J Syst Sci Syst Eng (June 2016) 25(2):159-176 ISSN: 1004-3756 (Paper) 1861-9576 (Online)
DOI: 10.1007/s11518-016-5306-4 CN11-2983/N

BOM-BASED DESIGN KNOWLEDGE REPRESENTATION AND REASONING FOR COLLABORATIVE PRODUCT DEVELOPMENT*

Gongzhuang Peng[1] Huachao Mao[1] Hongwei Wang[2] Heming Zhang[1]

[1] *National CIMS Engineering Research Center, Tsinghua University, Beijing, 100084, China*

pgz12@mails.tsinghua.edu.cn

maomaer@gmail.com

hmz@mail.tsinghua.edu.cn (✉)

[2] *School of Engineering, University of Portsmouth, Anglesea Read, Portsmouth PO1 3DJ, UK*

Hongwei.Wang@port.ac.uk

Abstract

Modern product development becomes increasingly collaborative and integrated, which raises the need for effectively and efficiently sharing and re-using design knowledge in a distributed and collaborative environment. To address this need, a framework is developed in this research to support design knowledge representation, retrieval, reasoning and fusion, which takes account of structural, functional and behavioral data, various design attributes and knowledge reasoning cases. Specifically, a multi-level knowledge representation based on the Base Object Model (BOM) is proposed to enable knowledge sharing using Web services technologies. On this basis, a multi-level knowledge reuse method is developed to support the retrieval, matching and assembly of knowledge records. Due to the tree structure of BOM, both depth-first and breadth-first searching strategies are employed in the retrieval algorithm while a novel measure is proposed to evaluate similarity. Moreover, a method based on the D-S evidence theory is developed to enable knowledge fusion and thus support effective decision-making. The framework has been implemented and integrated into an HLA-based simulation platform on which the development of a missile simulation example is conducted. It is demonstrated in the case study that the proposed framework and methods are useful and effective for design knowledge representation and reuse.

Keywords: Complex product development, multi-level knowledge reuse, knowledge fusion, Base Object Model, D-S evidence theory

---

* This research is supported by the National Natural Science Foundation of China (Grant No.61374163), the National Key Technology R&D Program (Grant No. 2012BAF15G00), the National High Technology Research and Development Program (863 Program) of China (Grant No.2013AA041302).

1. Introduction

The design and development of complex products is characterized by its high complexity and large scale. Specifically, it involves the coordination of various resources, emphasizes the development and integration of multidisciplinary models, and requires the consideration of issues from all phases in the whole lifecycle. With the rapid advancement of computer-aided product design and manufacturing, Information Technology (IT) has an increasingly important role to play in complex product development. Recently, the Industry 4.0 concept was proposed as a forward-looking project under the German government's High-Tech Strategy, which is becoming a hot topic and has spread all around the world (Böhler 2012). In this context, a number of issues as follows need to be supported by the next-generation product design and development systems:

1. Modern product development is more often done collaboratively, by geographically and temporally distributed teams during the different phases of the design process (Szykman 2001). Design engineers and domain experts from different disciplines need to share information and resources to solve a design problem on one IT-enabled platform (Wang 2010).

2. To meet the increasingly fast-changing and customized needs in industry, agile, rapid and efficient development and maintenance of product models has become more critical. As a result, the methods and tools that support and improve reuse of design ideas and knowledge are greatly needed. In particular, Web services technologies prove to be promising for supporting a flexible and dynamic environment where system integration and interoperation can be rapidly developed and deployed.

3. Modern information and communication technologies such as Cyber-Physical Systems, Big Data or Cloud Computing help to increase productivity, quality and flexibility within the manufacturing industry. In this context, it is necessary to develop advanced tools to effectively and efficiently process a huge amount of design data and information. In particular, the methods and algorithms for analyzing big design data are also needed.

A number of tools and techniques have been used and they have greatly improved productivity in the design and manufacture of new products. At the same time, experienced design engineers still play a significant role in defining and analyzing problems, creating solutions, and making decisions. A simple reason for this is that most design activities depend upon the experiences obtained in previous projects (Wang 2012). In order to search for valuable design information, engineers spend about 60% of their working time on finding the previously-designed components which have detailed design features similar to those considered in a new design (Li 2004). This has resulted in great interests in both academic and industry to develop methods for representing and indexing product information (Szykman 2000).

Based on the complex product development framework, a multi-level design knowledge model is proposed in this research. Such a model not only facilitates the capture of multi-level multidisciplinary engineering knowledge throughout the design process but can also support its subsequent retrieval and reuse in a collaborative environment. Specifically, a number of research questions are to be answered in this research: (1) what kinds of design knowledge should be included in the model; (2) how to represent and reuse different kinds of knowledge effectively and efficiently; (3) how the method is supposed to be applied to real-world applications.

The rest of this paper is organized as follows. Section 2 reviews previous studies related to this work. The structure and contents of the multi-level product knowledge are described in Section 3. Section 4 details the development of a multi-level knowledge representation based on the BOM. To efficiently reuse knowledge records based on the model, methods for effective retrieval and reuse are described in Section 5. Then, in Section 6, the BOM-based multi-level model is implemented and integrated into a HLA-based simulation system as an independent module. After that, implementation of a prototype system and evaluation of the methods developed are given in Section 7. Finally, conclusions and future work are discussed in Section 8.

2. Related Work

Computer-Aided Design and Computer-Aided Manufacturing (CAD/CAM) technologies become very popular in the product design and manufacturing industry in recent decades. With the wide application of these tools and IT in design, a lot of design documents are created and stored as electronic files. Product Lifecycle Management (PLM) systems are nowadays widely used in industry to manage both design data and design processes during the entire lifecycle from inception, through engineering design and manufacture, to service and disposal of manufactured products. Knowledge-Based Engineering (KBE) applications which aim to develop computational methods for knowledge coding, retrieval and reasoning have been extensively researched and published (Chapman, 1999). Great progress has been made in the knowledge management area, yet the shortcoming is that these systems are effective in managing specific data such as 2D/3D CAD models, drawings and their associated documents but fail to offer high-level semantics together with previous design information (Bilgic 1997).

A different design of knowledge model is greatly needed to overcome this limitation. Goel et al., (1997) proposed the Structure-Behavior-Function (SBF) model in which design cases are indexed by function and then mapped to their structure in the KRITIK system. The structure-to-function mapping of previous designs and process is able to provide guidance in adapting the knowledge to a complete new design. Bracewell et al. (2009) developed an integrated representation scheme that uses design rationale to organize and integrate the important tacit knowledge (i.e. engineering ‘know-why’ knowledge about products and design processes that are missing in other electronic materials).

Based on the categorization of product knowledge, various methods have been developed for capturing and representing design knowledge. Design knowledge is supposed to be conveniently represented and shared in a practical manner throughout the development cycle. Shen et al. (2007) designed and implemented an agent-based service-oriented integration architecture for sharing knowledge and supporting collaborative work within organizations. Specifically, an agent is viewed as an individual collection of primitive components, that can support the capture and reuse of design knowledge. Kim et al. (2006) proposed a new paradigm of ontology-based assembly design which makes assembly knowledge both machine-interpretable and easy to share using the OWL (Ontology Web Language) and SWRL (Semantic Web Rule Language). Modelica is developed as an object-oriented, declarative and multi-domain modeling language for component-oriented modeling of complex systems (Modelica Association, 2012). It has been increasingly used in many automotive OEMs including Ford, General Motors, Toyota, BMW and Daimler (Tate 2008). Peng et al., (2014) used the Base Object Model (BOM) which is essentially a reusable package of information representing multi-level knowledge with fine granularity for effective understanding and retrieval.

As product information is encoded in a variety of forms, retrieving an existing design is difficult using current methods. A number of techniques have been proposed in the literature to address the knowledge retrieval issue. Li et al., (2004) performed a survey of the existing tools and techniques and identified three prominent types of retrieval, namely shape-based retrieval, knowledge-based retrieval, and ontology-based retrieval. Iyer et al. (2005) provided a detailed survey of the state-of-the-art 3D shape searching technique. Wang et al. (2012) proposed a retrieval method of design rationale records by exploiting the inherent structure of design records. As design knowledge is stored in databases, the development of data mining techniques (e.g. decision tree, fuzzy reasoning, D-S evidence theory, Bayesian network and neural network) has become a subject of intensive research in the knowledge discovery domain,

To verify and validate the proposed model, the need to develop collaborative simulation infrastructure is raised. According to the communication methods between the graphical interface and the simulation engine, these simulation infrastructures can be divided into the following categories: remote simulation which makes use of middleware technologies such as CORBA, JavaBeans, CGIs and so on; component-based simulation which supports high reusability of software components; distributed simulation which manages simulations over a network of computers through the Web (Byrne 2010). The High Level Architecture (HLA) is an important and heavily researched standard to support distributed simulations. These technologies will be integrated in our distributed system for collaborative product development.

3. Multi-level Product Knowledge

As discussed above, knowledge model is the core of the design knowledge reuse framework. The design and development of new products involves a complex process from the abstract requirement analysis phase to the specific engineering design phase. Design knowledge can offer designers useful information about how previous designs evolved and how data exchanges happen in different phases. Such a model is supposed to be able to effectively describe different pieces of product knowledge together with the corresponding information associated with the design process to support knowledge re-use. Table 1 shows some kinds of knowledge that form part of the knowledge representation scheme.

Table 1 Product knowledge representation

Definition	Content	Description
Function	Overall function, discipline-related functions, subsystem functions	To describe the function of the model and to store artifacts with respect to what they do
Structure	Assembly parts, mechanical parts	To express the structure of the model and the corresponding subsystems
Attribute	Performance parameters, design parameters	To express all kinds of static attributes in the design process
Behavior	State machine, interface functions	To describe the inheritance and mapping relations of design knowledge using equations
Model Reasoning	Previous cases, reasoning models	To store information about dependencies or relationships that link decisions to the product

The effectiveness and efficiency of the design process relies very heavily on designers' knowledge on different engineering domains and more importantly on how to approach design problems. Design engineers determine the appropriate parameters of each small module gradually based on the general performance metrics. A fairly standard technique currently used is to represent a model hierarchically with various levels of resolution and depth of aggregation to allow interaction between one another. Such a method is called a multi-level model and generally the following rules are applicable.

1) The less detailed content a knowledge model involve, the better. The same design problem is viewed from different perspectives as engineers in different design phases actually pay attention to different aspects and levels on the same design objects. For example, in the functional definition phase, engineers define the main technical specifications of the product based on requirements, and will not focus on the particular choices of components. In the detail design phase, engineers from different disciplines and teams will have different design responsibilities.

2) Inheritance and interaction mechanism should be provided to ensure the association of design information between different design phases. The complex development goals can be decomposed into small indicators according to the hierarchy relationship and the degree of coupling, thus the difficulty of development is reduced and the foundation for collaborative activities is established.

As shown in Figure 1, each knowledge model mainly contains five parts: the function of a design component, the structure of the design model that includes this component, all kinds of parameters associated with the component, the internal causal behaviors and interfaces related to other components, and precious cases that the designers can refer to. Function, structure, attribute and behavior are generally decomposed further down to sub-functions, sub-structures, sub-attributes and sub-behaviors. The relationship among groups of related structures is based on the top-down design process and the inheritance relationships among groups of related attributes is represented by mathematical equations. The static attribute information presents the description and data information that are necessary for model initialization and simulation running. The behavior information represents the changing process of the multi-level model by using the changing conditions, results and algorithms of the model that are defined in the resolution-related information of a component.

A well-structured knowledge representation offers various pieces of knowledge created during the design process to fulfill the information needs of engineering designers. The representation based on the BOM enables the decomposition of functions into sub-functions and the decomposition of processes into sub-processes. Once a basic high-level knowledge which formulates the high level modeling information of a product is defined, other levels of knowledge are decomposed and implemented by using the basic high-level knowledge as a design proceeds.

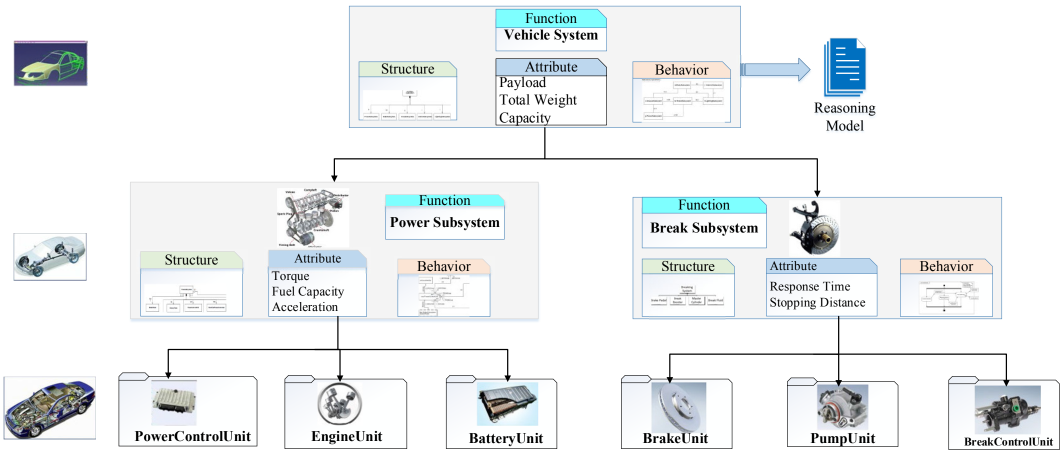

Figure 1 Multi-level knowledge representation for a vehicle design

4. Knowledge Representation Based on BOM

The representation language determines the methods used to capture and retrieve design knowledge, and, as such, it is important to select an appropriate and powerful representation method. The BOM concept is based on the assumption that piece-parts of simulations and federations can be extracted and reused as modeling building-blocks or components (BOM Group, 2006). The BOMs serve to address the efficient and convenient needs in the development of complex products, especially with regard to reusability. As a general-purpose modeling language for systems engineering applications, it supports the specification, analysis, design, verification, and validation of a broad range of complex products.

Figure 2 provides an illustration of the BOM template, which is composed of four major components: model identification, conceptual model definition, model mapping and object model definition. As design knowledge involves diverse information including product function, behavior and structure, all of which describe the system design target from a variety of viewpoints. Furthermore, design engineers need various aspects of knowledge across all the design phases. Some of them are related to computational models and some of them are related to tacit knowledge. As such, design knowledge invovles integrated information with multidisciplinary representation during different design phases rather than just electronic files or isolated pieces of data. As to the elements, the static structure of a component such as entities and attributes is defined by the HLA Object Model, while the dynamic behavior is defined by the patterns of interplay and the state machine. Consequently, the architecture of multi-level complex product knowledge and its mapping to the BOM template is developed to facilitate knowledge representation and management, as shown in Figrue 2.

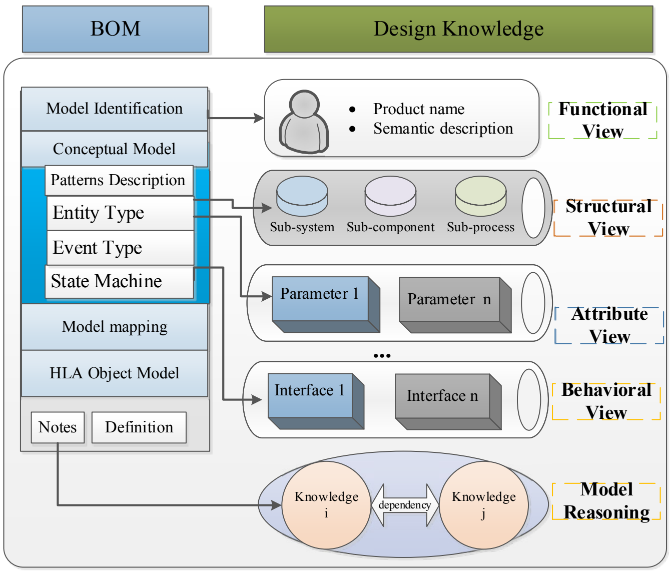

Figure 2 Structure of design knowledge representation based on BOM

a) Functional View

Like the design goal of Model Identification for BOMs, the functional view is used to document certain key metadata about design knowledge. This view provides management of product development and some general information for model developers, such as product name, product level and other semantic description about design knowledge which facilitates convenience of use, easiness of identification and reusability of models. Figure 3 shows an example of a Functional View file along with some annotations explaining the various elements.

b) Structural View

This view involves the entities representing specific objects of a design model. Specifically, a product is decomposed into component parts that include sub-systems, sub-functions and sub-processes. When a new product is developed, the corresponding requirement is analyzed and decomposed into suitable levels of sub-modules which can be easily implemented or cannot be decomposed any more. Model reasoning is the reference part in the BOM structure. Figure 4 shows an example of a structural view file in the development of a missile system.

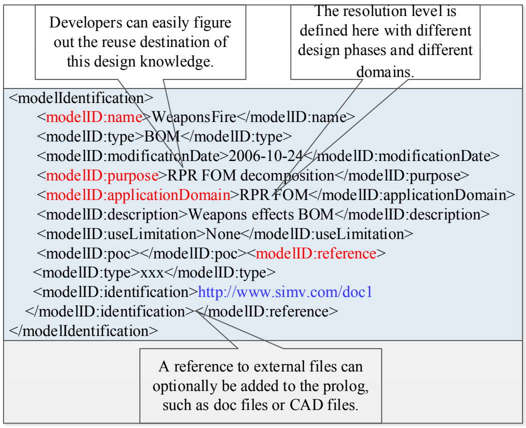

Figure 3 Sample BOM files for the Functional View

c) Attribute View

This view describes the input and output interfaces of the component. In the design process, design knowledge can be reused only by understanding these well-defined attributes and applying them to new problems. MathML is a markup language for describing mathematical notation and capturing both its structure and content (W3C, 2014). The goal of MathML is to enable mathematics to be served, received, and processed on the World Wide Web, just as HTML has enabled this functionality for text.

```
<entityType idtag="id3">
    <name>carsystem</name>
   <characteristic>
     <name>BodySubsystem</name>
     <semantics />
   </characteristic>
   <characteristic>
     <name>PowerSubsystem</name>
     <semantics />
   </characteristic>
   <characteristic>
     <name>BreakSubsystem</name>
     <semantics />
   </characteristic>
</entityType>
```

Figure 4 Sample BOM files for the Structural View

```
<stateMachine>
    <name>PowerSystem</name>
    <state>
                <name>Power</name>
         <exitCondition>
              <exitAction>AerodynamicDesign
           </exitAction>
              <nextState>PowerSystem</nextState>
         </exitCondition>
    </state>
    <state>
                <name>PowerSystem</name>
           <exitCondition>
               <exitAction>PayloadComputing
             </exitAction>
               <nextState>EnginePlan</nextState>
           </exitCondition>
     </state>
<stateMachine>
```

Figure 5 Sample BOM files for the Behavior View

d) Behavioral View

The dynamical behavior and interactions of multi-level knowledge are established in this view. Direct links between different domains and levels are used to describe the inheritance and mapping relations of design knowledge. Procreator can transform parent model into children models according to these decomposition rules. Figure 5 displays an example of a Behavioral View file, in which the left is piece of XML corresponding to the State Machine in BOM.

5. Retrieval and Reuse of Knowledge Based on the D-S Evidence Theory

The aim of knowledge reuse is to retrieve a set of components from the knowledge library to meet the functional or structural requirements and assemble these components into a correct and useful model for a new problem. As discussed above, a multi-level knowledge representation produces vast amount of BOM files and other materials during the design process. Compared with some specific information types, such as geometric and pictorial information, the text data in BOM files is relatively easier to retrieve. However, when the magnitude of interacting design knowledge in a large-scale product design comes to millions which is common in aircraft development, an effective retrieval method is necessary for reusing design knowledge.

5.1 Similarity Calculation

Knowledge matching is the most complicated step of the retrieval and reuse method, which is aimed at evaluating and refining the retrieved knowledge from all possible solutions to find the optimal solution. The key factor of evaluating design knowledge lies in the matching of feature set. For each design requirement, a number of features can be identified using an abstract description and on this basis form a feature set. Then features contained by the retrieved design knowledge are compared with the feature set. The knowledge covering more features in the set generally has a higher degree of matching, meaning better meeting the reuse requirements. In this work, a similarity measure is used to calculate the degree of matching through the weighted value of semantic relevance and parameter consistency, according to different parts of the knowledge model.

5.1.1 Parameter Similarity

The computation of parameter similarity is based on the attribute view part of the knowledge model. In accordance with the weight of each feature in the design requirement, the similarity of each components in the knowledge database is measured. Let $g = \{g_1, g_2, \cdots, g_m\}$ represent the feature set of design requirement k, and m is the node number or the knowledge number of the set. $f = \{f_1, f_2, \cdots, f_n\}$ represents the feature set of the retrieved knowledge k', and n is the node number. The parameter similarity $Sim_{para}(k, k')$ is calculated as follows:

$$Sim_{para}(k, k') = \sum_{i=1}^{m} w_i(g_i) \times s_i(g_i, f_i). \quad (1)$$

In Equation (1), $w_i(g_i)$ is the weight value of the ith feature after normalization processing. On the basis of summarizing engineering practices, the weights of attribute feature can be determined. The weights of features largely reflect the importance of particular objects for a component. For example, a gear is equipped with a number of features in which modulus and the number of teeth have greater weights than the height and material type.

$s_i(g_i, f_i)$ represents the similarity of the two values g_i and f_i , which can be represented as Equation (2):

$$s_i(g_i,f_i)=\begin{cases}1-\dfrac{|g_i-f_i|}{\max(g_i,f_i)-\min(g_i,f_i)}, \\ 1.\end{cases} \tag{2}$$

5.1.2 Semantic Similarity

The computation of parameter similarity mainly aims to find a piece of knowledge which is similar in terms of both meaning and functionality. So far, several types of approaches to measuring semantic similarity computation have been introduced (Harispe 2013): the geometric approach that evaluates the relative positions of two words in the semantic space defined by the context vectors; the set based approach that is characterized by the approach adopted to express the features of a set of classes; and the information theoretical approach that relies on the comparison of two classes according to their commonalities and differences. This paper defines a hybrid measure which takes into account some of the elements in the approaches mentioned above and combines the structural relationship among multi-level elements.

Figure 6 gives an example of the multi-level knowledge representation in the top-down product design process and the corresponding semantic tree. Each node in the tree represents a piece of design knowledge and the edge is weighted according to the dependency relationship between nodes. The similarity is estimated as the taxonomical distance of two nodes defined in a taxonomic tree, which is based on the analysis of the lengths of the paths linking the piece of knowledge concerned.

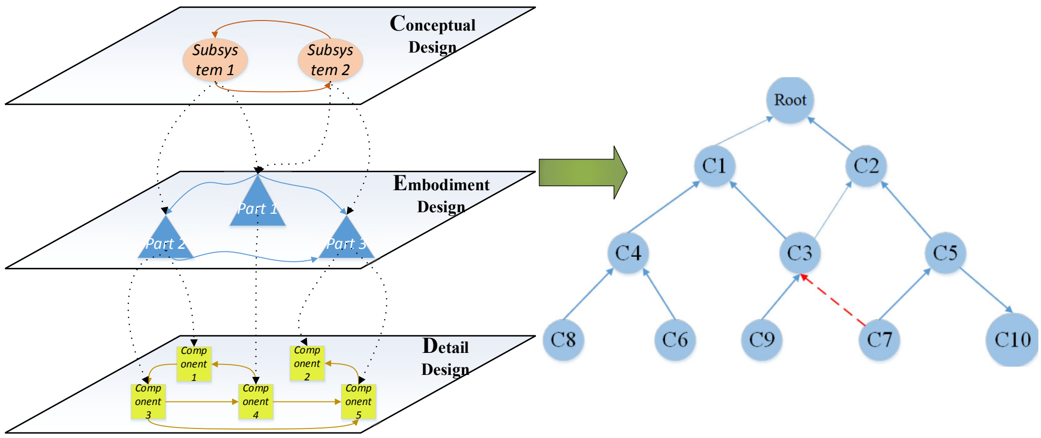

Figure 6 An example of a multi-level semantic graph

Let Rd denote the reuse degree, which satisfies the following constraints.

$$\begin{cases}Rd(i)\geq 0, \quad i=1,\cdots,n, \\ Rd(HR)\geq Rd(LR), \\ Rd(HR_i)=\sum_{j=1}^{m}\mu_j Rd(LR_{ij}).\end{cases} \tag{3}$$

In Equation (3), $Rd(HR)$ is the reuse degree of high level knowledge; $Rd(HR)$ is reuse degree of low level knowledge; $Rd(LR_{ij})$ represents all of the models that contain the high level knowledge; and u_j is the corresponding weighting factor. Then denote $sp(C_1,C_2)$ as the shortest path between two nodes C_1 and C_2. The length of a path has been defined as the sum of the weights associated to the edges which compose the path. The semantic similarity between C_1 and C_2 can then be represented using Equation (4):

$$Sim_{sem} = \begin{cases} \dfrac{\varepsilon(Rd(C_1)+Rd(C_2))}{sp(C_1,C_2)\times 2\times max\_depth}, & C_1 \neq C_2, \\ 1, & C_1 = C_2. \end{cases} \quad (4)$$

In the equation, $\varepsilon > 0$ represents a factor weighting the contributions of the various properties so as to define a personalized information retrieval approach. The parameter max_depth corresponds to the depth of the tree.

5.2 Retrieval Algorithm

According to whether models are at the same level, the multi-level knowledge reuse can be divided into two different patterns, namely horizontal reuse and vertical reuse. Specifically, the former has a focus on constraint relations within the same levels, including the input-output relationship, time factor, logical relationship and so on. The latter emphasizes the model deduction and dependencies between different levels. The vertical reuse pattern plays a more significant role in the development of complex products, which is also the focus of this study.

To facilitate knowledge retrieval, each piece of knowledge is linked to an index according to the tree-based structure of design knowledge, which will be the main retrieval term. To ensure the accuracy of the search process, semantic description rules of the domain can also be added as retrieval terms.

Since the multi-level knowledge is stored in the form of a tree structure, the Depth-First Search (DFS) and Breadth-First Search (BFS) methods are applied to the retrieval of design knowledge naturally. A tree search starts at the root and explores nodes from there, looking for a goal node that satisfies certain conditions and requirements.

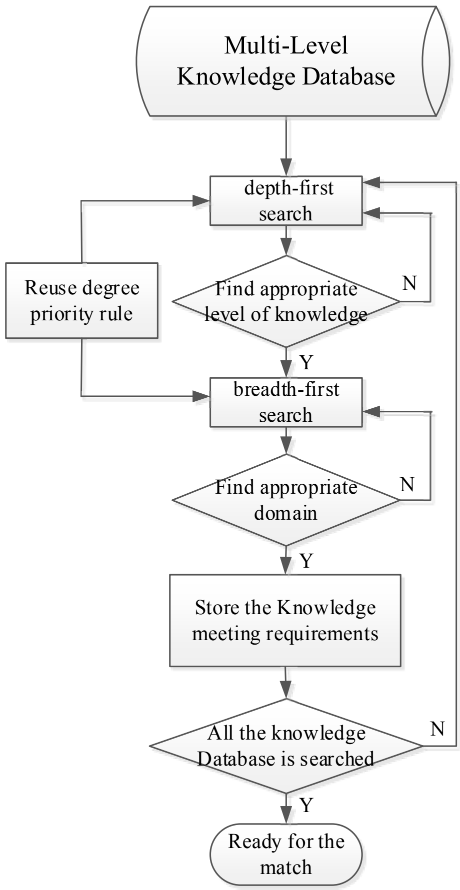

Figure 7 Flowchart of the knowledge retrieval algorithm

As shown in Figure 7, The DFS algorithm explores a domain all the way to a high-level knowledge before backtracking and exploring another domain if the model lies in this area. The BFS algorithm explores knowledge node nearest to the knowledge root node before exploring nodes further away.

5.3 Knowledge Fusion Method Based on the D-S Evidence Theory

As the retrieved knowledge belongs to multiple disciplines, an effective reasoning and fusion method is necessary to integrate heterogeneous knowledge together and finally to realize providing product design decisions for mechatronic product development designers and electronic product enterprise's policymakers through the whole lifecycle. The D-S evidence theory allows one to combine evidence from different sources and arrive at a degree of belief that takes into account all the available evidence. Specific to the engineering design process, the D-S approach is aimed at assembling the most appropriate knowledge related to different components of a product or a part, which proceeds through the following steps.

Step 1: Structure the power set $2^X = \{\theta_1, \theta_2, \theta_3, \cdots, \theta_n\}$ to represent all possible features of a system under consideration. The evidence set $\{m_1, m_2, m_3, \cdots, m_i\}$ is the set of all components that form the combining framework.

Step 2: Assign a belief mass to each element of the power set that compose a system. The mass $\mathrm{m}(\theta_1)$ of θ_1, as a given member of the power set, expresses the proportion of all relevant and available evidence that supports the claim that the actual state belongs to θ_1 but to no particular subset of θ_1. The similarity calculation discussed in Section 5.1 is used here to represent the belief mass.

Step 3: Based on the mass assignments, define the upper and lower bounds of a probability interval. Specifically, it is bounded by two non-additive continuous measures called support and plausibility represented using Equation (5) and Equation (6), respectively.

$$\text{Support}\,\mathrm{Bel}(\mathrm{X}) = \sum\nolimits_{Y \subseteq X} m(\mathrm{Y}), \tag{5}$$

$$\text{Plausibility}\,\mathrm{Pl}(\mathrm{X}) = 1 - \sum\nolimits_{\mathrm{Y} \subset \overline{\mathrm{X}}} m(\mathrm{Y}). \tag{6}$$

Step 4: According to Dempster's rule of combination, fuse separate beliefs estimates from multiple knowledge sources that are to be integrated in a cumulative manner. Specifically, the joint mass is calculated from the two sets of masses m_1 and m_2 using the following form:

$$(m_1 \oplus m_2)(\theta_1) \triangleq \frac{1}{1-K} \sum\nolimits_{\Psi \cap \Phi = \theta_1} m_1(\Psi) m_2(\Phi). \tag{7}$$

In the above equation, $K = \sum\nolimits_{\Psi \cap \Phi = \varnothing} m_1(\Psi) m_2(\Phi)$ is a measure of the amount of conflict between the two mass sets.

Step5 Select the knowledge combination with the highest belief mass and construct the corresponding decision rules on the basis of the specific design problem. The decision accounts for both the differences and the relations between essentially different types of knowledge. According to different problems, the answer form may be a description of knowledge pieces or a conclusion to the decision-making about the recommended cases.

6. A Case Study

Missile is a typical complex product which involves collaborative design and simulation of multidisciplinary models such as the dynamic model, aerodynamic model, structural model, control model and so on. The application of this system is aimed at improving the economic property and reducing lead-time as well as the initial-manufacture cost. Furthermore, it helps to facilitate sharing and reusing product design knowledge in new product research and development, which makes it easier to generate new designs by adapting older models.

A prototype has been developed to integrate our knowledge-based solution with the distributed simulation system, namely the COSIM platform. Block diagram technology is proposed to implement the multi-level modeling procedure. The Graphical User Interfaces (GUIs) of the prototype system are created using MFC technology and AddFlow plug-in components. MySQL database management system is installed to store the initialization data and data generated throughout the modeling and simulation process. The system can provide four main functionalities to support system design and simulation, namely multi-level modeling, multiple views, component transform and system simulation.

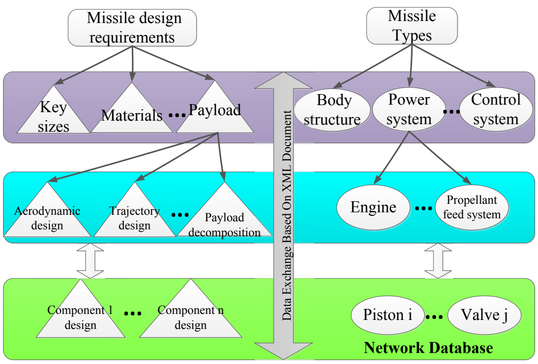

Figure 8 The development process of a missile

To understand the design knowledge better, the process of a missile development is shown in Figure 8. Introducing a new model of missile generally takes years from inception to assembly. The missile design task is assigned to engineering designers with basic requirements, such as the shooting rate performance, payload metric and so on. With the help of CAD tools, designers develop basic concept sketches that help them visualize the proposed vehicle's appearance. Based on this simulation, they then construct different models that can be studied by experts from various domains. Specifically, aerodynamic engineers review the models, studying air-flow parameters and doing feasibility studies. Trajectory engineers calculate the path of model during a flyby and try to minimize or maximize some measure of performance within specified constraint boundaries. Only after all models have been reviewed and accepted are tool designers permitted to begin building the tools that will manufacture the component parts of the new model.

The design process relies very heavily on designers with knowledge about all kinds of domains and a lot of prior knowledge, which unfortunately affects development efficiency. A well-structured knowledge representation offers various materials created during the design process to fulfill the information needs of engineering designers. The representation based on BOM enables the decomposition of functions into sub-functions and the decomposition of a process into sub-processes. Once a basic high-level knowledge which formulates the high level modeling information of a product is defined, other levels of knowledge are then decomposed and implemented based on the basic high-level knowledge.

During the design process of a particular subsystem, to best meet the whole features of the customized requirements, all the related knowledge needs to be assembled into a larger system. The similarity between each piece of knowledge and the feature set can be calculated using the methods described in Section 5. As shown in Figure 9, $\{i1, i2, i3, i4\}$ represent the different indicators of technical design requirements, which covers various disciplines. $\{m1, m2, m3\}$ represents models retrieved from the knowledge database with the largest similarity. $\{A1, A2, A3, A4\}$ are system parameters of $m1$. In general the model only meets a particular part of the product needs. For example, $m1$ best meets system security requirements while $m2$ meets the maneuverability requirements. In order to analyze these data more efficiently, design engineers need to be supported by the system by using the D-S evidence theory.

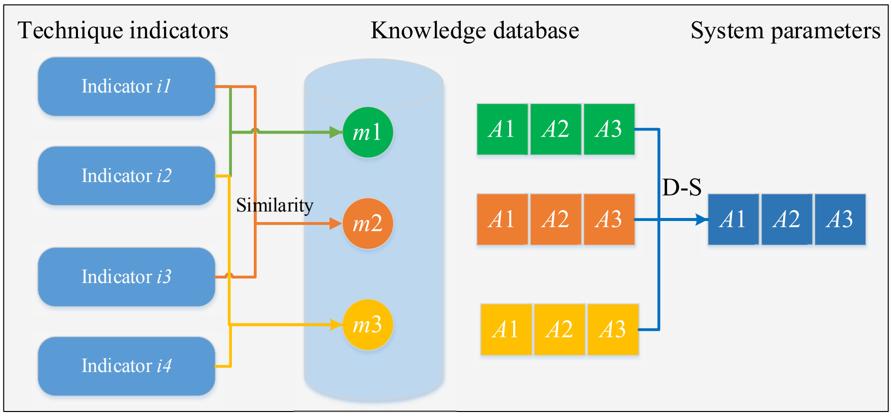

Figure 9 Fusion reasoning framework of design knowledge

As shown in Table 2, the feature set contains three features all of which are independent of each other, while one of the combinations is made up of three knowledge records. The steps to solve the fusion problem are as follows.

Table 2 Knowledge fusion using the D-S evidence theory

	Feature 1	Feature 2	Feature 3
Knowledge 1	0.40	0.40	0.20
Knowledge 2	0.36	0.54	0.10
Knowledge 3	0.12	0.60	0.28
Combination	**0.1133**	**0.8496**	**0.0368**

a) Calculate the normalization factor.

$$k = \sum_{A1 \cap A2 = \varnothing} m1(A1)m2(A2) = 0.62. \quad (8)$$

b) Fuse the first two data set $m1$ and $m2$.

$$m(A) = \frac{1}{1-K} \sum_{Ai \cap Aj = A} m1(Ai)\, m2(Aj). \quad (9)$$

The fusion results are then figured out as follows.

$$\begin{aligned} m12(A1) &= 0.3789 \\ m12(A2) &= 0.5684 \\ m12(A3) &= 0.0527 \end{aligned} \quad (10)$$

c) To fuse $m3$ with $m12$, calculate the normalization.

$$k' = \sum_{Ai \cap Aj = \varnothing} m12(Ai)m3(Aj) = 0.5987. \quad (11)$$

d) Calculate the final result.

$$m'(A) = \frac{1}{1-k'} \sum_{Ai \cap Aj = A} m12(Ai)m3(Aj). \quad (12)$$

The last row highlighted using bold font shows the similarity between the combination and each of the three features, which can then provide decision-making advices for the designers.

The multi-level knowledge representation is supposed to support multidisciplinary simulation in a distributed environment, which enables the collaborative work of users focusing on different tasks. Defined under the IEEE standard 1516, the High Level Architecture (HLA) provides specifications for managing distributed simulation components based on a federation framework allowing for run-time interoperability and reuse of simulations.

Figure 10 shows the simulation of the missile design process, which represents the design of several subsystems including control and guiding system, movement and dynamic system, optimizer system, target system and radar system. The retrieved BOM files are converted into federates of HLA and then these components are assembled to form a federation in a virtual simulation environment. The development process is iterated until a satisfactory solution is generated.

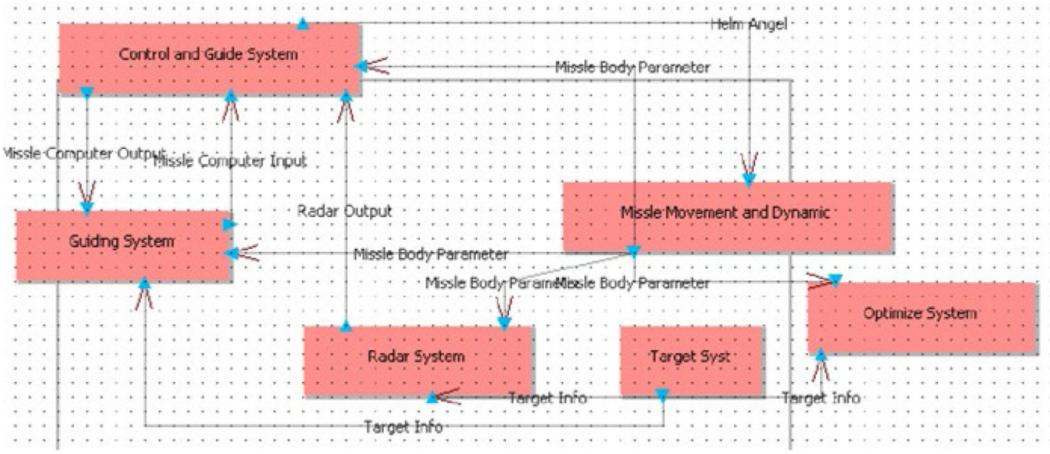

Figure 10 Simulation of the missile system

7. Conclusion and Future Work

The development of modern complex products requires a more integrated, digital and collaborative methodology. It is already common practice to employ knowledge reuse in complex product development. In this context, it is necessary to develop an integrated design framework for collaborative product development which is capable of capturing, representing, retrieving and assembling design knowledge. Such a framework will allow geographically distributed engineers to work collaboratively in a virtual environment powered by Web services. The need to develop such a system raises a number of issues such as the model specification, the dynamic interaction, the indexing and matching algorithms, etc. All these issues need to be well resolved before this framework can be implemented and applied in industry.

This paper presents the design of a BOM based multi-level knowledge representation model for product design. This model includes several major components for facilitating knowledge representation and management. The reuse process is divided into three steps, namely retrieval, matching and assembly. The model and methods have been implemented and integrated with a HLA-based simulation tool. A case study has been undertaken and the reuse method based on the multi-level knowledge model is used in a missile design problem. A number of conclusions can be drawn on the basis of this preliminary work. Firstly, BOM-based models are able to represent multi-faceted knowledge and it is very helpful for supporting the collaborative work of distributed designers. Secondly, management of design knowledge involves lots of issues such as retrieving and assembling knowledge records. Thirdly, the method based on the D-S evidence theory can fuse information from different sources so as to make reasonable decision advices. Fourthly, the BOM model can be converted into federates, which shows that it is easy to integrate the proposed framework with HLA-based simulation platforms. Future work will focus on using ontology to support semantic composability of multi-level knowledge. Besides improving capabilities of modeling technology, load-balance on parallel simulation should also be taken into consideration. Extended test-bed models will also be used for further investigation.

8. Acknowledgments

This research is supported by the National Natural Science Foundation of China （Grant No.61374163）, the National Key Technology R&D Program (Grant No. 2012BAF15G00), the National High Technology Research and Development Program (863 Program) of China (Grant No.2013AA041302). The original version of this paper was presented at the 18th IEEE CSCWD Conference held in Taiwan, China in May 2014.

References

[1] Bilgic, T. & Rock, D.(1997). Product data management systems: state of-the-art and the future. Proceedings of the 1997 ASME Design Engineering Technical Conferences and Computers in Engineering Conference. Paper No. DETC97/EIM-3720, Sacramento, CA, 14-17 September 1997.

[2] Böhler, T.M. (2012). Smarte produkte und fabriken revolutionieren die industrie. Produktion Magazin, 5 October 2012.

[3] Bracewell, R., Wallace, K., et al. (2009). Capturing design rationale. Journal of Computer-aided Design, 41 (3): 173-186.

[4] Byrne, J., Heavey, C., et al.(2010). A review of Web-based simulation and supporting tools. Simulation Modelling Practice and Theory, 18 (3): 253-276.

[5] Chapman, C.B. & Pinfold, M.(1999). Design engineering - a need to rethink the solution using knowledge based engineering. Knowledge-Based Systems, 12 (5–6): 257-267.

[6] Goel, A., Bhatta, S., et al. (1997). Kritik: an early case-based design system. In: Maher, M., Pu, P. (eds.), Issues and Applications of Case-Based Reasoning in Design, pages 87-132. Mahwah, NJ: Erlbaum.

[7] Harispe, S., Ranwez, S., et al.(2013). Semantic measures for the comparison of units of language, concepts or instances from text and knowledge base analysis. Available

via DIALOG. http://arxiv.org/abs/1310.1285. Cited 6 December, 2013.

[8] Iyer, N., Jayanti, S., et al.(2005). Three-dimensional shape searching: state-of-the-art review and future trends. Computer-Aided Design, 37 (5): 509-530.

[9] Kim, K.Y., Manley, D.G., et al. (2006). Ontology-based assembly design and information sharing for collaborative product development. Computer-Aided Design, 38 (12): 1233-1250.

[10] Li, Z. & Liu, M.(2004). Review of product information retrieval: representation and indexing. In: Proceedings of ASME 2004 Computers and Information in Engineering Conference, 4: 971-979, Salt Lake City, UT, 28 September -2 October, 2004.

[11] Mao, H.C., Peng, G.Z., et al.(2013). Choosing models of appropriate resolutions for simulation: a MRM approach. 13th International Conference on Systems Simulation, 188-199, Singapore, 6-8 November, 2013.

[12] Modelica Association. (2012). Modelica - a unified object-oriented language for systems modeling language specification. Available via DIALOG. https://www.modelica.org/documents/ModelicaSpec33.pdf/view. Cited 9 May, 2012

[13] Peng, G.Z., Mao, H.C., et al.(2013). BMRSS: BOM-based multi-resolution simulation system using components. 13th International Conference on Systems Simulation, 485-496, Singapore, 6-8 November 2013.

[14] Peng, G.Z., Mao, H.C., et al.(2014). Multi-level knowledge representation and retrieval of complex product design based on BOM. In: IEEE 18th International Conference on Computer Supported Cooperative Work in Design (CSCWD), 226-230, Hsinchu, May 21-23, 2014, IEEE.

[15] Shen, W.M., Qi, H., et al. (2007). An agent-based service-oriented integration architecture for collaborative intelligent manufacturing. Robotics And Computer-Integrated Manufacturing, 23 (3): 315-325.

[16] SISO Base Object Model Product Development Group (2006). SISO-STD-003-2006, Base Object Model (BOM) Template Specification. Available via DIALOG. http://www.boms.info/standards.htm.

[17] Szykman, S., Sriram, R. D., et al. (2000). Design repositories: engineering design's new knowledge base. Intelligent Systems, 15 (3): 48-55.

[18] Szykman, S., Sriram, R.D., et al. (2001). The role of knowledge in next-generation product development systems. Journal of Computing and Information Science in Engineering, 1 (1): 3-11.

[19] Tate, E. D., Sasena, M., et al. (2008). Model embedded control: a method to rapidly synthesize controllers in a modeling environment. Paper presented at the 6th International Modelica Conference, University of Applied Science Bielefeld, Germany , 3-4 March 2008.

[20] Wang, H.W., Johnson, A.L., et al.(2012). The retrieval of structured design rationale for the re-use of design knowledge with an integrated representation. Advanced Engineering Informatics, 26(2), 251-266.

[21] Wang, H.W. & Zhang, H.M.(2010). A distributed and interactive system to integrated design and simulation for collaborative product development. Robotics and Computer-Integrated Manufacturing, 2 6(6): 778-789.

[22] W3C.(2014). Mathematical Markup Language (MathML) Version 3.0 2nd Edition.

Gongzhuang Peng is currently a doctoral student of the National Engineering Research Centre of Computer Integrated Manufacturing System (CIMS-ERC) in Tsinghua University, Beijing, China. He received his Bachelor degree in the Department of Automation from Beihang University, Beijing, in 2012. His research interest includes multidisciplinary modeling, collaborative simulation, and knowledge management.

Huachao Mao is currently a doctoral student of Viterbi School of Engineering in University of Southern California. He received his Bachelor degree in the Department of Automation in Beihang University, Beijing, in 2012; Master degree in the National Engineering Research Centre of Computer Integrated Manufacturing System (CIMS-ERC) in Tsinghua University, Beijing, China. His research interests include multidisciplinary modeling and collaborative simulation.

Hongwei Wang is currently a Senior Lecturer in Engineering Design at the School of Engineering, University of Portsmouth. Prior to joining the school, he completed his PhD in the Engineering Design Centre in the University of Cambridge. He obtained a BEng (Electronic and Information Sciences) with distinction from Zhejiang University and an MSc (Control Science and Engineering) with distinction from Tsinghua University in 2004, 2007 respectively. His research interests are in the application of information and computing technologies to address specific design issues, for example, knowledge and information management, collaborative product development, collaborative modeling and simulation and sustainable design.

Heming Zhang is currently a professor in the National Engineering Research Centre of Computer Integrated Manufacturing System (CIMS-ERC) in Tsinghua University, China. He received his PhD degree in mechanical engineering from Zhejiang University (China) in 1995. He joined the faculty of Automation Department in Tsinghua University after two years of Postdoctoral Fellow in CIMS-ERC. His research interests include multidisciplinary modeling and collaborative simulation, service oriented modeling and simulation, concurrent and collaborative design.