Rapid Design System for Agricultural Machinery Using Knowledge-Based Engineering: Case Study of a Wheeled Combine Chassis

S. Fu, T. Lan, Y. Du, E. Mao, Z. Zhu, Z. Li

Highlights

- A knowledge-based rapid design system for combine chassis is proposed.
- Object-oriented knowledge representation uniformly describes the multi-source heterogeneous design knowledge.
- Multivariate linear regression analysis ratiocinates further unknown design principles behind existing products.

Abstract. *In the design of agricultural machinery, the lack of systematic and structured knowledge utilization systems results in low development efficiency and poor reusability of design knowledge. This study considers the design of a combine chassis and focuses on the application of knowledge-based rapid design to agricultural machinery. As a typical sophisticated agricultural machine, combines have a complicated design that requires the integration of multiple disciplines according to the crop types, production areas, and ability of the designers. Hence, a knowledge-based design system for a wheeled combine chassis is proposed. By integrating object-oriented technology with a mixed reasoning strategy, multi-source heterogeneous design knowledge can be applied in completing the chassis design task. To date, there are more than 2000 design ideas and 350 parameter models in the knowledge database. In addition, tacit design knowledge acquired by a knowledge discovery method can be employed to perfect the design and improve the reliability of the product. The design of a combine chassis demonstrates that the knowledge-based rapid design of agricultural machinery is completely feasible, and the design system significantly reduces the design workload, shortens the development cycle, and improves design efficiency and knowledge utilization.*

Keywords. *Combine chassis, Knowledge-based design system, Knowledge-based engineering, Rapid design.*

To satisfy customer demands for diversification and individuation, the market for agricultural machinery is gradually changing from large-scale production to small-batch customization. Chinese agricultural machinery enterprises are facing significant challenges in their target markets (Du et al., 2019). First, the traditional mode of agricultural machinery design, which is based on tracking and imitating foreign products, has been seriously impacted and can no longer meet the market demand, and the reliability of the designed products has been questioned by customers. Second, frequent configuration changes and variant designs have led to increased research and development costs. Repetitive tasks such as manual calculations and literature reviews consume much of the designers' time during the design process. A large amount of design knowledge is involved in the design of agricultural machinery, and the lack of a systematic and structured knowledge utilization system severely limits the designers' efforts to improve product quality. Knowledge-based rapid design is widely used in advanced manufacturing fields, such as automobiles, aerospace, and shipbuilding (Cui et al., 2015; Engel et al., 1990; Quintana-Amate et al., 2017; Stenholm et al., 2015) and combines knowledge-based engineering (KBE) and CAD to assist designers in reasoning, judgement, and decision-making, thus enhancing the customization, automation, and intelligence of the product design. The unified expression and management of design knowledge are conducive to the effective inheritance and reuse of such knowledge, which has become vital in changing the current status of the design of agricultural machinery (Zhang and Bernard, 2018).

To improve the development efficiency of the product, and reduce the development and management costs, many well-known agricultural machinery enterprises (e.g., John Deere, CNH, AGCO, and YTO) have established product data management and product lifecycle management (PDM/PLM) systems. These systems achieve resource integration, process management, data storage, and knowledge accumulation using various automation and information

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technologies (Panetto et al., 2012). The PDM/PLM concept provides an important foundation for the realization of knowledge-based design for agricultural machinery. Regarding the actual status of PDM/PLM in agricultural machinery companies, there are still many limitations. A large amount of multi-source heterogeneous data and design knowledge are generated in the design and cooperation processes of the upstream and downstream agricultural machinery firms. There are many prominent problems, such as poor data consistency, low levels of sharing, and information islands, making it difficult for designers to achieve effective reuse and inheritance of knowledge and design resources. Additionally, it is inconvenient for designers to manually retrieve design knowledge that they wish to reuse.

Researchers and enterprises around the world have attempted to realize knowledge-based rapid design of agricultural machinery. A knowledge-based parametric CAD modeling system for spur gear design was developed by Jayakiran Reddy and Pandu Rangadu (2018). Their system incorporated the rules of the America Gear Manufacturers Association (AGMA) in design computations and parametric modeling using SolidWorks software. Li et al. (2012) developed a knowledge-based rapid design system for the chassis of a high-speed transplanter by combining design knowledge with an inference engine and a parametric model. Chen et al. (2013) studied the reasoning mechanism of design knowledge for a combine gearbox and successfully developed a parametric design system. Based on the AD principle, a knowledge-based rapid design system was developed for the generation of complex gearboxes for large wheeled tractors (Shangguan et al., 2015). A case-based reasoning method based on multiple-attribute decisions has been proposed for the design of agricultural machinery. This method focuses on improving the retrieval efficiency of case knowledge (Zhao et al., 2017). However, there are few related studies on knowledge-based design for agricultural machinery in the literature. The complexity of agricultural machinery and the unified expression and reuse of multi-source heterogeneous design knowledge are still the greatest challenges to implement knowledge-based rapid design of agricultural machinery.

Design of a combine, a typical high-end agricultural machine, is a complicated task requiring the integration of multiple disciplines and is greatly influenced by crop types, production areas, and the designers themselves (Jiang et al., 2013). Most designers are heavily dependent on their own experience and the existing data on combines, especially the performance data of foreign products (Myhan and Jachimczyk, 2016). For example, the chassis of a combine is critical to the performance and reliability of the whole machine. The chassis technology of self-propelled combines in China is taken from imported machines, such as the American John Deere 1000 Series chassis, the German CLAAS chassis, and the Russian CK-3 chassis. Because of a lack of localized improvements, it is difficult to fully adapt to the agronomic requirements and the supporting mechanization technology in China. In this study, the design of a combine chassis is taken as the research object to indicate the necessity and feasibility of realizing knowledge-based design of agricultural machinery. In the preliminary design stage especially, decision-making based on the designers' expertise and heuristic knowledge are important factors because the available information is limited and cannot be fully supported by the formal design procedure. In this situation, it is necessary to establish a standardized process for the knowledge-based design of a combine chassis, integrating KBE with the combine chassis design system. The architecture of knowledge storage and intelligent utilization is constructed via the developed system. These aspects are systematically discussed in this article. With the help of KBE, the design system for a chassis is integrated with design reasoning and knowledge management. This reduces the rework time and waste of resources and also shortens the development cycle and improves the quality and reliability of the chassis.

Materials and Methods

Knowledge-Based Architecture for Combine Chassis Design

This study focuses on the design of a wheeled combine chassis, the basic structure of which is shown in figure 1. Considering that the mass of a self-propelled combine is mainly concentrated at the front of the chassis, a wheeled combine is usually driven by the front wheels and steered by the rear wheels. The chassis mainly consists of four subsystems, i.e., walking system, drivetrain system, steering system, and braking system. The knowledge-based design process of the combine chassis is shown in figure 2.

As shown in figure 2, there are two design modes for designers to choose from. One is the overall design mode, and the other is the component design mode. For the overall design mode, using the design input interface, the available overall design parameters of combines are collected to define the target case. Next, the combine chassis cases in the case base are retrieved for comparison with the target case. A similarity value of 1 denotes that the same instance can be reused. If the similarity value is greater than the similarity threshold, the retrieved case can be modified and essentially reused. Otherwise, there is no similar case, and a redesign is necessary. Modification is mainly for those parts in similar cases where the feature similarity is less than the threshold

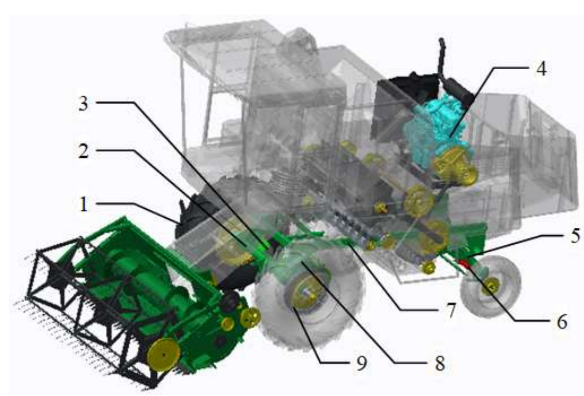

Figure 1. Basic structure of wheeled combine chassis: 1 = driving wheel, 2 = front axle, 3 = brake, 4 = engine, 5 = rear axle, 6 = steering system, 7 = combine frame, 8 = gearbox, and 9 = wheel reductor.

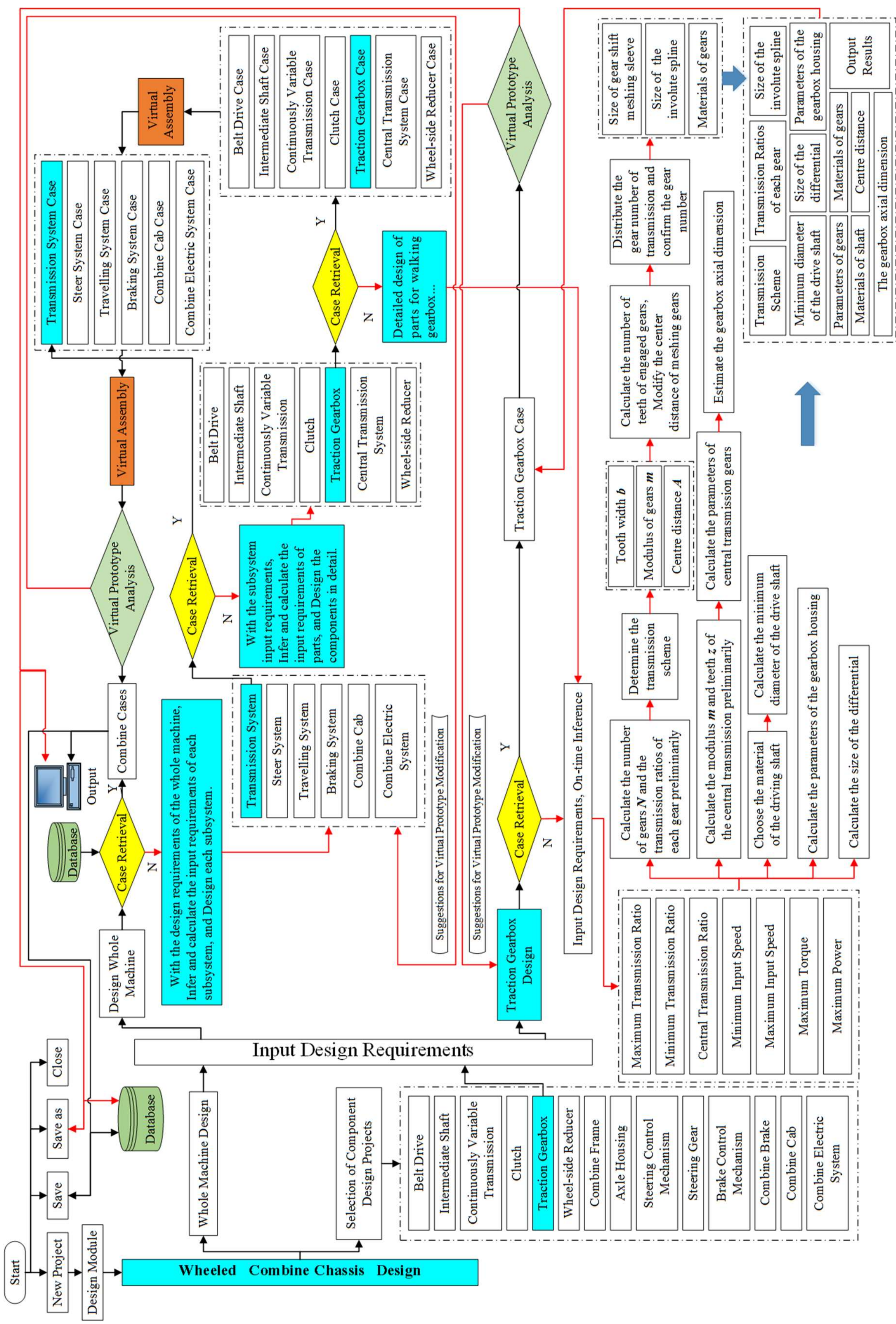

Figure 2. Knowledge-based design of wheeled combine chassis.

value. The designer makes the corresponding modifications according to the system prompts and design requirements to complete the case learning process. Finally, the modified case is saved in the case base and exported as the suggested solution via the human-computer interaction interface.

MODELING KBE-BASED COMBINE CHASSIS DESIGN

KBE mainly integrates professional knowledge, domain knowledge, mature design experience, the choice of design parameters based on experimental data, material data, user feedback, and relevant design standards and norms into the design system through logical judgments and deductions, thus achieving knowledge-based design of a product (Yang et al., 2012). Knowledge accumulation and updates can be realized through the management of the knowledge base using KBE, thus preventing knowledge loss and obsolescence. Generally, KBE is summarized as knowledge acquisition, knowledge representation, and knowledge-based reasoning, as described in the following sections.

KNOWLEDGE ACQUISITION

In traditional methods, design knowledge is mainly obtained by consulting the literature or manuals, experimental analysis, and expert interviews. This approach is inefficient and makes it hard to acquire tacit knowledge that is not directly described by tangible media, e.g., the designers' experience and the design principles behind the data (Jałowiecki et al., 2017; Quintana-Amate et al., 2015). Knowledge discovery in databases offers a new way of solving this problem, e.g., artificial intelligence technologies such as data mining are used to summarize and identify effective, new, and available knowledge and rules from relevant data. It is no longer necessary to completely rely on human design experience to achieve stable scientific and digital design (Alonso et al., 2012). The explicit and tacit knowledge acquisition for the design of a wheeled combine chassis are described as follows.

Explicit Knowledge Acquisition

Explicit knowledge refers to information that can be clearly expressed through equations, texts, and charts. In the design of a wheeled combine chassis, for example, the main design parameters of the chassis are usually determined from the overall parameters of the whole machine (i.e., working width, production rate, and allocation of engine power). The working width (B) is calculated as follows:

$$B = \frac{qC}{v_m A}\left(\frac{\beta}{1+\beta}\right) \quad (1)$$

where
C = 666.66
q = throughput (kg s^{-1})
v_m = average operating speed of combine (m s^{-1})
A = average crop yield (kg mu^{-1})
β = grain-straw rate (0.8).

According to the working width and average operation speed, the production rate (Q) is calculated as follows:

$$Q = 5.4\eta B v_m \quad (2)$$

where η is the productivity factor, which ranges from 0.7 to 0.8 in a wheat field and from 0.4 to 0.8 in a rice field.

The required power of the combine (P, kW) is the sum of the required power of all parts (Wei et al., 2007):

$$P = P_g + P_t + P_x + P_y + P_b \quad (3)$$

where
P_g = header power (kW)
P_t = power consumed by threshing drum (kW)
P_x = walking power (kW, see eq. 4)
P_y = power consumption of threshing device except for threshing drum (kW)
P_b = reserve power of engine (kW, P_b is approximately 20% of P).

$$P_x = Mgv_m f / \eta_t \times 10^{-3} \quad (4)$$

where
M = total mass of combine (kg)
g = gravitational acceleration (N kg^{-1})
f = coefficient of rolling resistance (e.g., f ranges from 0.08 to 0.3 in a dry field and is approximately 0.3 in a wet field)
η_t = efficiency of walking system (0.85 to 0.9).

Tacit Knowledge Acquisition

To obtain the tacit knowledge behind the product information, the overall parameters of 61 different combines were collected. These parameters include the overall dimensions, throughput, engine power, mass, and working width. Subsequently, the correlations between the design requirements and the overall parameters of combines were analyzed using SPSS (IBM, Armonk, N.Y.). Scatter plots and multivariate linear regression were combined to determine the relationships between the overall size of the combine, e.g., length (L), width (W), height (H), and mass (M), and input parameters such as throughput (q), working width (B), and engine power (P). The correlation coefficients are listed in table 1. Analysis of variance (ANOVA) and significance tests were employed to check the accuracy of each model. Significant data ($p < 0.05$) were introduced into the model, and non-significant data ($p > 0.10$) were eliminated from the model. Subsequently, a global significance test (F test) and the coefficient of determination (R^2) were applied to test the homogeneity of variance for both the sample and the total predicted value and to inspect the goodness-of-fit of the model.

The final fitting curves are shown in figure 3. The results showed that the regression models were highly significant ($p < 0.05$). For the length model in figure 3a, the p-value was 0.0015 with an F-value of 157.149. The fitness of the model was further confirmed by the R^2 value, which was calculated to be 0.727, and the value of the adjusted coefficient of determination (adjusted R^2 = 0.722) was high and confirmed that the model was significant. The same analysis showed that the other models fitted well, except the fitting model for

Table 1. Correlation coefficients between design requirements and combine parameters.

	B	*q*	*P*	*L*	*W*	*H*	*M*
B	1	0.782	0.818	0.791	0.811	0.810	0.930
q	0.782	1	0.923	0.715	0.649	0.722	0.817
P	0.818	0.923	1	0741	0.658	0.821	0.847
L	0.791	0.715	0.741	1	0.876	0.849	0.899
W	0.811	0.649	0.658	0.876	1	0.741	0.875
H	0.810	0.722	0.821	0.849	0.741	1	0.893
M	0.930	0.817	0.847	0.899	0.875	0.893	1

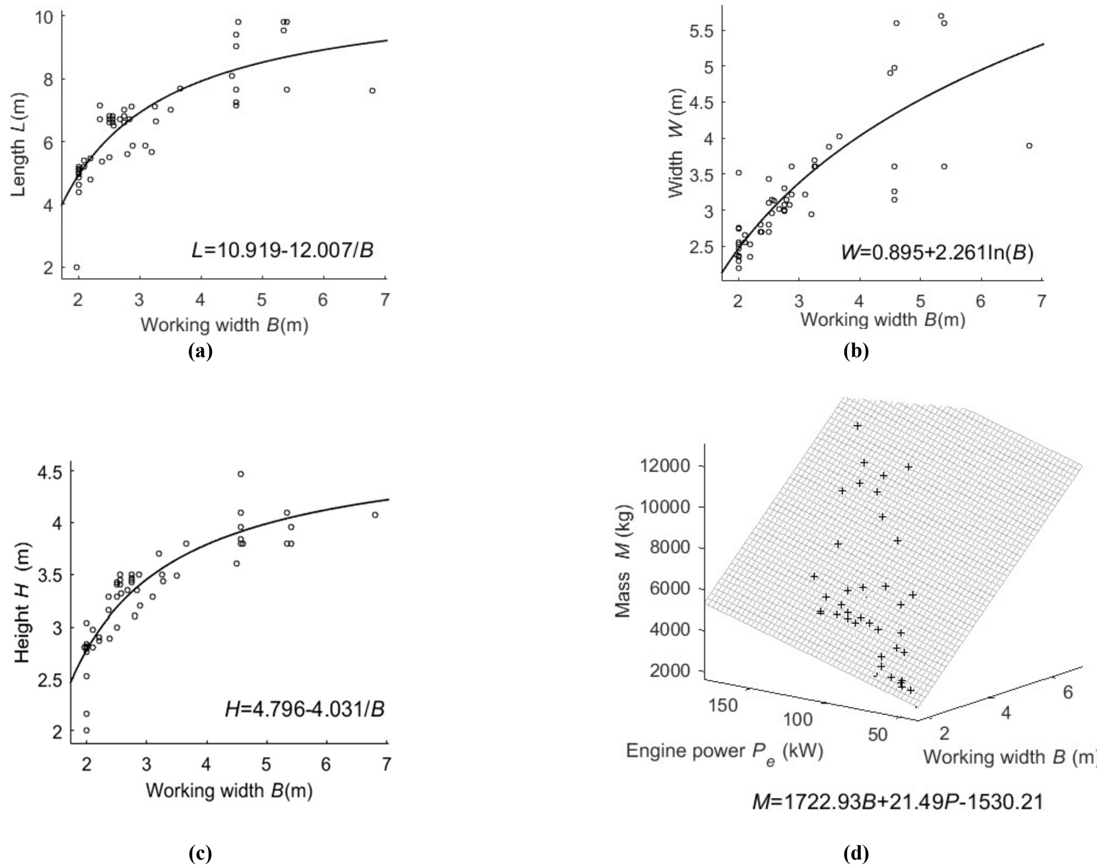

Figure 3. Fitting analysis of various combine parameters: (a) length, (b) width, (c) height, and (d) mass.

mass (fig. 3d). Although the adjusted R^2 value was 0.884, the root mean square error (RMSE) was 915.002, which indicates that the model is for reference only. These fitting models could help designers estimate the structural parameters of a combine to optimize the design of the product.

Knowledge Representation

Knowledge representation is the premise and basis of knowledge use and reasoning (Chandrasegaran et al., 2013). Currently, common methods of knowledge representation include the production rule, frame representation, object-oriented representation, ontology-based representation, semantic network, and first-order predicate logic rule. In this study, taking into consideration the sources and various types of design knowledge for combines, object-oriented knowledge representation (OOKR) was used in the knowledge-based design of a combine. OOKR integrates the production rule and frame representation, as shown in figure 4, encapsulating the attributes, relationships, and behavior of objects and rules, and describes the structure and relationships between objects by their inheritance and constraints.

Knowledge-Based Reasoning

Knowledge-based reasoning is the process of reasonably and effectively deducing another judgment from a known judgment stored in the knowledge base system to solve practical problems according to a strategy. According to the knowledge type, knowledge-based reasoning methods include rule-based reasoning (RBR) (Zhang et al., 2016), case-based reasoning (CBR) (Liu and Xi, 2011), and modeling-based reasoning (MBR) (Rubio et al., 2013). RBR relies on the production rule representation method, the core of which is deductive reasoning, and is widely used because of its high inference efficiency, strong reasoning ability, and ease of implementation. However, a lack of learning ability means that RBR is powerless if the problem goes beyond the scope of the system. CBR overcomes the shortcomings of RBR and is more attuned with human cognitive logic, that is, the reasoning process is similar to the way humans solve problems. On the basis of comprehensive consideration of the characteristics of design knowledge for a wheeled combine chassis, a mixed reasoning strategy integrating CBR and RBR (Avdeenko and Makarova, 2017; Costa et al., 2012) is proposed in this study (fig. 5).

According to the prompts offered by the system, users are required to input certain design requirements. The system will then match the input design requirements with the case attribute set in the case base. If there is a reasonable design result, the instance will be output to the user. If there is no matching example, the rule base in the database will be used to calculate and deduce the design result, and then a rationality check is carried out to obtain information about unqualified design parts and possible suggestions. Finally, a reasonable overall design result is output.

Different from RBR (eq. 5), the case retrieval determines the efficiency of the CBR system:

$$\text{If } P \text{ then } Q \tag{5}$$

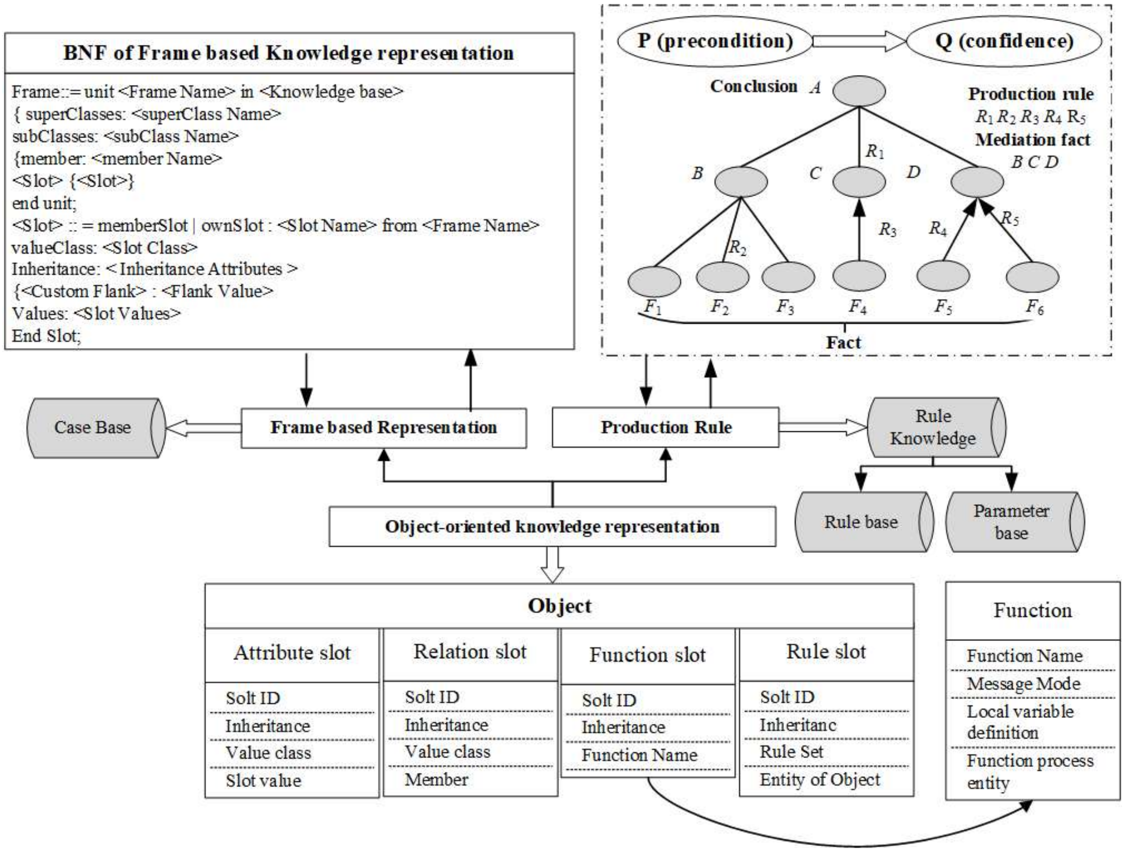

Figure 4. Object-oriented knowledge representation.

where

P = preconditions, which indicate when the condition is true

Q = conclusion or response when P is true.

The most commonly used indexing methods are the nearest neighbor, inductive, and knowledge-based methods (Montani et al., 2015). This study uses the nearest neighbor to determine the most similar instances for designers to consult and reuse during the design process. Instance attributes and descriptions generally contain different data types (e.g., numeric, descriptive, and range attributes). Each data type adopts a different similarity calculation method. Suppose the two design cases are $\mathbf{P} = (p_1, p_2, \ldots, p_n)$ and $\mathbf{Q} = (q_1, q_2, \ldots, q_n)$, where p_i and q_i ($i = 1, 2, \ldots, n$) denote the ith corresponding attribute of instances **P** and **Q**, respectively. For numeric attributes, the Euclidean distance between **P** and **Q** can be calculated as follows:

$$DIST(\mathbf{P},\mathbf{Q}) = \sqrt{\sum_{i=1}^{n} w_i \left(p_i - q_i\right)^2} \tag{6}$$

where w_i are the weights of all attributes in the case $w_i \in \boldsymbol{W}$ $[w_1, w_2, \ldots, w_n]$.

Because of the different orders of magnitude, numerical attributes may produce large errors in future calculations. Hence, it is necessary for attributes to be normalized as follows:

$$p_{ij} = \frac{p_{ij} - p_{i,min}}{p_{i,max} - p_{i,min}} \tag{7}$$

where

p_{ij} = value of the ith attribute in the jth instance

$p_{i,max}$ and $p_{i,min}$ = upper and lower bounds, respectively, of all instances for that attribute.

The similarity of the cases is calculated as follows:

$$Sim(\mathbf{P},\mathbf{Q}) = \frac{1}{1 + DIST} \tag{8}$$

For discrete data, the similarity is calculated as follows:

$$DIST(p_i, q_i) = \begin{cases} 0 & p_i = q_i \\ 1 & p_i \neq q_i \end{cases} \tag{9}$$

$$Sim(p_i, q_i) = \begin{cases} 0 & p_i \neq q_i \\ 1 & p_i = q_i \end{cases} \tag{10}$$

According to the above, the similarity of **P** and **Q** is calculated as follows:

$$Sim(\mathbf{P},\mathbf{Q}) = \sum_{i=1}^{n} w_i Sim(p_i, q_i) \tag{11}$$

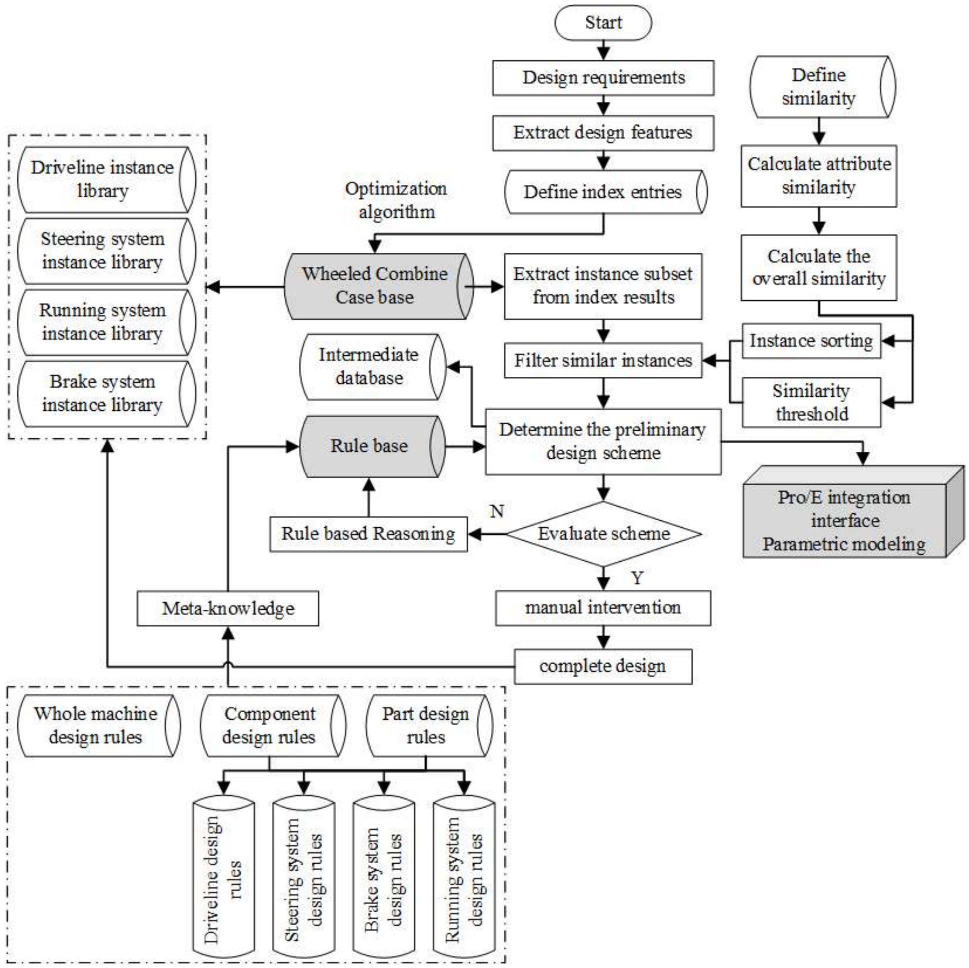

Figure 5. Mixed reasoning strategy integrating CBR and RBR.

CONSTRUCTION OF KNOWLEDGE DATABASE FOR COMBINE CHASSIS DESIGN

The knowledge base is defined as the collection of experience, cases, rules, and other knowledge. As described above, knowledge can be summarized into a number of rules, analysis, and problem-solving strategies and placed in a particular document or database to constitute a knowledge base. Additionally, the knowledge base can achieve classification and management of the design knowledge and provide the designers with the best guidance and recommendations during the design process (Curran et al., 2010; Juang et al., 2008). Figure 6 shows the main functional composition of the knowledge base. After logging into the management system via the interaction interface, users can access the database and browse, query, add, modify, and delete knowledge within the scope of their authority. In addition, administrators can perform user management, code management, knowledge management, and maintenance. The knowledge base in the design system can also have an interaction interface, online reasoning, user help, and other functions.

The case base mainly stores the assembly relationships and instance parameters of the whole machine, system, and parts of existing wheeled combines, as well as the standard parts, hydraulic components, and electrical components. The assembly relationships, instances, and instance parameter tables can be stored in a database according to the structure shown in figure 7. The various rule knowledge and instance knowledge of the parts are related to each other by the component ID. The modular storage of rule knowledge and case knowledge facilitates the retrieval and reuse of the

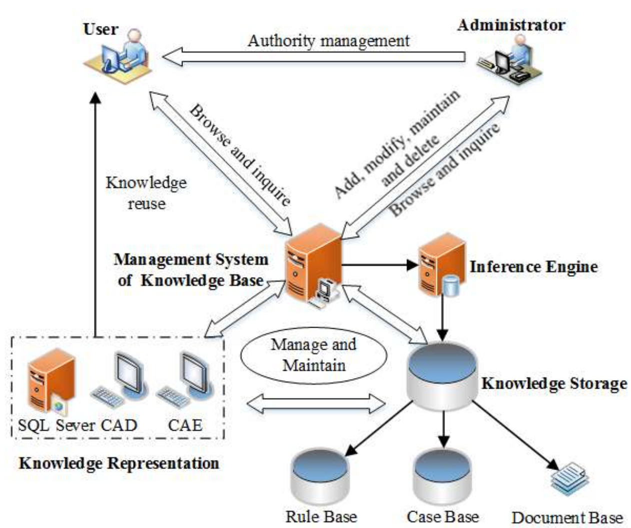

Figure 6. Main functional composition of knowledge base.

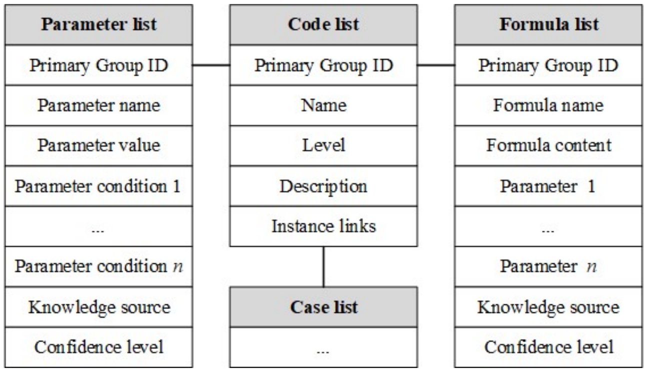

Figure 7. Data relationship in knowledge base.

knowledge. Thus far, more than 2000 design ideas for wheeled combine chassis have been collected in the knowledge base developed with Microsoft SQL Server 2008 (Microsoft Corp., Bellingham, Wash.).

Establishment of Parametric Model Database

The 3D parametric model database is the output form of the design product. The complete parametric model is necessary for later design verification and optimization. The model database includes the whole machine and parts model base, standard parts base, and general parts base, as shown in figure 8. The standard parts base contains the standard parts commonly used in mechanical design and can be designed as a series of model libraries using the family table parameterization method. The whole machine and part model libraries mainly store existing mature design case models. According to the actual needs of users, common models or systems are built and stored in a general parts base for convenience of high-frequency reuse. Limited by design resources and commercial confidentiality, there are few design cases for combines. In fact, there are more than 350 parametric models of standard parts and four sets of design cases of whole machines.

Results and Discussion

The ultimate goal of this study is to develop a set of knowledge-based design systems for wheeled combine chassis. Essentially, the process of solving problems with the design system is the process of reasoning and using knowledge. The design platform mainly integrates the knowledge base, knowledge base management system, inference engine, and Pro/Engineering secondary development module (Parametric Technology Corp., Boston, Mass.). With the support of Pro/Toolkit, Pro/Engineering enables users to create and develop their own graphical user interface. With the guidance of the system architecture, the design system for a wheeled combine chassis was developed based on Visual Studio 2010 (Microsoft Corp., Bellingham, Wash.). The design case of a wheeled combine chassis was considered to verify the effectiveness of the design system.

As shown in figure 9, a human-computer interaction interface was designed to integrate the main design information, including the management menu, model display, design tree, operation options, and main design process. The designer only needs to provide seven values that are essential for combine design to obtain the estimated parameters of the whole machine. All calculations are carried out in the background by calling functions. The inference engine gives the parameter setting range according to the relevant knowledge stored in the knowledge base. In the operation options, "Calculate" invokes the inference engine to calculate the design parameters. The calculated results are displayed in the output box. The basic design parameters for the whole machine are generated based on RBR and can be modified by changing the design requirements if the outputs are unsatisfactory.

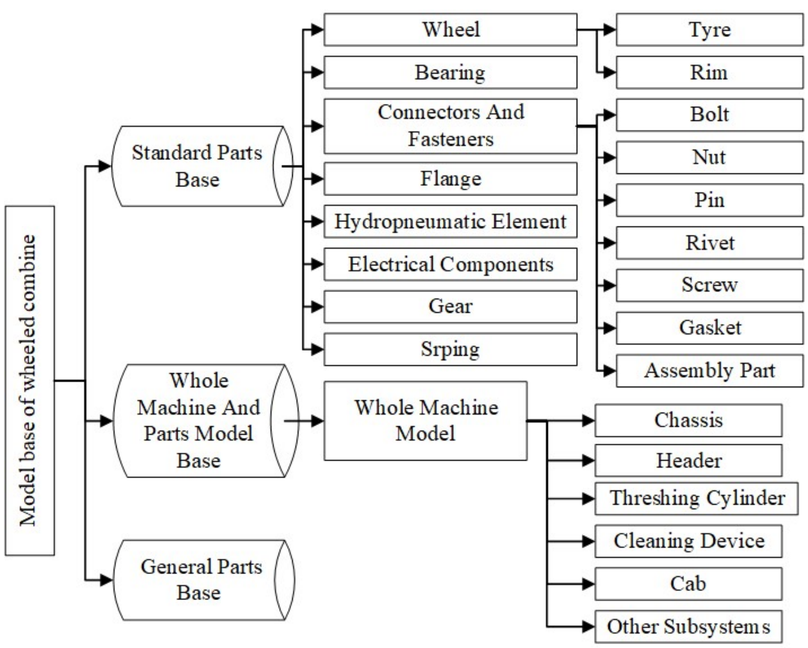

Figure 8. Model base of chassis for wheeled combines.

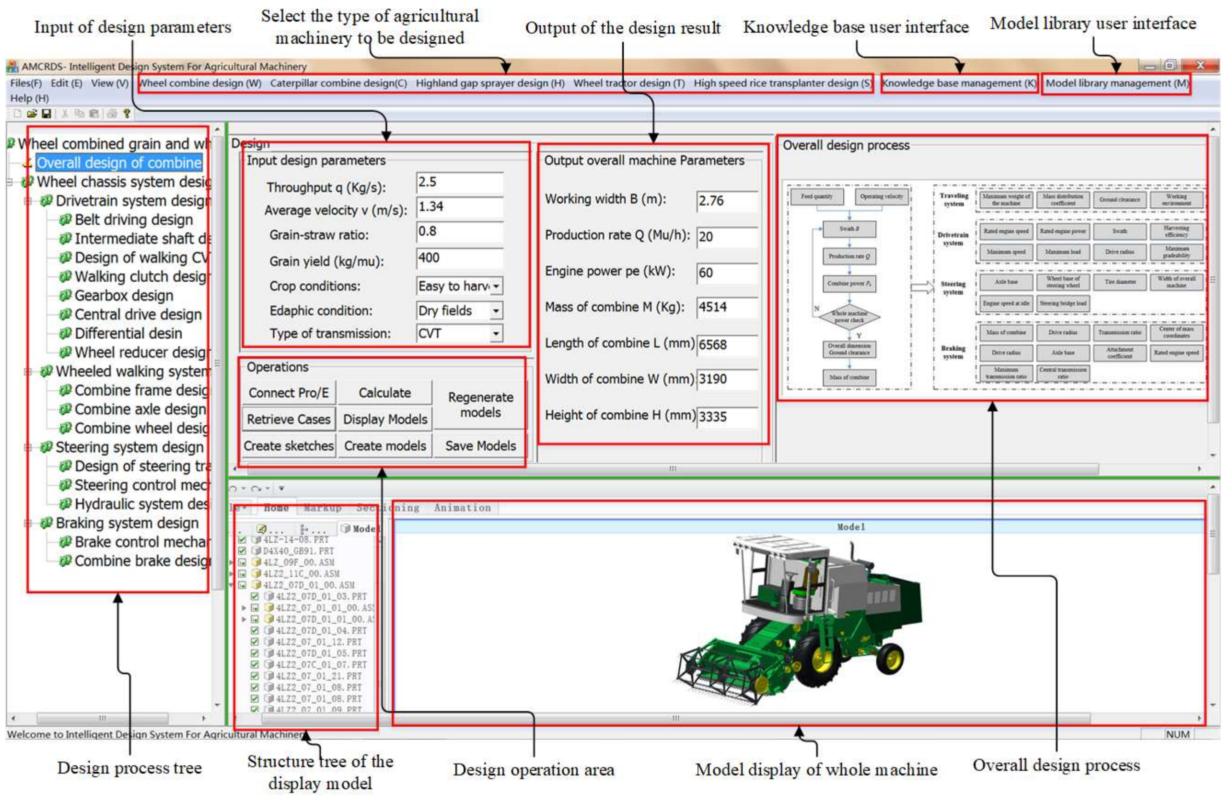

Figure 9. Design system for wheeled combine chassis.

After the calculation stage, the computed parameters are applied to obtain a 3D model of the designed chassis. This is done by the following steps: (1) select "Connect Pro/E" to either start or interlink Pro/E as preparation, (2) select "Retrieve models" to reuse similar cases in the database by calculating the similarity of the case attributes, (3) select "Regenerate the model" to carry out the regeneration of the 3D model, (4) "Display model" displays the designed model of the components to provide a better view of the internal structure and a detailed layout, as shown in figure 10, and (5) "Create models" is used to redesign the combine chassis in Pro/E. Finally, "Save models" saves and uploads the model to the model database as a satisfactory design to be reused in subsequent design tasks.

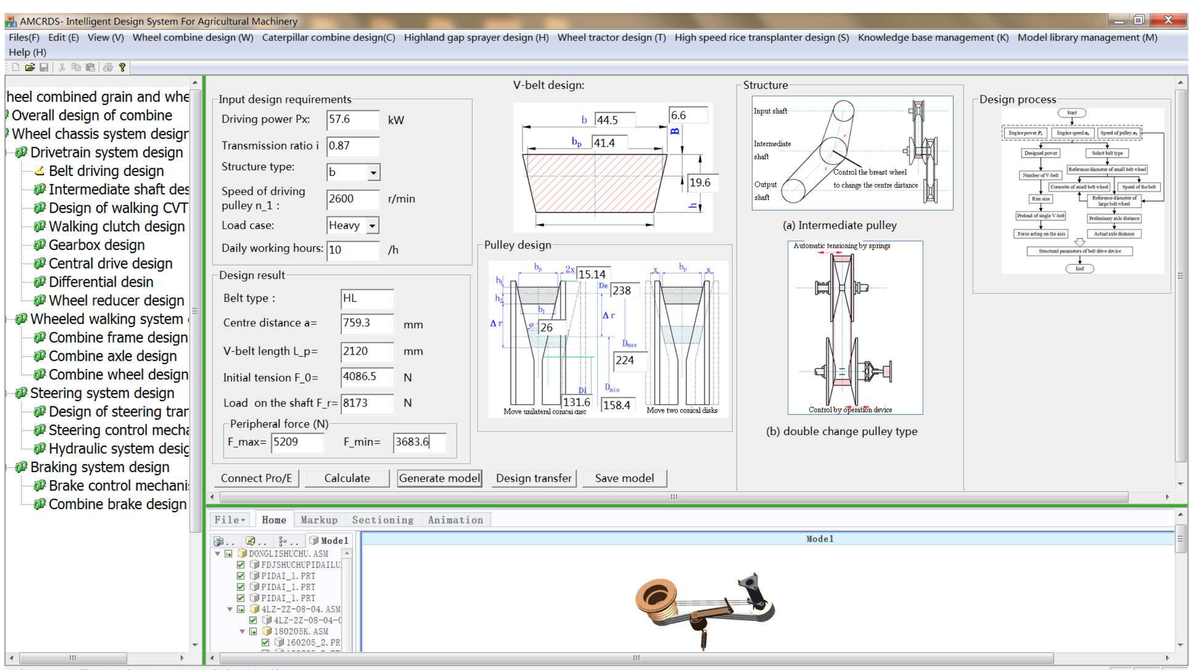

Figure 10. V-belt design of travelling CVT.

Table 2. List of similarity retrieval results.

	Length (L, mm)	Width (W, mm)	Height (H, mm)	Working Width (B, m)	Throughput (q, kg s^{-1})	Combine Mass (M, kg)	Power (P, kW)	Similarity (Sim)
Target	6668	3190	3335	2760	2.5	4514	60	-
Case 1	6360	2710	3220	2360	2	4360	55.86	0.6527
Case 2	6720	3150	3230	2500	3	4300	56	0.7454
Case 3	6700	2950	3280	2800	2.5	4340	61	0.9183
Case 4	6670	2710	3255	2360	3	4500	62	0.6601
Case 5	7000	2980	3470	2750	8	6880	129	0.5840
Case 6	6700	2700	3280	2360	4	4650	75	0.6513
Case 7	6800	2960	3400	2560	8	5400	129	0.5832
Case 8	6650	3750	3420	2500	6	5400	92	0.6640

In the case of retrieval of a previous design, the attribute weight vector (W) is used, as shown in equation 12:

$$W = [0.05, 0.05, 0.05, 0.3, 0.2, 0.05, 0.3] \quad (12)$$

The retrieval results of similar cases are presented in table 2, in which case 3 is most similar to the target case, with a similarity of 0.9183. This shows that case 3 could be redesigned as a template, enabling the reuse of case knowledge. The model of the retrieved case would then be displayed in the model display area.

Figure 11 illustrates the results of the chassis design process. With the help of the design system, the design process of the chassis has been further standardized, with significantly improved inheritance and reuse of design knowledge. As stated earlier, these efforts greatly promote the efficiency of the design of agricultural machinery, reduce the development costs, and improve the quality and reliability of the products.

Conclusions

This article has described the application of knowledge-based design to agricultural machinery, taking a wheeled combine chassis as an example. By combining knowledge-based engineering (KBE) with rapid design, a method for the knowledge-based design of a combine chassis was proposed. According to the characteristics and current design status of wheeled combine chassis, object-oriented technology and hybrid reasoning integrating CBR and RBR enable the uniform description and reuse of heterogeneous design knowledge. Moreover, a design knowledge database, i.e., a standard parts library, knowledge rule base, and case library, was constructed to manage and share the design knowledge. This knowledge database can be regenerated as further knowledge and experience become available. The design system developed in this study is mainly intended to standardize the design process of wheeled combine chassis, freeing designers from time-intensive and detailed tasks such as CAD modeling and repetitive calculations, and allowing them more time for creative design work. The feasibility and effectiveness of the design system were verified with a design case.

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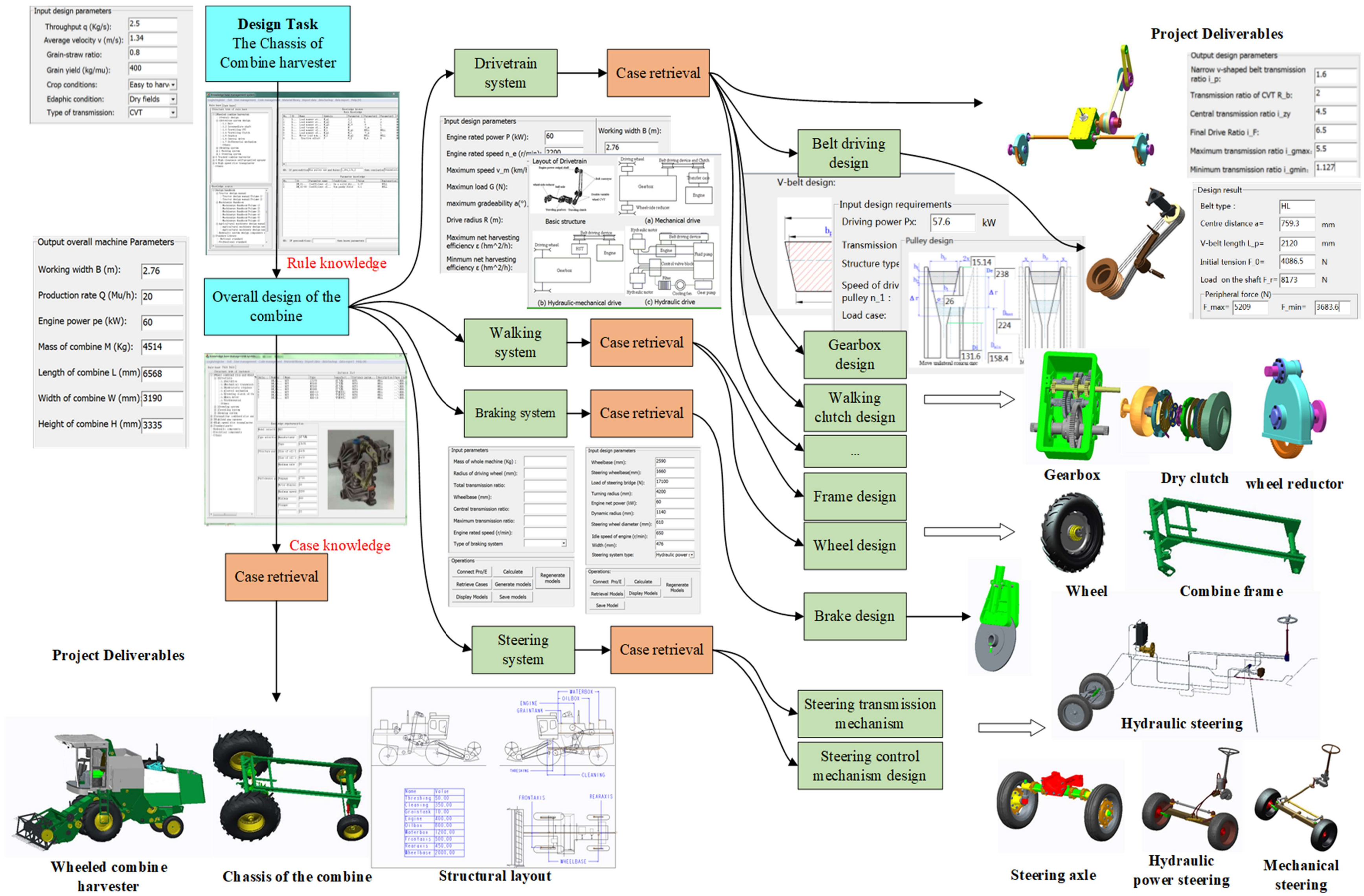

Figure 11. Implementation of the knowledge-based design for the wheeled combine chassis.

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