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Integrated method for intelligent structural design of steel frames based on optimization and machine learning algorithm

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ABSTRACT

Optimization methods using metaheuristic algorithms have been widely used in steel frame design to improve the inefficient traditional design method due to repeated model tuning and massive mechanical analysis. However, the random search feature of them may easily result in poor performances. In this paper, combining metaheuristic algorithms and machine learning methods, a highly integrated method based on an on-line model training, updating and parameter tuning process is proposed to improve the performance of the optimization algorithm with general forms and parameters. It reduces the impact of the iterative mechanism and parameter setting of metaheuristic algorithms on their performance. Such method is introduced to intelligent structural design of steel frames including three steps. The standard optimization process is conducted to search optimal design and simultaneously collect the mechanical analysis data of the structure. Then the data is adopted to generate and update surrogate models of structural responses dynamically while an analysis-based feature engineering and an automatic model tuning technique are employed to improve the model accuracy. Finally, a much more efficient procedure is presented to obtain potential solutions which are used to improve the convergence rate and performance of standard optimization. Four cases are used to study the effectiveness of the integrated method and the influence of different settings is discussed, as well as its generality. As a conclusion, the proposed method can achieve structural safety and economic benefit of steel frames, which exhibits superiorly in terms of robustness, optimal results and computational cost even in large-scale optimization problems of complicated frames.

1. Introduction

The construction industry development has been accelerated due to the urbanization. However, the traditional structural design method based on mechanical analysis and expert experiences requires large amount of labor force and computational cost, making it lag behind the growth of the high-turnover and fast-paced construction industry [1–3]. To conduct a practical project, it's always a trail-and-error procedure and the priority is to make the structure satisfy safety demands [4,5]. According to architectural functions and structural constraints based on the standard codes, repeated parametric modeling and finite element analysis (FEA) are conducted to obtain a reasonable design [6–8], which are computationally expensive. Although designers have rich experiences of practical engineering projects, such work still takes couples of days or even a month. In addition, the architectural design obtained by such method is usually conservative or with high structural redundancy because manual adjustment is difficult to make a tradeoff between the safety and economic benefit of the construction. Therefore, the traditional design method is inefficient and cannot easily obtain an economic structure.

To overcome the abovementioned limitation of the design process, the optimization method is adopted. In recent years, the steel frame, as a common type of structures in high-rise buildings, has been widely applied in engineering practice due to its several advantages, e.g., light weight, great earthquake-resistant performance and convenient construction. The optimization of steel frames has earned a great concern in academic field and such problem has been researched for years. The overall objective is to minimize the frame weight or the material cost of the structure subjected to multiple code-stipulated constraints [9–11]. The metaheuristic technique has emerged, which is paid considerable attention in the last two decades. It doesn't need derivative information and has many applications in various disciplines such as mechanics,

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economics and medicine [12]. In engineering practice, the metaheuristic algorithm is an effective tool to improve the optimization design efficiency especially for complicated structures e.g., steel frames [13]. The basic components of it include diversification and intensification. The former one guarantees the adequate search in global domain of the feasible region, while the later one exploits the local region to quickly converge to the optimal solution. Without performing an exhaustive search, a group of individuals that spread over the design space are generated to investigate the vicinity of potential solutions. Based on specified rules, the search direction is updated at each step and the final design can be gradually obtained. The effectiveness of such method derives from its concept of reference to the natural phenomena, such as genetic algorithm (GA) based on survival of the fittest [16], particle swarm optimization (PSO) simulating animal behaviors [17] etc. Despite various metaheuristic algorithms perform well for steel frame optimization [18–23], there are still some limitations as follows. 1) Member size, also the design variable, is usually selected from a designated section list. The obtained result is within limited ranges and may not be the economic structure. However, the member shape itself has several parameters (e.g., flange width, web height, flange and web thickness for an I-shape) related to the optimization in many practical projects [24] where final member sizes are not in the section list from design codes (e.g., YB3301-2005 [25], GBT 6728-2017 [26]). Therefore, the optimization problem becomes much more complicated and cumbersome with more design variables. The effectiveness of proposed algorithms in literatures needs to be examined. 2) The structural optimization design based on population-based algorithms benefits from its random search feature, which entails a large number of FEAs to conduct fitness evaluation. The structural analysis results generated during optimization process are not well exploitative to guide the search direction at each iteration. For complex structures, it may consume dozens of hours or couples of days to conduct optimization once, resulting in low efficiency and convergence, as well as poor robustness. 3) The optimization performance relies on the iterative mechanism and parameter setting of the algorithm, which needs repeated manual adjustment, resulting in great computational cost. These limitations pose a serious barrier in practical application of those algorithms for computationally expensive steel frame optimization.

Machine learning is a kind of artificial intelligence which can automatically learn the specific pattern from the collected dataset to achieve the prescribed objective and assist in decision-making. One of its applications is the surrogate model, which has been extensively studied and used for data prediction in multiple fields for years [27,28]. The commonly used models include deep neural network (DNN) [29], support vector machine (SVM) [30], LightGBM [31] etc. In engineering field, they have been employed to various application scenarios, such as load-carrying capacity estimation of semi-rigid connected steel structures [32], performance assessment and optimal design of concrete beam [33], etc. In structural optimization, the established surrogate model is used for substitution of time-consuming FEA and approximation of simulation results [34,35]. For example, the optimum design problem of geometrically nonlinear space truss was conducted with FEA replaced by an DNN model. As a result, the optimization efficiency is improved by reducing mechanical evaluations and saving computing resource. The optimization employed with the surrogate model is called surrogate-based optimization (SBO). However, it also involves several difficulties as follows. 1) The model development in most studies is independent from structural optimization, which is an off-line model training process. Before optimization starts, large-scale samples (usually tens of thousands) are necessarily prepared, which require computationally expensive FEAs, leading to cost-prohibitive data collecting process. 2) To obtain available model, hyperparameters that much affect the model accuracy and training speed, need to be manually determined by repeated adjustment and sensitivity analysis of them. It is also an off-line and time-consuming model tuning process, which cannot ensure the predictive performance best. 3) Current researches of SBO focus on the component-level or simple structures (e.g., trusses), where only a few surrogate models are built to approximate responses considered in optimization such as the drift ratio. But the practical structural design involves a large number of other indexes including the stress, stability and geometry of structural members. To completely substitute FEA of the structure, dozens of models are always required to be established especially for complex structures, e.g., steel frames. In general, the optimization algorithm is not well integrated with the surrogate model and SBO for complex problems in practical utilization is rarely studied.

In view of this, a novel and efficient optimization method of steel structures subjected to various constraints and load combinations based on surrogate models is proposed to address the practical design problem. Compared to other studies where design variables are selected from a list, this paper focuses on more complicated optimization problem. The sizes of all section parameters of steel members are changeable, resulting in much higher-dimensional variables. Such cases of steel frame design in practice are very common especially in China and other cities. The main contributions of such method include:

1) Integrated method. The optimization algorithm is highly and systematically combined with numerous surrogate models considering both structure- and component-level responses;
2) On-line model training and updating process. It does not need to prepare data samples before optimization. The structural analysis results generated from iterations in optimization are collected to automatically develop models and dynamically enhance their prediction accuracy during optimization process;
3) On-line model tuning process. The model hyperparameters are automatically tuned during optimization process, reducing the time cost and difficulty of their determination;
4) Model substitution and prediction process. Models are used to substitute FEA and obtain potential solutions to improve the capabilities of optimization algorithm without significantly increasing the computational cost. It reduces the reliance and impact of the iterative mechanism and parameter setting of metaheuristic algorithms on their performance;
5) Generality of method. The proposed method can be easily extended to various structural optimization problems.

The paper is constructed as follows. Section 2 describes the structural optimization problem of steel frames. Section 3 presents the automatic design method integrating the surrogate model and the optimization algorithm. Section 4 provides the results of the structural design and the model generation to show the efficiency of the proposed method. The influence of model integration parameters and feature engineering is studied, as well as the generality of the method. The aim is to effectively improve the performances of traditional metaheuristic algorithms by integrating with surrogate models, which provides references to steel frame design and even other types of structures in engineering practice.

2. Structural optimization problem

The structural design of steel frames is a discrete optimization problem according to the standard codes (e.g., GB 50011-2010 [36], JGJ 99-2015 [37] and GB 50017-2017 [38]). In this paper, the problem focuses on seismic resistance and cost economy of the structure. Multiple constraints including structure-level and component-level are considered. The wind-resistant design and multi-objective optimization will be studied in future work.

For a general optimization problem, the mathematical formulation is defined as

$$\begin{array}{r}\text{find } \boldsymbol{x} = \{x_1, x_2, \dots, x_n\} \\ \text{minimize } f(\boldsymbol{x}) \\ \textit{subject to } g_i(\boldsymbol{x}) \leqslant 0 \ (i = 1, 2, \dots, m)\end{array} \tag{1}$$

where $\boldsymbol{x}$ is the design variable with n dimensions; $g_i(\boldsymbol{x})$ is the constraint function; $f(\boldsymbol{x})$ is the objective function.

2.1. Design variable

The structural members of steel frames are composed of columns and beams, the section of which is I-type. They are divided into different groups based on expert experiences and the categories of members in different structures will be described in the following part of case studies. In previous studies [18–23], the variable is selected from a designate list of steel element, making the obtained result within limited ranges. However, final member sizes are not in the prescribed list for many engineering projects, e.g., [24]. Such method cannot be used in practical projects where the member shape itself has several parameters related to optimization design. Therefore, in this paper, four design parameters are separately considered for each type of member, namely the total height, the flange width, the web thickness and the flange thickness. Their values (Table 1) are manually specified in a wide range to study the effectiveness of the proposed method. The optimization problem is more complex with larger size of the searching space.

2.2. Structural constraint

Table 2 shows the classification of all structural constraints to be considered in the optimization problem.For structure-level, the inter-story drift ratio (IDR) constraint value g^{idr} is defined as

$$g^{\mathrm{idr}} = \max\left(\frac{|idr_i|}{idr^{\mathrm{lim}}}\right) \leqslant 1 \tag{2}$$

where idr_i is the maximum IDR in story i; idr^{lim} is the limit value of IDR in multistory steel frames that is adopted as 1/250.

For component-level, the strength constraint value of members g_i^{σ}, the stability constraint values of members including g_i^{sx} in x direction and g_i^{sy} in y direction, the geometry constraint values of members including the web height to thickness ratio of beams g_i^{wt} and the slenderness ratio of columns g_i^{λ} are defined as

$$g_{\mathrm{i}}^{\sigma} = \frac{|\sigma_i|}{\sigma^{\mathrm{lim}}} \leqslant 1 \tag{3}$$

$$g_i^{sx} = \frac{N_i}{\varphi_{ix} A_i f} + \frac{\beta_{imx} M_{ix}}{\gamma_{ix} W_{ix}(1 - 0.8 N_i / N'_{iEx})\mathrm{f}} + \eta \frac{\beta_{ity} M_{iy}}{\varphi_{iby} W_{iy} f} \leq 1 \tag{4}$$

$$g_i^{sy} = \frac{N_i}{\varphi_{iy} A_i f} + \eta \frac{\beta_{itx} M_{ix}}{\varphi_{ibx} W_{ix} f} + \frac{\beta_{imy} M_{iy}}{\gamma_{iy} W_{iy}(1 - 0.8 N_i / N'_{iEy}) f} \leq 1 \tag{5}$$

$$g_i^{wt} = \frac{\mathrm{b}wh_i / bwt_i}{\min(85 - 120\rho_i,\ 75)} \tag{6}$$

$$g_i^{\lambda} = \frac{\lambda_i}{\lambda^{\mathrm{lim}}} \tag{7}$$

where i is the member group. For the strength constraint, σ_i is the maximum stress; σ^{lim} is the yielding strength of steel that is adopted as 235 MPa. For the stability constraint, N_i and A_i are the axial force and section area; f and η are the strength design value and the section influence coefficient; M_i, γ_i, φ_i, φ_{ib}, β_{im}, β_{it}, W_i, N'_{iE}, which all have values in x and y directions, are the moment, the coefficient of section plastic development, the global stability coefficient under axial compression, the global stability coefficient under bending moment, the in-plane equivalent moment coefficient, the out-of-plane equivalent moment coefficient, the section modulus, the Euler force, respectively. For geometry constraint, bwh_{i}, bwt_{i} and ρ_{i} are the web height, the web thickness and the axial compression ratio for beams; λ_{i} is the slenderness ratio of columns and λ^{lim} is the limit value of it that is adopted as 100.

Table 1
Range of design parameters of each structural member (mm).

Parameter	Total height	Flange width	Web thickness	Flange thickness
Range	[100, 600, 8]	[50, 600, 8]	[4, 20, 1]	[5, 30, 1]

Note: [lower limit, higher limit, increment].

Table 2
Classification of strucutral constraints.

Constraint classification	Item	Equation
Structure-level	Inter-story drift ratio	(2)
Component-level	Strength and stability of members, web height to thickness ratio of beams, slenderness ratio of columns	(3)~(7)
Target for pre-test strategy	Width to thickness of overhanging flange of columns, web height to thickness ratio of columns, width to thickness of overhanging flange of beams	(8)~(10)
Target for surrogate model	Structure-level and component-level constraints	(2)~(7)

The aforementioned constraints are evaluated after FEA. In addition, some geometry constraints that can be calculated before FEA are directly integrated into the initialization and updating of the population during the optimization process. Such work will be described in Section 3.1 as the constraint pre-test strategy. Those constraints are defined as

$$cfw_i / cft_i \leqslant 13 \times \varepsilon \tag{8}$$

$$\mathrm{c}wh_i / cwt_i \leqslant 52 \times \varepsilon \tag{9}$$

$$\mathrm{bf}w_i / bft_i \leqslant 11 \times \varepsilon \tag{10}$$

where cfw_{i}, cwh_{i}, cft_{i}, cwt_{i} are the overhanging flange width, the web height, the flange thickness, the web thickness of columns in group i; bfw_{i} and bft_{i} are the width and the thickness of overhanging flange of beams in group i; ε is the correction factor of steel grade.

2.3. Objective function

In the structural optimization, the total weight of building materials is the main concern for designers. In this paper, the aim is to minimize total weight of steel frames without violating the structural constraints. To consider both structure-level and component-level constraints simultaneously, the external penalty method is employed to ingrate the objective function with the degree of code stipulation violations as a comprehensive estimation indicator of the optimal design. As a result, the optimization problem is simplified to an unconstrainted one. The penalty function P_w is defined as

$$P_w = W + \alpha \sum_{i=1}^{n} V_i \tag{11}$$

where n is the total number of structural constraints that is obtained based on the number of member groups; α is the penalty factor (=100) that is determined based on average structural weights that are obtained in multiple structural analysis results of studied steel frames; W is the total weight of building materials, which is defined as

$$W = \rho \sum_{i=1}^{N} A_i l_i \tag{12}$$

where A_{i} and l_{i} are the area and total length of members in group i; ρ is the density of the steel as 7.85×10^{-9} t/mm^3; N is the number of member group. V_i is the auxiliary function to consider the violation degree of the i^{th} constraint and defined as

$$V_i = \begin{cases} 0, & g_i \leqslant 1 \\ 1, & g_i > 1 \end{cases} \tag{13}$$

where g_i is the constraint value calculated according to the equation (2)~(7) in Section 2.2. After optimization, the initial structures with insufficient constraints finally converge to the optimal one which can meet all the constraints, while the total penalty value of V is 0. As can be observed, a better design is a structure with smaller penalty function value.

3. Integrated method based on surrogate model and optimization algorithm

In previous studies [34,35], SBO method has limited application scenarios e.g., simple truss structures, and is always based on an off-line model training and tuning procedure. Before optimization, large-scale samples (usually more than ten thousand) are prepared and extensive manual parameter adjustment is required, resulting in computationally expensive data collecting and modeling process. In addition, the performance highly relies on the effectiveness of the optimization algorithm itself. The aforementioned disadvantages of SBO restrict its application for the design of complex structures. To improve this, an integrated method based on an on-line modeling, tuning and updating procedure is proposed to structural design for steel frames. Such method consists of three parts as follows: 1) standard optimization process; 2) surrogate model generation; 3) optimization prediction. The conceptual flowchart of the proposed method is illustrated in Fig. 1 and the details will be introduced in the following sections.

3.1. Optimization method

To reduce the result reliance on algorithm-specific parameters and iterative mechanism, an efficient method in step 2~3 is proposed to enhance the algorithm performance (e.g., convergence rate) and the details are described in Section 3.3. Therefore, only two traditional algorithms with general forms and parameters are adopted in step 1 as optimizers to show the effectiveness of the proposed method that is highly integrated with surrogate models. GA and PSO are taken as examples in this paper. However, to make those algorithms better suitable for optimization of steel frames with categorized member groups, only few modifications are employed including the constraint pre-test and component-based strategies [39]. They will not have much influence on the algorithm performance. In addition, to better and faster exploit potential optimal solutions in step 3, an algorithm based on multi-population mechanism whose effectiveness has been studied in literature [39] is employed. The aforementioned algorithms are self-programed by Python.

Constraint pre-test strategy

To reduce invalid individuals which cannot satisfy geometry constraints, the constraint pre-test strategy (Fig. 2) is introduced to newly generated individuals during iterations. Before FEA, each structural member is estimated by geometry constraints using equation (8)~(10) and the integer encoding scheme is adopted for its section sizes. Design variables are regenerated until meeting those constraints, otherwise they are randomly initialized if such process is repeated a specified number of times. The constraint pre-test strategy is introduced to all discussed optimization algorithms.

Modified GA ("MGA)

The pseudo-code of MGA is shown in Fig. 3. The Roulette Wheel Selection (RWS) is used for selection operation and the component-based strategy is adopted in crossover and mutation. For each member group, one point among four parameters of the design variable shown in Table 1 is randomly chosen to perform those two operations. In addition, the elite strategy, where the best individual among history solutions is used to replace the worst one in the current iteration, is implemented to avoid result degradation in random search.

Algorithm 1 MGA	**Algorithm 2** MPSO
Initialize population and algorithm parameters	Initialize population and algorithm parameters
while not terminate	**while not terminate**
Fitness evaluation	Fitness evaluation
Selection by RWS	Adaptive inertia weight
Crossover based on member group	Obtain *Pbest* of each particle and *Gbest* of population
Mutation based on member group	Update positions of particles based on member group
Elite strategy	Duplicate particle regeneration
end	**end**
Return the best solution	Return the best solution

Modified PSO (MPSO)

In MPSO (Fig. 4) with the component-based strategy, the particle position is updated based on its own historical best solution and the global one among population as following

$$X_{ij}^{t+1} = X_{ij}^{t} + \omega V_{ij}^{t} + c_1 r_1 \left(Pbest_{ij}^{t} - X_{ij}^{t}\right) + c_2 r_2 \left(Gbest_{j}^{t} - X_{ij}^{t}\right) \tag{14}$$

where i is the i^{th} particle and j is the j^{th} member group; $Pbest_{ij}^{t}$ is the historical best solution of j member group in particle i and $Gbest_{j}^{t}$ is the global best solution of j member group among population; V_{ij}^{t} and X_{ij}^{t} are the velocity and the position of j member group in particle i respectively; c_1 is the learning factor of individual behavior in linearly decreasing trend; c_2 is the learning factor of social behavior in linearly rising trend; r_1 and r_2 are random numbers from [0, 1]; ω is the linearly decreasing inertia weight defined as

$$\omega = \begin{cases} \omega_{\min} + (\omega_{\max} - \omega_{\min})(f_i - f_{\min})/(f_{ave} - f_{\min}), & f_i \leqslant f_{ave} \\ \omega_{\max}, & f_i > f_{ave} \end{cases} \tag{15}$$

where $\omega_{\max}$, $\omega_{\min}$ are the maximum and minimum inertia weight; $f_{\min}$ and f_{ave} are the minimum and average fitness of population respectively; f_i is the fitness of particle i. In addition, to prevent repetitive FEAs from two identical particles after updating, one of the duplicated particles is replaced by a randomly produced one.

Modified multi-population PSO (MPPSO)

Algorithm 3 MPPSO

Initialize population and algorithm parameters
while not terminate
Fitness evaluation
for each population

(*continued on next page*)

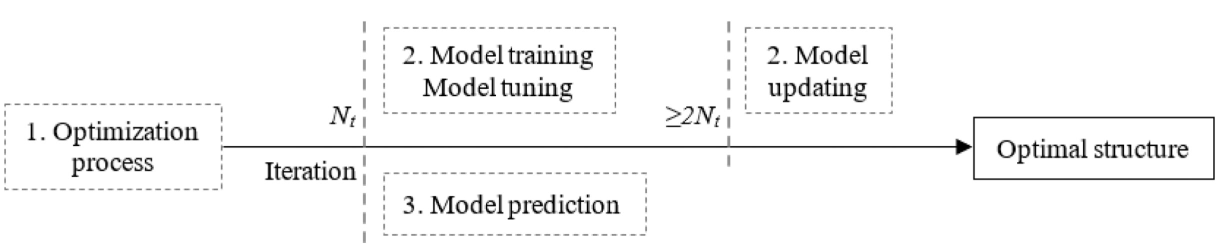

Fig. 1. Conceptual flowchart of the integrated method.

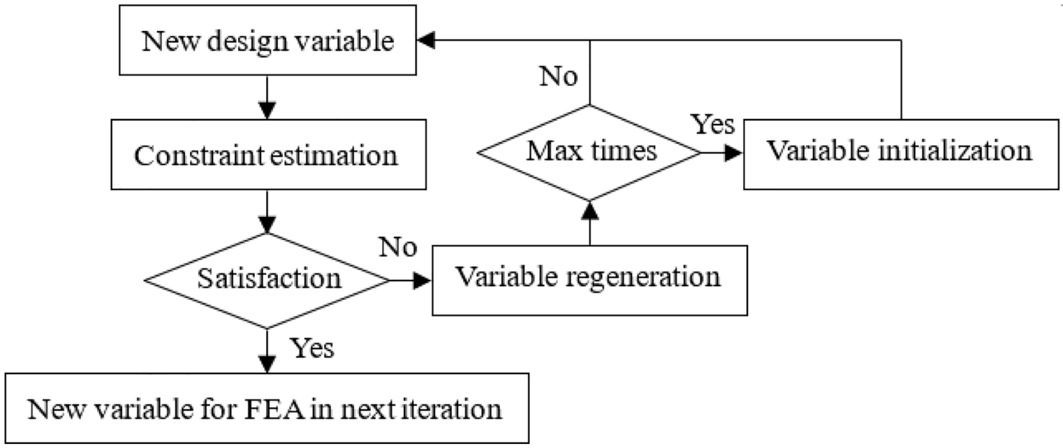

Fig. 2. Constraint pre-test strategy.

Algorithm 1 MGA

Initialize population and algorithm parameters
while not terminate
  Fitness evaluation
  Selection by RWS
  Crossover based on member group
  Mutation based on member group
  Elite strategy
end
Return the best solution

Fig. 3. Pseudo-code of MGA.

Algorithm 2 MPSO

Initialize population and algorithm parameters
while not terminate
  Fitness evaluation
  Adaptive inertia weight
  Obtain *Pbest* of each particle and *Gbest* of population
  Update positions of particles based on member group
  Duplicate particle regeneration
end
Return the best solution

Fig. 4. Pseudo-code of MPSO.

(*continued*)

Algorithm 3 MPPSO

  Rank population in a fitness descending order
  Obtain *Gbest* and generate model particle based on member group
  Update particle positions based on member group using model particle and *Gbest*
 end
 Collaboration of multiple populations for every defined number of iterations
end
Return the best solution

In the multi-population algorithm, multiple parallel populations (mp) are used and each one is an independent optimizer with different algorithm parameter settings. The collaboration of them can exchange information among optimizers periodically (for every t_m iteration), resulting in faster convergence rate and better robustness [39]. Such mechanism is also adopted in the modified multi-population PSO (Fig. 5) which is used for model prediction. In addition, instead of $Pbest_{ij}^t$ in equation (14), the position of the particle is updated based on member group using a model particle pm_j^t that is the weighted average positions from m particles randomly selected from a ranked group of particles in a fitness descending order. The model particle is defined as

$$pm_j^t = \sum_{i=1}^{m} \frac{f_i X_{ij}^t}{\sum_{k=1}^{m} f_k} \tag{16}$$

3.2. Machine learning method

In the structural design of steel frames, the surrogate model is employed to substitute the fitness evaluation to obtain the predicted individuals, helping improve the performances of the standard optimization process. To achieve this, three machine learning algorithms are used to build the prediction model and the results are compared with each other to find the best one that is suitable for the studied problem in this paper. The input is the design variable and the output corresponds to structural responses.

Feature engineering (FE)

In the optimization problem of steel frames involving highly nonlinear and nonconvex equations, the explicit correlation between the input and the output is missing, which may result in less accurate model. Therefore, a feature engineering based on the mechanical analysis is introduced to the training step to enhance prediction performances of the model. D-value method is very suitable for steel frames, which can be simplified as a multiple degrees-of-freedom spring-mass system, to calculate their responses. Therefore, taking IDR as an example to explain, the lateral-force resisting stiffness D_k of a steel frame in the k^{th} story can be defined according to such method as

$$D_k = \sum_{i=1}^{n} \alpha_i^{k,c} \frac{12EI_i^{k,c}/l_i^{k,c}}{h_k^2} \tag{17}$$

where h_k is the story height; $I_i^{k,c}$, $l_i^{k,c}$ and $\alpha_i^{k,c}$ are the bending stiffness, length and correction factor of the i^{th} column in the k^{th} story; n is the total number of columns in the k^{th} story. Therefore, IDR in the k^{th} story (idr_k) can be defined as

$$\mathrm{idr}_k = F_k/(h_k \times D_k) \tag{18}$$

where F_k is the seismic force allocated to the structure in the k^{th} story

Algorithm 3 MPPSO

Initialize population and algorithm parameters
while not terminate
    Fitness evaluation
    for each population
        Rank population in a fitness descending order
        Obtain *Gbest* and generate model particle based on member group
        Update particle positions based on member group using model particle and *Gbest*
    end
    Collaboration of multiple populations for every defined number of iterations
end
Return the best solution

Fig. 5. Pseudo-code of MPPSO.

that is calculated by the equivalent base shear method.

In this way, the explicit functional relationship between IDR and the design variable is obtained. As can be seen in the equation (18), F_k is calculated from the component self-weight that is related to its section area *A*. D_k is the lateral-force resisting stiffness that corresponds to member bending stiffness *EI*. Those are high-dimensional features in structural analysis and can be easily obtained. Therefore, *EI* and *A* of steel columns and beams are introduced to the design variable as feature engineering when FE is used in this paper. Such method can be easily generalized to the design of other types of structures, but it may be hard to obtain an accurate model for the structure with strong nonlinear relationship between design variables and responses.

Support vector regression (SVR)

SVR (Fig. 6) is the application of support vector machine method for regression problems and coded by the package scikit-learn in this paper. By generating a hyperplane with the kernel function, SVR can map the input data to a higher dimensional feature space. The aim is to minimize the distance between the samples that are the farthest from the hyperplane. The target is to minimize the prime problem as following

$$\begin{gathered} minimize\ \frac{1}{2}\omega^T\omega + C\sum_{i=1}^{n}(\zeta_i + \zeta_i^*) \\ subject\ to\ \mathrm{y}_i - \omega^T\phi(x_i) - b \leqslant \varepsilon + \zeta_i,\ \omega^T\phi(x_i) + b - \mathrm{y}_i \leqslant \varepsilon + \zeta_i^* \end{gathered} \tag{19}$$

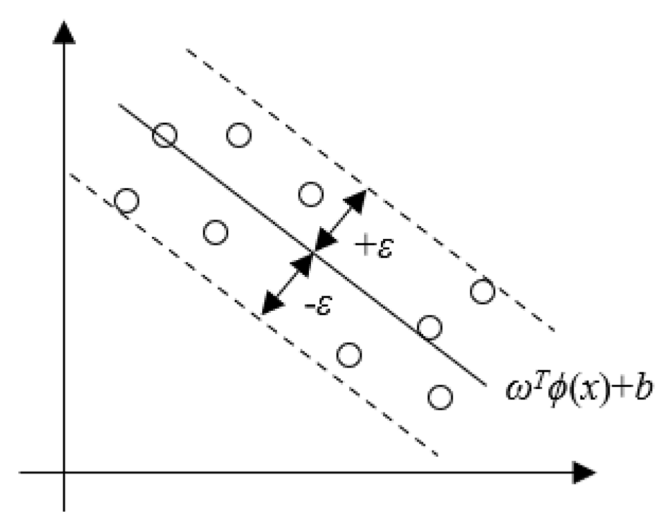

Fig. 6. SVR.

where y_i is the test value; *C* is the regularization parameter to make a balance between the error and model complexity; *n* is the number of samples; ζ_i, ζ_i* (positive values) are slack variables to describe positive and negative deviation of outliers; ε is the error between the test and predicted value; $\phi(x)$ is the mapping function; $1/2\omega^T\omega$ is the regularization to be minimized. Further details can be found in [40].

Deep neural network (DNN)

DNN (Fig. 7) is a machine learning method simulating the biological system of human brains and usually used to represent the nonlinear relationship of the investigated data. It is coded by the package torch in this paper. A common model includes three parts i.e., the input layer, the hidden layer and the output layer. Each layer consists of a set of neurons which can transform information from former units to further units by using weight functions and activation functions. This is forward propagation defined as

$$z_{i+1} = f(\omega_i z_i + b_i) \tag{20}$$

where z_i is the output value of layer *i* and z_0 represents the input variable; *f* is the activation function such as Sigmoid, Tanh, Rectified Linear Unit (ReLU); ω_i is the weight function and b_i is the bias. Training process of DNN is to minimize the prediction error the by backpropagation algorithm, where the weights and biases of each neuron are continuously adjusted. More details can be found in [40,41]. In this paper, the size of input is the dimension of design variables and the output is one value related to predicted structural responses in each model. According to Table 3, the number of hidden layer and the neuron number in each

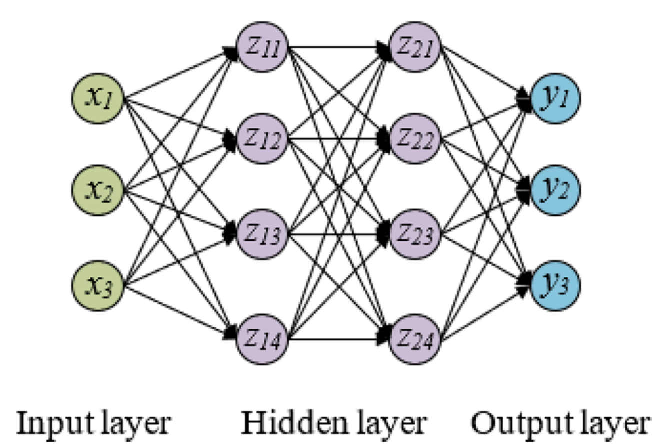

Fig. 7. DNN.

Table 3
Initial parameter settings of algorithms.

Algorithm	Parameter
SVR	C: 0.01, 0.1, 0.5, 0.8, 1; kernel: 'linear', 'poly', 'sigmoid'; test_size: 0.2, 0.3, 0.4
DNN	split: 0.8, 0.7, 0.6; batch_ratio: 0.05, 0.1, 0.2; hidden_layer: 1, 2, 3, 4; hidden_neuron: 10, 20, 50, 80, 100, 150, 200; activation: Sigmoid, ReLU, Tanh; optimizer: SGD, Adam, Adagrad, Adadelta, RMSprop; learning_rate: 0.1, 0.01, 0.001; epochs: 50, 100, 200, 500
LightGBM	num_leaves: 8, 16, 32, 64; learning_rate: 1, 0.1, 0.01, 0.001; feature_fraction: 0.5, 0.6, 0.7, 0.8, 1; bagging_fraction: 0.5, 0.6, 0.7, 0.8, 1; bagging_freq: 1, 3, 5, 7, 10; num_boost_round: 50, 100, 200, 500
Standard GA	pop: 20; iter_max: 50; pc: 0.8; pm: 0.01
MGA	pop: 30, 50, 80; iter_max: 100; pc: 0.8; pm: 0.01
MPSO	pop: 30, 50, 80; iter_max: 100; c1: 3; c2: 1; ω_{min}: 0.5; ω_{max}: 0.8
MPPSO	pop: 50; iter_max: 200, c1: [2, 3], c2: 4- c1, ω_{min}: [0.3, 0.5], ω_{max}: [0.7, 0.9], t_m:1; mp:5

hidden layer are both determined by model tuning with standard GA.

Light gradient boosting machine regression (LightGBM)

LightGBM is a kind of gradient boosted decision tree methods, also a boosting method that combines a number of weak learners based on decision trees to constitute a stronger one to improve model prediction performances. In LightGBM, subsequent iterations are fit to the residual error of the previous one and the model is generated based on the leaf-wise strategy, where only one leaf with the largest split gain is split each time. Such strategy can reduce the complexity of the training data and lead to more complicated trees. Moreover, two other techniques, namely Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB), are also introduced in the model. GOSS conducts down-sampling of instances to remain samples with large gradients while randomly select samples with small gradients. Based on the principle of the histogram based splitting, EFB integrates features to a number of mutually exclusive bundles to reduce feature dimensions. It is coded by the package lightgbm in this paper.

3.3. Integrated method and intelligent design process

Three steps (Fig. 8) are involved as follows:

Step 1: standard optimization process. The intelligent design of steel frames is composed of structural analysis and optimization algorithm. In this paper, repeated modeling and FEA are conducted by the finite element software MSC.Marc to obtain the mechanical results of population, while the optimization is performed by Python to achieve design variable updating and two algorithms are discussed including MGA and MPSO. When the termination criterion is met, the optimal steel frame of the studied case is output. In addition, the multi-core parallel computing technique is used to accelerate FEA process.

Step 2: surrogate model generation. The model generation, parameter tuning and model updating is based on an on-line procedure. The training dataset is generated from the FEA results during optimization process. Two cases are considered in this step. Case 1: when the iteration i first reaches step N_t, the model is trained based on the mechanical results produced in the previous iterations while its hyper-parameter tuning is automatically conducted by standard GA which doesn't require human intervention. As a result, the optimal surrogate model with best hyperparameters is currently obtained and those hyperparameters remain unchanged in subsequent iterations. Case 2: when the iteration i reaches step mN_t ($m > 1$), new results are created and combined with previous one to form a new dataset with more

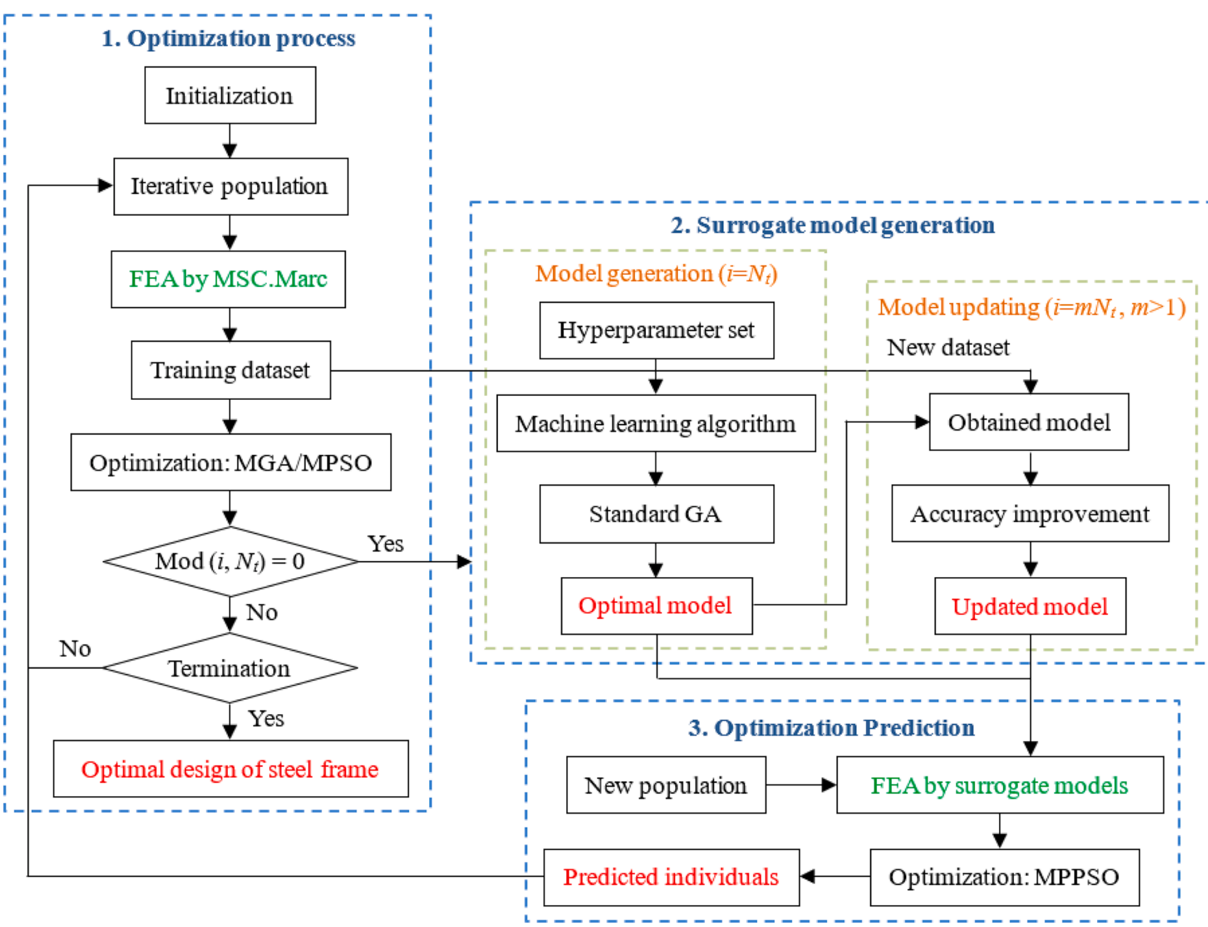

Fig. 8. Flowchart of the integrated method based on surrogate model and optimization algorithm.

information and larger range. It is used to dynamically update the obtained model if the prediction accuracy can be improved.

Step 3: surrogate model prediction. For every N_t iteration, the obtained surrogate models in step 2 are used to create new individuals with MPPSO. Similar to but different from the process in step 1, a newly generated population is optimized by MPPSO but FEA is substituted by surrogate models. This step is high-efficient to obtain more potential individuals which are then introduced into the iterative population in step 1 to guide its search direction and accelerate its convergence rate.

4. Discussion of results

4.1. Application for optimization design of the steel frame

In this section, the optimization design of a steel frame is investigated. The density and the elastic module of steel are 7850 kg/m^3 and 206 GPa respectively. The representative value of gravity load (RG) is obtained by the dead load of 5 kN/m^2 and the live load of 2 kN/m^2. The seismic force is considered as horizontal load (EX, EY) by the equivalent base shear method. The design characteristic period of ground motion and the damping ratio are 0.35 s and 0.02 respectively. To perform more practical design problem, load combination is considered to obtain the most unfavorable structural responses including 1.2RG + 1.3EX and 1.2RG + 1.3EY according to the design codes [36–38]. As shown in Fig. 9, two standard stories (SS) are adopted and five member groups are employed for each SS including the beam in the edge (BL), the beam in the middle (ZL), the column in the corner (JZ), the column in the edge (BZ) and the column in the middle (ZZ). The optimization problem is with 40-dimensional design variable and 8.27×10^{62} searching space. To discuss the effectiveness and efficiency of the proposed method, the results of optimization by the integrated method and metaheuristic algorithms without surrogate models (e.g., MGA and MPSO) are compared with each other.

4.1.1. Results of surrogate models

In this section, the aim is to select one machine learning algorithm to conduct the structural design latter. The performances of three methods in Section 3.1 are discussed including the mean square error (MSE), the R-squared (R^2) and the generation time. To obtain the model, the training dataset is selected from FEA results of the studied steel frame and the data scales are adopted as 200, 300 and 500. Similar to the process in step 2, a new population of initial hyperparameters is used for model tuning of each model by standard GA to obtain its best setting. Table 3 illustrates the initial hyperparameter setting of machine learning algorithms and optimization algorithms.

The surrogate model of the drift ratio of the steel frame is taken as an example. The prediction results are shown in Table 4. The MSEs of all data in all cases are small even if a very small data scale as 200 is used. Such scale will be used in the following description. Fig. 10 shows the correlation between actual and predicted drift ratios of models using different machine learning methods. Except for SVR, the other two models exhibit great prediction performances with good fitting between those values. MSE of all data for SVR is 1.16, which is much larger than the one for DNN (0.08) and LightGBM (0.07). In addition, SVR has the R^2 of test data as 0.81, which is 17.3% and 12.0% smaller than DNN (0.98) and LightGBM (0.92) respectively. It shows that the prediction accuracy of DNN and LightGBM models is higher than the one of SVR. In terms of the computational cost, LightGBM performs better than DNN due to a significant reduction of model generation time from 11764.2 s to 89.6 s. It is much favorable in the design of the studied steel frame when a total of 37 surrogate models are required to be created during optimization. Therefore, LightGBM will be used as the machine learning method in the structural optimization design of steel frames latter.

4.1.2. Results of structural optimization design

The results of the integrated method (marked with '_ML') and traditional optimization methods without surrogated models (Fig. 11 and Table 5) are compared with each other. The optimization of each case is conducted for 10 runs. Fig. 11(a)~(b) shows examples of responses of optimal steel frames by four algorithms. Those structures have the stresses of structural members lower than the yielding strength of the material and most of them are under 75%. The maximum IDRs of those frames are also smaller than the limit value. It illustrates that the obtained optimal steel frames in all cases don't violate code-stipulated constraints. For MPSO and MGA with larger population size, the calculation time is larger but the obtained weights tend to be better. For example, compared to MPSO30, the calculation time (4.4 h) is amplified by 209.8% for MPSO80 but the optimal design has its weight (144.3 t) 13.2% smaller. This is because population with larger size can perform more comprehensive exploration in a wider search space and has greater

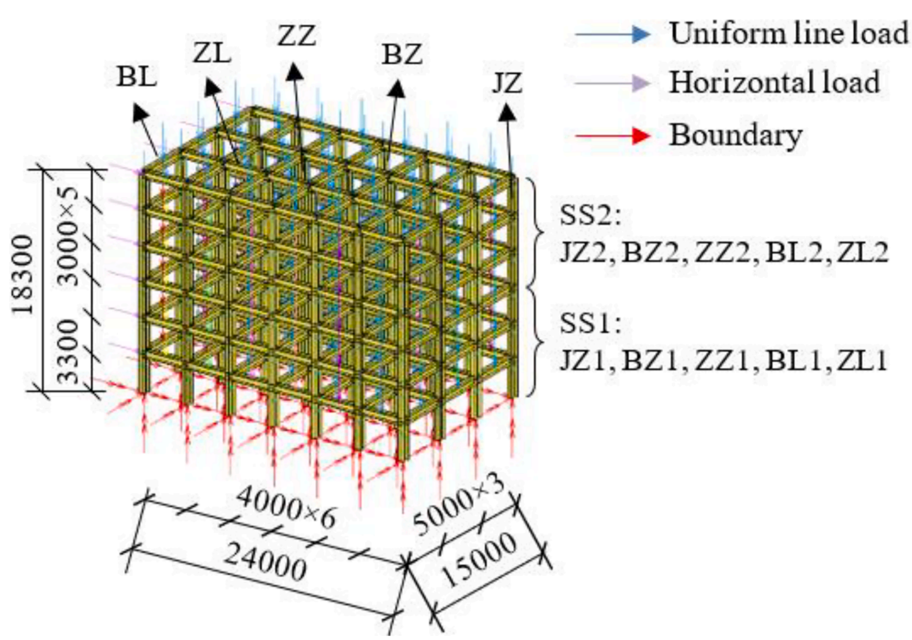

Fig. 9. Geometry and load of the designed steel frame (mm).

Table 4
Prediction results for optimal models with best hyperparameters.

Algorithm	SVR			DNN			LightGBM		
Dataset scale	200	300	500	200	300	500	200	300	500
MSE of all data	1.16	1.79	1.12	0.08	0.04	0.04	0.07	0.09	0.07
R^2 of train data	0.69	0.61	0.70	0.98	1.00	1.00	0.99	1.00	1.00
R^2 of test data	0.81	0.57	0.63	0.98	0.97	0.97	0.92	0.92	0.91
Generation time (s)	10238.9	13790.8	16464.5	11764.2	2121.0	3968.6	89.6	76.7	93.3
Best hyperparameter settings of model with data scale of 200	C: 1; kernel: 'poly'; test_size: 0.2			split: 0.8; batch_ratio: 0.1; hidden_layer: 4; hidden_neuron: 150; activation: ReLU; optimizer: Adadelta; learning_rate: 0.1; epochs: 500			num_leaves: 64; learning_rate: 0.1; feature_fraction: 0.8; bagging_fraction: 0.7; bagging_freq: 10; num_boost_round: 500		

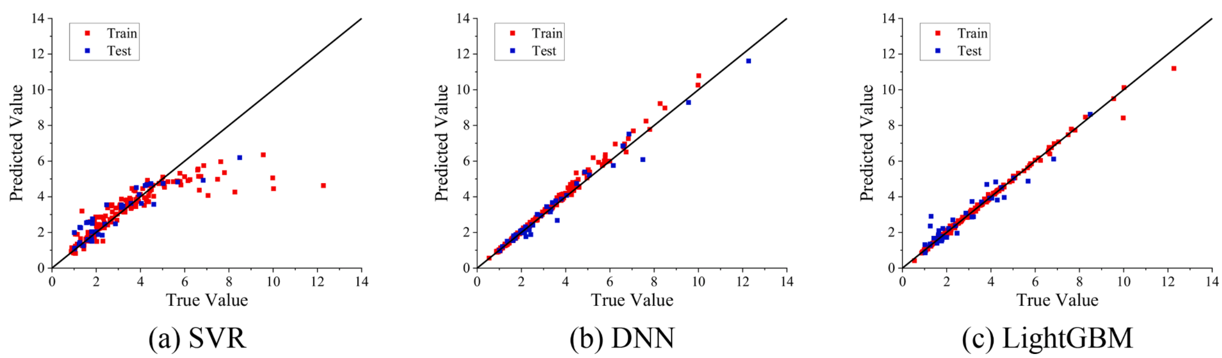

Fig. 10. Correlation between actual and predicted drift ratios using different models (data scale: 200).

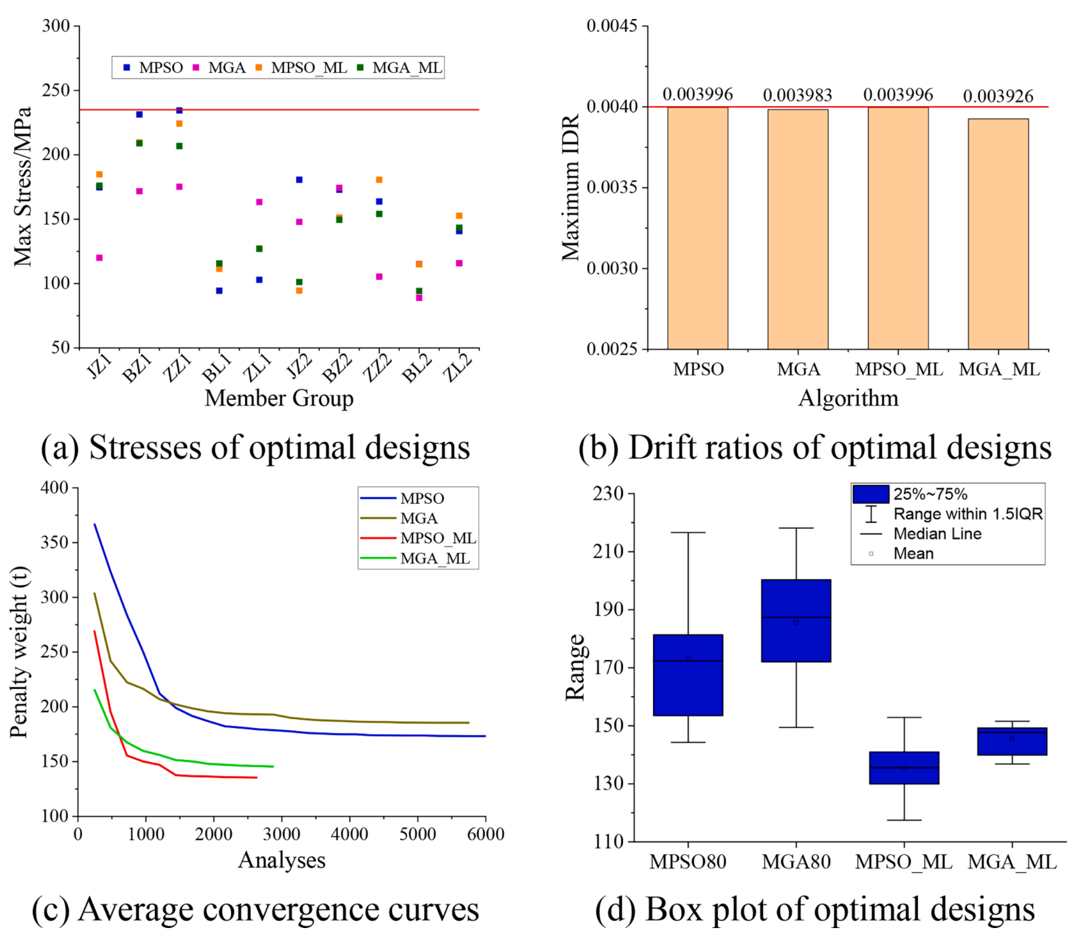

Fig. 11. Optimization results of the studied steel frame.

Table 5
Optimization results of the studied steel frame.

Algorithm	MPSO			MGA			MPSO_ML	MGA_ML
Population size	30	50	80	30	50	80	30	30
Optimal weight (t)	166.3	155.2	144.3	185.6	166.9	149.4	117.5	136.8
Average weight (t)	198.5	179.2	173.3	208.2	190.4	185.5	135.4	145.5
Worst weight (t)	274.4	216.5	216.6	242.1	218.6	218.2	152.9	151.6
Std. weight (t)	31.4	20.4	21.6	19.3	14.2	22.0	9.9	4.9
Calculation time (h)	1.4	2.3	4.4	1.3	2.8	4.2	3.1	2.8

chance to obtain better design. In addition, compared to MPSO30, the average (173.3 t), worst (216.6 t) and standard deviation (std.)(21.6 t) weight of final results for MPSO80 are respectively reduced by 12.7%, 21.1% and 31.3%. Such phenomenon is also observed in the case of MGA. Therefore, the population size of 80 is used in the subsequent discussion of results for metaheuristic methods without surrogated models.

Compared to traditional methods, the integrated method uses surrogate models generated and dynamically updated during optimization to create predicted individuals to significantly improve the performance of the standard optimization process with high computational efficiency. MPSO_ML and MGA_ML both perform better than MPSO80 and MGA80. For example, the optimal frame for MPSO_ML weights 117.5 t, which is 18.6% smaller than the one for MPSO80 (144.3 t). The average weight is 135.4 t that is 21.9% lower than that of MPSO80. Similarly, the optimal design (136.8 t) and the average design (145.5 t) of MGA_ML are 8.4% and 21.6% lighter than those of MGA80, respectively. When surrogate models are used, the total computational cost shows a great reduction. MPSO_ML requires much less calculation time (3.1 h) to obtain the optimal design than MPSO80 (4.4 h). The computational time of MGA_ML (2.8 h) is reduced by 33.7% compared to MGA80 (4.2 h). The faster convergence rate and better ability to obtain better structures of the integrated method than the traditional one can also be seen from Fig. 11(c)~(d). In addition, the std. weights of MPSO_ML (9.9 t) and MGA_ML (4.9 t) are 54.1% and 77.7% much less than those of MPSO80 (21.6 t) and MGA80 (22.0 t), respectively. Therefore, compared to traditional algorithm, the integrated method that shows better robustness is more useful in the structural optimization problem of the studied steel frame for saving analysis time and obtaining lighter design. The optimal frames can achieve both structural safety and economic benefit. Furthermore, no matter whether surrogate models are used or not, due to learning behaviors among particles, MPSO-based method outperforms MGA-based one. For example, the optimal weights of MPSO80 (144.3 t) and MPSO_ML (117.5 t) are 3.4% and 14.1% lower than those of MGA80 (149.4 t) and MGA_ML (136.8 t) respectively. The average calculation times for optimization by two methods are similar, which shows that to obtain better results does not increase the computation cost. Therefore, only the MPSO-based algorithms are used in the subsequent discussion of results.

Fig. 12 shows the MSE losses of train and test data during optimization (taking the model of drift ratio as an example), as well as the best predicted design for each N_t iteration. When the iteration i first reaches N_t, the model training and hyperparameter tuning of LightGBM are completed. In this phase, the MES losses of train and test data are 0.0092 and 1.0660 respectively, which are much smaller than initial ones. In subsequent iterations ($=mN_t$, $m > 1$), more samples of FEA results are collected for model updating during optimization. When the iteration reaches $4N_t$, those losses perform a significant decrease and respectively reduce to 0.0029 for train data and 0.0499 for test data. R^2 reaches 0.9988 at this time, which shows an improved prediction accuracy of the obtained surrogate model as the iteration proceeds. Additionally, the predicted optimal designs for each N_t iteration are presented, e.g., 122.2 t in the iteration $2N_t$. As a result, more potential solutions can be obtained in step 3 of the integrated method and used to promote the structural optimization.

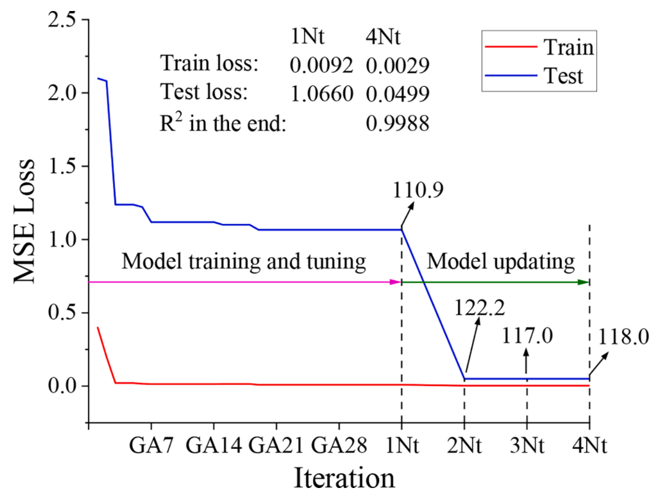

Fig. 12. MSE losses of data and predicted optimal designs during optimization.

4.2. Influence of model integration parameter settings

In this section, the influence of related factors of model integration is discussed including feature engineering, the model generation and updating interval, the number of predicted individuals. Table 6 summarizes the optimization results of the proposed method which exhibits high efficiency with the calculation time in all cases about 2~3 h.

4.2.1. Influence of feature engineering

Machine learning algorithm is an effective tool to build up the relationship between different datum. When the original design variable is used for surrogate model training, the input are all low-dimensional features which represent section sizes of structural members. As a result, the best design is a frame that weights 145.1 t. However, when *EI* and *A* of columns and beams are introduced as feature engineering, the explicit function between such high-dimensional features and the structural response such as IDR is established, which enhances the training process and results in the model with more prediction accuracy. Therefore, compared to the optimization result for the optimal design without using FE (145.1 t), the one in any case where FE is employed can obtain lighter frames and the reduction ratio is within the range of 2.5~12.5%. Such method is based on the theory of structural analysis, which can be conveniently extended to other types of structures.

Table 6
Optimization results of the studied steel frame using different model updating interval and number of predicted individuals by MPSO_ML.

Feature engineering	No	Yes	Yes	Yes	Yes	Yes
N_t	10	5	10	15	10	10
Preds	10	10	10	10	30	2
Optimal weight (t)	145.1	134.9	132.0	138.4	127.0	141.5
Average weight (t)	151.5	139.5	134.4	153.4	127.6	155.5
Worst weight (t)	160.2	147.3	138.2	169.9	128.2	172.7
Std. weight (t)	6.3	5.6	2.7	12.9	0.5	13.0
Calculation time (h)	2.4	3.5	2.4	2.4	3.4	2.0

4.2.2. Influence of model generation and updating interval

In step 2, the iteration interval of standard optimization process N_t is used to control the frequency of model generation and updating. When smaller value is adopted for N_t, the total number of model training is larger, which takes greater analyses and calculation time. Meanwhile, the optimal design prediction (step 3) is also conducted more times, which may result in the degradation of solutions due to more intervention in population generated in step 1 by predicted individuals. The calculation time (3.5 h) for Case $N_t = 5$ is 45.8% greater than the other two cases. In contrast, when N_t is larger, smaller effect of surrogate model on the standard optimization can be observed because less model prediction is performed. For example, Case $N_t = 10$ obtains the lightest frame with the weight of 132.0 t, which is 2.2% and 4.6% lower the one for Case $N_t = 5$ and Case $N_t = 15$ respectively. The average weight (134.4 t) and std. weight (2.7 t) of designs for Case $N_t = 10$ are reduced by 3.7~12.4% and 51.8~79.1% respectively. Therefore, a suitable setting of N_t (=10) helps convergence to better optimization results.

4.2.3. Influence of the number of predicted individuals

In step 3, based on multiple surrogate models of structural responses to substitute FEA analysis, new optimization different from that in step 1 can be conducted to obtain predicted individuals with much lower computational cost. As illustrated in Table 6, with larger number of predicted individuals *Preds*, more potential solutions are created to guide the population generated in standard optimization process (step 1) to search for the space with more possibility to get better results. The optimal frame weights 127.0 t for Case *Preds* = 30, which is 3.8% and 10.2% smaller than the one for Case *Preds* = 10 and Case *Preds* = 2 respectively. In Case *Preds* = 30, the std. weight of designs is only 0.5 t, which shows that the robustness of the integrated method using larger *Preds* is much better than the other two cases. However, Case *Preds* = 30 presents more calculation time (3.4 h) that is 41.7% and 70% greater compared to the other cases respectively. Therefore, the value of *Preds* is very important, which has a great influence on the optimization result. It can be determined according to the tradeoff between the analysis time and the final solution.

4.3. Application for more complicated steel frames

To exhibit the generality of the integrated method, three additional cases (Fig. 13) are discussed. Compared to the structure shown in Fig. 9, Case 1 and Case 2 (40 dimensions) are more complicated frames with larger heights and stories, which demonstrates the spatial complexity of the structure. In addition, to further study the effectiveness of the integrated method, the search scale for Case 3 (60 dimensions) reaches 2.38 $\times 10^{94}$, which exhibits both the spatial complexity of the structure and the dimensional complexity of the optimization problem. The number of member groups in each SS and the load information are the same as described in Section 4. For optimization of those complicated frames, it's hard to find the structure without violating the constraints because randomly generated population in initialization always has small lateral stiffness. Therefore, a supplemental operation is employed, where the difference operation is conducted between each individual in initial population and the structure with the maximum values of the design variable, which is defined as

$$X_i = X_i + r(Y - X_i) \tag{21}$$

where X_i is the i^{th} individual in initial population; r is the random number within [0,1]; Y is the frame with the maximum value of the design variable.

Table 7 summaries the results of three cases, which shows greater performances of the integrated method when compared to the metaheuristic algorithm without surrogate models. In all cases, MPSO_ML obtains optimal frames with lighter weights than MPSO80 and the reduction ratios are within 13.5~16.7%. Compared to MPSO80, the average and worst weights of frames for MPSO_ML are reduced by 12.0~16.9% and 8.3~18.5% respectively. In addition, the computational cost is much smaller when using the integrated method especially for Case 3, where the calculation time are reduced to 12.0 h from 23.3 h with the decreasing ratio of 48.6%. The aforementioned results are very favorable in practical engineering design. As a conclusion, the integrated method performs superiorly even in much larger-scale optimization problem of much more complicated frames.

5. Concluding remarks

An integrated method based on optimization and machine learning algorithm is proposed for intelligent structural design of steel frames subjected to code-stipulated constraints. A three-step procedure is adopted to efficiently exploit FEA results of the structure generated during optimization. Firstly, the optimal design is searched based on a

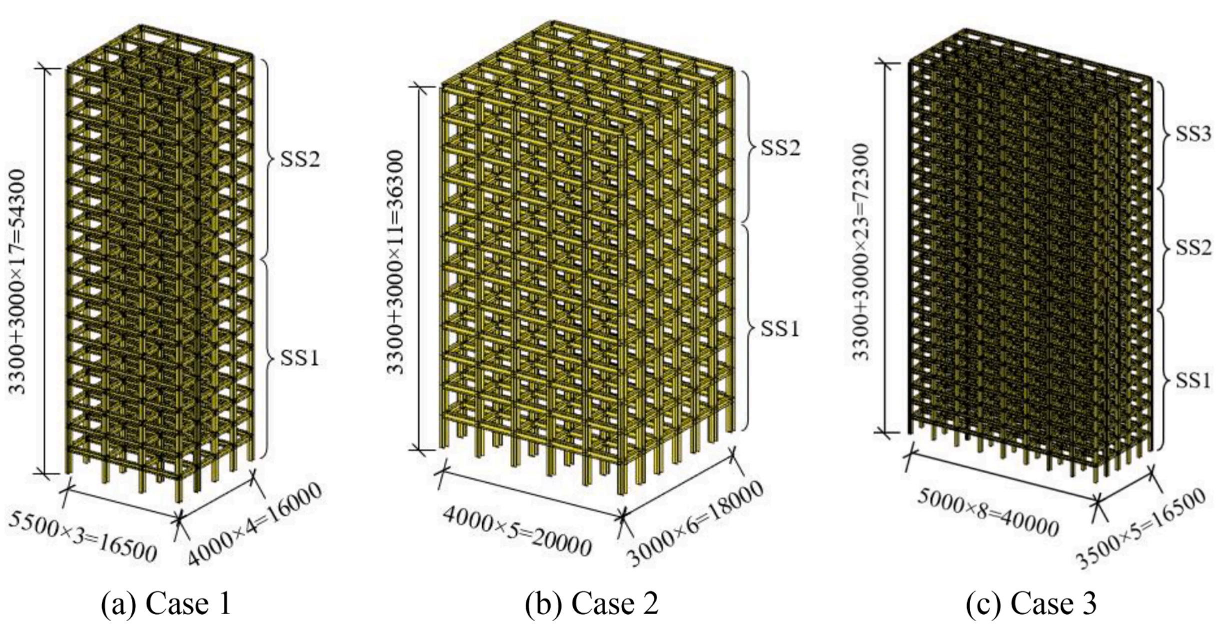

Fig. 13. Geometry of steel frames (mm).

Table 7
Results of more complicated optimization problems of steel frames.

Steel frame	Case 1		Case 2		Case 3	
Algorithm	MPSO80	MPSO_ML30	MPSO80	MPSO_ML30	MPSO80	MPSO_ML30
Optimal weight (t)	497.6	430.3	438.0	364.9	1791.0	1524.3
Average weight (t)	504.8	444.2	447.6	387.5	1844.7	1532.5
Worst weight (t)	518.4	458.2	456.4	418.3	1894.4	1543.9
Std. weight (t)	9.6	11.4	7.5	22.5	42.3	8.3
Calculation time (h)	7.4	4.3	12.1	6.8	23.3	12.0

built-up standard optimization process. Next, the structural analysis results are collected to generate surrogate models, whose hyper-parameters are automatically determined using optimization method. The data created in subsequent iterations and a structural analysis-based feature engineering are used to dynamically update and enhance the model accuracy. Finally, those models are used to substitute FEA to obtain predicted solutions to further improve the performance of standard optimization process. To demonstrate the effectiveness of the proposed method, four cases of steel frames are studied and the influence of different algorithm settings is discussed. The conclusions are as follows.

- Compared to SVR and DNN, LightGBM performs better in prediction of structural responses of steel frames, which has larger R^2 of train and test data, and smaller MSE of all data. The total training time by LightGBM is much less than the other two, which is suitable for optimization problem with multiple models required to be created.
- For the optimization problem of the studied frame, metaheuristic algorithms without surrogate models present better performances when larger population size is employed and MPSO-based method outperforms MGA-based one. Compared to them, the integrated method exhibits superiorly in terms of robustness, optimal results and computational cost. In addition, a significant reduction of MSE losses of train and test data for surrogate models can be observed during optimization, which illustrates the effectiveness of model updating.
- For the integrated method, the analysis-based feature engineering, a suitable model generation and updating interval (e.g., 10), and larger number of predicted individuals (e.g., 10) are recommended to obtain lighter designs with high efficiency. The proposed method has great generality, which performs well even in much larger-scale optimization problem of much more complicated frames. Compared to MPSO, MPSO_ML has the optimal designs 13.5∼16.7% lighter and the calculation time reduced by 48.6% at most.

The main contribution of the work is to propose a highly integrated method based on an on-line model training, updating and parameter tuning process. Compared to SBO method in previous studies, it does not need to prepare data samples before structural optimization. The models that replace FEA can be used to obtain more potential solutions with much low computational cost to improve capabilities of traditional optimization method. It reduces the impact of the iterative mechanism and parameter setting of metaheuristic algorithms on their performance. The proposed method can be easily generalized to other structural optimization problems. Further research is in process to improve the accuracy of surrogate models with small training samples and the application of proposed method in optimization of other structures.

CRediT authorship contribution statement

Wenchen Shan: Validation, Methodology, Visualization. **Jiepeng Liu:** Supervision. **Junwen Zhou:** Conceptualization, Methodology, Software, Formal analysis, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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