

Automatic Acquisition and Utilization of Stress Characteristic Knowledge for Excavator Boom Structural Optimization

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Abstract. To improve the efficiency of coordinating the lightweight goal and structural performance for excavator boom, a knowledge-based optimization mechanism is proposed. By this mechanism, the stress characteristics in excavator boom can be extracted automatically at first. After that, stress characteristics knowledge can be acquired based on Monte Carlo simulation and processed under multistate constraint. Depending on the cycle operation between knowledge utilization module and optimization module, the strategy of utilizing characteristic knowledge to guide the structural optimization can be realized. Finally, different testing cases are taken in the structural optimization of excavator boom as examples to demonstrate the feasibility and effectiveness of proposed method.

1. Introduction

Excavator is one kind of important engineering machinery, which often works under multiple working conditions. How to improve its comprehensive performance is still a research focus [1, 2]. In particular, boom is the largest load-bearing part in the working equipment of excavator and affects the performance of excavator directly. But the contradictory between lightweight goal and structural performance is usually difficult to be coordinated during the structural optimization of boom. This difficulty is more serious when considering multiple working conditions. It is necessary to seek effective methods to overcome above trouble. In recent years, many researches are focused on the method of combining knowledge engineering with intelligent design to improve the efficiency of design, which has been utilized in the design of aircraft, ships and other fields [3, 4]. However, coordinating the lightweight goal and structural performance is still a bottleneck. Therefore, a new strategy of automatic acquiring and utilizing stress characteristic knowledge for excavator boom structural optimization is proposed in this paper.

2. A new knowledge-based intelligent optimization mechanism

In order to realize the automatic knowledge acquisition and utilize knowledge to guide the structural optimization, a knowledge-based intelligent optimization mechanism is constructed, which is shown in figure 1. This mechanism includes nine modules, some of which are illustrated as follows:

Solid modeling module is constructed to realize batch modeling by connecting VC++ with Pro/Engineering. Boom samples required for characteristic extraction are generated by this module.

Kinematics and kinetostatics analysis module is constructed to calculate the forces of boom, which are required to the loading of finite element analysis.

Characteristic extraction module is constructed to extract characteristic automatically by connecting VC++ with ANSYS. This module includes two sub-modules, i.e., the stress survey sub-module and the stress characteristic extraction sub-module. Firstly, using the stress survey sub-module, the stress characteristic (SC) regions for boom samples can be identified by the method of



finite element analysis and danger evaluation. And then, characteristic stress, i.e., the maximum stress in every SC region, can be extracted by the stress characteristic extraction sub-module.

Data processing module is constructed for analyzing the data generated by characteristic extraction module.

Knowledge processing module can be used for acquiring stress characteristic knowledge, which includes the evaluation knowledge of characteristic regions, the influence evaluation knowledge and the main influence factors (MIF) knowledge. All knowledge is saved in knowledge base.

Knowledge utilization module and knowledge-based intelligent optimization module are constructed to form a loop. By these two modules, the strategy of utilizing characteristic knowledge to guide the structural optimization can be realized.

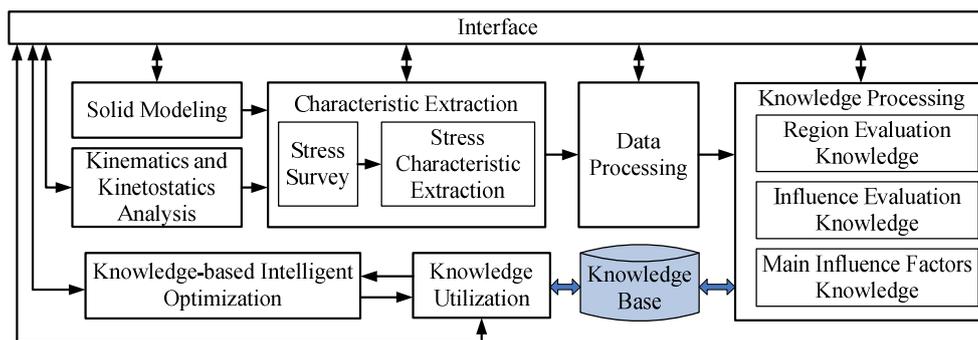


Figure 1. Knowledge-based intelligent optimization mechanism.

3. Automatic acquisition and utilization of stress characteristic knowledge

3.1. The method of automatic knowledge acquisition

Knowledge acquisition is carried out before optimization, which includes two steps shown in figure 2.

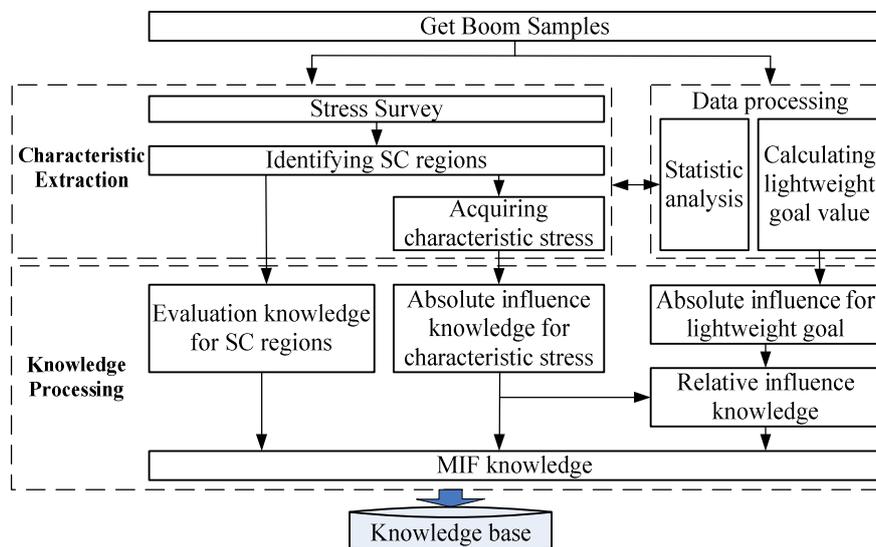


Figure 2. The process of knowledge acquisition before optimization.

The first step is characteristic extraction. In order to coordinate stress distribution, the SC regions need to be identified as the controlled targets. But most types of excavator boom have continuous geometric shape, which makes it more difficult to determine the SC regions. Therefore, the double-step stress survey [5] is carried out to explore the dangerous regions where the maximum stress often occurred. Those dangerous regions are taken as SC regions, and the maximum stress in SC region is called characteristic stress.

The second step is knowledge processing. In this step, the evaluation knowledge for SC regions, the influence evaluation knowledge and the MIF knowledge can be acquired. The first part is the evaluation knowledge for SC region. After SC regions identified, the times of occurring danger for every region is counted and the danger grade is evaluated. The second part is influence evaluation knowledge, which includes absolute influence knowledge and relative influence knowledge. In order to extract absolute influence knowledge for characteristic stress, the Monte Carlo simulation technique and the Spearman rank correlation analysis method are used. The Spearman rank correlation models between structure variables and characteristic stresses are constructed. And then, the Spearman correlation coefficients are taken as the absolute influence knowledge for characteristic stresses. Similarly, the absolute influence knowledge for lightweight goal is acquired. According to absolute influence knowledge, the relative influence knowledge of the structure variables for characteristic stress and lightweight goal are acquired.

After that, MIF knowledge is reasoned under multi-state constraints. The general expression of rule is shown as Rule 1, and the meaning of the symbols is shown in table 1.

Rule1: IF c_1 and c_2 and (c_3 or c_4) and c_5 , THEN r_1 and r_2 ;

Table 1. Meaning of the symbols in Rule1.

Symbols	Meaning
	Adjusting expectation for corresponding state;
c_1	$c_1 = 1$: In state1, lightweight priority. Stress is better to be reduced, but allowed to increase greatly.
	$c_1 = 2$: In state2, lightweight priority. Stress is better to be reduced, but allowed to increase slightly.
	$c_1 = 3$: In state3, stress reduction must be ensured.
c_2	The danger grade of SC regions.
c_3	The absolute influence knowledge for characteristic stress.
c_4	The absolute influence knowledge for lightweight goal.
c_5	The relative influence knowledge.
r_1	The influence grade for characteristic stress.
r_2	Adjusting weighting

3.2. The strategy of knowledge utilization.

Knowledge utilization module is connected with knowledge-based intelligent optimization module to form a loop. According to the evolution population, the corresponding stress characteristic knowledge saved in knowledge base can be acquired to guide the optimal searching of next generation. The cycle of utilizing knowledge to guide optimization is shown in figure 3, which includes three important parts.

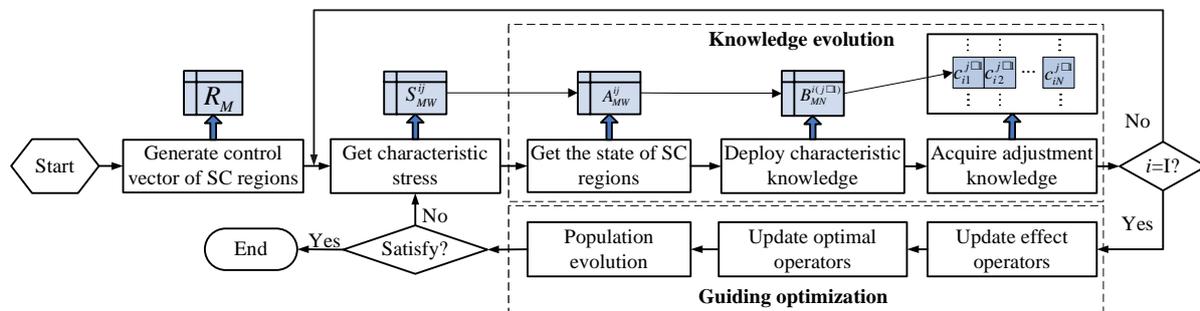


Figure 3. The cycle of utilizing knowledge to guide optimization.

Generate control vector of SC regions. Because of the different danger situation occurring in different SC regions, the control strategy for SC regions should be identified before optimization. According to the evaluation knowledge, SC regions can be divided into three classes. The first class called main control region has the highest adjustment priority. The second class called conditional

control region is often depended on geometry of boom. The third class called auxiliary control region has the lowest adjustment priority. The control vector of SC regions is generated to guide knowledge deployment and knowledge integration, as well as coordinate knowledge conflict.

3.2.1. Knowledge evolution. In order to match corresponding knowledge from knowledge base, it is necessary to get the information of individuals firstly. For each individual, because excavator often works under multiple working conditions, the characteristic stresses of individual in every condition should be extracted and saved in a matrix. And then, the states of SC regions for such individual can be identified by the rules. According to the state of each SC region in every condition, the corresponding MIF knowledge can be matched, which is integrated and combined to the adjustment knowledge vector of such individual.

3.2.2. Guiding optimization. In order to utilize adjustment knowledge to guide the optimal searching, the effect operators are designed according the optimization algorithm. In this paper, the genetic algorithm is utilized, so that some effect operators, such as elitist preservation influence operators, selection influence operators, crossover influence operator and mutation influence operators [6], are designed. After acquiring adjustment knowledge, the effect operators are updated. And then, the genetic operators are also updated to realize knowledge-based population evolution.

4. Application

The structural optimization of gooseneck type boom for medium-sized excavator is taken as an example, in which the lightweight goal of minimizing the volume of boom under four working conditions [7] is proposed. By using the mechanism shown in figure 1, the SC regions are identified and shown in figure 4. And then, the stress characteristic knowledge is acquired and saved in knowledge base.

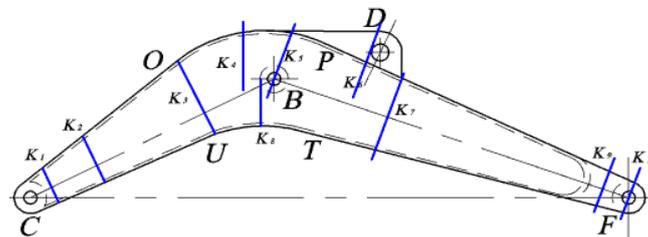


Figure 4. The SC regions of gooseneck type boom.

In order to verify the feasibility and effectiveness of proposed method, four testing cases with different control strategies for SC regions are shown in table 2.

Table 2. Control strategies for SC regions in testing cases.

Case Number	Main control region	Conditional control region	Auxiliary control region
Case 1	Maximum stress in boom	—	—
Case 2	Maximum stress in boom	—	—
Case 3	K_1, K_2, K_7, K_{9-10}	K_{3-4-8}	—
Case 4	$K_1, K_2, K_5, K_6, K_9, K_{10}$	K_{3-4-8}	K_7

Case 1 is the traditional experience design case and only the maximum stress in the boom is controlled. Case 2 uses the existing genetic algorithm and also only controls the maximum stress. Case 3 includes four main control regions, i.e., K_1, K_2, K_7 and the region combining K_9 with K_{10} . The conditional control region in this case is the combined control of K_3, K_4 and K_8 , but the auxiliary control region is not considered. Case 4 includes six main control regions, i.e., K_1, K_2, K_5, K_6, K_9 and K_{10} . The conditional control region in Case 4 is the same to Case 3, but the auxiliary control region is K_7 . In Case 3 and Case 4, knowledge is utilized to guide the genetic operators, which are illustrated in our preliminary work [6]. The results of testing cases are shown in table 3.

In table 3, it is shown that the volume of boom in Case 3 is decreased by 40.97% and 4.76% comparing with Case 1 and Case 2 respectively. Comparing with Case 3, the volume is further reduced in Case4, but the maximum stress is not increased. DM represents the maximum difference value of stress among four digging conditions. Comparing all of testing cases, the value of DM in Case 3 and Case 4 are much less than that in Case 1 and Case 2.

Table 3. The results of testing cases.

Case	Volume (m^3)	Maximum Stress under Four Digging Conditions (MPa)				DM (MPa)
		Condition 1	Condition 2	Condition 3	Condition 4	
Case 1	0.1662	166.25	180.05	243.27	145.59	97.68
Case 2	0.1030	186.44	165.37	236.17	180.92	70.80
Case 3	0.0981	192.25	188.14	234.98	189.23	46.84
Case 4	0.0967	201.68	176.57	233.57	187.59	57.00

In addition, the evolution processes of Case 2, Case 3 and Case 4 are shown in figure 5. The evolutionary rate of Case 4 is the fastest and Case 3 is secondly, which indicates that the searching capacity can be improved greatly under the guidance of stress characteristic knowledge.

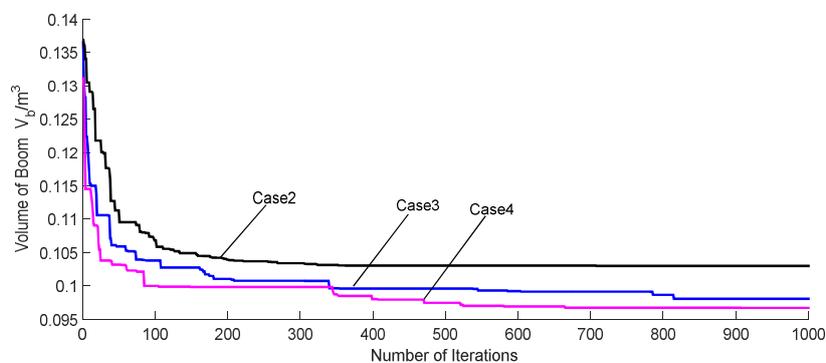


Figure 5. The evolution processes of Case 2, Case 3 and Case 4.

The comparing of characteristic stresses for Case 3 and Case 4 is shown in table 4, where M_{max} represents the value of characteristic stresses in every control region; E_{tr} represents the difference between characteristic stress and allowable stress.

Table 4. The comparing of characteristic stresses for Case 3 and Case 4. MPa.

Name	Item	K_1	K_2	K_5	K_6	K_7	K_9	K_{10}	K_{3-4-8}
Case 3	M_{max}	214.58	205.85	144.41	158.72	167.53	234.98	181.23	164.91
	E_{tr}	30.42	39.15	100.59	86.28	77.47	10.02	63.77	80.09
Case 4	M_{max}	233.57	223.62	164.94	186.81	145.43	222.56	186.50	162.61
	E_{tr}	11.43	21.38	88.06	58.19	99.57	22.44	58.50	82.40

In table 4, although the genetic operators in Case 3 and Case 4 are the same, the knowledge guiding to the optimization are different. In Case 3, the values of E_{tr} in K_5 and K_6 are larger than other regions. Similarly in Case 4, the maximum value of E_{tr} is in the auxiliary control region K_7 . It is indicated that the priority of control regions may influence the stress distribution. The result also shows that the average value of E_{tr} is 60.97MPa in Case 3, but this value is decreased by 55.25MPa in Case 4, which means the situation of equal strength in Case 4 is better than in Case 3.

5. Conclusion

By verifying the proposed strategy of automatic acquiring and utilizing stress characteristic knowledge, the conclusions are shown as follows:

The proposed knowledge-based intelligent optimization mechanism can acquire knowledge from RC regions automatically.

The priority of control RC regions as well as the strategy of utilizing knowledge may influence the efficiency and effectiveness of optimization greatly.

Utilizing stress characteristic knowledge to guide optimization, the effectiveness of coordinating the conflict between structure performance and lightweight goal can be improved remarkably.

6. References

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