the furniture look and feel less good. So, furniture design helps systems need to figure out how to strike a good balance between all of the design aims. Multi-objective optimisation has some benefits when it comes to tackling these kinds of multi-objective trade-off situations. Multi-objective optimisation is different from traditional single-objective optimisation because it looks at multiple objective functions at the same time and gives a set of alternatives that make up the optimal solution set of Pareto. This lets designers pick the best solution for their design needs when they have to make trade-offs between different objectives. Multi-objective optimisation approaches have been widely utilised in engineering design and product optimisation to solve problems with several objectives that are in conflict, and they have worked well (Pereira et al., 2022). So, adding multi-objective optimisation to the furniture design process should help solve the problem of having different and conflicting design goals in a systematic way and provide design solutions that work well in many ways.

In short, the complicated structural features and changing rules of evolution in the field of furniture design set the limits of graph modelling and multi-objective optimisation approaches. By combining ST-GNN's ability to model space and time with the benefits of multi-objective optimisation in solving trade-offs, it should be possible to build an intelligent design assistance system that can model structures and optimise objectives. This would make the furniture design process smarter and more standardised. There have been some early attempts to use deep learning and optimisation methods for design optimisation tasks in the field of industrial design, but there are not any systematic fusion modelling and optimisation strategies for furniture design yet. This is a unique situation because it involves structural diagrams and time-series evolution. So, suggesting a way to help design furniture that uses both ST-GNN and multi-objective optimisation is useful for both theoretical research and real-world use.

1.2 Innovations of study

This paper suggests a new way to help with furniture design called FD-STGMO. It is based on the combination of ST-GNN and multi-objective optimisation. It aims to solve the problems of not being able to model structures well enough, not having dynamic design features, and having trouble coordinating conflicts between multiple objectives in the current furniture design process. The research in this publication is new in four significant ways compared to what has been done before:

1. A dynamic modelling framework for furniture design based on ST-GNN: this study uses ST-GNN to help design furniture. For the first time, the process of designing furniture is seen as a series of structural graphs that change over time. The time dimension is included to simulate how the structure of the furniture changes over time. We build furniture parts and their connections as spatial-temporal graphs that change over time. This lets us model and extract features of both local changes and the overall evolution of the structure during the design process. It also gets around the problems with traditional GNN when it comes to modelling static structures.
2. Multi-objective optimisation-driven design scheme generation mechanism: this paper addresses the issue of multiple-objective constraints in furniture design by creating a scheme generation mechanism that combines multi-objective optimisation with structural stability, material use, functionality, and aesthetic quality as multi-objective functions. It then uses optimisation algorithms to find the best solution set of Pareto, which gives designers a range of balanced design options that improve the scientific and flexible nature of the design decision-making process.
3. A design assistance system for the synergy of ST-GNN and multi-objective optimisation: the FD-STGMO method suggested in this paper combines the structural modelling and design state prediction features of ST-GNN with the solution balancing and optimisation features of multi-objective optimisation. This makes structural modelling and multi-objective optimisation work together; at the design data analysis layer, ST-GNN shows the structural dynamic aspects and the trend of the solution's evolution. At the design output layer, multi-objective

optimisation makes sure that all of the objectives are met and optimised. The end-to-end intelligent furniture design help method system is built.

4 System validation and application exploration based on simulation datasets: this work puts together two sets of simulation data and makes a test set with the order of structural diagrams and design parameters to make sure that the approach is being developed in line with what people actually require. During the experimental validation phase, we systematically compare the performance benefits of FD-STGMO to those of the traditional GNN model and single-objective optimisation strategy in terms of structural consistency, scheme diversity, and optimisation quality. This is done to prove that the proposed method works and is useful for engineering applications.

2 Spatial-temporal graph neural network

GNNs are a type of deep learning model that is made to work with data that is structured like a graph. GNNs may operate directly with graph data in non-Euclidean space, which is different from classic convolutional neural networks (CNNs) and recurrent neural networks (RNNs), which mostly deal with data in normal Euclidean space. Graph data is made up of nodes and edges. Nodes are things, and edges are the connections or interactions between those things. GNN learns to represent nodes and the whole structure of the graph well by moving and combining information across nodes (Han et al., 2022). The main idea behind it is to let nodes combine more general structural information layer by layer by repeatedly adding features from nearby nodes. This lets us see how the network is structured and how features are spread out. GNN is used a lot in social network analysis, recommender systems, predicting molecular structures, knowledge graphs, and other areas. It makes graph data processing much better.

But traditional GNNs are usually used for static graph structures, which mean that the interactions between nodes and edges stay the same during the learning process. They cannot simulate how network topologies and node attributes change over time. In fact, there are numerous situations when graph data has a significant temporal aspect, including when traffic changes in traffic networks, relationships change in social networks, and signals change in sensor networks. To deal with these spatial-temporal dynamic data, ST-GNN has been suggested as a way to simulate both the structure of a graph and its temporal dynamics at the same time.

ST-GNN does a great job of combining modelling challenges in both space and time. In the spatial dimension, ST-GNN uses graph convolution techniques to find topological correlations between nodes (Izadi et al., 2025). By combining the information from node neighbours and updating the feature representation of each node, graph convolution learns the spatial properties of the graph structure. Like regular GNNs, the spatial modelling part can pick up on both permanent and temporary characteristics of graph structure.

In the time dimension, ST-GNN uses RNN and its better equivalents, like long short-term memory (LSTM) network and gated recurrent unit (GRU), to show how node properties evolve over time (Dong et al., 2023). The LSTM network solves the problem of the classic RNN's gradient disappearing when it works with extended time sequences by adding forgetting gates, input gates, and output gates. It can also successfully capture the long-term temporal dependency. The GRU structure is shorter and has forgetting gates and input gates, which cuts down on the number of parameters while still being able to describe time well. These temporal modelling modules assist ST-GNN find patterns and trends in the changing dynamics over time and make it better at responding to changes.

The general process that ST-GNN uses to do its calculations is as follows: at each time step, graph convolution is used to extract the spatial features of the current graph structure. Then, the temporal module processes the spatial feature sequences of a series of time steps to learn the rules for how they change over time (Liang et al., 2022). Finally, the spatial-temporal representations of nodes or graphs are created. Given the graph data with time series length T, the feature set X_t represents the graph signal at each time step, and the output H_t of the ST-GNN model at time t can be shortened to:

$$H_t = \text{TemporalModule}\left(\text{GraphConv}\left(X_t\right), H_{t-1}\right) \quad (1)$$

where GraphConv(·) is the graph convolution operation, TemporalModule(·) is commonly an LSTM, GRU, or temporal convolutional network that captures the temporal dependencies, and H_{t-1} is the hidden state of the previous time step.

The Laplace set of graphs is the basis for the specific graph convolution process, which is defined as follows:

$$H_t^{(l+1)} = \sigma\left(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}H_t^{(l)}W^{(l)}\right) \quad (2)$$

$$\tilde{A} = A + I \quad (3)$$

where $H_t^{(l)}$ is the set of node features for layer l at time step t, $\tilde{D}$ is the degree set of the neighbour set, $W^{(l)}$ is the set of trainable weights for layer l, and $\sigma(\cdot)$ is the nonlinear activation function. This method normalises the set of neighbours and gives more weight to the features of adjacent nodes so that they all point to the current node.

ST-GNN has done amazing things in many areas, like predicting traffic flow, recognising actions, monitoring the environment, and analysing financial time series. It can represent both spatial structure and temporal dynamics at the same time. For instance, ST-GNN can use information about the layout of the road network and real-time traffic state sequences to make accurate predictions about how the roads will be in the future (Edalatpanah and Pourqasem, 2025). In tasks that involve recognising human actions, the accuracy and reliability of action recognition are improved by learning about the spatial and temporal features of skeletal key points at the same time.

Even while ST-GNN works very well, its computational cost and memory use go up a lot as the size of the graph and the length of the time series increase (Zhu et al., 2022). This makes it hard to train and use the model efficiently. Also, it is still hard to capture long-term dependencies, and graph structures that change over time make it harder for models to adjust. Future research should focus on lightweight model design, efficient time-series modelling methods, and adaptive learning of dynamic graph topologies to make ST-GNN even more useful and applicable.

In short, ST-GNN is a temporal extension of graph neural networks that efficiently combines spatial structure with temporal dynamic properties. This makes it a useful tool for modelling and analysing complicated spatial-temporal graph data. As ideas and technology connected to ST-GNN continue to grow, it will become increasingly useful and valuable in real-world situations.

3 Multi-objective optimisation

Multi-objective optimisation is a big part of optimisation that deals with hard issues that have more than one goal, and these goals often conflict with each other. In real life, decision makers typically have to deal with a lot of different needs. For example, when designing a product, they may need to improve performance while lowering costs and energy use. When managing resources, they may need to be efficient while still being fair and sustainable. Because these goals limit each other and there is not a single way to measure the best solution, multi-objective optimisation focuses on finding reasonable trade-offs between many goals and a set of solutions known as Pareto optimal solutions, which show the best balance of different goals.

The main premise behind Pareto optimal solutions is that there is no other option that can increase all goals at the same time without giving up at least one of them. The Pareto frontier is made up of all of these solutions. It shows the trade-offs between the goals and gives the decision maker a range of options. This is how multi-objective optimisation helps us make better and more flexible decisions when dealing with real-world issues that are quite complicated. It does this by looking at both the pros and cons of the solutions and the variety of the options.

There are two primary types of multi-objective-optimisation methods: conventional mathematical planning approaches and newer heuristic algorithms. To turn a multi-objective problem into a single-objective problem that can be solved, traditional methods like the weighted sum method and the ε-constraint method frequently use a linear combination of objective functions or apply constraints (Rohilla, 2020). These kinds of methods require a lot from the math involved in the problem and work well for convex optimisation problems with simpler structures. However, they do not work as well for problems with very nonlinear, multi-peaked, and complicated constraints, and it is hard to see the whole picture of the Pareto frontier.

Heuristic algorithms, on the other hand, are very good at searching the whole space and can handle nonlinear, non-convex, and high-dimensional objective problems. These algorithms mimic the processes of selection, crossover, and mutation that happen in biological evolution. They optimise many objective functions at the same time and get closer and closer to the multi-objective Pareto-optimal solution set. The non-dominated sorting genetic algorithm II (NSGA-II), the multi-objective particle swarm optimisation (MOPSO), and others are well-known algorithms that have become the most common ways to do multi-objective optimisation (Mu'Tasim and Rashid, 2023). They do this by keeping the populations diverse and using the technique of non-dominated sorting to find a good balance between how quickly the solutions converge and how evenly they are distributed.

With the rise of computational intelligence technology in recent years, machine learning and deep learning-based multi-objective optimisation methods have slowly started to show up. For instance, multi-objective Bayesian optimisation based on the agent model makes it much easier to evaluate complex functions by creating an approximation model of the objective function (Di Fiore et al., 2024). This is useful for optimising systems that are expensive to compute. Also, techniques like reinforcement learning have been used on dynamic multi-objective optimisation issues to make the algorithms even more adaptable and efficient.

Multi-objective optimisation still has a lot of problems to solve, especially in high-dimensional objective spaces, where keeping the diversity of solutions and the efficiency of the search are two big ones. When there are more objectives, the Pareto front becomes more complicated, which makes it hard for standard algorithms to cover the global optimal solution set evenly (Czajkowski and Kretowski, 2019). Also, as the problem gets bigger, it puts a lot of stress on computer resources. There is an urgent need to provide lightweight and parallelised optimisation techniques. At the same time, picking the final solution from the Pareto frontier needs to take into account the decision maker's preferences and use multi-criteria decision-making (MCDM) methods so that the outcomes of multi-objective optimisation may really help with the decision-making process (Tran, 2020).

Multi-objective optimisation techniques are very useful in many areas, including smart manufacturing, where they help find the best way to combine cost, quality, and production cycle; energy system optimisation, where they help find the best way to balance power generation efficiency and environmental impact; and smart transportation, where they help find the best way to balance congestion mitigation and emission control. As real-world issues become more complicated and varied, a lot of research is now focused on creating smart, efficient multi-objective optimisation algorithms and encouraging their use in more areas.

In short, multi-objective optimisation offers complete and adaptable answers for complicated systems by balancing many conflicting goals. It is based on solid theory and has a lot of potential for use in many areas. In the future, multi-objective optimisation will work better with sophisticated computing technology and smart algorithms to help with the complicated process of making decisions and help scientific and engineering sectors grow.

4 Furniture design assistance methods

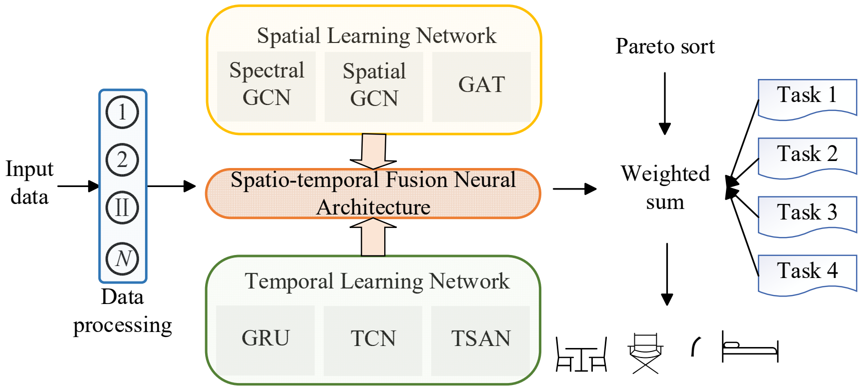
4.1 Implementation of furniture design assistance methods

This research suggests the furniture design aid technique FD-STGMO, which uses ST-GNN and multi-objective optimisation to make an intelligent, dynamic-aware, and multi-objective balanced furniture design help system (see Figure 1). The method has five main parts, which are:

4.1.1 Data acquisition and pre-processing

The data acquisition and pre-processing module is the first step in the FD-STGMO furniture design assistance method. Its job is to turn the complicated and varied structural data from the furniture design process into high-quality dynamic diagram sequences that the ST-GNN can use as input. Furniture design data includes the geometric dimensions, material properties, connection methods of furniture components, and the dynamic changes in the relationships between components during the design process. This data comes from CAD design software, sensing devices, or design change records, and it makes up the multi-source time series data of furniture design.

Figure 1 Framework of furniture design assistance methods (see online version for colours)



This module first turns the furniture structure at each time point into a graph model G^t. The nodes in the graph represent the parts of the furniture, and the attributes of the nodes are shown as variables x_i^t. The node number is i = 1, 2, …, N, and the time step is t = 1, 2, …, T. The set of edges is made up of the set of neighbours A_t, which shows how the components are connected and how they fit together. Because of this, the full process of designing furniture is shown as a series of time-step graphs:

$$G = \{G^1, G^2, \ldots, G^T\} \tag{4}$$

$$G^t = (X^t, A^t) \tag{5}$$

$$X^t = [x_1^t, x_2^t, \ldots, x_N^t]^T \tag{6}$$

where X^t is the set of features for all nodes at time step t.

To get rid of the disparities between different feature scales and how they affect model training, the module normalises the node features (Xiao et al., 2019). It does this by utilising the standard deviation normalisation approach, which is calculated like this:

$$\hat{x}_i^t = \frac{x_i^t - \mu_i}{\sigma_i} \tag{7}$$

where μ_i is the mean and σ_i is the standard deviation of the i^{th} node feature in all the time series data. This normalisation makes sure that the distribution of the node features in the time dimension stays the same. This helps the model learn spatial-temporal dynamic patterns in a stable way.

This module also enforces time synchronisation processing to make sure that the timestamps of different data sources and sensor samples are the same. This makes sure that each time-step data in the graph sequence matches up correctly and that time misalignment does not cause feature confusion or model misjudgement. Missing value interpolation and anomalous data rejection are also part of data preparation. These steps help make the data more reliable and accurate (Hırca and Türkkan, 2024).

The process above efficiently turns the original multi-source and multi-dimensional furniture design data into standardised, structured, and time-sequenced spatial and temporal map data. This provides a solid data foundation for the ST-GNN's subsequent spatial structural feature extraction and time-series evolution modelling. It also makes sure that the design assistance system can accurately capture the dynamic changes in the furniture design and help create and improve intelligent design solutions.

4.1.2 Dynamic spatial-temporal map modelling

The dynamic spatial-temporal graph modelling module employs ST-GNN to describe structural information that changes over time and space during the furniture design process. First, the module uses graph convolution to extract spatial features from the furniture structure graph at each time step. By combining the attributes of nodes and their neighbours, the graph convolution does a good job of capturing the local topological information and relationships between nodes. This gives a rich spatial representation for the analysis of the next time step.

After getting the spatial features H_t at each time step, the module uses GRU to model the time series of the spatial feature sequences at the next time step. The update-gate and reset-gate techniques of GRU let it dynamically manage the flow of information (Ma et al., 2023). This keeps the long-term dependencies and gets rid of the irrelevant information, which lets it accurately represent the evolutionary tendency of the furniture design structure.

We can write the time-series state updating method of GRU like this:

$$S^t = GRU\left(H^t, S^{t-1}\right) \tag{8}$$

The function GRU(·) takes the hidden state from the previous time step (S_{t-1}) and the spatial feature from the current time step (H_t) and combines them to give the spatial-temporal hidden state S_t at the present moment.

The module uses the fusion function to merge the spatial feature H_t with the temporal hidden state S_t at the current instant. This lets it make full use of spatial and temporal information. To get the most out of the spatial and temporal information, the module uses the fusion function to merge the spatial feature H_t with the temporal hidden state S_t at the current moment. This creates the final spatial-temporal representation Z_t:

$$Z^t = \phi\left(H^t, S^t\right) \tag{9}$$

where $\phi(\cdot)$ is a nonlinear mapping function that combines spatial and temporal information to make feature expression more complex and useful (Yao et al., 2019).

This module not only fully extracts the structural features of the furniture design process in space but also captures how those features change over time. This greatly improves the design assistance system's ability to see and predict how the structure of the furniture will change over time and space.

4.1.3 Structural condition prediction

The structural state prediction module takes the structural dynamic elements of the furniture design that were found in the spatial-temporal modelling phase and turns them into a forecast of the structural state in the future design phase. The design of furniture is an ongoing and evolving process. Adding, removing, and changing the connections between furniture parts during the design iteration will cause the local and overall structure to alter over time. So, based on the structural knowledge that is already available, being able to forecast the future state of the structure is very important for guiding the design process's optimisation and decision making.

The module starts by taking the comprehensive spatial-temporal representation Z^t output from the dynamic spatial-temporal graph modelling module as input. Then, it uses feed-forward neural networks to model how the structural state will change at the current design stage and make predictions about how it will change in the future.

Design behaviour changes the geometric qualities and functional statuses of furniture components at the node level (Fu et al., 2023). This is why the module creates a node state prediction function $f_{\text{pred}}(\cdot)$, which uses the current spatial-temporal features Z^t to make a set of predictions about the node state for the next time step:

$$\hat{Y}^{t+1} = f_{\text{pred}}\left(Z^t\right) \tag{10}$$

where $\hat{Y}^{t+1}$ is the state feature prediction of N pieces of furniture at time $t + 1$ in the F-dimensional attribute space. To improve the modelling ability of the evolution law of node attributes, the node state prediction function uses a fully connected neural network with many layers and a nonlinear activation function.

The connecting relationship and topology of furniture parts are the most important parts of the overall design at the structural level. This is why the module includes the structural relationship prediction function $g_{\text{pred}}(\cdot)$, which uses the current spatial-temporal characteristics to guess the neighbourhood set of the furniture structure in the next stage. It is also used to show how the connections between components change and how the overall structural framework evolves over time:

$$\hat{A}^{t+1} = g_{\text{pred}}\left(Z^t\right) \tag{11}$$

where $\hat{A}^{t+1}$ is the collection of projected structural neighbours, which shows how connected the parts are at time $t + 1$. A nonlinear mapping based on graph decoding or an ensemble regression model is used to make the prediction function work (Ahmed et al., 2023). An ensemble regression model or a nonlinear mapping based on graph decoding is used to create the prediction function. These models can make structural graphs that change over time.

It is important to note that this module models node state prediction and structural relationship prediction at the same time and improve them both. The node-level prediction looks at how local component aspects change over time, while the structural-level prediction looks at how global connection changes and is rebuilt. Together, these two types of predictions model the changing process of furniture design.

This module uses a multi-step prediction strategy and a sliding window mechanism during training to make the prediction more accurate and stable. By gradually predicting the structural states at multiple future time steps, the model can better model long sequential design processes.

The structural state prediction module not only gives a good idea of how the local and overall structures will change over time during the furniture design process, but it also gives the multi-objective optimisation module all the information it needs to make a complete and consistent design evolution path. This creates a closed-loop structural modelling system that goes from feature extraction to design evolution.

4.1.4 Multi-objective optimisation scheme generation

The multi-objective optimisation module is meant to help furniture designers deal with conflicting and limiting goals by coming up with a variety of balanced design options based on predictions of how the structure will behave. When designing furniture, the structural stability, use of materials, usefulness, and aesthetic quality are sometimes limited by one another.

To do this, the module first models the problem of making furniture design solutions as a standard multi-objective optimisation problem. Let X be the parameters of the furniture design scheme, and let the set of multi-objective functions that go with it be:

$$F(X) = \{f_1(X), f_2(X), \ldots, f_m(X)\} \tag{12}$$

where $f_1(X)$ is the function that evaluates the structural stability of the furniture, $f_2(X)$ is the goal for optimising the use of materials, $f_3(X)$ measures the functionality score, and $f_4(X)$ measures the aesthetic quality. There are $m = 4$ goals. The goal of multi-objective optimisation is to lower all of the above objective functions at the same time while staying within the design space limit Ω. We can say the problem like this:

$$\min F(X) \quad \text{subject to} \quad X \in \Omega \tag{13}$$

Some of the Ω limitations are design requirements like making sure that the solutions can really be used and make sense, as well as lower limits on structural stability and limits on materials and space.

The NSGA-II algorithm is used as the optimisation core in this module to find a dynamic balance and trade-off between multiple objective optimisation functions. The future design structure output from the structural state prediction module gives the optimisation search its first population. This helps the search find a viable design region. NSGA-II uses a non-dominated sorting and congestion distance computation strategy to filter out candidate solution sets that are not worse than each other on multiple objective functions during the optimisation process (Verma et al., 2021). It then extends and optimises the Pareto frontiers in the next evolutionary process. In each generation of optimisation, the population hierarchy is first sorted according to the non-dominated ordering, and the crowding distance is used to keep the diversity of solution sets. Selection, crossover, and mutation processes create a new generation of populations that improve coverage and optimisation in the target space. The population slowly moves closer to the Pareto optimal frontier during the iterative phase. The optimisation process can be written as:

$$X^* = \arg\min_{X \in \Omega} F(X) \tag{14}$$

where X^* is a group of design solutions in the final Pareto-optimal solution set. Each of these solutions achieves trade-off optimality on the multi-objective function.

When optimising multiple objectives, the creation of the multi-objective solution set depends not only on the performance of each individual objective function, but also on the prediction results of the structural state, which act as a dynamic guide for evolution to make sure that the design solutions created are in line with the trend of structural evolution. As the optimisation process goes on, the system changes the population evolution strategy based on how the objective function changes. This makes sure that the search direction is in line with the new design requirements, and in the end, it gives out a variety of design solutions that are balanced across multiple objectives.

The module outputs a Pareto frontier solution set P with high-quality furniture design options that meet the termination requirements of the optimisation iterations, such as the maximum number of iterations or the convergence of the objectives.

$$P = \left\{X_1^*, X_2^*, \ldots, X_k^*\right\} \tag{15}$$

where X_i^* is the i^{th} Pareto optimum solution, and k is the size of the solution set. Each solution finds a balance between structural stability, material use, utility, aesthetic quality, and other factors (Makinde et al., 2024). The designer can choose the best design option from this set based on the actual needs, or they can make more local changes and improvements.

To sum up, this module builds a multi-objective optimisation solution generation mechanism by combining the multi-objective optimisation method with the structural state prediction results. This allows for a wider range of solutions to be generated and a more balanced optimisation of those solutions under the multi-objective constraints in furniture design.

4.1.5 Collaborative integration and design decision support

The collaborative integration and design decision support module is the main link between the different parts of the FD-STGMO methodology. Its goal is to get ST-GNN and multi-objective optimisation processes to work together closely and give each other feedback in real time.

The ST-GNN module is in charge of modelling space and time and predicting how the structure will change over time in the furniture design process. The multi-objective optimisation module, on the other hand, changes the optimisation process based on the structural dynamics provided by the ST-GNN. This creates a feedback loop between the structural evolution trend and the multi-objective optimisation search. The system dynamically calls the ST-GNN module during the optimisation process to predict and evaluate the structural state of the candidate design solutions. This way, the optimisation algorithm does not just look at the static objective function value; it also looks at the evolutionary reasonableness and structural feasibility of the solutions over time.

Let X_t be the current candidate solution for multi-objective optimisation. ST-GNN predicts its structural state as follows:

$$S_{t+1} = \text{STGNN}\left(X_t\right) \tag{16}$$

where S_{t+1} is the structural state feature matrix at time step $t + 1$, which shows how logical the current design solution is in the process of structural evolution. The multi-objective optimisation approach adds a structural evolution evaluation term to the objective function to change the way the fitness computation works in real time (Jiang et al., 2022). We can write the total fitness function like this:

$$F\left(X_t\right) = \alpha \cdot \sum_{i=1}^{m} f_i\left(X_t\right) + \beta \cdot \Psi\left(S_{t+1}\right) \tag{17}$$

where $\Psi(S_{t+1})$ is the structural evolution rationality evaluation function predicted by ST-GNN, α and β are the weighting coefficients of the target performance and structural evolution factors. By adding the ST-GNN prediction results to the fitness evaluation, the optimisation algorithm dynamically avoids design solutions that are structurally impossible or that evolve in a way that does not make sense during the selection and variation phases. This means that the optimisation search process is always guided by structural dynamic information.

At the same time, the ST-GNN module gets new solutions from the optimisation process all the time for structural prediction and state update. This builds a closed-loop optimisation mechanism based on dynamic structural learning and multi-objective optimisation that keeps adding design data and improving feature learning. The combination of ST-GNN and multi-objective optimisation works together in the following ways: on the one hand, ST-GNN's temporal and spatial structure dynamically takes part in the multi-objective optimisation process. On the one hand, ST-GNN's prediction results are used in the multi-objective optimisation process to help make decisions and screen results. On the other hand, the optimisation module's new design solutions keep adding to ST-GNN's input data, which helps the model learn and improve its structural dynamic features.

Finally, the collaborative integration and design decision support module gives a set of design solutions that take into account the target performance and the logic behind structural evolution. It also shows the structural dynamic prediction results along with the optimisation solutions, creating an intelligent furniture design assistance system that combines prediction, optimisation and decision support.

4.2 Data sources

This study uses a multi-dataset fusion strategy to create a large and varied database of furniture constructions that can be used by ST-GNN and multi-objective optimisation-based furniture design aid methods for dynamic modelling of multi-category furniture.

First, the PartNet dataset is the main source of data. It was created by a group of academics from Stanford University, the University of California, San Diego, Simon Fraser University, and Intel AI Labs to give detailed and hierarchical 3D part information. PartNet has classes for furniture like chairs, tables, cabinets, and more. There are 26,671 3D models in the collection, which are divided into 24 object classes. These models have a total of 573,585 part occurrences. The PartNet dataset is meant to help with a lot of different tasks, like form analysis, modelling and simulating moving 3D scenes, functional analysis, and more. PartNet has categories for furniture like chairs, tables, cabinets, and more. Each model is made up of several parts, and these elements are connected to each other in a hierarchical way. This dataset has a lot of structural information, which is good for turning the furniture design process into a series of dynamic graphs that change over time. This makes it easier for ST-GNN to learn about the spatial-temporal features of furniture structures. At the same time, fine-grained structural information gives a wide range of design options for creating multi-objective optimisation design solutions.

Table 1 shows the specific statistics data.

This paper also talks about the ShapeNet dataset, which is a large-scale, well-annotated 3D shape dataset created by researchers from Princeton University, Stanford

University, and the Toyota Institute of Technology Chicago. It is a supplement to PartNet, which does not include bed furniture models. Bed furniture has unique structural and functional needs in real life. ShapeNet's semantic segmentation approach can be used to combine manual annotation and algorithmic segmentation to provide part segmentation and connectivity creation of bed furniture. However, its fine-grained part annotation is not as detailed as PartNet's. The structural information that is created in this way can work with PartNet furniture model structure data. This makes furniture design assistance approaches more useful.

Table 1 Statistics of major furniture categories in the PartNet dataset

Furniture category	*Approximate number of models*	*Approximate average number of parts*
Chair	3,900+	20–25
Table	2,000+	15–20
Cabinet	1,500+	20–30

In the data preprocessing stage, the original 3D models of PartNet and ShapeNet are first standardised, which includes normalising the coordinates and simplifying the topology. Then, each furniture model is turned into a graph structure, with nodes representing furniture parts and edges showing how the parts are connected. To suit ST-GNN's needs for dynamic modelling, a dynamic structural evolution sequence is created to make a time-series structural graph by simulating the process of changing the design. Based on the preprocessing findings from ShapeNet, the dynamic structure sequence of bed furniture is then expanded by the matching time-sequence simulation.

In short, this paper combines the PartNet and ShapeNet datasets to create a dynamic spatial-temporal graph dataset that includes a wide range of furniture types, such as chairs, tables, cabinets, and beds. This dataset provides a wide range of training and validation data for ST-GNN and multi-objective optimisation methods, and it makes sure that the FD-STGMO method can be used in a lot of different situations and works well in general.

5 Experimental setup and results

5.1 Experimental setup

The experiment takes place on a high-performance computing infrastructure with NVIDIA RTX 3090 GPUs. The hardware setup comprises an Intel Xeon Gold processor and 64 GB of RAM, which ensures that the model training and multi-objective optimisation techniques run smoothly. The software environment is based on Python 3.8, the deep learning framework is based on PyTorch version 1.12, and the optimisation technique is based on the NSGA-II package, which is available to everyone

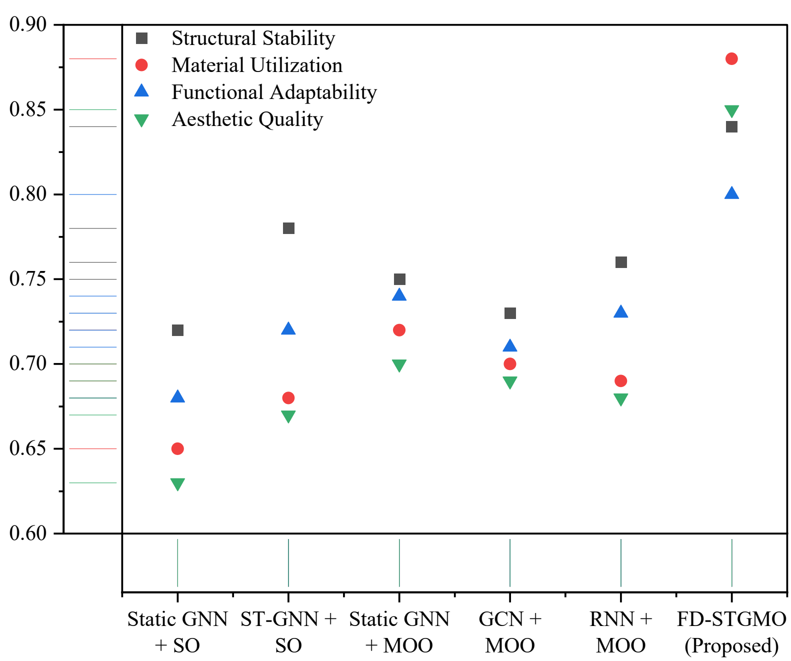
The ST-GNN section of the model has three graph convolutional layers and two GRU layers. It has 128 hidden layer units, and the activation function is ReLU. The Adam optimiser is utilised during training. The learning rate starts at 0.001, the batch size is 32, and there are 100 rounds of training. The cosine annealing scheduling approach slowly lowers the learning rate to speed up the model's convergence and make training more stable. steadiness of training. To make sure the results are strong and can be used in other situations, all the experiments are cross-validated using a five-fold discount.

5.2 Experiment 1: performance comparison experiment

The goal of this experiment is to test the benefits of the furniture design assistance method (FD-STGMO) based on ST-GNN with multi-objective optimisation (ST-GNN) that is suggested in this paper. The focus will be on how well it works in terms of structural stability, material use, functional adaptability, and aesthetic quality. We look closely at FD-STGMO's capacity to develop and optimise it by comparing it to a number of other approaches.

The experiment used five different ways to compare. The static GNN combined with single-objective optimisation (static GNN + SO) shows how well the traditional static structure works with single-objective optimisation. The ST-GNN combined with single-objective optimisation (ST-GNN + SO) shows how temporal dynamic modelling can help. Static GNN combined with multi-objective optimisation (static GNN + MOO) looks at how multi-objective optimisation works on static structures. The GCN combined with multi-objective optimisation (GCN + MOO) serves as an alternative baseline for optimising static structures. Finally, the RNN combined with multi-objective optimisation (RNN + MOO) looks at how sequential modelling can help with design. This work suggests the FD-STGMO approach, which combines ST-GNN and multi-objective optimisation to try to find a superior design solution.

Figure 2 Performance comparison of different methods in furniture design assistance tasks



The four dimensions of structural stability, material utilisation, functional adaptability, and aesthetic quality are all measured in the experiment. The higher the score, the better the performance. To make sure the comparison is fair, all methods are trained and tested on the same dataset and in the same experimental setting. Figure 2 shows the outcomes of the experiment.

The results in the figure show that the FD-STGMO suggested in this research has the best structural stability, with a score of 0.84, which is far better than all the other methods that were tested. FD-STGMO uses the dynamic modelling power of ST-GNN and the multi-objective equilibrium mechanism to its full potential. This lets it effectively capture the changing rules of the local and overall structure during the furniture design process, which leads to higher structural stability.

FD-STGMO also got a maximum score of 0.78 for using materials. Compared to static GNN + MOO (0.72) and GCN + MOO (0.70), FD-STGMO can fully take into account the use of materials and the strength of the structure during the optimisation process. It can also accurately control the spatial relationship between the components through dynamic feature modelling and avoid using unnecessary materials. This shows how multi-objective optimisation can help with material optimisation goals in real life. The system that simply uses RNN + MOO for material use has a score of 0.69, which shows that pure sequence modelling cannot easily take the position of graph structure optimisation at the spatial level.

FD-STGMO had a higher score of 0.88 for functional adaptability. The approach in this paper can fully balance a number of design needs that come from multi-objective optimisation, which is better than static GNN + SO (0.68) and ST-GNN + SO (0.72). The solution that is made is better at balancing structural functionality and diversity. Also, GCN + MOO and RNN + MOO score 0.71 and 0.73, respectively, on this index, which is lower than FD-STGMO. This shows that combining structural modelling and optimisation modules in a way that works together is very crucial for enhancing the functional level.

FD-STGMO also got the highest grade of 0.85 for aesthetic quality. This paper's method is better at combining the many different constraints of function and form in the design solution than other ways. This makes the design solution look better. The aesthetic quality of static GNN + SO and GCN + MOO is only 0.63 and 0.69, respectively. This means that it is hard to improve the look and visual quality of the furniture design by merely using static structure or a single optimisation objective.

In general, FD-STGMO gets the top scores on all four evaluation indexes. This shows how important it is for ST-GNN and multi-objective optimisation to work together. The experimental results clearly show that the method in this paper is better for multi-objective optimisation, dynamic structure optimisation, and improving overall design performance. They also show that using only the traditional GNN, single-objective optimisation, or a simple time-series model will not give the same design optimisation results.

5.3 Experiment 2: module contribution analysis experiment

We set up a module contribution analysis experiment (also called an ablation experiment) to find out more about how each important module of FD-STGMO affects the overall performance. By making several different models for taking out or replacing the essential modules, the function of the ST-GNN module and the multi-objective optimisation module in design aid and how much they help are looked at. All of the experiments are done on the same dataset and hardware, and the optimisation goals and evaluation indices are the same for all of them. This makes sure that the results can be compared.

This experiment sets up four models for comparison:

1 FD-STGMO w/o MOO, which gets rid of the multi-objective optimisation module and only uses ST-GNN with a single-objective optimisation strategy

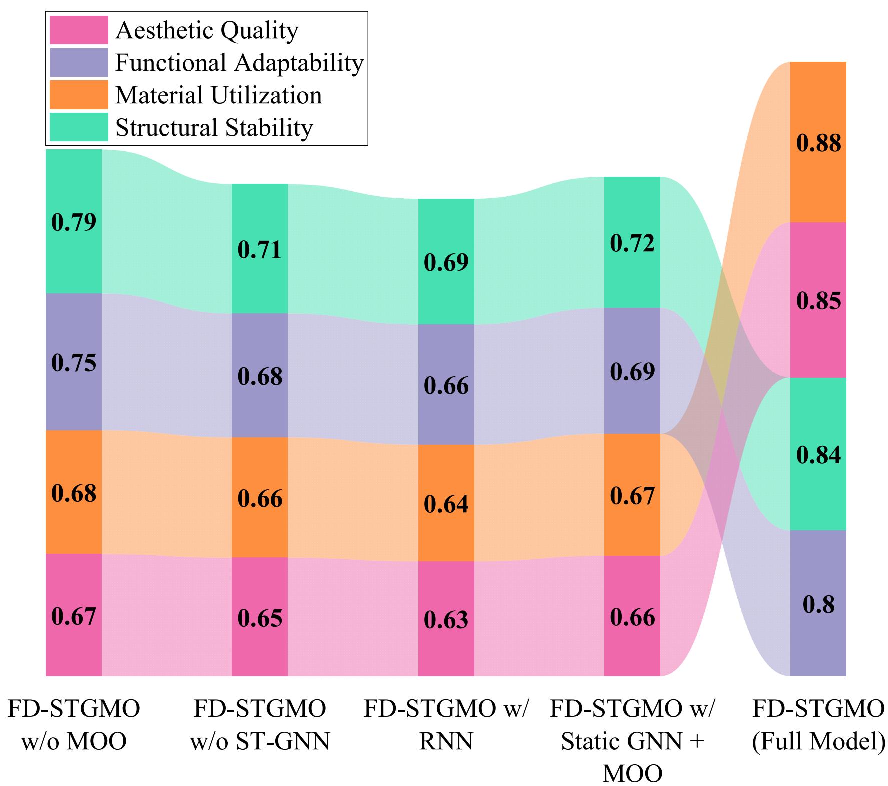
2 FD-STGMO w/o ST-GNN, which gets rid of the ST-GNN module and replaces it with static GNN for structural modelling

3 FD-STGMO w/ RNN, which uses RNN instead of ST-GNN for graph structure modelling and timing processing

4 FD-STGMO w/ static GNN + MOO, which uses static GNN with multi-objective optimisation as a baseline to test the performance of static structure modelling and optimisation.

The full FD-STGMO was the control group. Figure 3 shows the outcomes of the experiment.

Figure 3 Module contribution analysis results in furniture design assistance tasks (see online version for colours)



The experimental results show that the full FD-STGMO does the best job on all four evaluation indexes. For example, it gets 0.84 for structural stability and 0.80 for functional flexibility, which is much better than any of the other module alternatives. On the other hand, taking out the ST-GNN module (FD-STGMO w/o ST-GNN) only gave it a structural stability of 0.71 and a functional adaptability of 0.68. This shows that the ST-GNN is very important for tracking how the structure changes and how components evolve during the furniture design process. Without this ability to describe dynamic graphs, the model's ability to show how local changes sync up with the overall evolution of the structure is quite limited. This makes the design solution perform poorly in terms of structural stability and functionality.

The multi-objective optimisation module is a big step forward for the design solution's multi-objective performance. The figure shows that when the multi-objective optimisation module (FD-STGMO w/o MOO) is taken out, the material utilisation and aesthetic quality indicators drop to 0.68 and 0.67, which are 0.10 and 0.08 lower than the full model. This suggests that the multi-objective optimisation module effectively solves the problem of multi-objective constraints in the process of furniture design and is able to achieve balanced optimisation between structural stability and aesthetic quality, generating diversified and functional design solutions. It can find a balance and come up with a variety of design options that consider both form and function.

After switching the ST-GNN module for a regular RNN (FD-STGMO w/ RNN), all four indicators go down even more. The structural stability and functional adaptability metrics dropped to 0.69 and 0.66, respectively. This shows that the RNN, which only uses time-series modelling, cannot capture complex graph-structural dependencies and spatial features. As a result, the model is not very good at dynamic structural modelling and design state prediction. The absence of structural modelling capacity also led to a drop in the material use and aesthetic quality, which shows that this lack of skill ultimately influences the multi-objective optimisation results.

The FD-STGMO w/ static GNN + MOO scheme does a little better than the RNN scheme on a few metrics, but there is still a big gap between it and the entire model. This version only gets a 0.72 for structural stability, which is substantially lower than FD-STGMO's 0.84. This shows that the GNN, which is only based on static structural modelling, is hard to adapt to the changing interactions between components and the shape of the structure in furniture design. This makes the multi-objective optimisation module less useful.

The full research demonstrates that the ST-GNN module is very important for modelling and predicting the state of dynamic structures, while the multi-objective optimisation module lets us optimise many objectives and make trade-offs in design solutions. The two work together to create a full architecture of FD-STGMO, which makes sure that the design assistance system has all the benefits in terms of practicality and flexibility. The results above prove that the proposed method architectural design is both reasonable and useful.

6 Conclusions

The subject of intelligent furniture design aid is addressed in this work by proposing a furniture design assistance method (FD-STGMO) based on ST-GNN and multi-objective optimisation. The ST-GNN and multi-objective optimisation methods work well together to make the intelligent design process go from analysing design data to generating an optimisation plan.

This work systematically tests the proposed FD-STGMO approach using performance comparison experiments and module contribution analysis studies in the experimental validation section. The results of the performance comparison experiments show that FD-STGMO is better than the traditional baseline method in terms of structural consistency, solution diversity, and multi-objective optimisation effect. This proves that the method in this paper has many advantages when it comes to multi-dimensional design indexes. The two sets of experiments show that the collaborative and integrated design approach of structural modelling and optimisation described in this research works well and is useful for engineering.

This paper suggests the FD-STGMO approach for helping with furniture design, and it has worked well so far. However, it does have some problems. The ST-GNN that was chosen depends on data that has all of the structural and temporal information. On the other hand, the model's stability and accuracy when predicting need to be enhanced when dealing with missing or noisy sequence data in real design situations. On the other hand, NSGA-II is good at optimising multiple objectives, but it can take a long time to converge and find a local optimum when there are more objectives or complicated design constraints. This makes it less effective and efficient for large-scale optimisation problems. Also, the method in this work mostly focuses on automatic creation and optimisation, and it does not take into account the designer's preferences or interaction information. This means that it does not offer much help for customisation in real design situations.

To solve the problems listed above, future research can be improved in the following three ways. First, we will look at the ST-GNN architecture at the modelling level. This architecture combines graph self-encoder and uncertainty modelling to make it more resistant to incomplete graph structures and noisy time series, as well as to improve the structural stability and generalisation ability of dynamic modelling. Second, at the optimisation level, we will look into intelligent optimisation strategies based on reinforcement learning or neural evolution to make the global search more powerful and the optimisation process faster when there are many objectives and complex constraints. Finally, at the level of system architecture, the goal is to include the human-computer interaction mechanism in the optimisation process and create an adjustable and understandable interactive design optimisation framework based on the dynamic feedback and preference modelling of designers. This will allow for the synergistic fusion of design generation and artificial creativity, which will make the system more usable and acceptable to users during the actual design process. With the changes mentioned, the furniture design help technique will move towards becoming more intelligent, personalised, and useful.

Declarations

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The author declares that he has no conflicts of interest.

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