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An Extension Decision Tree Algorithm for Lightweight Design of Autobody Structure

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ABSTRACT

The lightweight design of autobody involves multiple objectives and requires the collaboration between various disciplines. To improve the existing autobody lightweight designs, it is necessary to establish an accurate and objective evaluation method for lightweight effect. This paper proposes an extension decision tree (EDT) algorithm for lightweight design of autobody. The algorithm solves the contradictions in the autobody lightweight design were solved through divergence and convergence. The workflow of the solving process is shaped like a scalable diamond. Specifically, the knowledge of autobody structure was described accurately by extension modeling and extension divergence reasoning. Then, the lightweight design of autobody structure and material was achieved through extension transforms. Next, the EDT algorithm was constructed based on extension theory and the DT algorithm, and used to evaluate the lightweight effect of autobody. Finally, the effectiveness of the proposed algorithm as verified through a case study and a computer-aided engineering (CAE) simulation. The results show that our algorithm can accurately predict the weight reduction effect of autobody based on the case data, and generate a set of intelligent strategies to optimize the current design. The research results shed new light on intelligent evaluation of autobody lightweight design with multiple objectives and constraints.

1. INTRODUCTION

With the upgrading of industrial structure and the promotion of green policies, the market share of new energy vehicles is growing year by year. Compared with traditional cars, new energy vehicles consume a limited amount of energy, create a few noises and cause no pollution [1, 2]. However, the popularity of new energy vehicles has been limited by the short cruising range. The cruising range can be improved through lightweight design of autobody, which accounts for much of the weight of the vehicle [3-7]. In fact, the lightweight design of autobody needs to achieve multiple objectives through the collaboration between various disciplines. In addition to reducing the autobody weight, the designer must consider an array of vehicle features, including mechanical properties, process difficulty, and production cost. This calls for a complete and objective method to evaluate the lightweight effect of autobody design [8-10].

Many scholars have attempted to reduce the weight of autobody. For instance, Sorenson et al. [11] optimized the sound transmission loss of lightweight autobody structure by balancing the surface density between sheet metal and the barrier. From the environmental perspective, Mayyas et al. [12] assessed different lightweight designs and electric powertrains through a lifecycle analysis on energy cost and CO2 emissions, shedding light on the combined effect of lightweight and electrification. Based on analytical drive design, Lv et al. [13] put forward a lightweight multi-objective optimization method for closed body in white (BIW), which effectively reduces the mass of closed BIW and improves the lightweight rate. Wang et al. [14] developed a lightweight design of the BIW based on implicit parametric model, which reduces the weight of the autobody without sacrificing its static and dynamic performance. However, the above studies have not fully disclosed the implicit relationship between the materials of autobody structure and the multiple objectives/constraints of lightweight design, failing to explore knowledge representation or reasoning. The development of the information technology and computer technology has created a large amount of knowledge in carboy design on the Internet, laying a good basis for the evaluation of lightweight effect of autobody design.

The decision tree (DT) is a popular classification and prediction algorithm [15-19]. The DT can extract the relationship between data features and classes in a set of disordered, irregular cases, and, on this basis, classify the current data in an accurate manner [20-23]. Therefore, the DT has been widely used for multi-feature index evaluation. For example, Khedr et al. [24] improved the Iterative Dichotomiser 3 (ID3) algorithm for DT learning, based on data partitioning and parallelism. Cherfi et al. [25] presented the very fast C4.5 (VFC4.5) DT algorithm, which outperformed the very fast DT (VFDT) algorithm in building DTs. To achieve image population density classification, Wang et al. [26] proposed a multi-class classification method based on the DT, support vector machine (SVM) and particle swarm optimization (PSO). Han et al. [27] designed a frequent mode DT for processing variable data streams, which greatly improves the processing accuracy of data streams in the steady state. The DT enjoys can classify and predict the case data well.

If the prediction effect falls short of the design requirements, however, it is impossible for the DT to generate a new intelligent design. To solve the problem, the extension theory has been introduced to develop an extension DT (EDT) algorithm.

The extension theory mainly studies the possibility of expanding things with a formal model, providing new insights into the intelligent solution to contradictions. The expansion is achieved through methods called extension transform. The EDT algorithm merges the extension transform with the DT seamlessly: whenever the prediction effect of the DT falls short of the design requirements, the extension strategy will be generated. The EDT algorithm has a good application prospect in case-based design. Guo and Zou [28] created a building planning prediction method based on DT classification, which promotes the computer-aided extension in building planning. Wen and Li [29] put forward an ontology knowledge expansion analysis tree and improved the extension strategy generation system. Overall, the research on the EDT algorithm concentrates on the elementary transformation theory of extension transform. There is no report on the construction of the primitive model or the realization of the extension thinking mode.

In the light of extension modelling, extension reasoning, extension transform and the DT, this paper aims to evaluate the lightweight effect of multi-objective autobody design, which is achieved through the collaboration of various disciplines, and disclose the implicit relationship between the materials of autobody structure and the multiple objectives/constraints of lightweight design, using the case data from the Internet. The most significant contribution is the design of an EDT algorithm for the lightweight design of autobody. Firstly, the autobody parts and joining technology were described with matter-element model and relation-element model, respectively, and diverged based on the divergence rules of multiple objects and features, providing the knowledge of the autobody structure. Next, the ID3 algorithm was combined with extension transform to accurately evaluate the lightweight effect and generate new design strategies, solving the contradictions in lightweight effect prediction. Furthermore, the authors developed a calculation model for extension transform difficulty, which overcomes combination explosion, eliminates redundant solutions, and identifies the optimal extension strategy. Finally, a computer-aided engineering (CAE) simulation was conducted to verify the mechanical properties (e.g. torsional stiffness and bending stiffness) of the autobody optimized by our EDT-based design. The research results help to improve the autobody weight under multiple constraints.

2. AUTOBODY LIGHTWEIGHT DESIGN BASED ON EXTENSION DECISION TREE

2.1 Primitive modeling and divergence reasoning for autobody structure knowledge

A huge amount of knowledge is involved in the lightweight design of autobody. There is the dynamic knowledge about design actions (e.g. structural optimization, material replacement and performance improvement), the static knowledge about object properties (e.g. autobody parts, technological types and material property), and the relational knowledge between different things (e.g. the joining technology for components).

The different types of knowledge must be described accurately in the design process. Therefore, the concept of extension primitives was introduced to illustrate the autobody structure by matter-element model and relation-element model. The autobody structure was divided into autobody parts and joining technology. The autobody parts include the BIW, decorative part, covering part, chassis part, etc., while the joining technology consists of welding, mechanical assembly, bonding, etc.

Regarded as static knowledge, the autobody parts were described by the matter-element model $M = (Om, Cm, Vm)$, where Om is the name of the autobody part, Cm is the feature, and Vm is the interval of the feature. According to the divergence rules of multiple objects and features, the object Om was diverged into $Om = [Om1, Om2, Om3, Om4...]$, where Omi is one of the autobody parts, namely, the BIW, decorative part, covering part, and chassis part, while the feature Cm was diverged into $Cm = [Cm1, Cm2, Cm3, Cm4...]$, where Cmi is one of the features, namely, the component weight, material property and cost. Then, the divergence tree for the matter-element model M of the static knowledge can be established as:

$$
M \mapsto \begin{cases}
\mathbf{M1} = \begin{bmatrix} O_{m1} & C_{m11} & V_{m11} \\ & C_{m12} & V_{m12} \\ & \cdots\cdots & \cdots\cdots \\ & C_{m1i} & V_{m1i} \end{bmatrix} = \begin{bmatrix} BIW & component\ weight_{11} & value_{11} \\ & material\ properties_{12} & value_{12} \\ & \cdots\cdots & \cdots\cdots \\ & cost_{1i} & value_{1i} \end{bmatrix} \\
\mathbf{M2} = \begin{bmatrix} O_{m2} & C_{m21} & V_{m21} \\ & C_{m22} & V_{m22} \\ & \cdots\cdots & \cdots\cdots \\ & C_{m2i} & V_{m2i} \end{bmatrix} = \begin{bmatrix} decorative\ part & component\ weight_{21} & value_{21} \\ & material\ properties_{22} & value_{22} \\ & \cdots\cdots & \cdots\cdots \\ & cost_{2i} & value_{2i} \end{bmatrix} \\
\mathbf{M3} = \begin{bmatrix} O_{m3} & C_{m31} & V_{m31} \\ & C_{m32} & V_{m32} \\ & \cdots\cdots & \cdots\cdots \\ & C_{m3i} & V_{m3i} \end{bmatrix} = \begin{bmatrix} covering\ part & component\ weight_{31} & value_{31} \\ & material\ properties_{32} & value_{32} \\ & \cdots\cdots & \cdots\cdots \\ & cost_{3i} & value_{3i} \end{bmatrix} \\
\mathbf{M4} = \begin{bmatrix} O_{m4} & C_{m41} & V_{m41} \\ & C_{m42} & V_{m42} \\ & \cdots\cdots & \cdots\cdots \\ & C_{m4i} & V_{m4i} \end{bmatrix} = \begin{bmatrix} chassis\ part & component\ weight_{41} & value_{41} \\ & material\ properties_{42} & value_{42} \\ & \cdots\cdots & \cdots\cdots \\ & cost_{4i} & value_{4i} \end{bmatrix}
\end{cases} \tag{1}
$$

Regarded as relational knowledge, the joining technology was described by the relation-element model $R = (Or, Cr, Vr)$, where Or is the name of the joining technology, $Cr = [Cr1, Cr2, Cr3]$ is the feature of the joining technology, and $V = [Vr1, Vr2, Vr3, Vr4]$ is the interval of the feature. According to the divergence rules of multiple objects and features, the object Om was diverged into $[Or1, Or2, Or3 \ldots]$, where Ori is one of the components of the joining technology, namely, welding, bonding and mechanical assembly, while the feature $Cr = [Cr1, Cr2, Cr3]$ was diverged into $Cr = [Cr1, Cr2, Cr3 \ldots.]$, where Cri is one of the features, namely, into technology difficulty, connection quality, and positional relationship. Then, the divergence tree for the relation-element model R of the relational knowledge can be established as:

$$R \mapsto \begin{cases} \mathbf{R1} = \begin{bmatrix} O_{R1} & C_{R11} & V_{R11} \\ & C_{R12} & V_{R12} \\ & \ldots\ldots & \ldots\ldots \\ & C_{R1i} & V_{R1i} \end{bmatrix} = \begin{bmatrix} welding & technology\ difficulty_{11} & value_{11} \\ & connection\ quality_{12} & value_{\mathbf{12}} \\ & \ldots\ldots & \ldots\ldots \\ & positional\ relationship_{\mathbf{1}i} & value_{\mathbf{1}i} \end{bmatrix} \\ \mathbf{R1} = \begin{bmatrix} O_{R1} & C_{R21} & V_{R21} \\ & C_{R22} & V_{R22} \\ & \ldots\ldots & \ldots\ldots \\ & C_{R2i} & V_{R2i} \end{bmatrix} = \begin{bmatrix} bonding & technology\ difficulty_{21} & value_{21} \\ & connection\ quality_{22} & value_{\mathbf{22}} \\ & \ldots\ldots & \ldots\ldots \\ & positional\ relationship_{\mathbf{2}i} & value_{\mathbf{2}i} \end{bmatrix} \\ \mathbf{R1} = \begin{bmatrix} O_{31} & C_{R31} & V_{R31} \\ & C_{R32} & V_{R32} \\ & \ldots\ldots & \ldots\ldots \\ & C_{R3i} & V_{R3i} \end{bmatrix} = \begin{bmatrix} mechanical\ assembly & technology\ difficulty_{31} & value_{\mathbf{31}} \\ & connection\ quality_{32} & value_{\mathbf{32}} \\ & \ldots\ldots & \ldots\ldots \\ & positional\ relationship_{\mathbf{3}i} & value_{\mathbf{3}i} \end{bmatrix} \end{cases} \tag{2}$$

Based on formulas (1) and (2), the matter-element model M of autobody parts and the relation-element model R of the joining technology can be obtained, respectively.

In this way, the autobody knowledge can be described accurately from the aspects of the object, the feature, the feature quantity, etc. Drawing on extension theory, the primitive model B of the autobody structure can be established as:

$$B = (M_1 \oplus M_2 \oplus M_3 \oplus M_4) \oplus (R_1 \oplus R_2 \oplus R_3) \tag{3}$$

where, $M_{1\sim4}$ are the models of the BIW, the decorative part, the cover part and the chassis part, respectively; $R_{1\sim3}$ are the models of welding, bonding and mechanical assembly, respectively. Based on formula (3), an entity-relationship (E-R) model can be constructed for the knowledge of autobody design (Figure 1).

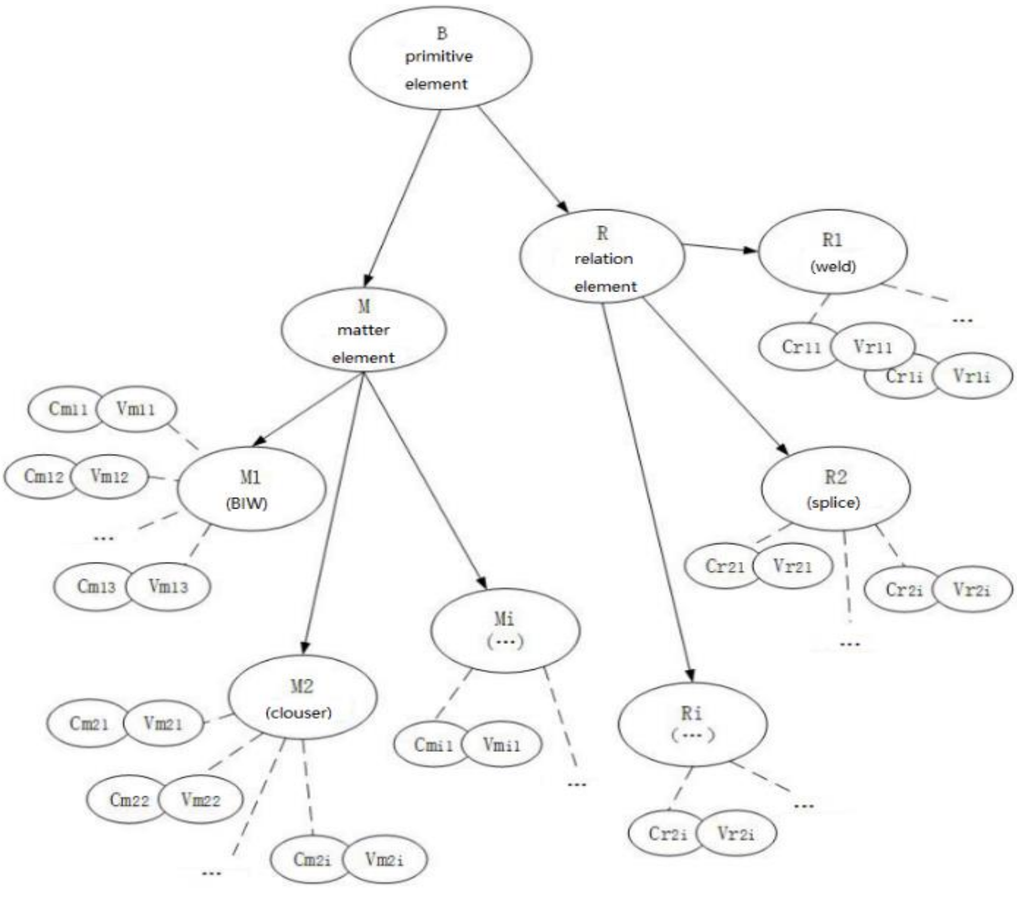

Figure 1. The E-R model of the knowledge of autobody design

2.2 Optimization of lightweight material and structure through extension transforms

There are two aspects of autobody lightweight design: the lightweight design of material and the lightweight design of structure. The former reduces the weight of the autobody by using lightweight materials, and the latter reduces the number of parts through structural optimization. Following the principle of extension reasoning, a desirable lightweight design should be prepared by extending the design ideas through transforms like displacement, addition, deletion, expansion, contraction and decomposition.

The material lightweight technology, which pursues weight reduction by material replacement, can be expressed as a displacement transform $T_1\Gamma = \Gamma'$; where, T_1 is the displacement transform, Γ is the original material and Γ' is the transformed material. According to the different properties of the transformed material Γ', the displacement transform T_1 can be diverged into high-strength steel transform T_{11}, ultra-high-strength steel transform T_{12}, aluminum alloy transform T_{13}, magnesium alloy transform T_{14}, composite material transform T_{15}, etc.

The structural lightweight technology, which pursues weight reduction through structural optimization and material reduction, can be expressed as a deletion transform $T_2\Gamma = \Gamma\Theta\Gamma'$, where T_2 is the deletion transform, Γ is the original structure and Γ' is the transformed structure. According to different design methods, the deletion transform T_2 can be diverged into size transform T_{21}, topography transform T_{22}, topological transform T_{23}, etc.

Based on the above two technologies, the divergence tree for the autobody lightweight design can be established as:

$$T \mapsto \begin{cases} T1 \mapsto \begin{cases} T11 = High-strength\ steel\ transform \\ T12 = Ultra-high-strength\ steel\ transform \\ T13 = Aluminum\ alloy\ transform \\ T14 = Magnesium\ alloy\ transform \\ T15 = Composite\ material\ transform \end{cases} \\ T2 \mapsto \begin{cases} T21 = Size\ transform \\ T22 = Topography\ transform \\ T23 = Topological\ transform \end{cases} \end{cases} \tag{4}$$

As shown in formula (4), the autobody lightweight design T can be diverged into high-strength steel transform T_{11}, ultra-high-strength steel transform T_{12}, aluminum alloy transform T_{13}, magnesium alloy transform T_{14}, composite material transform T_{15}, size transform T_{21}, topography transform T_{22}, topological transform T_{23}, etc. In this way, the lightweight design is accurately described in terms of material property and autobody structure. From the perspective of extension, the extension transform of the autobody lightweight design T can be established as:

$$T = T1 \oplus T2 = (T11 \oplus T12 \oplus T13 \oplus T14 \oplus T15) \oplus (T21 \oplus T22 \oplus T23) \tag{5}$$

2.3 Extension decision tree model for autobody lightweight design

The DT is a tree-like prediction model, in which the conditional probability distribution is defined by the branch structure on the feature space. As a result, the DT can find the relationship between the features and classes in a set of disordered, irregular cases, and predict the class of new data based on features. Despite being extensively applied in effect prediction, the traditional DT model cannot generate new designs if the current design fails to satisfy the requirements. Therefore, it is necessary to create a new DT model that effectively integrates effect prediction with strategy generation.

The EDT model seamlessly merges the DT model and the extension strategy generation. Specifically, the DT model is used to predict the design effect. If the original strategy falls short of the demand, the extension transform is performed to generate a new strategy. In autobody lightweight design, the EDT model consists of several parts, namely, the construction of competitive products database, primitive modeling and divergence reasoning of autobody structure, classification and prediction of ID3 algorithm, to name but a few.

(1) The construction of competitive products database

Perform competitive products analysis on the massive data of the Internet of Things (IoT). Through the analysis, collect the weight, performance, size, price and other parameters from various models. Next, select the competitive products with similar positioning of the current product, and evaluate the lightweight effect of these products. Then, obtain the parameters of the autobody parts, joining technology, weight, cost and lightweight effect of the competitive products, and consolidate them into a competitive products database.

(2) Primitive modelling and divergence reasoning of autobody structure

Build a knowledge model of autobody structure based on the concept of extension primitives. Taking the autobody parts as static knowledge, construct the matter-element model of autobody parts like the BIW, decorative part, covering part and chassis part, diverge the model into sub-models of each part according to the divergence rules of multiple objects and features, and import related data from the bill of materials (BOM). Taking the joining technology as relational knowledge, build the relation-element model of processes like welding, bonding and mechanical assembly, diverge the model into sub-models of each process according to the divergence rules of multiple objects and features, and import related data from the bill of materials (BOM).

(3) The classification and prediction of ID3 algorithm

The DT is a tree-like classification algorithm. According to information theory, the DT algorithm can be categorized into the ID3 algorithm, C4.5 algorithm, classification and regression tree (CART) algorithm, etc. Among them, the ID3 algorithm relies on the information gain of information theory for feature selection. In each iteration, a top-down search is performed through the decision space to select the feature with the largest information gain for splitting. Compared with the other DT algorithms, the ID3 algorithm is fast and easy to use, and thus widely adopted for data mining. Therefore, this algorithm is selected here for decision reasoning, which covers the following steps:

Step 1. Calculation of information entropy of a random variable

Let $X = \{X_1, X_2, \cdots, X_n\}$ be a random variable containing n samples, and $P = \{P_1, P_2, \cdots, P_n\}$ be the probability of occurrence of each sample. Then, the information entropy of variable X can be computed by:

$$I(X) = -\sum_{i=1}^{n} P_i \log_2 P_i \tag{6}$$

As shown in formula (6), the system instability is positively correlated with the number of uncertain factors within the random variable X. In other words, the greater the information entropy, the more the information required to make a clear description of the random variable.

Step 2. Calculation of information entropy of the classification system

Let $A=\{A_1, PA_2, \cdots, A_m\}$ be a feature of the classification system, and $P=\{P(A_1), P(A_2), \cdots, P(A_m)\}$ be the probability of occurrence for each class. The sample data can be classified by feature A. Then, the information entropy of the classification system can be computed by:

$$I(A)=-\sum_{i=1}^{m} P(A_i)\log_2 P(A_i) \tag{7}$$

Step 3. Calculation of information gain

The information gain refers to the information entropy difference between a random variable and the classification system. The information gain can be computed by:

$$G(A)=I(X)-I(A) \tag{8}$$

The greater the information gain, the more important the feature is to the decision-making process.

Step 4. Creation of a complete DT model

Select the feature with the largest information gain as the split node, and represent each "parent-child" path in the "if…then" form. Moreover, traverse the possible decision space, and classify the static, dynamic, and relational knowledge contained in the design, creating a complete DT model.

Step 5. Judgement of the necessity to generate a new design

Substitute the primitive model of the current design into the DT algorithm, and determine the features of each sub-node branch. If it satisfies the design requirements, take the current design as the optimal solution; otherwise, extend the autobody parts model and the joining technology model, and construct the divergence tree model to generate a new design.

Step 6. Optimization of lightweight material and structure through extension transforms

If the current lightweight design is predicted to fall short of the demand, perform extension transforms to generate a new strategy, including high-strength steel transform T_{11}, ultra-high-strength steel transform T_{12}, aluminum alloy transform T_{13}, magnesium alloy transform T_{14}, composite material transformT_{15}, size transform T_{21}, topography transform T_{22}, topological transform T_{23}, etc.

Step 7. Analysis of the difficulty in extension transform

According to the divergence rule of multiple objects and features, the divergence reasoning of the autobody structural element model B and the autobody lightweight design T are prone to combination explosion, which brings too many solution sets. To solve the problem, the concept of extension transform difficulty was introduced to select the optimal design for the convergence of design thinking. The extension transform difficulty can be computed as:

$$\textit{extension transform difficulty} = \prod(\textit{transform coefficient}+\mathbf{1})\mathbf{-1} \tag{9}$$

where the *transform coefficient* is determined on a case-by-case basis: If the features belong to different classes but fall on the same level in the material of lightweight design, type of connection process, etc., the transform coefficient should be set to 1 no matter how the transform is performed; if the features fall on different levels in terms like the lightweight effect, the transform coefficient should be set to 1, when the transform increases the features by one level, and set to 2, when the transform increases the features by two levels.

2.4 Implementation of extension decision tree algorithm

As shown in Figure 2, the EDT model for autobody lightweight design include the construction of competitive products database, primitive modeling and divergence reasoning of autobody structure, classification and prediction of ID3 algorithm, extension transforms based on material and structural lightweight technologies, analysis of extension transform difficulty, etc.

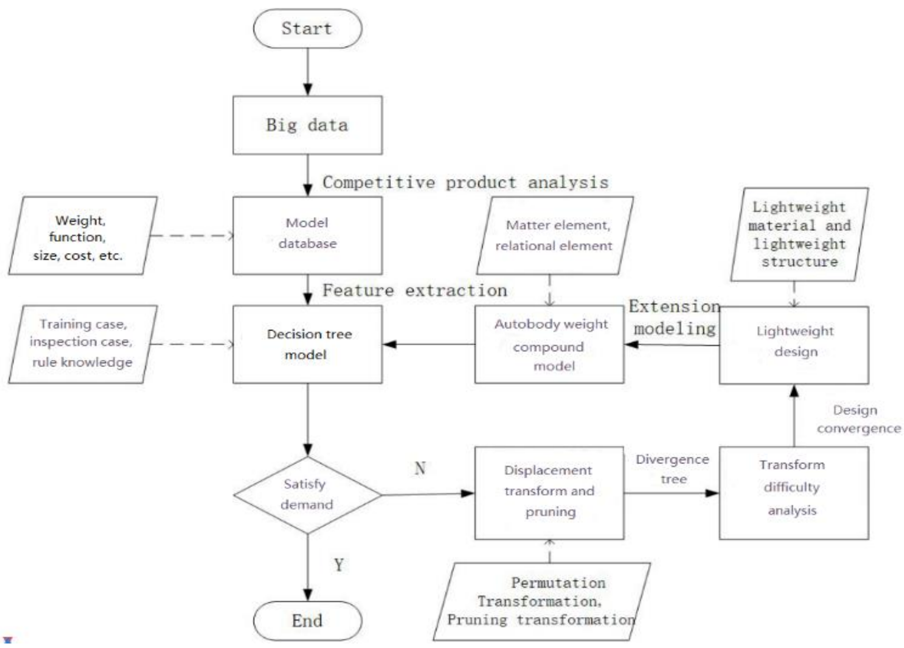

Figure 2. The EDT model for autobody lightweight design

The algorithm for the EDT model can be implemented in the following steps.

Step 1. Take multiple factors (e.g. weight, size, cost and mechanical properties) as reference indices, perform competitive products analysis to screen and extract the information of competitive products from a huge amount of data on the Internet, and consolidate the extracted information (e.g. weight, cost, process type, material property, autobody parts and lightweight effect) into a competitive products database.

Step 2. Construct the information gain calculation model based on formulas (6)-(8). Then, set up the ID3 model with features (e.g. weight, cost, process type, material property and autobody parts) as non-leaf nodes, and lightweight effect as the leaf node. To ensure the modelling accuracy, divided the case data into a training set and a test set at the ratio of 3:1.

Step 3. Establish the autobody parts model, the joining technology model and the primitive model of autobody structure for the current design, according to formulas (1)-(3), respectively. Then, construct the divergence tree of autobody structure according to the divergence rules of multiple objects and features, which can express the knowledge of autobody structure accurately from the aspects of object, feature and feature quantity.

Step 4. Substitute the primitive model of autobody structure into the ID3 model to classify and predict the lightweight effect of the current design. If the classification result meets the design requirements, jump to Step 7; otherwise, go to Step 5.

Step 5. Perform extension transforms (e.g. displacement transform, addition and deletion) to optimize the current autobody material and structure (formulas (4) and (5)), carry out divergent reasoning of lightweight design according to the divergence rules of multiple objects and features, and generate a set of new strategies with the aim to satisfy the design requirements.

Step 6. Calculate the difficulty in extension transform by formula (9) to evaluate the set of strategies, choose the least difficult extension strategy, and go back to Step 3.

Step 7. Conduct a CAE simulation to verify the mechanical properties (i.e. bending stiffness and torsional stiffness) of the current design. If these properties meet the design requirements, go to Step 8; otherwise, go back to Step 5.

Step 8. Select the current design as the optimal solution, and terminate the autobody lightweight design process.

3. CASE STUDY AND CAE SIMULATION

As mentioned before, the autobody lightweight design needs to achieve multiple objectives and requires the collaboration between various disciplines. Besides the autobody weight, many other evaluation indices should be considered throughout the design process, including but not limited to the cost, type of process, material property, and mechanical properties. The evaluation indices being selected must be comprehensive, suitable and stable. Moreover, the indices should be classified to make the data accessible and the DT algorithm efficient. The easily accessible indices were classified to Level I and evaluated first. The typical Level I indices include weight, cost, process type, and material property, all of which are recorded in the BOM or process list. The indices that are hard to obtain (e.g. the mechanical properties can only be obtained through the CAE simulation) were allocated to Level II and evaluated later.

In this paper, the EDT algorithm for autobody lightweight design is established to judge the lightweight effect based on Level I indices like weight, cost, process type and material property. The specific steps of the algorithm are as follows:

Step 1. Selection of evaluation indices

Evaluate the lightweight effect of each competitive product through statistical analysis, challenge method, competitive analysis, etc. Divide the competitive products into excellent, medium and poor levels, and take the results as the outcomes of the DT. Then, set up the branches of the DT based on Level I indices like weight, cost, process type and material property. Finally, classify the features of the BIW by the DT.

Step 2. Construction of the DT model

Select 200 cases from the competitive product database to serve as data samples (Table 1).

Table 1. Data samples of competitive products

Serial number	Parts name	Joining technology	Weight	Material property	Cost	Lightweight effect
1	Covering part	Mechanical assembly	Substantially decreased	I High-strength steel	Medium	Excellent
2	BIW	Welding	Substantially decreased	III Aluminum alloy	Medium	Medium
3	Decorative part	Bonding	Invariant	V Composite material	Medium	Poor
4	Chassis part	Mechanical assembly	Substantially decreased	II Ultra-high strength steel	Low	Medium
5	Covering part	Welding	Invariant	III Aluminum alloy	Low	Poor
...	...					...
200	Decorative part	Mechanical assembly	Slightly decreased	IV Magnesium alloy	Low	Excellent

After determining the evaluation indices and judgement result, divide the above data samples evenly into 20 parts, allocate 15 parts to the training set for constructing the DT model, and allocate the remaining 5 parts to the test set for verifying the model. An example of the DT model for autobody lightweight design is shown in Figure 3.

Step 3. Application of the DT model

Establish the autobody element model of the current design, and extract the Level I indices (e.g. weight, material property, process type, cost) from the model. Then, substitute the indices into the DT model to predict the lightweight effect of the design. If the design cannot meet the requirements, generate a new design strategy through extension transform.

Here, the current design is a lightweight design of the BIW, in which the weight is "Substantially decreased", the material property is "III aluminum alloy", the process type is "welding", and the cost is "medium". Then, the DT algorithm predicted that the lightweight effect is "general", failing to meet the design requirements.

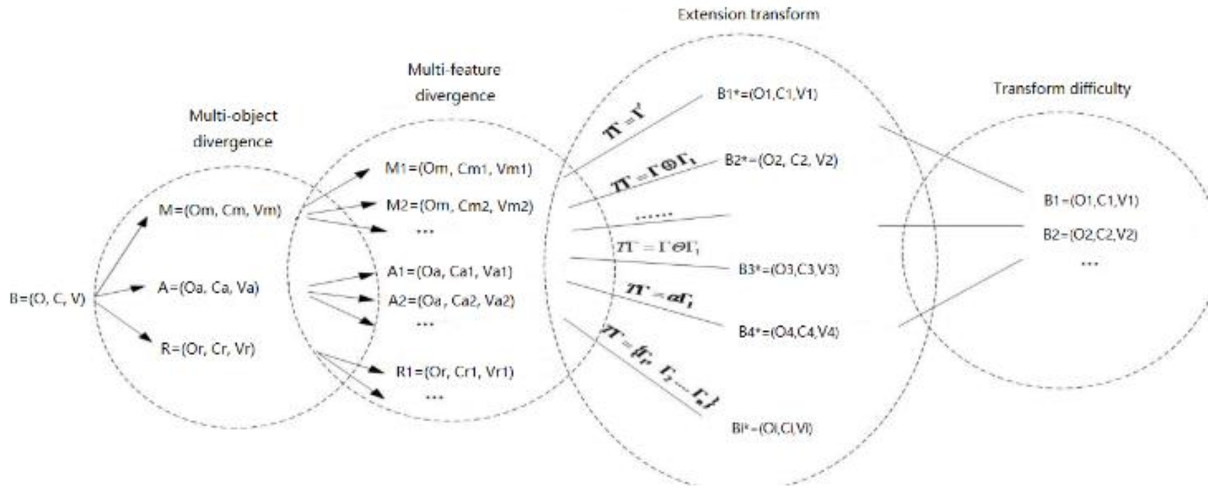

Figure 3. An example of the DT model for autobody lightweight design

Table 2. Sorting results of extension strategies

Serial number	Extension Transform strategy	Weight	Material property	Process type	Cost	Lightweight effect
1	$T_{11}\oplus T_{21}$	Substantially decreased	I High-strength steel	Mechanical assembly	Medium	Excellent
2	$T_{11}\oplus T_{22}$	Substantially decreased	I High-strength steel	Welding	Low	Excellent
3	$T_{12}\oplus T_{21}$	Slightly decreased	II Ultra-high strength steel	Welding	Low	Excellent
4	$T_{13}\oplus T_{21}$	Slightly decreased	III Aluminum alloy	Mechanical assembly	Medium	Excellent
…	…					

Step 4. Generation of extension strategy

To achieve the "excellent" lightweight effect, perform extension transforms of lightweight material and structure of the autobody element model:

$$
\begin{aligned}
&T_{11} \bullet M_1(BIW, Material, \mathrm{I}) = M_1'(BIW, Material, \mathrm{I}) \\
&T_{12} \bullet M_1(BIW, Material, \mathrm{I}) = M_1'(BIW, Material, \mathrm{II}) \\
&T_{13} \bullet M_1(BIW, Material, \mathrm{I}) = M_1'(BIW, Material, \mathrm{III}) \\
&T_{14} \bullet M_1(BIW, Material, \mathrm{I}) = M_1'(BIW, Material, \mathrm{IV}) \\
&\qquad\qquad \cdots
\end{aligned} \tag{10}
$$

Step 5. Sorting of extension strategies

Calculate the extension transform difficulty of each strategy generated through extension transforms, and sort the strategies by the difficulty in ascending order. The sorting results are shown in Table 2.

As shown in Table 2, the top-ranking strategy $T = T_{11} + T_{22}$ was selected as the optimal strategy. The BIW structure and implementation of the optimal strategy are displayed in Figure 4 and Table 3, respectively.

Step 6. The CAE simulation and results analysis

Perform a CAE simulation of the BIW, with bending stiffness and torsional stiffness as Level II evaluation indices. The simulation results are presented in Figures 5 and 6 and Table 4.

The simulation results show that the axial displacement, bending stiffness and torsional stiffness of the selected extension strategy met the design requirements. Hence, the autobody lightweight design process based on the EDT algorithm was terminated. The autobody lightweight design generated by the extension transforms is the optimal design to satisfy the design requirements.

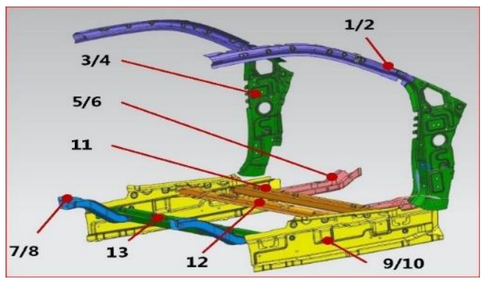

Figure 4. The structure of the BIW

Table 3. Implementation of the optimal strategy

Extension transforms	Lightweight method	Lightweight location	Process
T11	Lightweight material	3/4 and 13	Ordinary carbon steel → 22MnB5 ultra-high strength steel
T21	Lightweight structure	11 and 12	Round beam→Square beam

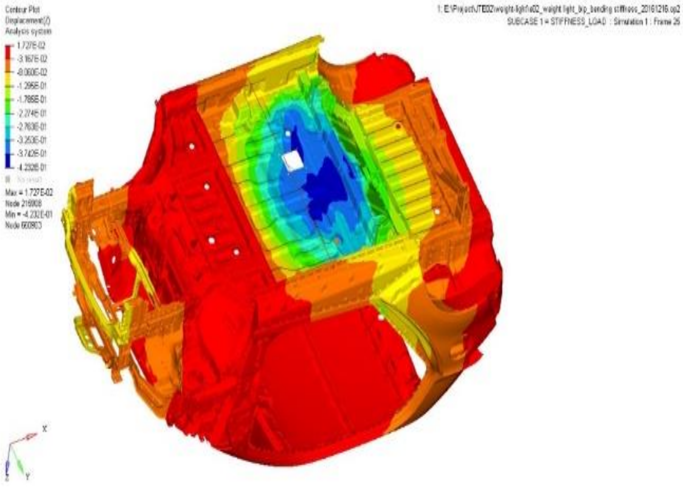

Figure 5. The CAE results on bending stiffness

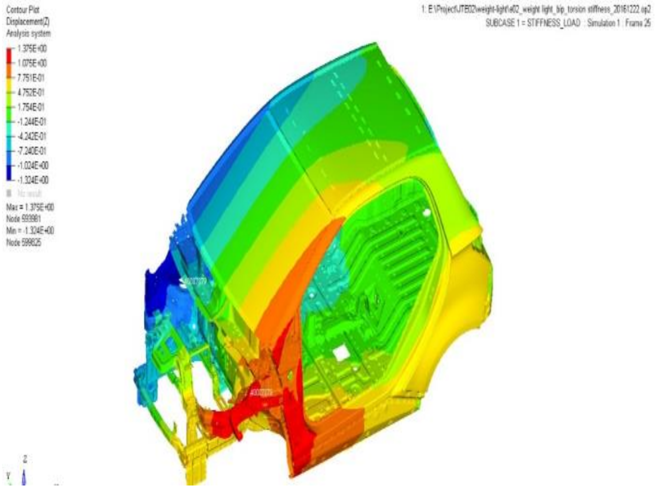

Figure 6. The CAE results on torsional stiffness

Table 4. The CAE results on bending stiffness and torsional stiffness

Type of load	Load	Z-axis displacement	Bending stiffness	Torsional stiffness	Qualified?
Axial force	750 (N)	0.073mm	20,548 (N/mm)	——	Yes
Torque	1,000 (N·m)	1.04mm	——	8671 (N·mm/deg)	Yes

4. CONCLUSIONS

This paper proposes an EDT algorithm for autobody lightweight design. Firstly, a matter-element model for autobody parts and a relation-element model for joining technology were established to accurately illustrate the knowledge about autobody structure. Next, the autobody structure was optimized and the autobody material was replaced through extension transforms for lightweight material and lightweight structure. Furthermore, an EDT algorithm for autobody lightweight design was constructed based on extension modeling, divergence inference and extension transform, and its implementation steps were explained in details. In this way, the contradictions in the autobody lightweight design were solved through divergence and convergence, generating an accurate prediction strategy for lightweight effect. The workflow of the solving process is shaped like a scalable diamond. The effectiveness and feasibility of the proposed algorithm were verified through a case study on the BIW lightweight design and the CAE simulation.

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