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Finite-element analysis case retrieval based on an ontology semantic tree

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Abstract

The widespread use of finite-element analysis (FEA) in industry has led to a large accumulation of cases. Leveraging past FEA cases can improve accuracy and efficiency in analyzing new complex tasks. However, current engineering case retrieval methods struggle to measure semantic similarity between FEA cases. Therefore, this article proposed a method for measuring the similarity of FEA cases based on ontology semantic trees. FEA tasks are used as indexes for FEA cases, and an FEA case ontology is constructed. By using named entity recognition technology, pivotal entities are extracted from FEA tasks, enabling the instantiation of the FEA case ontology and the creation of a structured representation for FEA cases. Then, a multitree algorithm is used to calculate the semantic similarity of FEA cases. Finally, the correctness of this method was confirmed through an FEA case retrieval experiment on a pressure vessel. The experimental results clearly showed that the approach outlined in this article aligns more closely with expert ratings, providing strong validation for its effectiveness.

Introduction

As a widely used numerical calculation method in the engineering field, finite-element analysis (FEA) technology is of great importance for improving innovation ability, ensuring product quality, and reducing production costs (Hughes, 2012). The FEA process often involves the following stages: problem identification, preprocessing, computation, and post-processing (Wriggers et al., 2007; Xu et al., 2019). At each stage of the analysis process, engineers need to determine many types of decision-making tasks, such as classifying problems, selecting computation model parameters (e.g., geometric simplification, and finite element type and size), determining the numeric algorithm type and parameters, and evaluating the numeric results (Wriggers et al., 2007). The accuracy and reliability of the FEA result are highly dependent on the quality of the decisions made at each stage of the analysis process.

One approach to improve the quality of decision-making is to obtain decision-making-related references from existing solved cases (Zhan et al., 2010; Badin et al., 2011; Numthong and Butdee, 2012; Kestel et al., 2019). The references include how to simplify the geometric model, how to determine the type and size of the finite element, how to determine the boundary conditions, and how to select the analysis algorithm. Therefore, the decision-making results in solved cases can help the decision-making process of the current analysis task.

The case-based reasoning (CBR) method that models the process of solving a problem by establishing the analogy relation between the current problem and previously solved problem(s) is proposed to facilitate the use of information from previously solved FEA cases (Wriggers et al., 2007; Zhao et al., 2009; Khan et al., 2014; Khan and Chaudhry, 2015). Wriggers et al. (2007) proposed a knowledge-based system for the intelligent support of the preprocessing stage of engineering analysis in the contact mechanics domain. Khan and Chaudhry (2015) proposed an adaptive FEA-integrated system based on the CBR method for mesh selection. Wang and Rong (2008) presented a CBR method for welding fixture design. According to the above research results, the key tasks of the CBR-based FEA process are representation in terms of FEA cases and retrieval of solved cases that are most similar to the current case.

One of the most promising approaches to represent the FEA case is through the use of ontologies. Yoshioka et al. (2004) demonstrated a physical ontology-based support system for knowledge-intensive engineering called the Knowledge-Intensive Engineering Framework to integrate multiple engineering models and allow more flexible use of them. Sun et al. (2009) proposed an ontology-based framework that included a hierarchy transfer approach and a three-stage automated FEA method for automated FEA to help users to define the appropriate finite element model more easily. Grosse et al. (2005) proposed a formal set of ontologies for classifying analysis modeling knowledge to enable robust knowledge sharing. Xu et al. (2019) proposed that FEA modeling processes can be expressed as the entities and relations among entities in an ontology tree to obtain the FEA script grammar. These results suggest that the FEA process can be modeled as ontologies in terms of a set of concepts within a domain and the relationships between them.

Another key technology of the CBR-based FEA system is the similarity estimation between FEA cases. A common similarity retrieval method in the engineering field is to express the case using the word level-based method,, such as keyword mathching (Salton et al., 1975), feature vectors (Korenius et al., 2007), topic extraction, (Lin, 2020) and vector space model (VSM) (Figueiras et al., 2012), and then calculate the similarity between the two vectors using the Euclidean or cosine distance (Hu et al., 2013; Ke et al., 2020). The elements in the vector are either keywords or entities within the ontologies. Similarity measures based on VSM have been applied to a variety of tasks, such as the retrieval of information in collaborative engineering projects (Figueiras et al., 2012), relaxed lightweight assembly (Hu et al., 2013) customer demand data for remanufacturing processes (Ke et al., 2020), and the data in IoT (Internet of Things) (Sang et al., 2019). However, this type of calculation method lacks the structure information between entities, making it difficult to measure the similarity between the two cases from a semantic point of view. Another option to define similarity measures for cases is through the use of embeddings (Zou et al., 2020). For example, Xu et al. (2021) used the word2vec model to obtain semantic information from fault data for fault classification. Cordeiro et al., (2019) proposed that the doc2vec model can be used to measure the semantic similarity of text in the oil and gas domain. Cai et al. (2019) proposed a deep learning and word embedding method to represent industrial alarm data to predict alarm information. Reimers and Gurevych (2019) used the Sentence-BERT (SBERT) model to improve the document retrieval system for the supply chain domain (Sant Albors, 2021). Furthermore, with the advancement of cross-modal embedding techniques (Rehman et al., 2018, 2019), embedding the multimodal data within cases can also lead to further enhancements in case retrieval performance. However, although the embedding method can express context information, structure information between objects in cases is not considered in the similarity calculation.

For these reasons, a semantic similarity calculation method for FEA cases based on ontology is proposed that aims at resolving the difficulty of representing and retrieving solved FEA cases. Considering that FEA models are often encapsulated and difficult to represent directly, the FEA task is used as the index for the FEA case. The FEA tasks are expressed structurally using ontologies. Through instantiating the ontology based on the named entity recognition (NER) method, the structural FEA tasks are constructed automatically. These structural FEA tasks are organized into a semantic tree. By comparing the structural similarity of the semantic trees, a similarity comparison algorithm for FEA cases is proposed. Finally, the most relevant FEA cases can be obtained by comparing the structural similarity of the semantic trees.

Methods

With the accumulation of FEA cases, how to identify the most similar cases from these solved cases has become one of the key technologies in the CBR-based FEA system. An FEA case mainly includes the data of the FEA modeling process that consists of the FEA task, FEA solution, FEA model, and FEA result (Saarelainen et al., 2014; Joshi, 2004). The FEA task is the textual description of the analysis problem, which includes the mechanical device classification, aim of the analysis, contact pair identification, material properties definition, and contact problem properties definition. Therefore, the description of the FEA task can be considered as a requirement of a specific FEA modeling process, and this description is used as the index for the FEA case.

The FEA task description is typically text described in natural language, which needs to be transferred into a structured representation. Based on the structured representation of the FEA task description, an FEA case retrieval method is proposed. Figure 1 provides an insight into the overall process. In the first step, the ontology of the FEA modeling process is constructed and then the structured representation of the FEA task description is obtained by instantiating the ontology according to the task description. Finally, based on semantic tree technologies, a similarity comparison algorithm is proposed.

Representation of the description of FEA tasks

The description of FEA tasks is generally in the form of natural language, which is particularly applicable to large-scale enterprises where the process of design and analysis requires the collaboration of several departments (Saarelainen et al., 2014; Nosenzo et al., 2014), and to the engineering field where the analysis results need to be checked, such as pressure vessels (Gupta and Vora, 2014; Niranjana et al., 2018). To form a representation that can be processed by a computer, first, an ontology of the FEA modeling process is constructed, then text processing technology is used to obtain the entities of the task description, and finally, the ontology is instantiated to form a structured description of the FEA task based on the entities.

An ontology is a clear and accurate description of a conceptualization (Uschold and Gruninger, 1996). An ontology can be easily transformed into a storage form that can be understood by a computer. Additionally, an ontology can express domain knowledge through the semantic definition of terms and axioms. Many research results have demonstrated that an ontology can be used to formally define the FEA task (Wriggers et al., 2007; Sun et al., 2009). Figure 2 shows the ontology of the FEA task. The ontology is divided into a set of classes, where each class represents information about the product, the aim of the analysis, the material, and the working conditions. The *Product information* class describes the analysis object, including its equipment name, part name, and design requirements. The *Analysis aim* class describes the purpose of FEA in the case, such as stress analysis or fatigue analysis. The class of *Material and Physical data* describes material information and its physical data about the analysis object, such as *Material designation* and *Material characteristic.* The *Working condition* class can be subdivided into the *Design condition* and *Operating condition* classes. The *Design condition* represents the condition used in the product design stage, such as design pressure or design temperature. The *Operating condition* represents the various loads and constraints that act on the analysis object during the operating state. The class hierarchy forms the ontology, which defines the general terms and state relations between the classes of the FEA modeling process.

The semantic representation of the FEA task of the buffer tank of a reciprocating piston compressor is shown in Figure 3. In the figure, each entity is obtained by instantiating the ontology according to the textual FEA task of the buffer tank.

Structural representation of an FEA case

Based on the ontology of the FEA task, the structural description of the FEA problem could be represented by instantiating the

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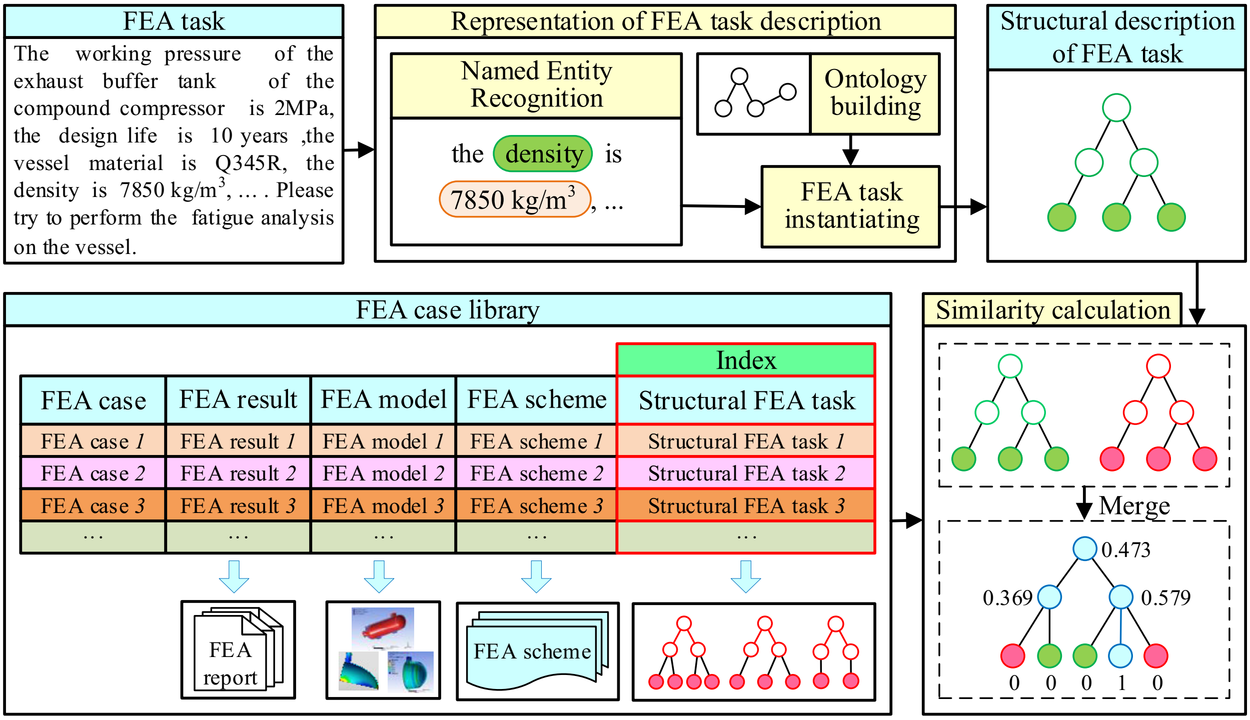

Figure 1 Framework of FEA case retrieval.

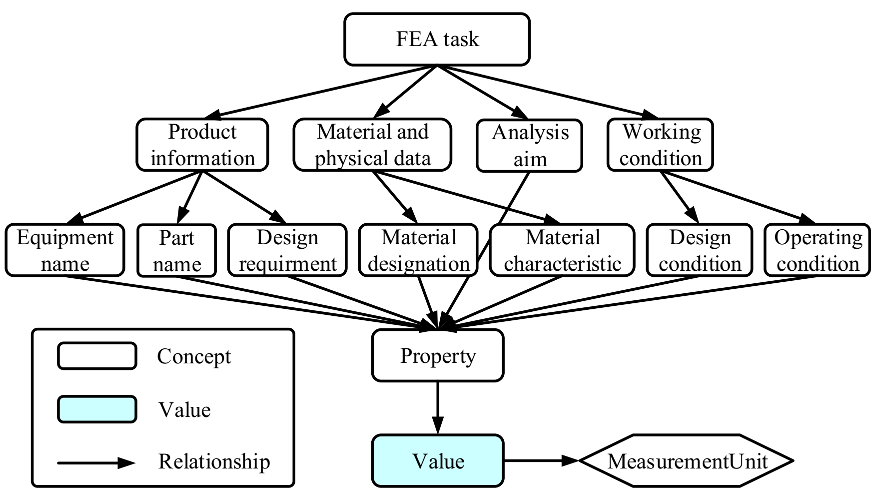

Figure 2 Ontology of FEA task.

ontology. In the instantiation process of the FEA task, the specific entities that are contained in the textual description of the analysis problem are added to the classes of ontology. As described in the previous section, these classes are the leaf nodes of the ontology, which include *Equipment name*, *Part name*, *Analysis requirement*, *Analysis aim*, *Material designation*, *Material characteristic*, *Design condition*, and *Operating condition*. To accurately identify the entities in the textual description and their subordinate class, the NER method is adopted to establish the connection between the entity and the class of the ontology.

In this study, the Bert-BiLSTM-CRF model (Xie T et al., 2020) is adopted to instantiate the FEA task ontology. Initially, the labeled corpus is transformed into the word vector through the BERT pretraining language model. Then the word vector is input into the BiLSTM module for further processing. The conditional random field (CRF) module is used to decode the output result of the BiLSTM module to obtain a predictive annotation sequence. Finally, each entity in the sequence is extracted and classified to complete the entire NER process.

The BIO mode is used to label entities, that is, B (Begin) represents the starting position of an entity, I (Inside) indicates that the word is inside the entity, and O (Outside) indicates that the word does not belong to any entity. For each entity, types are also designed to describe the entity. All entity types are listed in Table 1. These entity types are the classes corresponding to the leaf nodes in the FEA task ontology. Specifically, the entity types in the product information are "Equipment name," "Part name," and "Design requirement." The entity types of the material and physical data

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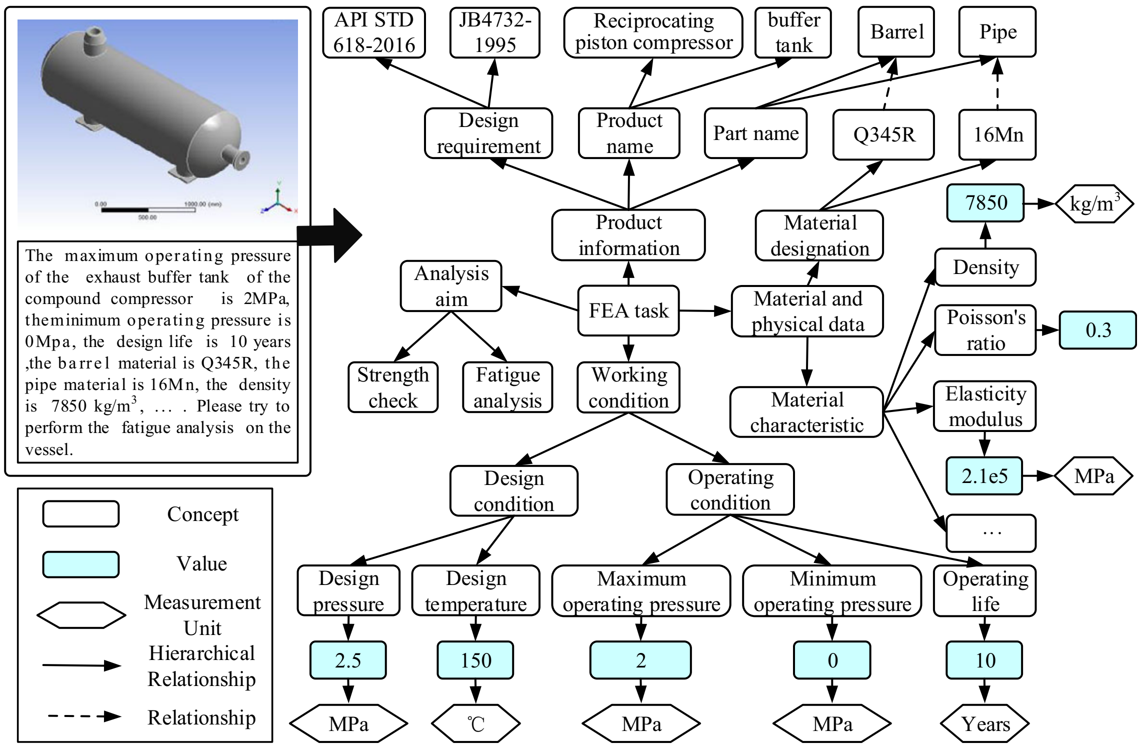

Figure 3 Semantic representation of the FEA task of a buffer tank.

Table 1. Labels of the FEA task description

Attribute	Abbreviations	Individual
Equipment name	EN	Reciprocating piston compressor
Part name	PN	Elliptical head
Design requirement	DR	Designed life
Analysis aim	AA	Stress analysis
Material designation	MD	Q345R
Material characteristic	MP	Poisson's ratio
Design condition	DC	Design pressure
Operating condition	OC	Working pressure

are "Material designation" and "Material characteristic." The entity types of the working conditions are "Design condition" and "Operating condition."

For instance, B-PN indicates that the entity is the starting word of the *Product name* entity. For the sentence "Carrying out stress analysis on the exhaust buffer tank", the entity labels are shown in Table 2.

Finally, the identified and classified entities of the FEA problem description are added as individuals to the class of the FEA task ontology. Consider the representation of the description of the FEA problem of the buffer tank as an example, as shown in Figure 4. The top panel of Figure 3 shows the FEA task ontology. Additionally, the bottom panel of Figure 4. shows the textural description of the FEA problem of the buffer tank (part). After NER, the entities are identified, as shown in the green box, and the value of the entity is shown in the orange box.

Semantic comparison method

After the FEA task description is instantiated according to the FEA ontology, the tree-structured representation of the task description is obtained. To obtain the semantic similarity comparison between two task descriptions, a comparison method is proposed based on the multi-tree structure (Hajian B et al., 2011).

Suppose that two given trees T_1 and T_2, as shown in Figure 5a and Figure 5b, respectively, represent two FEA task descriptions. The main steps in comparing the similarity of the two trees are as follows:

(1) Merge T_1 and T_2 into tree T_m, as shown in Figure 5c.
(2) Obtain the similarity of T_1 and T_2 according to the relationship between each node of tree T_m.

The algorithm for merging two trees is shown in Algorithm 1. First, tree T_m is created with empty nodes. Then, each node N_i^1 in T_1 is selected from bottom to top, and N_i^1 is compared with each node in tree T_2. If N_j^2 is the same as N_i^1 in T_2, nodes N_i^1 and N_j^2 are combined into a new node. The new node and its child nodes are added to tree T_m. Finally, the merged tree T_m is returned, as shown in Figure 5c dotted (solid) white nodes only come from T_1 (T_2), and blue nodes belong to the two trees.

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Table 2. Example of entity labels

Sentence	Carrying	out	stress	analysis	on	the	exhaust	buffer	tank
Label	O	O	B–AA	I–AA	O	O	B–EN	I–EN	I– EN

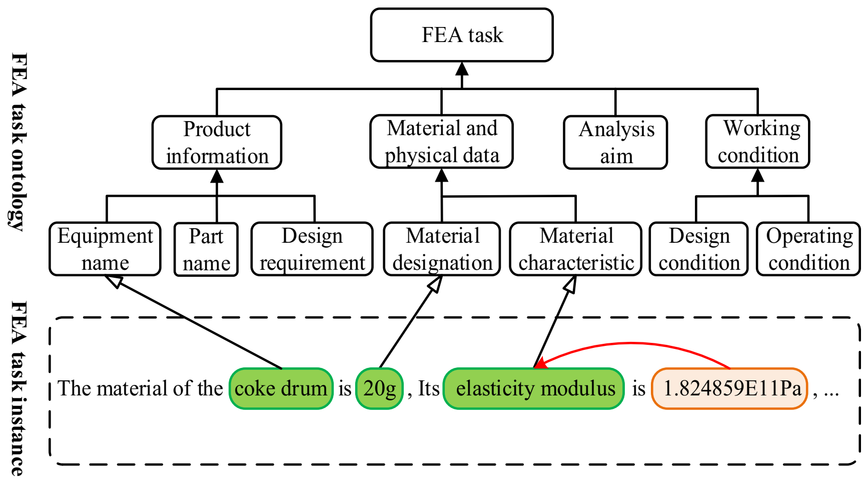

Figure 4 Instantiation of the FEA task description.

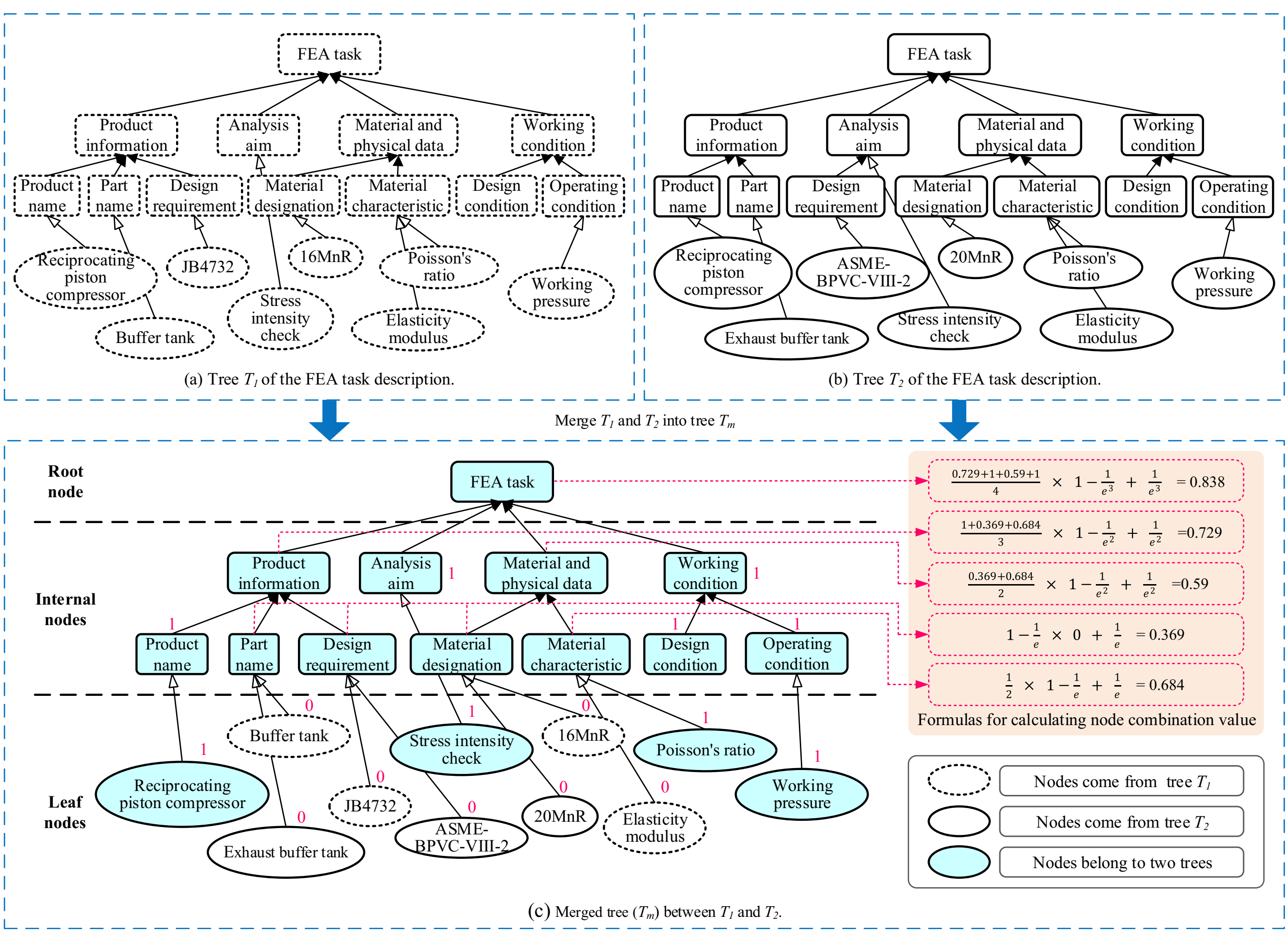

Figure 5 Merge two trees of FEA task description T_1 and T_2 into tree T_m. T_1 represent the FEA case ontology semantic tree 1; T_2 represent the FEA case ontology semantic tree 2; T_m represent the Merged tree between T_1 and T_2.

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Algorithm 1. Merge two trees

Input: trees T_1 and T_2
Output: merged tree T_m

T_1 _nodes ← T_1.all_node()
T_2_nodes ← T_2.all_node()
T_1_nids ← T_1_nodes.identifier
T_1_nids ← T_2_nodes.identifier
T_m ← T_1.tree()
add_node ← List()
FOR T_1_nid **in** T_1_nids:
  IF T_1_nid **in** T_2_nids:
    T_m _node ← T_m.get_node(T_1_nid)
  ELSE:
    IF T_1_nid **not in** add_node:
      parent_nid ← T_1.parent(T_1_nid)
  T_m _node ← T_m.get_node(parent_nid)
      NT ← T_1.subtree(T_1_nid)
      NT_nodes ← NT.all_node()
      NT_nids ← NT_nodes.identifier
      add_node ← add_node + NT_nids
      T_m.paste(T_m _node, NT)
RETURN T_m

After the two trees are merged, the similarity between the FEA task descriptions represented by the two trees can be calculated according to the merging results of the two trees. The leaf nodes on the merged tree are derived from the entities of the FEA task document, and the internal nodes on the merged tree represent the conceptual description of the FEA problem. Therefore, each node of the merged tree can be traversed according to the bottom-up process, and the corresponding combination value of each node can be calculated in turn. The combination value of the root node of the merged tree is the similarity result.

The combination value of nodes in the merged tree is calculated, respectively, according to their node types. There are three types of nodes in the merged tree: leaf nodes, internal nodes, and the root node. Additionally, the value of the FEA task can be represented as follows: v_{ss}stands for a single scalar value; $v_{mm}$is a min–max scalar value that has a maximum scalar value (v_{mm}^{max}) and minimum scalar value (v_{mm}^{min}); v_{str} is a string-type value. The single scalar value is the most widespread, such as pressure, temperature, and so forth The range value represents the minimum and maximum type value needed to describe a boundary such as 5–35 °C. The string-typed value is used for non-dimension-related values such as material designations.

When the type of node n_i belongs to the leaf node of the merged tree, the combination value is calculated using Eq. (1). Node n_i on the merged tree is from tree T_1 and tree T_2, which indicates that the two nodes of tree T_1 and tree T_2 are exactly the same; hence, the combination value of node n_i is set to 1. When the nodes are only from tree T_1 and tree T_2, the combination value of the node n_i is set to 0:

$$V^1(n_i) = \begin{cases} 1, \text{if } n_i \in T_1 \text{ and } n_i \in T_2 \\ 0, \text{otherwise.} \end{cases} \tag{1}$$

When the type of node n_i belongs to the internal node of the merged tree, the combination value $V^2(n_i)$ of node n_i is calculated using Eqs. (2) and (3). The calculation of $V^2(n_i)$ includes two parts. The first part is calculating the average of the combination values of all the children's nodes of n_i. The second part is related to the type of node n_i; the value $V^1(n_i)$ in Eq. (2) is given by Eq. (1). In Eq. (2), α is the adjustment factor, in this article $\alpha$was set to $e = 2.71$. The weight between node n_i and node c_i is calculated using the function *weight* (n_i, c_i) in Eq. (3), which indicates the importance of the relationship between nodes to the similarity calculation. Intuitively, the node on the merged tree belongs to tree T_1 and tree T_2, and the greater the depth of this node, the greater the combination value of this node. Additionally, the greater the depth of the node on the merged tree, the smaller the average value passed to the node by each child node of the node:

$$V^2(n_i) = \left(1 - \frac{1}{\alpha^{height(n_i)}}\right) A(n_i) + \left(\frac{1}{\alpha^{height(n_i)}}\right) V^1(n_i) \tag{2}$$

$$A(n_i) = \frac{1}{|children(n_i)|} \sum_{\forall c_j \in children(n_i)} weight(n_i, c_j)\, V^2(c_j). \tag{3}$$

The height function of n_i in Eq. (2) recursively calculates the height of node n_i, and the calculation function is given by

$$height(n_i) = \begin{cases} 0, & \text{if } n_i \text{ is leaf node} \\ \max[height(c_i)], c_i \in children(n_i), & \text{otherwise.} \end{cases} \tag{4}$$

When the type of node n_i belongs to the root node of the merged tree, the combination value can be obtained by calculating the average value of the combination value of each child node of the root node using Eq. (3). The combination value of the root node is the similarity between tree T_1 and tree T_2.

Additionally, the measuring equations (Mun D et al., 2011) are defined, as shown in Eq. (5), to calculate the similarity of the values.

$$Sim(v_1, v_2) \begin{cases} 1 - \dfrac{||v_{ss1}| - |v_{ss2}||}{|v_{ss1} + v_{ss2}|} & \text{if } v_{ss1} \neq v_{ss2} \\ 1, & \text{if } v_{mm}^{min} \leq v_{ss} \leq v_{mm}^{max} \\ 1, & \text{if } v_{str1} = v_{str2} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

Algorithm 2. Similarity of the two trees based on their merged tree

Input: trees T_1 and T_2, merged tree T_m
Output: similarity of T_1 and T_2

node ← n_i
stack ← empty stack
lastNodeVisited ← null
while not stack.isEmpty() **or** node ≠ null
  if node ≠ null
    stack.push(node)
    node ← node.left
  else
    peekNode ← stack.peek()
      if peekNode.nextchild ≠ null **and** lastNodeVisited ≠ peekNode.nextchild
        node ← peekNode.nextchild
    else
      if peekNode == LeafNode:
        if LeafNode.value ≠ null:
          V[peekNode.value] = Eq. (5)
          V[peekNode] = V[peekNode.value] * Eq. (1)
        else:
          V[peekNode] = Eq. (1)
      elif peekNode == RootNode:

V[peekNode] = Eq. (2)
else:
V[peekNode] = Eq. (3)
lastNodeVisited ← stack.pop()

The algorithm for the similarity of two trees based on their merged tree is shown in Algorithm 2. The algorithm traverses each node of the merged tree in turn according to the post-order traversal process and then calculates the combination value. The combination values are propagated from bottom to top in layers on the merged tree to integrate the relationship between the entity and the ontology into the similarity calculation; that is, if two trees representing FEA task descriptions have different entities, but these entities belong to the same class in the ontology, the similarity of the two trees can be improved through the above calculation process. The combination values and the calculation formulas of the nodes in the merged tree T_m are shown in Figure 5c.

Example

Case study

The proposed method was validated using the typical pressure vessel of the reciprocating piston compressor (Figure 6) as an example. The reciprocating piston compressor is one of the most widely used items of process equipment in the field of natural gas compression (Ribas et al., 2008; Farzaneh-Gord et al., 2015). Among the equipment in the reciprocating piston compressor, the buffer tank is the most common structure used to reduce the pulsation of gas flow. During the design process for the buffer tank using the design-by-analysis methodology, the preliminary design

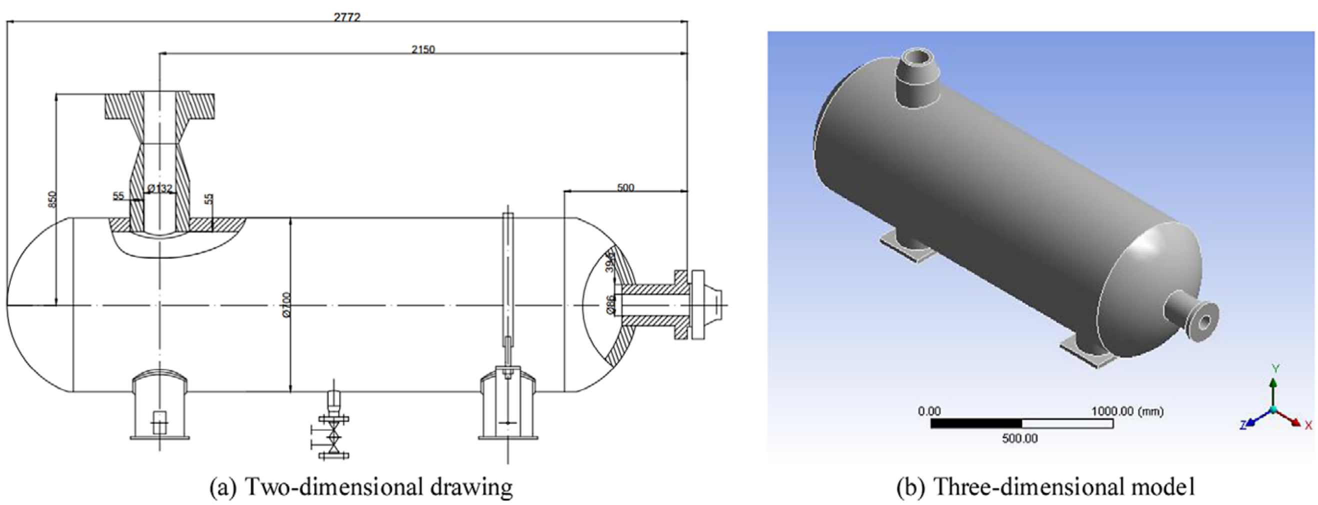

Figure 6 Geometry model of the buffer tank.

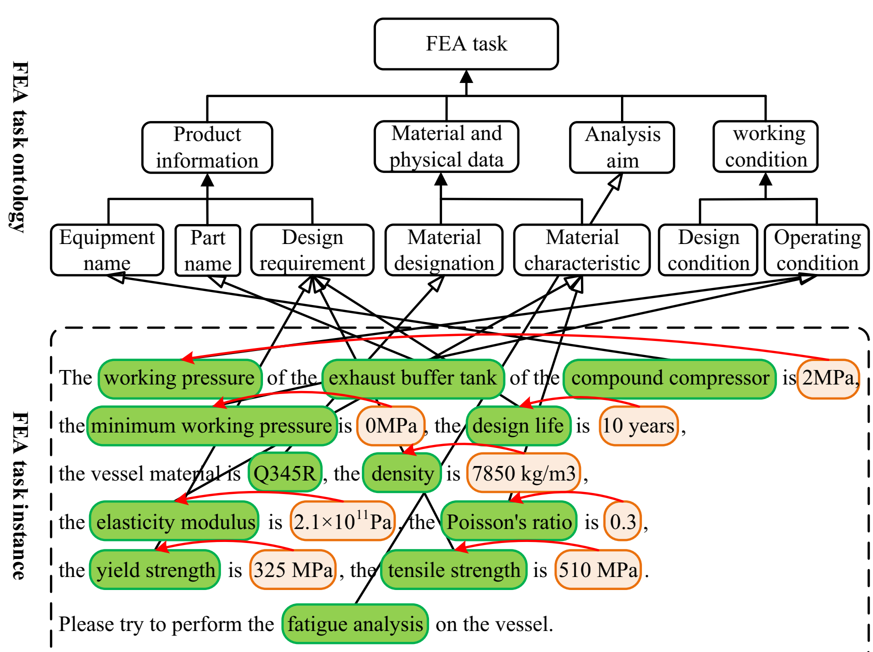

Figure 7 FEA task representation.

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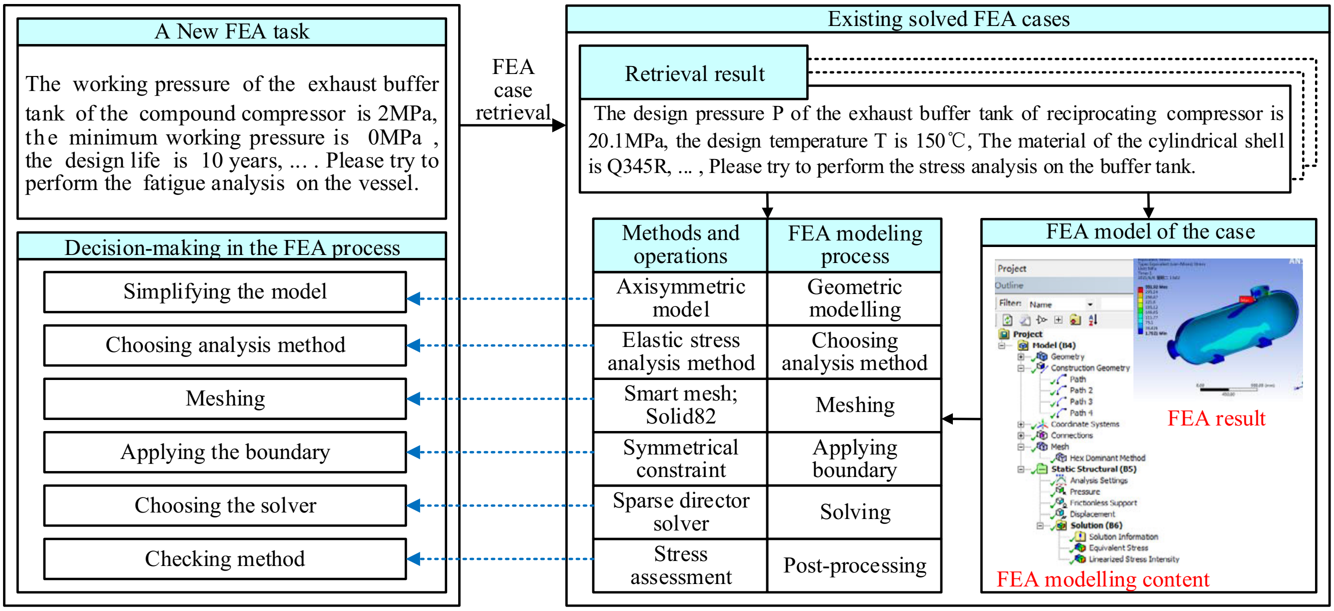

Figure 8 Existing solved case provides references for a new analysis task.

Table 3. The principle for scoring the similarity of FEA cases

Degree of similarity	Principle	Value of similarity
Similar	The analysis aim is the same. The product information and the working condition are almost the same. (Appendix case 4)	(0.75–1)
Generally similar	The analysis aim is almost the same, and there are certainly differences in the content of the product information, the working conditions or the materials, etc. (Appendix case 388)	(0.45–0.75)
Dissimilar	The two FEA cases are different, especially in terms of the product information and the analysis aim. (Appendix case 110)	(0–0.45)

Table 4. Average error of each task and total average error

Method	Total case pairs	Similar case pairs	Generally similar case pairs	Dissimilar case pairs
SBERT	0.4739	0.2705	0.2045	0.6015
VSM	0.2403	0.3919	0.0270	0.3270
Multitree	0.0790	0.3378	0.0216	0.0925
Multi–tree+weight	0.0549	0.0125	0.0702	0.0502

(including the product model, material, and dimensions) needs to be continuously adjusted according to the result of the FEA, such as changing the material, adjusting the wall thickness, and optimizing the structure.

The basic FEA modeling process can be divided into three phases: preprocessing, solving, and post-processing. Specifically, the analyst is required to perform operations that include constructing the geometry model, simplifying the model, ensuring the analysis method, setting the boundary according to the working condition, setting the material, meshing, choosing the solver, outputting the analysis result data, evaluating the results according to standards, and writing the analysis report. Several analytical operations are involved in decision-making, such as simplifying the model, choosing the analysis method, meshing, and choosing the solver. These analytical operations require a great deal of accumulated expertise, which makes it possible for analysts to improve efficiency and reduce the difficulty of analysis modeling by reusing the decision knowledge of FEA modeling in similar FEA cases. To retrieve a similar FEA case, the method proposed in Section title "Methods" is adopted to structurally represent the textual description of the FEA task for the buffer tank. The textual description is shown in the bottom panel of Figure 7. After the NER method is applied to instantiate the FEA task ontology according to the textual description of the FEA task, a structural FEA task of the buffer tank is generated, as shown in Figure 8. Subsequently, the analyst can use the represented FEA task to retrieve a similar FEA case.

Based on the retrieval result, the FEA operations of the retrieved case can provide references for the new task (Figure 8). For instance, the solving method of the new task can consider using the sparse director solver, and the element type of Solid82 can also be considered for the new task. Therefore, retrieving the case similar to the current task from the existing cases" library can provide important

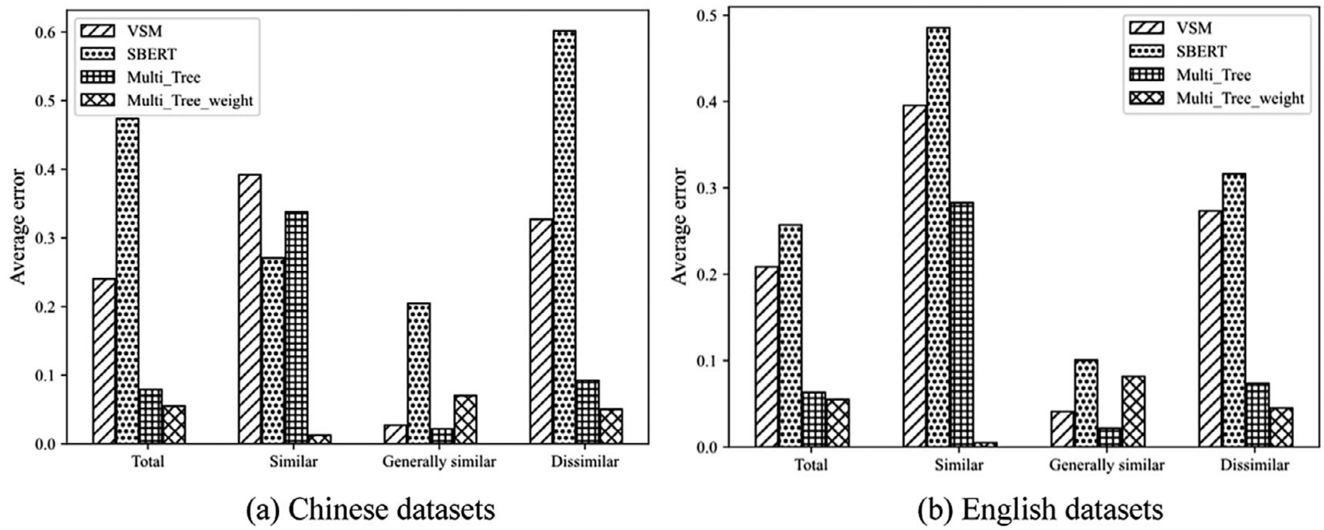

Figure 9 The average error of each method for the similarity measurement of FEA cases. VSM represent the method of vector space model; SBERT represent the method of sentence BERT; Multi_Tree represent the method of muilt-tree without weight; Multi_Tree_Weight represent the method of muilt-tree with weight.

references for the decision-making of the FEA process.(Detailed examples of reusing retrieved FEA cases are provided in Tables A2 to A4 of the Appendix).

Performance of the similarity between FEA cases

To validate the proposed method for retrieving FEA cases, 396 FEA cases in the pressure vessel field were built, where each case contained a problem description, FEA scheme, FEA model, and FEA result. Additionally, the problem description of each FEA case was structurally represented and used as the index of the case. The typical FEA cases used in this study are shown in the Appendix.

Considering the difficulty of directly evaluating the pros and cons of FEA case semantic retrieval methods, a dataset was constructed, which included several FEA case pairs. These FEA case pairs were obtained by matching the FEA cases in pairs randomly. Specifically, all the 396 FEA cases were cross-matching and duplication eliminated, and 78,210 FEA case pairs were obtained (all data set used in this article can be downloaded from https://github.com/song885280/FEASimData). Then, the similarity of the FEA case pairs was scored by four graduate students in the mechanical engineering department who had FEA capabilities. The similarity of each FEA case pair was scored in three degrees: similar, generally similar, and dissimilar. The degrees of similarity are scored according to the reusability of the retrieval FEA cases. The reusability of the FEA cases was considered to be the most relevant for the analysis purpose, followed by product information and working conditions. Table 3 shows the principle for scoring the similarity of FEA cases. We use a real number between 0 and 1 to measure the similarity of cases. That is, the number between 0.75 and 1 represents "Similar", the number between 0.45 and 0.75 represent "Generally similar", and the number less than 0.45 and greater than 0 represents "Dissimilar".

The average error (Manning et al., 2010) was used to evaluate the retrieval performance. The formula is as follows:

$$E = \frac{1}{N}\sum_{j=1}^{N}\left|S_j - S_j^p\right|, \tag{6}$$

where E is the average error, N is the number of case pairs, j is the index of the case pairs, j = 1, 2, 3,…, N; S is the case similarity obtained by the algorithm; and S^p is the case similarity scored by the 4 graduate students in Mechanical Engineering. They all have obtained the qualification of FEA granted by the Zhejiang University of Technology.

In order to compare the retrieval performance, three types of retrieval methods were performed: (1) the VSM (Figueiras et al., 2012); (2) the method of sentence BERT (SBERT) 2013 and (3) the method of multitree without weight. The performance of these methods is shown in Table 4, and the relative performance of each retrieval model is compared graphically in Figure 9. The average errors demonstrate that the VSM outperforms the SBERT and the multi-tree outperforms the VSM. The proposed method (multi-tree with weight) outperforms the method of multi-tree without weight. The weights (Eq. 3) of four sub-nodes of the root node are set as follows: 0.25, 0.5, 0.075, and 0.175. The main reason for the high performance of the multi-tree is the method's ability to measure the similarity between FEA cases at the semantic level. The semantic representation of FEA cases can be expressed by instantiating FEA ontology. On the other hand, this result points out the limitation of keyword-based searches of FEA cases. In addition, the Bert-based method cannot achieve a better method when three are no large-scale training corpus.

Discussion

This article proposed to index the textual description of the analysis problem to retrieve the FEA cases. Compared with the existing retrieval methods, VSM and SBERT, our method can not only improve the efficiency of FEA case retrieval but also improve the accuracy of FEA case retrieval. VSM is a widely used method for text retrieval in the engineering domain (Figueiras et al., 2012; Hu et al., 2013; Ke et al., 2020; Sang et al., 2019). With the development of natural language processing technology, The STOA model of SBERT (Reimers and Gurevych, 2019) has achieved superior performance in many tasks. The SBERT can embed the text into the vector, which can be used to measure the similarity of text. However, the SBERT does not work well in this article. The reason is that the SBERT model needs a large-scale training corpus, whereas the domain covered in this article lacks the training corpus. That is why we implement an ontology-based method to measure the similarity of FEA cases. To avoid the complexity of the ontology for the complete FEA cases, which include analysis problem, geometric model, and analysis report, we build the ontology of the FEA problem description. The FEA problem description mainly includes the analysis objectives, the materials, and the working conditions (Wriggers et al., 2007; Khan and Chaudhry, 2015). The text description of analysis problems can be expressed semantically by instantiating FEA ontology. This representation method can accurately extract the key variables that describe the FEA analysis process contained in the text description, and form a tree structure index according to the FEA ontology. Some related research (Han et al., 2008; Morinaga et al., 2005; Kallmeyer and Osswald, 2013; Plank and Moschitti, 2013) has shown that the tree structure can fuse semantic information. The tree structure of the FEA case not only contains the keywords but also represents the relation between the keywords. Certainly, if the data of the CAD model can be integrated into the index description, we believe it can improve the accuracy of FEA case retrieval.

We also designed a simple algorithm to calculate the similarity between two FEA cases based on the multi-tree data structure. The multi-tree measures similarity based on hierarchical relations that exist between attributes of the entities in an ontology. This method provides a useful tool to embed the domain knowledge of domain engineers into the retrieval model. The main reason that our method can improve retrieval performance is that the key factors affecting the similarity of FEA cases are embedded in the weight of multi-tree nodes. It should be noted that these weights are currently given by domain experts. In the follow-up study, we will consider using the machine learning algorithm to automatically calculate these weights. In addition, although the source language is assumed as Chinese, the proposed method is language-independent. We have translated all the corpus of FEA cases into English and given the results of case similarity to verify the generalizable of our method. The experiment results (Figure 9b) show that our method has also obtained good performance in these English datasets.

The purpose of FEA case retrieval is to reuse the cases. The existing research on FEA case reuse was focused on automatic FEA modeling by the method of CBR (Wriggers et al., 2007; Numthong and Butdee, 2012; Khan and Chaudhry, 2015). However, the application of these methods is highly dependent on the relevance of the case to the modeling task. For example, it is difficult to construct the FEA model by CBR if the geometric models of the case and the modeling task are highly dissimilar, which has prevented the application of the FEA case reuse methods. Therefore, this article proposes to improve the reusability of FEA cases by retrieving the FEA cases efficiently and accurately. In a retrieved FEA model, many components can be reused, such as model simplification methods, meshing methods, and post-processing methods, and so forth After obtaining the relevant case, the analyst can quickly complete the current FEA modeling task by consulting the reusable information in the cases. The proposed approach not only exploits the value of the knowledge contained in the FEA cases but also can offer support to less experienced simulation users.

Conclusion

This article proposed an approach for FEA case retrieval by taking the textual description of the analysis problem as the index. The analysis problem document generated in the early analysis stage contains abstract analysis descriptions. The structural analysis problem is expressed semantically by instantiating the FEA ontology. Based on the tree structure of the analysis problem, the similarity between two FEA cases is calculated by using the multi-tree-based similarity comparison algorithm. The experimental results clearly show that the proposed approach outperforms the compared existing retrieval methods. This demonstrated that the semantic representations of the text description of analysis problems can be captured accurately by instantiating FEA ontology.

Although the proposed method has significant advantages in FEA case retrieval, some limitations remain, such as (1) the textual description of the analysis problem does not include the geometric model, and (2) the ontologies involved in the experiment in the study were constructed manually. Therefore, in follow-up research, the retrieval of the geometric model will be integrated into case retrieval to further improve the retrieval accuracy. Furthermore, the automatic construction of structured FEA case ontology, as well as conducting CBR or parameterizing FEA modeling on the retrieved cases, are both areas worthy of in-depth research.

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Appendix

Table A1. Example of FEA case retrieval

Analysis object	FEA cases	Similarity
Compound compressor exhaust buffer tank, the working pressure is 2 MPa, the minimum working pressure is 0 MPa, the design life is 10 years, the container material is Q345R, the density is 7850 kg m^3, the elasticity modulus is 2.1 × 1011 Pa, Poisson's ratio is 0.3, yield strength 325 MPa, tensile strength 510 MPa, fatigue strength factor 0.8. Please carry out the fatigue analysis of the vessel based on the JB4732–1995 "Steel pressure vessel – Analytical Design".	Case 4: The maximum working pressure of the pressure–swing absorber is 0.25 MPa, the minimum working pressure is −0.1 MPa, the maximum working temperature is 200 °C, the matter in the vessel is alcohol, and the equipment is insulated. The material of the vessel is 0Cr18Ni9, the elasticity modulus is 2.0×10^5MPa, the Poisson's ratio is 0.3, the stress cycle of the adsorption tower is 1200s and the design life is 15 years. Please carry out the fatigue analysis of this variable pressure adsorption tower based on the ASME Boiler and pressure vessel Code Volume VIII–2 – Another Code for pressure vessel Construction.	Similar
	Case 260: The working pressure is −0.098~0.40.4 MPa, the design pressure is −0.1~0.60.6 MPa, the working temperature is 150°C, the design temperature is 180° C, the corrosion margin is 0.15 mm, the material of the cylinder head is 0Cr18Ni916MnR, the material of the connection tuber is 0Cr18Ni920G, the equipment is subjected to alternating load, the number of operations is 1 time 24 h, the annual operation time is 8000 h. The strength calculation conditions are 180°C, −0.1 MPa for external pressure and 0.6 MPa for internal pressure, and the Poisson's ratio is 0.3. Please use the JB4732–1995 Steel pressure vessels – Analytical Design to carry out the fatigue analysis of the tar tank.	Similar
	Case 388: The highest working pressure of the adsorption tower is 0.25 MPa, the lowest working pressure is −0.1 MPa, the highest working temperature is 200°C, the equipment material is 0Cr18Ni9, its elastic modulus is 2e5 MPa, Poisson's ratio is 0.3, the material is ethanol. Adsorption tower pressure cycle time for 1200 s, according to a year of work 360d calculation, the service life of 15 years, the number of load cycle for 3.888 × 105 times. Please carry out the fatigue analysis of the adsorption tower equipment based on the "ASME Boiler and pressure vessel Code Volume VIII–2 – Another Code for pressure vessel Construction."	Generally similar
	Case 110: The material of the tank is set as Q235 steel with the following mechanical properties: yield limit of 235 MPa, Poisson's ratio of 0.25, elasticity modulus of 200 GPa and tensile strength of 370 MPa. wind speed of 36 ms for a 12–magnitude typhoon is the basic wind speed. Based on the JB4732–1995《Steel pressure vessels—Design by Analysis》, please perform the stress analysis and analyze the effect of wind load, self–weight and internal oil pressure on the tank structure.	Dissimilar

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Table A2. Example 1 of reusing retrieved FEA case

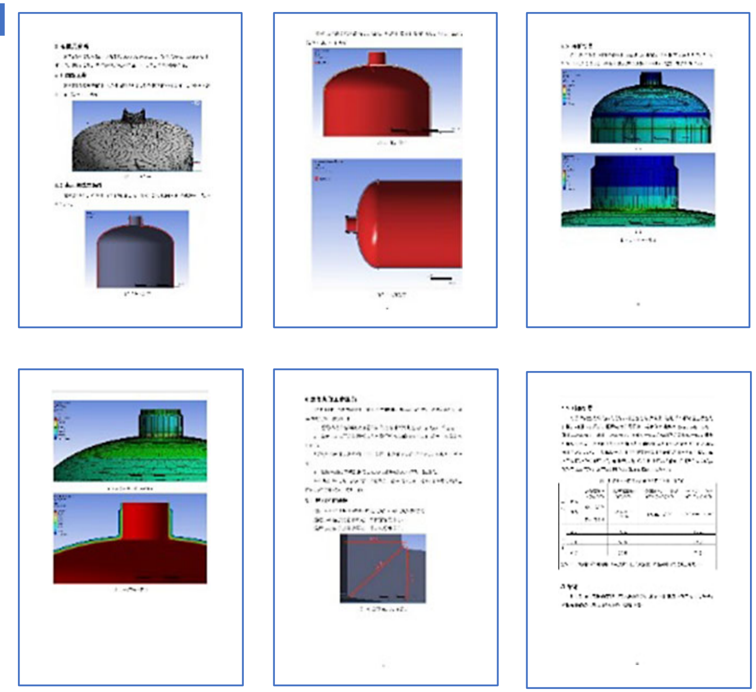
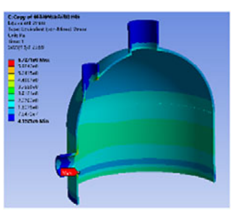
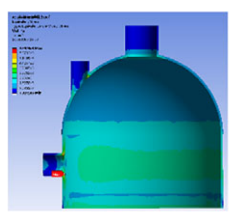
<table>
<tr><th>New FEA task</th><th colspan="2">Retrieved FEA case（Similarity: similar）</th></tr>
<tr><td>FEA task description:
The pressure vessel is designed to operate within a pressure range of 0 to 3MPa and at a temperature of 150°C. It is subjected to 5000 cycles per year, with a design lifespan of 10 years. The vessel specifications are as follows: The material used for the vessel is Q345R, with a density of 7850kg/m^3, an elastic modulus of 2.1 x 10^{11}Pa, a Poisson's ratio of 0.3, a yield strength of 325MPa, and a tensile strength of 510MPa. Conduct the stress assessment.</td><td>FEA task</td><td>The head nozzle of a certain pressure vessel operates at a pressure of 2.5MPa, with a design pressure of 2.75MPa. The hydraulic test pressure is set at 3.54MPa. It functions within a temperature range of 10 to 250°C, with a design temperature of 280°C. The materials used for the head, shell, and nozzle are all S30408 austenitic stainless steel, with the nozzle being a forged pipe. The elastic modulus of S30408 austenitic steel is 1.95e105MPa. The average linear expansion coefficients are respectively 1.725e-5/°C. The Poisson's ratio is 0.3. Conduct the stress assessment and strength analysis of the structure.</td></tr>
<tr><td>Reusable analysis methods and operations:
Geometric Modeling: Symmetry Simplification
Analysis method: Elastic stress analysis method
Meshing: Smart partitioning using hexahedral elements with an element size control of 10mm.
Applying constraints: Apply constraints in the symmetric region of the vessel cross-section based on symmetry. Apply displacement constraints on the end face of the pipe joint.
Applying Loads: Apply internal pressure. Apply balanced loads on the end face of the pipe joint.
Post-processing: Generate stress distribution contour plots, equivalent von Mises strain distribution contour plots, and temperature distribution contour plots. Also, employ stress categorization methods, analyze stress paths, and assess stress classifications.
Assessment methods: Stress classification, primary stress intensity assessment, secondary stress intensity assessment, total stress intensity assessment.</td><td rowspan="2">FEA model/ FEA report</td><td rowspan="2"></td></tr>
<tr><td>Comparison of analysis results:

Analysis result based on case resuing

Original alalysis result</td></tr>
</table>

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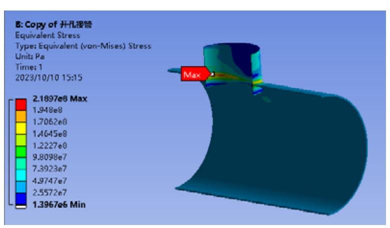
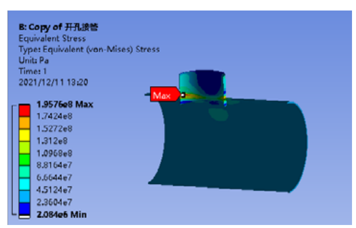
Table A3. Example 2 of reusing retrieved FEA case

<table>
<tr><th>New FEA task</th><th colspan="2">Retrieved FEA case（Similarity: similar）</th></tr>
<tr><td>FEA task description:
The large opening of a pressure vessel cylinder adopts thick-walled forged pipe. The operating pressure of the equipment is 2.01MPa, the operating temperature is 220℃, the design pressure is 2.35MP, and the design temperature is 265℃. The body diameter of the cylinder is 3550mm, the wall thickness is 54mm, and the material is S30408. The elastic modulus of S30408 at the design temperature of 265 degrees Celsius is 1.781×105MPa, Poisson's ratio is 0.31, and the allowable stress of the material is 119.6MPa. Utilize the analysis and design method to analyze and check the large opening hole of the cylinder.</td><td>FEA task</td><td>This analysis pertains to an opening nozzle on a pressure vessel, featuring a vessel inner diameter of 2000mm and a wall thickness of 30mm. The nozzle has an outer diameter of 530mm, a wall thickness of 15mm, and an inner extension length of 195mm. The outer transition has a fillet radius of 30mm, while the inner transition has a fillet radius of 15mm. The vessel is subjected to an internal pressure of 1.2MPa. The material used is 16Mn, with an elastic modulus of 2.0e5MPa and a Poisson's ratio of 0.3. Performing the stress distribution within the opening nozzle region of the vessel.</td></tr>
<tr><td>Reusable analysis methods and operations:
Geometric modeling: Axisymmetric model
Analysis method: Elastic stress analysis method
Mesh: Smart mesh, Solid82
Applying constraint: symmetrical constraint, fixed constraint, displacement constraint
Solving: Sparse director solver
Post-processing: stress assessment, stress evaluation path, equivalent stress, stress Intensity, maximum principal stress
Assessment methods: Stress classification, primary stress intensity assessment, secondary stress intensity assessment, total stress intensity assessment.

Comparison of analysis results:




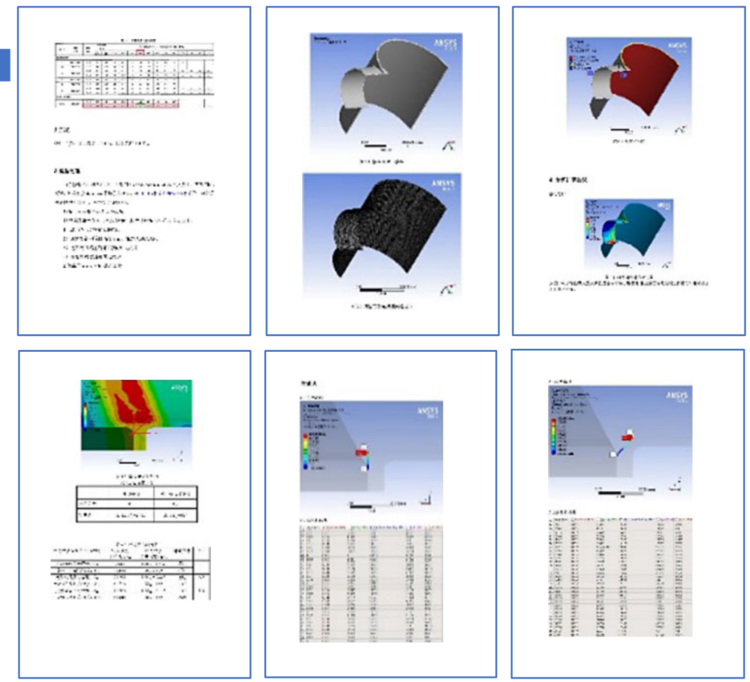
Analysis result based on case reusing   Original alalysis result</td><td>FEA model / FEA report</td><td></td></tr>
</table>

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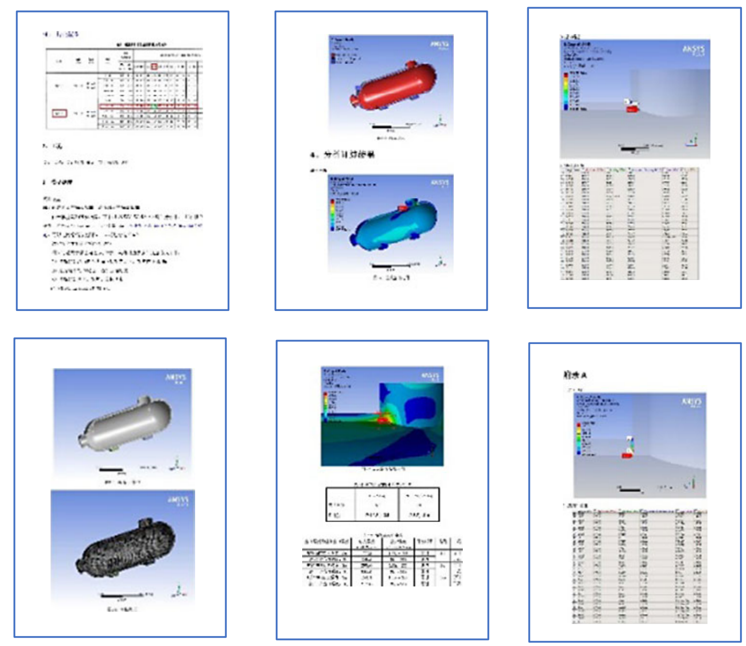
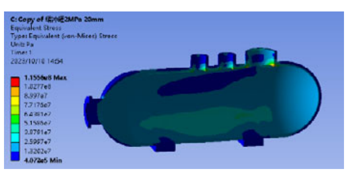
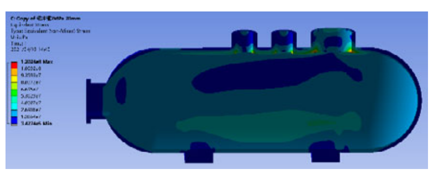
Table A4. Example 3 of reusing retrieved FEA case

<table>
<tr><th>New FEA task</th><th colspan="2">Retrieved FEA case（Similarity: similar）</th></tr>
<tr><td>FEA task description:
The tar tank is a horizontal, tilted, thin-walled, semi-jacketed container. The working pressure (inner cylinder / jacket) ranges from -0.098 to 0.4 MPa / 0.4 MPa. The materials for the cylinder body / heads are 0Cr18Ni9 / 16MnR, and the material for the nozzle is 0Cr18Ni9 / 20G. The material's Poisson's ratio is assumed to be 0.3. The equipment is subjected to alternating loads, operating once every 24 hours, with an annual operating time of 8,000 hours. Strength calculations are based on a temperature of 180°C, and the calculated pressures are -0.1 MPa for external pressure and 0.6 MPa for internal pressure. Using the finite element analysis method to conduct fatigue analysis on the tar tank, and evaluate the analysis results.</td><td>FEA task</td><td>The exhaust buffer tank of a certain reciprocating compressor has the following structural parameters: Temperature effects are not considered. The tank operates at a pressure of 2MPa, with a minimum operating pressure of 0MPa. The design lifespan is 10 years, taking into account maintenance and other factors, with operation planned for 360 days per year. The electric motor runs at a speed of 250 revolutions per minute, resulting in 2 compressions per rotation. The tank is constructed from Q345R material, with a density of 7850kg/m³, an elastic modulus of 2.1 x 10^{11}Pa, a Poisson's ratio of 0.3, a yield strength of 325MPa, and a tensile strength of 510MPa. The fatigue strength factor is 0.8. The objective is to determine the tank's fatigue life, stress amplitude, safety factor within the design life, damage, and stress amplitude conditions.</td></tr>
<tr><td>Reusable analysis methods and operations:
Analysis method: Elastic stress analysis method
Mesh: smart mesh, hex dominant method
Applying boundary: fixed constraint
Solving: Sparse director solver
Post-processing: stress assessment, total deformation deformation maximum principal stress, stress Intensity
Fatigue analysis: life, damage, safety factor, biaxiality indication, equivalent alternating stress, fatigue sensitivity
Assessment methods: Stress classification, primary stress intensity assessment, secondary stress intensity assessment, total stress intensity assessment</td><td rowspan="2">FEA model/ FEA report</td><td rowspan="2"></td></tr>
<tr><td>Comparison of analysis results:
 
Analysis result based on case reusing   Original alalysis result</td></tr>
</table>