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An Agile Innovation Design Method via Integrating LT Dimension and TRIZ

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Abstract

Agile innovation is becoming increasingly important for complex mechatronic products. Existing studies often remain at the project management level and offer limited operational guidance for conceptual structural design. This paper proposes an agile innovation design method that integrates the Length–Time (LT) dimension and Theory of Inventive Problem Solving (TRIZ) to translate user feedback into engineering-oriented conceptual solutions. First, user pain points are organized into a fishbone-based functional model, and core problems are mapped to LT dimensions using a natural-language processing rule set. Second, a neural network trained on cases of technological evolution predicts the corresponding TRIZ evolution law. Third, structurally similar engineering cases are retrieved based on LT-dimensional similarity and transformed into conceptual schemes by structural mapping. Finally, the technique for order preference by similarity to an ideal solution is used to rank alternative schemes with explicit normalization, distance calculation, and sensitivity checking. The method is demonstrated through the conceptual redesign of a vertical-axis wind turbine.

Keywords: agile innovation; complex mechatronic systems; functional model; technological evolution; LT dimension; Theory of Inventive Problem Solving (TRIZ)

1. Introduction

Driven by intense market competition and the move towards smart manufacturing, modern companies are compelled to shift to product design processes that emphasize flexibility, speed, and agility [1]. Unlike the traditional manufacturing era, today's complex mechatronic systems demand a design philosophy that can dynamically adapt to real-time changes [2]. The concept of agile innovation, originally popularized in the software development industry, has increasingly become a cornerstone of mechanical engineering. Compared with traditional waterfall development models, agile innovation emphasizes rapid and flexible responses to embrace changing requirements, alongside continuous collaboration between end users and product developers [3]. In mechanical product development, agility refers to rapid iteration of physical and digital prototypes and the integration of user feedback to refine product functionality and geometric structures [4].

The integration of agile thinking aligns with the inevitable trend towards intelligent manufacturing and digital twin-driven design. By leveraging digital twins and advanced simulations, designers can capture user interactions and feed them into the design loop in real time, enabling mechanical products to undergo rapid virtual iterations before

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physical manufacturing [5]. This agile innovation loop enables companies to maximize resource utilization and respond promptly to market changes, acting as a critical strategy for maintaining product differentiation and high quality [6].

Despite its proven advantages in rapid iteration, most existing agile innovation methods in the manufacturing sector still rely heavily on macro-level management stage-gate models [7]. While this approach minimizes disruption to existing organizational workflows, it lacks effective micro-level guidance for engineers, including specific technical structures, kinematic constraints, and material selections informed by user feedback [8]. This disconnect often leads to a situation in which, despite the growing popularity of agile concepts [9], large-scale equipment manufacturers remain relatively conservative in their exploration of actionable agile design methods [10]. Small and medium-sized enterprises, on the other hand, exhibit a greater urgency for agile innovation due to their need to rapidly pivot products and respond to niche user feedback. However, frontline engineers frequently lack systematic, engineering-oriented tools to translate agile principles into practical mechanical product design, especially in complex multi-physics environments.

According to the classical Pahl and Beitz design theory, a systematic design process model comprises four distinct stages [11]. In the Task Clarification stage, the technical team collects user requirements and clarifies the product's core functions prior to formal design implementation. The Conceptual Design stage focuses on identifying feasible scientific and engineering principles to address design challenges, generating multiple viable principle schemes and selecting the optimal conceptual solution. In the Embodiment Design stage, the selected conceptual scheme is transformed into specific geometric layouts and structural configurations to satisfy the requirements of structural strength, assembly performance, and manufacturing feasibility. The Detail Design stage completes the precise design of all components and delivers standardized engineering drawings and technical documents for practical production. This study mainly focuses on the first two stages of the proposed method to better integrate with the existing design workflow of engineers.

To overcome these structural design bottlenecks and facilitate rapid iterations, the Theory of Inventive Problem Solving (TRIZ) has gained widespread adoption owing to its high usability and rigorous logic [12]. TRIZ provides a robust, innovative framework derived from the analysis and mining of high-value patents, summarizing the objective laws that govern technological development. It systematically guides designers in resolving engineering contradictions without compromising other design functions. The appropriate application of TRIZ tools can significantly accelerate the innovation cycle, transforming vague user complaints into precise functional models [13]. Recent studies in design science highlight that integrating TRIZ with data-driven approaches can further compress the iteration cycle of mechanical components.

Simultaneously, the Length–Time (LT) dimension provides a novel form of dimensional expression that classifies physical quantities fundamentally by their dependence on space and time [14]. In the context of complex mechatronic systems, LT dimensions can more accurately and abstractly capture product performance issues than conventional descriptive parameters [15]. Thermodynamic, kinematic, and electromagnetic physical quantities can be unified under LT dimensions to accurately describe bottlenecks in product transmission, energy supply, and control mechanisms. Using LT dimensions as a bridging tool to integrate multidisciplinary design knowledge into the mechanical design process perfectly complements the requirements of agile innovation [16]. This allows for the rapid reconfiguration of physical principles when user feedback demands a fundamental shift in product behavior [17].

To the best of our knowledge, and based on recent reviews of intelligent design methodologies [18], no existing research has successfully coupled the LT dimension, TRIZ,

and agile innovation to explicitly drive the rapid iteration of mechanical products in response to user feedback. The core contribution of this paper is the proposal of an actionable agile innovation method tailored for product conceptual design. It greatly facilitates the rapid presentation and iteration of mechanical design solutions. By introducing LT dimensions, user-driven functional modeling, and technological evolution laws, the probability of achieving viable agile innovations is significantly increased. Furthermore, natural language processing technologies, neural network models, and the evaluation technique are integrated to reduce reliance on subjective expert experience, thereby accelerating the response to user needs.

2. Related Research

2.1. Agile Innovation in Mechanical Design

Traditional conceptual design methods, such as breakthrough, disruptive, and incremental innovations, are fundamentally outcome-oriented [19,20]. They often rely on linear and rigid processes that cannot accommodate late-stage user feedback. In contrast, the core of agile innovation lies in efficiently achieving innovative solutions through flexible iterations, continuous user participation, and cross-team collaboration in rapidly changing environments [21,22]. It frees engineers from the constraints of traditional linear design processes, driving the implementation of specific innovative products through continuous optimization [23].

Since the release of the Agile Manifesto in 2001 [24], research themes have evolved significantly from software development to cross-disciplinary integration. Existing research has successfully applied agile innovation concepts, such as the Agile-Stage-Gate model, to the R&D management processes of manufacturing enterprises [25]. Beaumont et al. [26] proposed embedding agile operations into existing development processes to create a more flexible problem-solving model. Cooper demonstrated, respectively, through case studies of technology-intensive companies, that hybrid product development models can rapidly adapt to changing customer needs and improve overall productivity [27]. Similarly, Albers [28] developed Agile Systems Design to manage mechatronic system development across multiple hierarchical levels.

Figure 1 illustrates the relationship between agile software development and agile mechanical product design. In software development, a problem can often be decomposed into functional modules and addressed through code-level iteration [29–31]. In mechanical design, a similar iterative logic applies, but each modification must be evaluated for structural integrity, motion compatibility, energy transmission, manufacturability, and safety. Therefore, the central challenge is not whether agile thinking can be applied to mechanical design, but how to transform it into a disciplined conceptual design procedure. Existing tools such as Quality Function Deployment, Axiomatic Design, Theory of Constraints, and Design for Six Sigma can translate customer needs into engineering requirements [32,33]. However, they provide limited support for rapidly generating new physical structures when user feedback implies a change in system behavior.

With the advent of Industry 4.0, agile innovation in mechanical engineering has been revitalized through the integration of Smart Manufacturing technologies [34]. The deployment of Cyber–Physical Systems enables continuous monitoring of physical assets, bridging the gap between user-operational data and product design [35]. This paradigm shift enables manufacturers to transition from traditional mass production to mass customization, in which agile principles are used to iteratively refine product architectures in response to real-time operational feedback.

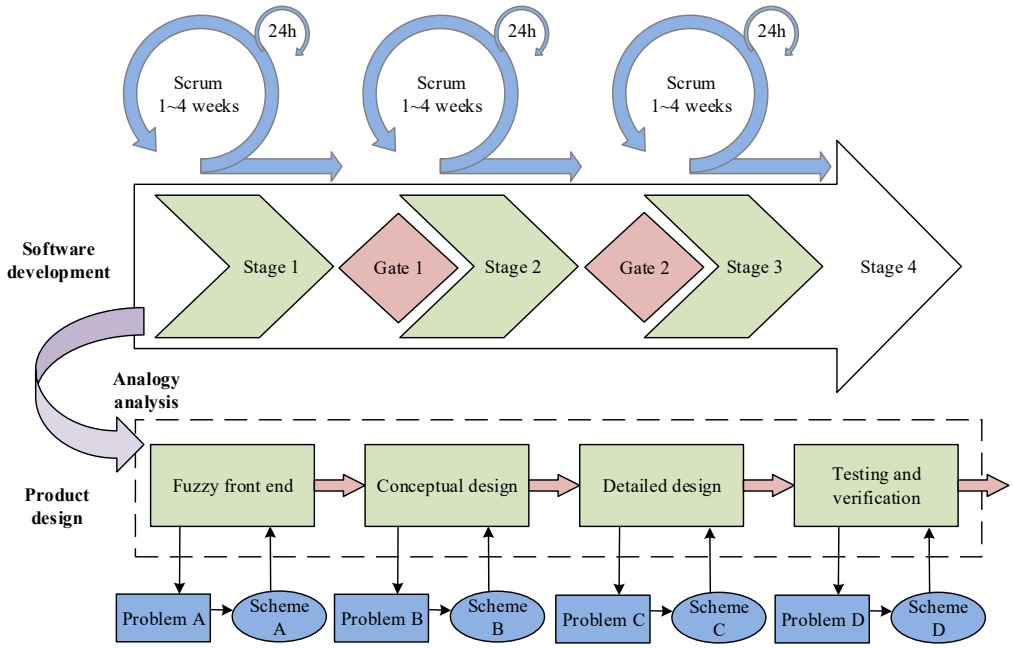


Figure 1. Similarities between software development and product design.

Furthermore, Digital Twin technology has emerged as a revolutionary enabler for agile iterations in complex mechanical systems. By creating high-fidelity virtual replicas of physical entities, designers can conduct rapid virtual testing and modifications before committing to expensive physical prototypes. Recent advancements have demonstrated that embedding AI-driven control systems into digital twins significantly enhances the adaptive learning and decision-making capabilities of robotic systems in dynamic environments [36]. This virtual-to-physical loop is the essence of modern agile innovation and severely compresses the iteration cycle.

Despite these technological advancements, a critical gap remains in the conceptual design phase. Modifying a specific mechanical subsystem based on digital twin feedback is far more challenging than altering software code because of multiphysics coupling. Therefore, it is urgently necessary to leverage robust problem-solving frameworks and dimensional analysis tools to redefine the agile product development process. By doing so, engineers can systematically resolve the physical contradictions introduced by rapid iterations, thereby fully realizing the potential of user-driven agile innovation.

2.2. TRIZ in the Era of Smart Manufacturing

TRIZ (Theory of Inventive Problem Solving) is a systematic innovation methodology that abstracts patterns of human invention throughout history to distill universal principles [37,38]. It transcends the limitations of traditional trial-and-error methods, allowing designers to efficiently identify innovative solutions by resolving engineering-related contradictions. TRIZ has gained widespread applicability because it provides a comprehensive set of analytical tools, including contradiction matrices and substance-field analysis, tailored for various innovation scenarios [39].

As shown in Table 1, technological evolution laws constitute another critical pillar of TRIZ, objectively reflecting the frequent interactions between components and their environments during the product lifecycle [40]. These laws empower users to anticipate medium- to long-term design solutions. For instance, He et al. proposed a Rainflow evolution model to enable innovative improvements in complex product functions [41]. Similarly, Mao et al. integrated deep learning with evolution patterns to elucidate the mechanisms of contradiction transformation [42].

Table 1. Contents of the technological evolution law.

No.	Name	Content
L1	Law of Increasing Degree of Ideality	Increasing product revenue, reducing costs, and minimizing side effects can all improve idealization.
L2	Law of Non-Uniform Evolution of Sub-Systems	The emergence of an unbalanced state is due to certain subsystems in the product developing at a higher level than other subsystems to meet new demands.
L3	Law of Increasing Dynamism	The product's structure is more flexible, enabling adaptation to changes in performance levels, environmental conditions, and diverse functional requirements.
L4	Law of Transition to a Supersystem	Integrating a single system into a dual or multi-system is a form of product upgrade. The integrated product offers improved performance and useful new features.
L5	Law of Transition to a Micro-Level	Functions performed by macroscopic materials, such as shafts, levers, and gears, can be performed by microscopic materials, thereby resolving conflicts that arise in products.
L6	Law of Completeness	The complete product consists of four subsystems: power, transmission, execution, and control.
L7	Law of Shortening of Energy Flow Path	The basic condition for product operation is that energy can be transferred from the power subsystem to the execution subsystem, and this path should be shortened to improve performance.
L8	Law of Increasing Controllability	Controllability refers to the degree to which a product's state can be achieved within specified time constraints. The better the controllability, the shorter the time required to achieve the desired state.
L9	Law of Harmonization	In actual operation, the main components or subsystems of a product must work together and coordinate. This is a reliable guarantee that the product will complete its preset movements or operations.

However, the fundamental flaw of classical TRIZ lies in its mismatch with modern, highly agile innovation scenarios. Born in the industrial age and derived primarily from structural patent documents, traditional TRIZ is often perceived as too rigid for the complexity and cross-disciplinary nature of products in the digital age [43]. The current trajectory of TRIZ improvement focuses on Computer-Aided Innovation [44–46], aiming to transform it from a specialized structural tool into a universal, agile innovation language capable of handling massive datasets.

To align with the frontiers of mechanical design, recent studies have begun integrating TRIZ with Knowledge Graphs and big data analytics [47]. This integration enables the automatic extraction of inventive principles from vast unstructured industrial data, significantly accelerating the contradiction–resolution process. Moreover, in the context of intelligent manufacturing, complexity management has become a significant challenge; TRIZ-driven

algorithms are now being used to navigate the uncertainties inherent in globalized supply chains and multidisciplinary product architectures [48].

Therefore, embedding TRIZ into an agile innovation framework is highly logical. While agile methodology provides the iterative loop and user-centric focus, TRIZ provides the "engine" to quickly resolve technical bottlenecks encountered during each rapid iteration. This integration ensures that when user feedback calls for a structural change, designers do not rely on blind brainstorming but instead on proven evolutionary trends to rapidly synthesize feasible, high-quality conceptual variants.

2.3. LT Dimension and Complex System Modeling

To accommodate the multi-physics nature of modern mechanical systems, dimensional analysis has been heavily relied upon to standardize engineering parameters. The LT dimension, conceptualized by Bartini, represents a radical shift, classifying all physical quantities solely in terms of space and time [49]. Using group theory and topology, it was demonstrated that diverse physical constants and thermodynamic variables could be unified into a two-dimensional matrix [50], thereby validating the scientific viability of the LT dimension for abstracting complex phenomena.

To facilitate practical engineering research, the LT table was established. Each cell in Table 2 encompasses one or more physical quantities, spanning from kinematics to electromagnetism. This structure is not static; it can be dynamically tailored to reflect specific subfields of physics required for a given design problem. Bushuev [51] represented LT dimensions in matrix form to estimate the spatiotemporal resources consumed during energy conversion, providing crucial insights for constructing physical principles in complex machinery.

Table 2. Partial contents of the LT table.

Dimension	$[L^{-1}]$	$[L^{0}]$	$[L^{1}]$	$[L^{2}]$	$[L^{3}]$	$[L^{4}]$	$[L^{5}]$
$[T^{-6}]$				$[L^{2}T^{-6}]$	$[L^{3}T^{-6}]$	$[L^{4}T^{-6}]$	$[L^{5}T^{-6}]$
$[T^{-5}]$			$[L^{1}T^{-5}]$	$[L^{2}T^{-5}]$	Surface power	$[L^{4}T^{-5}]$	Power
$[T^{-4}]$		$[L^{0}T^{-4}]$	Pressure gradient	Pressure	Stiffness/ Surface tension	Force	Energy/ Temperature
$[T^{-3}]$		$[L^{0}T^{-3}]$	Current density	Magnetic field strength/ viscosity	Current	Impulse	Angular momentum
$[T^{-2}]$	$[L^{-1}T^{-2}]$	Mass density/ Angular acceleration	Linear acceleration/ Magnetic induction intensity	Voltage	Quality/ Power capacity	$[L^{4}T^{-2}]$	Moment of inertia
$[T^{-1}]$	Charge density	Frequency/ Angular velocity	Linear velocity	Area change rate	Volume change rate	$[L^{4}T^{-1}]$	$[L^{5}T^{-1}]$
$[T^{0}]$	Curvature	Angle/ Radian	Length	Area	Volume	$[L^{4}T^{0}]$	
$[T^{1}]$	Resistance/ Reactance	Period	$[L^{1}T^{1}]$	$[L^{2}T^{1}]$	$[L^{3}T^{1}]$		
$[T^{2}]$	Self-sensing/ Mutual sensing	$[L^{0}T^{2}]$	$[L^{1}T^{2}]$	$[L^{2}T^{2}]$			
$[T^{3}]$	$[L^{-1}T^{3}]$	$[L^{0}T^{3}]$	$[L^{1}T^{3}]$				

The application of LT dimensions in transportation and energy sectors has demonstrated significant advantages. Kotikov [52] applied LT dimensions to assess the energy efficiency of heavy-duty trucks and quantitatively compared them with freight railways. Rajić [53] argued that LT dimensions help designers easily navigate complex scenarios, such as aerospace equipment development, by abstracting away superficial design parameters. Kuznetsov [54] further extended its use to evaluate the sustainability of engineered systems, showcasing its versatility across macroscopic domains.

As a highly abstract interdisciplinary tool, the LT dimension is particularly suited for the conceptual design of complex mechatronic systems [55]. In the era of smart manufacturing, products are no longer purely mechanical; they involve intricate flows of data, energy, and materials. Wang [56] suggested that mapping radical design problems to their corresponding LT dimensions reveals hidden commonalities, enabling cross-domain technology transfer. By utilizing LT dimensions as search indices, designers can uncover latent parameters that govern the next generation of system architecture.

Furthermore, recent advancements in digital twin modeling highlight the necessity for a standardized data ontology [57]. LT dimensions provide a universal language that allows sensor data from physical prototypes to be seamlessly mapped onto virtual models, regardless of whether the data is mechanical strain, thermal gradients, or electrical resistance. This standardized mapping is crucial for training AI-driven predictive maintenance models and optimizing equipment lifecycles in real time [58].

Table 3 summarizes the differences between related approaches and the proposed method. Although agile innovation, TRIZ, LT dimensions, digital twins, and data-driven design have each been studied in previous research, they usually appear as separate methodological streams. Agile design emphasizes iteration and user participation but often lacks physical problem-solving operations. TRIZ provides powerful knowledge for solving contradictions, but does not naturally begin with dynamic user feedback. LT dimensions offer a compact representation of physical quantities but are rarely connected to agile design workflows. Data-driven methods can support classification and recommendation, yet their engineering interpretability is sometimes limited. The proposed method is designed to connect these streams in a way that remains understandable to practicing engineers.

Table 3. Comparison between representative design approaches and the proposed method.

Approach	Main Focus	Strength	Limitation
Scrum-based development	Team collaboration and iterative task management	Fast communication and flexible planning	Does not directly generate physical structures
Classical TRIZ	Contradiction matrix, inventive principles, Su-field analysis	Provides systematic innovation logic	Relies strongly on expert interpretation
Digital twin-driven iteration	Virtual monitoring, prediction, and optimization	Enables data feedback from physical systems	Often assumes that product architecture already exists
QFD/AD/DFSS	Requirement translation and design quality control	Clarifies customer needs and design constraints	Limited support for inventive structure generation
Proposed LT–TRIZ agile method	User-feedback-driven conceptual structure generation	Links pain points, LT dimensions, TRIZ evolution laws, structural mapping, and TOPSIS	Mainly supports concept generation rather than detailed simulation

3. Proposed Method

As illustrated in the framework in Figure 2, the proposed agile innovation design method encompasses three sequential stages. In the product analysis stage, the target product and its operating context are first clarified. User feedback, maintenance records, market complaints, design documents, and expert observations are collected as background information. A fishbone diagram is then used to organize possible causes of functional insufficiency from six perspectives: man, machine, material, method, environment, and measurement. Unlike a simple checklist, the fishbone model is used here to identify the functional object, harmful or insufficient action, affected component, and external supersystem. The core problem is then converted into one or more LT dimensions through an NLP-assisted rule-based classification process.

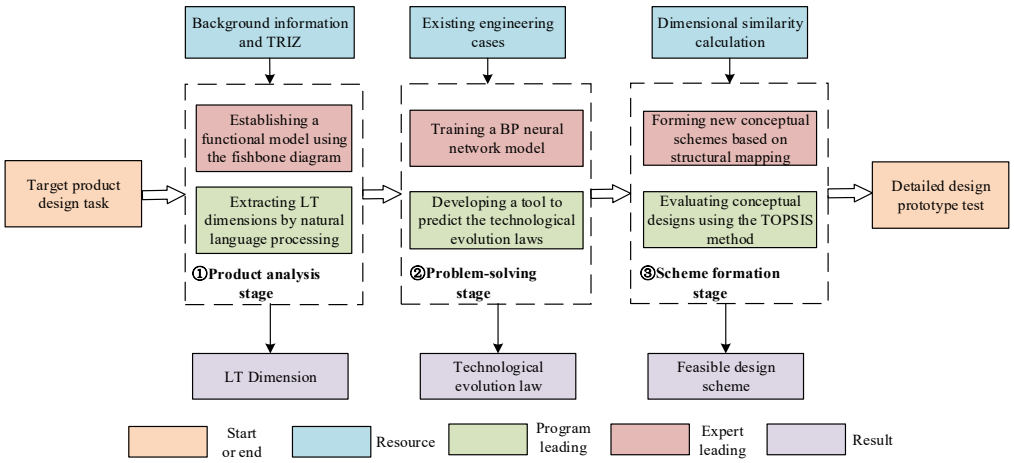


Figure 2. Framework of the proposed method.

In the problem-solving stage, the LT dimensions derived from the core problem are used as input nodes for a BP neural network. The neural network's output is one of the TRIZ technological evolution laws. The network is used as an auxiliary trend predictor rather than an autonomous decision-maker. Its prediction is therefore checked against the functional model and the problem's physical meaning before being accepted. This conservative use of the BP model is deliberate. Because the available dataset contains 100 curated technological evolution cases, the model is suitable for supporting concept exploration but should not be interpreted as a high-generalization classifier for all mechanical systems.

In the scheme formation stage, engineering cases associated with the predicted evolution law are retrieved from the case base. Their dimensional similarity to the target problem is calculated using LT indices. Cases with high similarity are selected as analogical sources for structural mapping. Several conceptual schemes are then generated by transferring relational structures rather than copying surface geometry. TOPSIS is used to rank the schemes according to Advancement, Difference, and Suitability. To improve reproducibility, this study explicitly reports the evaluation matrix, normalization method, criterion weights, distance calculation, relative closeness, and sensitivity check. Finally, during the detailed design stage, physical parameters, materials, and manufacturing processes are finalized, enabling the rapid development of physical prototypes to test the agile innovation outcomes.

3.1. Functional Modelling and LT Dimension Classification

Once the target product is defined, a preliminary functional model is constructed by aggregating relevant background information and user feedback. Because product failures or functional deficiencies may stem not only from internal component interactions but

also from external environmental conditions, an iterative modeling approach is required. To achieve accuracy, the classic fishbone diagram method from quality management [59] is applied to categorize functional issues across six dimensions: man, machine, material, method, environment, and measurement. As depicted in Figure 3, an isolated analysis of internal components may fail to pinpoint whether Component B or C is defective. However, the fishbone diagram effectively reveals that supersystems F and G exert non-standard actions on the product, which are transmitted to target D, thereby exposing the underperforming hidden Component E.

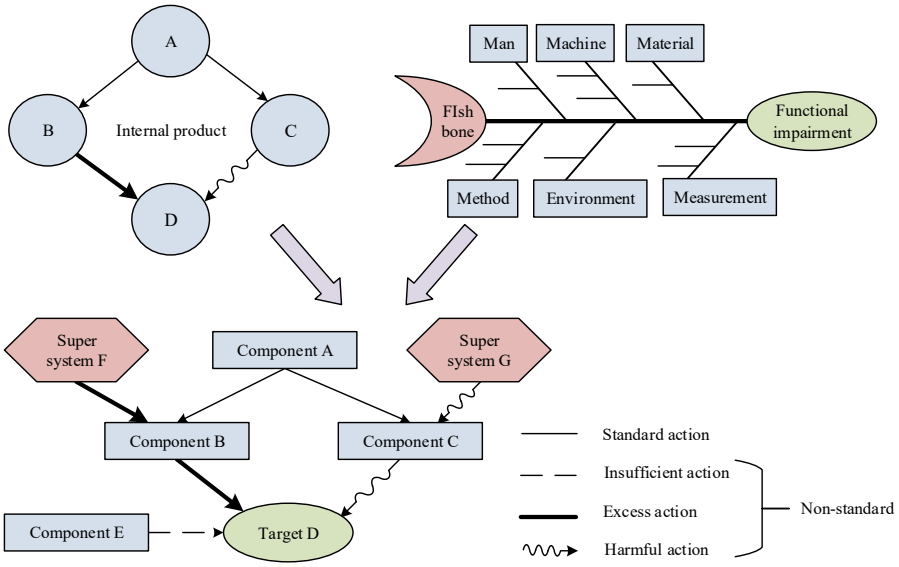


Figure 3. The process of constructing a functional model.

As the complexity of modern mechatronic products escalates, iterative improvements to a specific subsystem inevitably cascade to other parts, significantly impacting overall system reliability. Therefore, building upon Wang's research [60], this study filters through various interfering factors to isolate the core problems that fundamentally hinder product functionality.

After the core problem has been isolated, the corresponding LT dimensions are extracted using an NLP-assisted rule-based classification procedure. The role of NLP in this paper is practical and limited: it standardizes word segmentation, extracts physical action words and engineering nouns, and supports rule matching. It is not used as a black-box deep learning model that requires a large training corpus. This choice is consistent with the study's objective of improving transparency and reproducibility in conceptual design rather than building a general-purpose language model. The NLPIR-Parser is used to process Chinese or English problem statements and to output candidate keywords [61], which are then mapped to LT dimensions through predefined rules, as illustrated in Figure 4.

The LT mapping mechanism is formalized as follows. Let a core problem statement be denoted as P. After word segmentation and part-of-speech filtering, the keyword set is obtained as $K = \{k_1, k_2, \ldots, k_m\}$. Each keyword k_i is matched with a rule library $R = \{r_1, r_2, \ldots, r_s\}$, where each rule links a physical action or engineering quantity to an LT dimension L^aT^b. The candidate dimension set is denoted by $D(P) = \{La1Tb1, La2Tb2, \ldots, L^{aq}T^{bq}\}$. If multiple dimensions are obtained, the final LT dimensions are selected according to the physical effect in the fishbone-based functional model. In this study, no more than three LT dimensions are retained for one core problem to avoid over-fragmentation of the design target.

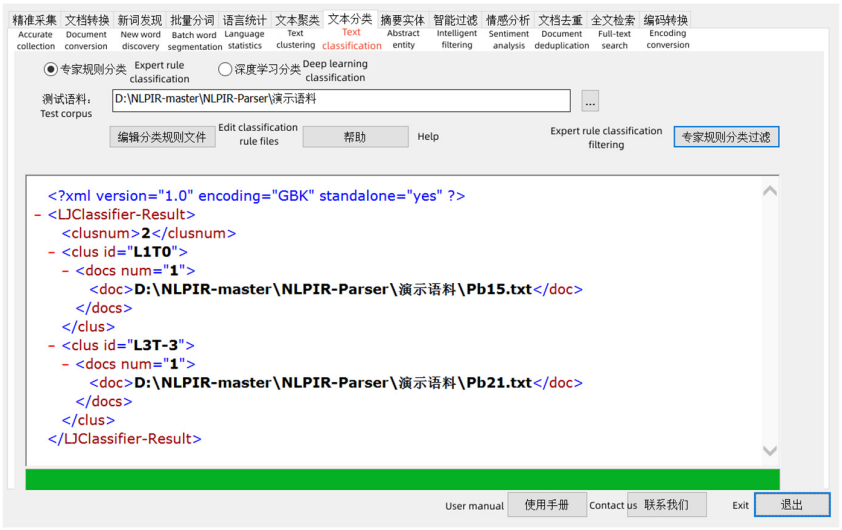


Figure 4. LT dimension classification results.

The rule base is constructed from engineering dimensional analysis and common physical expressions in mechanical design. Table 4 shows representative mapping rules. For instance, expressions such as "flow velocity is low", "rotational speed is insufficient", or "response is slow" are usually associated with velocity or frequency-related dimensions. Expressions such as "pressure drop", "weak aerodynamic force", or "insufficient load support" are mapped to pressure, force, stiffness, or energy-related dimensions according to the functional model. The rules are intentionally interpretable.

Table 4. Representative NLP-assisted LT dimension mapping rules.

Rule ID	Typical Keywords	Physical Interpretation	LT Dimension
R1	move, translate, flow, airflow, wind speed, conveying speed	Linear motion or fluid velocity	L^1T^{-1}
R2	rotate, rotational speed, angular velocity, frequency, oscillate	Rotational motion or periodic response	L^1T^{-1} or L^0T^{-1}
R3	accelerate, decelerate, impact, rapid change	Change of velocity with time	L^1T^{-2}
R4	force, thrust, drag, load, torque-related action	Mechanical action causing motion or deformation	Case-dependent, often L^4T^{-4}
R5	pressure, pressure drop, suction, compression	Force distributed over area or fluid pressure	L^0T^{-4} or related pressure cell
R6	power, energy output, energy loss, conversion efficiency	Energy transfer or energy conversion rate	L^5T^{-5} or related power/energy cell
R7	heat, thermal accumulation, cooling, temperature rise	Thermal effect or thermal exchange	L^2T^{-4} or related thermal cell
R8	support, stiffness, deformation, vibration	Structural resistance or dynamic stability	Stiffness or vibration-related LT cell

Although the program plays a leading role in this process, three experts in the design field independently established the mapping rules for LT dimensions. Their evaluations were required to pass the Kendall coefficient of concordance test. For samples with inconsistent mapping results: if two experts reached an agreement, the minority opinion would follow the majority. In cases where all three opinions differed, the expert team would revisit the original text to identify the keywords or specific operational behaviors responsible for the classification discrepancy.

The operating rules of the NLP-based LT classification are as follows. First, each selected core problem is recorded in the following format: "Under [operating condition], [acting object] produces [physical action] on [affected object], causing [insufficient or harmful effect]." This sentence template forces the design team to describe the problem using physical verbs rather than purely emotional adjectives. Second, NLPIR-Parser performs segmentation and extracts nouns, verbs, and adjective–noun phrases related to engineering phenomena. Third, stop words and non-physical emotional words are removed. Fourth, the remaining words are matched with the LT rule base. Fifth, if the deep-learning classification mode and the expert-rule mode of NLPIR-Parser give different results, the expert-rule result is used as the primary result, and the deep-learning result is used as a warning signal for manual review. Sixth, the final LT dimensions are checked against the fishbone model to confirm that they correspond to the dominant physical bottleneck.

3.2. Construction and Prediction of the Neural Network

The robustness and predictive accuracy of a BP neural network depend fundamentally on the quality and quantity of its training samples. These samples are meticulously sourced from authoritative papers, books, and patent documents related to technological evolution. For example, the LT scales of the metal pipe cutter are $[L^1T^{-1}]$, $[L^4T^{-4}]$ and $[L^5T^{-4}]$, which follows the L3 Increasing Dynamism. As shown in Figure 5, a dataset of 100 product cases was established. The high frequencies of occurrence of laws L3 and L4 indicate that, as products evolve towards supersystems, they not only accrue functionalities and structural complexity but also require greater dynamism to adapt to variable environments. Conversely, the lower frequencies of L8, L6, and L7 suggest that existing products have largely optimized their controllability, completeness, and energy flow paths, making breakthroughs in these areas more challenging. Notably, although L1 represents an idealized theoretical state and is absent from the sample, the neural network's output layer retains 9 nodes to preserve the mathematical completeness of the TRIZ evolutionary framework.

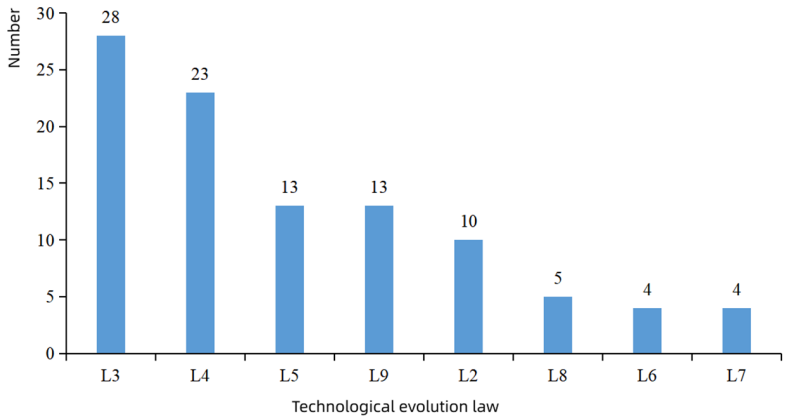


Figure 5. Distribution of training samples.

To effectively input LT dimensions into the BP neural network, a systematic numbering protocol is essential. The diagonal lines within the LT table encapsulate both spatial and temporal evolutionary trends, serving as a rich source of information for agile product innovation. The LT table is segmented into 17 diagonals from the top-left to the bottom-right [62]. Given that most mechanical engineering designs operate in macroscopic, low-speed 3D spaces, the sum of the LT dimension exponents is at most 3. The finalized numbering matrix is presented in Table 5 and corresponds to the neural network's input layer with 50 nodes.

Table 5. LT dimension numbering.

Dimension	$[L^{-2}]$	$[L^{-1}]$	$[L^{0}]$	$[L^{1}]$	$[L^{2}]$	$[L^{3}]$	$[L^{4}]$	$[L^{5}]$
$[T^{-6}]$						6	13	21
$[T^{-5}]$					5	12	20	29
$[T^{-4}]$				4	11	19	28	37
$[T^{-3}]$			3	10	18	27	36	44
$[T^{-2}]$		2	9	17	26	35	43	50
$[T^{-1}]$	1	8	16	25	34	42	49	
$[T^{0}]$	7	15	24	33	41	48		
$[T^{1}]$	14	23	32	40	47			
$[T^{2}]$	22	31	39	46				
$[T^{3}]$	30	38	45					

To maximize feature extraction from the input samples, the BP neural network's topology was rigorously optimized around its hidden layer. The Logsig activation function bridges the input to the hidden layer, while Purelin connects the hidden layer to the output layer. Iterative training on the dataset revealed that the validation error exhibited a convex trend in Figure 6; thus, the optimal number of hidden-layer neurons was empirically set to 15. To minimize training errors, the model is trained using the highly efficient Levenberg-Marquardt algorithm [63], which ensures rapid convergence and stability. The samples were randomly divided into training and test sets following the Pareto Principle (80/20). The corresponding confusion matrix is presented in Table 6. As shown in Figure 7, when the learning rate is set to 0.1, the model achieves optimal performance at the 769th epoch, with a prediction accuracy of up to 90%. Subsequent designers can add distinctive agile innovation cases in their respective fields to further enhance the proposed method's applicability.

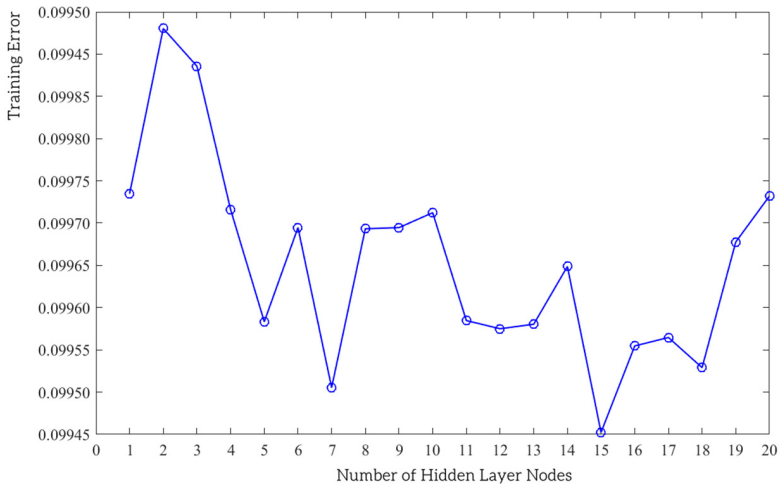


Figure 6. Variation trend of training error with hidden layer nodes.

Table 6. The confusion matrix.

Rule ID	R1	R2	R3	R4	R5	R6	R7	R8	R9
R1	0	0	2	0	0	0	0	0	0
R2	0	1	0	0	0	0	0	0	0
R3	0	0	6	0	0	0	0	0	0
R4	0	0	0	3	0	0	0	0	0
R5	0	0	0	0	2	0	0	0	0
R6	0	0	0	0	0	2	0	0	0
R7	0	0	0	0	0	0	0	0	0
R8	0	0	0	0	0	0	0	0	0
R9	0	0	0	0	0	0	0	0	4

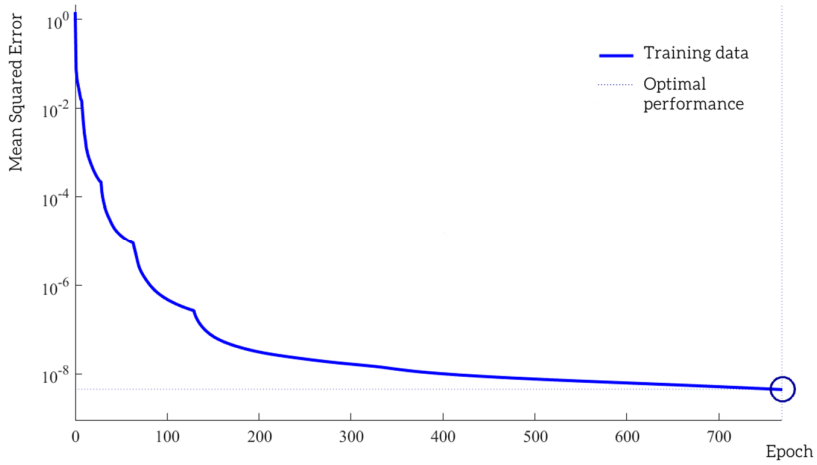


Figure 7. Training process of neural network.

3.3. Conceptual Scheme Acquisition and Evaluation

Structural Mapping Theory (SMT) provides a robust cognitive framework to operationalize the generation of specific design schemes [64]. SMT posits that analogical transfer should rely on comparing and mapping relational structures between two objects, rather than on superficial formal similarities. While laws of technological evolution dictate macro-level development trends, a single law often maps to multiple engineering cases. To rapidly and accurately pinpoint the optimal analogical source for agile iteration, cases are screened based on the target product's specific constraints. Using the LT dimension as a quantifiable index, cosine similarity effectively measures the structural congruence between cases [65]. Cases with a similar score near 1 indicate minimal barriers to structural transfer and are prioritized.

Taking the heating plate of a polyethylene pipe welder as an example, the four steps of SMT are illustrated in Figure 8 [66]. Step 1: Extract relevant engineering case information from the technological evolution knowledge base. The existing heating plate must be disassembled to weld the inclined pipe sections. The most similar product found in the case library is a gyroscope. Step 2: Replace the problematic components of the target product with corresponding components from the engineering case that achieve the desired functionality, thereby forming a functional model of the new solution. The rotating shaft structure remains unchanged, the outer ring becomes a support frame, and the inner ring becomes a plate surface. Step 3: Combine the target product's industry sector and usage scenarios with structural design analogies to derive an initial scheme. The interior of the plate surface should accommodate space for installing heating coils and control components. Step 4: The initial scheme may still have problems, which can typically be addressed in the following three scenarios: (1) When new conflicts arise in the scheme,

the invention or separation principle is applied from TRIZ. (2) When further performance improvements are needed, composite effect patterns are created by increasing the number of effects. (3) When cost reduction or avoidance of patent infringement is required, the trimming tool is used to remove redundant structures and reallocate system resources. It is found that the pipe welder also needs to perform cutting irregular surfaces by replacing parts. Based on the principle of multi-functionality, the tool and heating plate structures are merged.

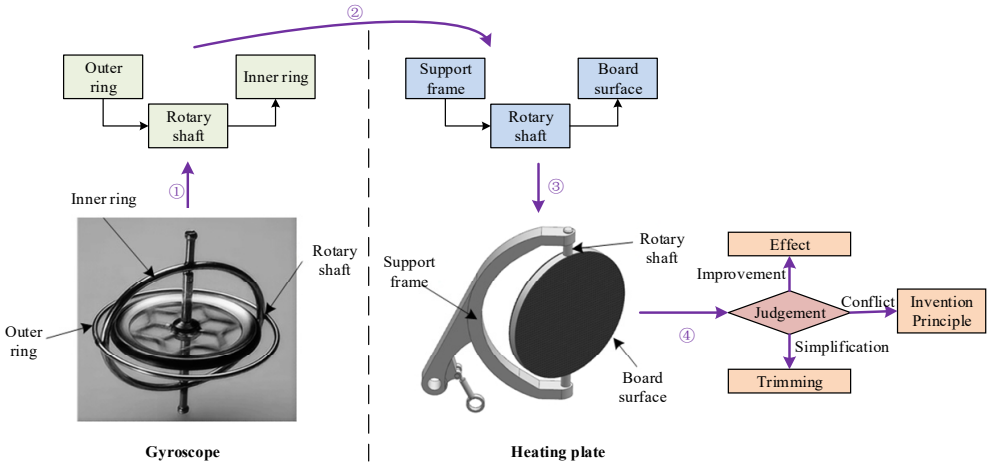


Figure 8. Structural mapping process of the pipe-welding machine.

Because several feasible schemes can be generated from a single evolution law, a multi-criteria decision-making method is required. TOPSIS is adopted because it ranks alternatives based on their distances from the positive and negative ideal solutions [67]. In the conceptual design stage, complete aerodynamic, structural, or energy-efficiency data are often unavailable. Aligned with the fundamental goals of agile innovation, the ranking criteria are established as Scheme Advancement (SA), Scheme Difference (SD), and Scheme Suitability (SS) [68], as listed in Table 7. SA evaluates the scheme's lifecycle and application potential; SD measures the degree of structural innovation compared to existing products; and SS assesses the new scheme's compatibility within the current technical ecosystem. Values ranging from 0 to 1 are assigned according to established conventions [69], with 0.9 indicating superior performance. Crucially, these data undergo rigorous statistical reliability analysis prior to ranking to validate the rationality of the criteria [70].

Table 7. Scoring anchors for conceptual scheme evaluation.

Criterion	Value = 0.1	Value = 0.5	Value = 0.9
SA	Mainly repeats existing structure with little evolutionary improvement.	Shows moderate improvement using a recognizable evolution direction.	Clearly reflects advanced evolution, such as dynamization, supersystem integration, micro-level replacement, or controllability improvement.
SD	Very similar to the current product; mainly parameter adjustment.	Contains visible structural or functional difference.	Provides a distinctly different solution principle or structural configuration.
SS	Difficult to manufacture, install, maintain, or align with user needs.	Generally feasible but still has several implementation concerns.	Highly compatible with user needs, manufacturing capability, installation space, and maintenance requirements.

The specific steps for ranking the schemes are as follows, with the calculations conducted in SPSS V23.0. (1) Construct the comprehensive evaluation decision matrix **X** in Equation (1). Each row represents a new conceptual scheme, with a total of n rows. (2) Weighted-normalize the decision matrix **X** to form the new matrix **R** using Equation (2). (3) Determine the ideal solution $\mathbf{R}^+$ and negative ideal solution $\mathbf{R}^-$ in Equation (3). (4) Calculate distance ${D_i}^+$ and ${D_i}^-$ from each new scheme to the positive ideal solution and negative ideal solution, respectively, using Equation (4). (5) Determine comprehensive ranking results among the new schemes based on the relative proximity C_i between the new schemes and the ideal solution using Equation (5). The closer C_i is to 1, the higher the new scheme's level of agile innovation will be.

In the base evaluation, equal weights are used because the three criteria represent complementary goals of agile conceptual design. To address possible subjectivity in criterion weights, a sensitivity analysis is added. Three additional weight settings are examined: SA-oriented weighting W_1 = (0.5, 0.25, 0.25), SD weighting W_2 = (0.25, 0.5, 0.25), and SS-oriented weighting W_3 = (0.25, 0.25, 0.5). If the top-ranked scheme remains unchanged or stays within the top two under these settings, the ranking is considered robust for early-stage conceptual selection. If the ranking changes substantially, the final decision should be postponed until more quantitative engineering evidence is available. This step prevents TOPSIS from being used as a mechanically deterministic decision tool.

$$\mathbf{X} = \left[x_{ij}\right],\ i = n,\ j = 3 \tag{1}$$

$$\mathbf{R} = \left[w_j r_{ij}\right], r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \tag{2}$$

$$\mathbf{R}^+ = \left(R^+_{\max 1},\ R^+_{\max 2},\ R^+_{\max 3}\right),\ \mathbf{R}^- = \left(R^-_{\min 1},\ R^-_{\min 2},\ R^-_{\min 3}\right) \tag{3}$$

$$D_i^+ = \sqrt{\sum_{j=1}^{3} \left(z^+_{\max j} - z_{ij}\right)^2},\ D_i^- = \sqrt{\sum_{j=1}^{3} \left(z^-_{\min j} - z_{ij}\right)^2} \tag{4}$$

$$C_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{5}$$

4. Case Study

To further illustrate the general applicability without overstating its validation, Table 8 lists several engineering scenarios in which the proposed method can be applied. These scenarios are not presented as full case studies. Instead, they show how user feedback across different mechanical systems can be transformed into LT dimensions and possible directions for TRIZ evolution. The purpose is to demonstrate that the method is not limited to the VAWT example while keeping the research focused on conceptual design and methodological transparency.

These scenarios suggest that the proposed LT–TRIZ agile method can support conceptual reasoning in robotics, manufacturing equipment, fluid machinery, agricultural machinery, and thermal systems. In all cases, the method should be understood as a front-end design aid. It helps designers ask better engineering questions and generate more structured concept alternatives. It does not remove the need for domain-specific verification. This boundary is especially important in applications involving safety, high-speed motion, pressure vessels, thermal runaway, or human–machine interaction, where detailed analysis and compliance testing are indispensable.

Table 8. Example engineering scenarios for applying the proposed method.

Engineering Scenario	Typical User Feedback	Possible LT Interpretation	Evolution-Law Direction	Conceptual Design Implication
Collaborative robot gripper	The gripper adapts poorly to objects with different shapes	Force, displacement, deformation, sensing response	Increasing dynamism; increasing controllability	Introduce compliant fingers, adaptive joints, or sensor-guided gripping surfaces
CNC machine tool cooling system	Local overheating occurs during long machining operations	Heat transfer, temperature rise, flow rate	Shortening of energy flow path; transition to a supersystem	Add directed coolant channels, heat pipes, or hybrid cooling–lubrication modules
Automated packaging equipment	The feeding mechanism jams when package size changes	Linear motion, friction, clearance, control timing	Increasing dynamism; harmonization	Design adjustable guide rails and synchronized feeding modules
Industrial pump system	Energy consumption is high under variable flow conditions	Flow velocity, pressure, power, energy loss	Increasing controllability; transition to a supersystem	Add variable-speed control, adaptive impeller geometry, or bypass optimization
Agricultural harvesting machine	Crop loss increases when terrain and crop density change	Cutting force, vibration, motion stability, sensing	Increasing dynamism; harmonization	Introduce height-adaptive cutting units and vibration-suppression structures
Thermal management module for batteries	Heat accumulates locally during peak load	Heat flux, temperature gradient, response time	Transition to a supersystem; shortening energy flow path	Combine phase-change materials, microchannels, and sensor-driven thermal control

4.1. Product Analysis of the VAWT

The strong demand for electricity in the manufacturing sector and environmental constraints have jointly driven the rapid development of the wind power industry [71,72]. Based on the rotor's structural configuration and the orientation of its axis relative to the airflow, wind turbines can be categorized into two types: horizontal- and vertical-axis. Compared to the horizontal-axis type, the vertical-axis type offers advantages such as a more stable structure, easier maintenance, and a longer service life, as the generator, gearbox, and braking system can all be installed on the ground.

However, VAWTs have drawbacks in applications. According to the identification results obtained via the fishbone diagram method in Table 9, the functional model illustrated in Figure 9 is established. Based on problem importance evaluation criteria, the core problems of VAWTs are: (1) they can only passively adapt to the wind speed conditions at the installation site, wasting near-ground wind energy resources, and are unable to guarantee effective operating time. (2) They can only respond to changes in horizontal wind direction and cannot adjust the longitudinal wind angle. By inputting the core problem content into the NLPIR-Parser, the results obtained by combining the LT dimensions of the two classification modes are No. 25 [L^1T^{-1}] and No. 29 [L^5T^{-5}].

Table 9. Fishbone analysis of the VAWT conceptual redesign problem.

Fishbone Category	Possible Causes	Design Interpretation	Relevance to Conceptual Redesign
Man	Installation position may be constrained by buildings, roofs, or maintenance access	The turbine must remain compact and easy to maintain	Added structures should not greatly increase installation difficulty
Machine	Rotor receives insufficient directed airflow; part of the wind bypasses the effective working region	Airflow capture and torque generation are limited	Airflow-guiding or energy-concentrating structures may be needed
Material	Added parts must resist outdoor weather and avoid excessive mass	Structural additions must remain lightweight and durable	Concepts requiring heavy or complex materials should be avoided
Method	Current structure lacks a clear mechanism to concentrate weak wind	The product passively accepts the incoming wind field	Passive or adaptive airflow guidance should be considered
Environment	Near-ground wind is weak, turbulent, and directionally variable	The external supersystem strongly affects turbine behavior	The design should interact more effectively with the surrounding wind field
Measurement	Wind direction and speed are not actively sensed or used for adjustment	Control response is limited	Sensor-assisted or self-adjusting structures may improve adaptability

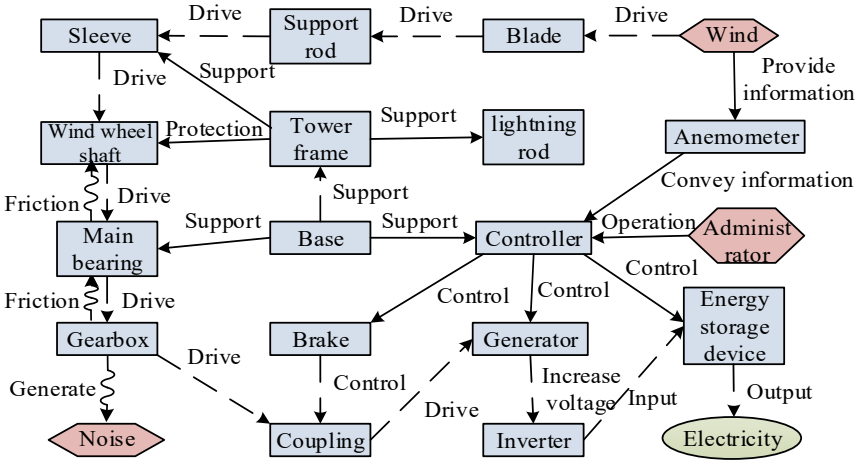


Figure 9. Functional model of the VAWT.

4.2. Problem-Solving of the VAWT

The two LT dimensions obtained from the core problems of VAWT are input into the technological evolution law prediction tool. The BP neural network model's prediction is the L4 Transition to a Supersystem. As shown in Table 10, some engineering cases of L4 are listed. Due to space limitations, specific technical descriptions and structural diagrams are omitted. They were ranked by their similarity to the VAWT, with cases with a similarity below 0.6 generally considered to lack reference value during the structural mapping process.

Table 10. Case studies on the technological evolution law.

Engineering Case	LT Dimension	Similarity	Rank	Availability
Counter-rotating helicopter	29, 44	0.76	6	Y
Multi-cylinder engine	25, 32	0.16	8	N
Electric spoiler	28, 29	0.77	5	Y
High-speed train	35, 25	0.07	10	N
Multistage rocket	25, 28	0.05	12	N
Remote control blinds	29, 34	0.93	2	Y
Liquid flow meter	11, 29	0.83	4	Y
Ultrasonic nebulizer	25, 33	0.16	8	N
Boiler exhaust device	29, 37	0.73	7	Y
Wind tunnel apparatus	11, 25	0.06	11	N
Magnetic levitation blower	18, 29	0.87	3	Y
Multi-purpose treadmill	25, 41	0.11	9	N
Electric sunshade umbrella	29, 41	0.94	1	Y
Variable-wing aircraft	28, 29	0.77	5	Y

The structural mapping process of the top-ranked electric sunshade umbrella is shown in Figure 10, forming conceptual scheme 1. The horizontal rod is designed as a retractable structure. It uses lightweight materials, resulting in lower bearing loads. Meanwhile, the tower extends support rods that not only adjust the diameter of the VAWT but also reinforce the horizontal rod. In extreme weather conditions, the vertical rod lowers the bearings, allowing the wind-collecting structure to retract and ensuring the safe operation of the VAWT.

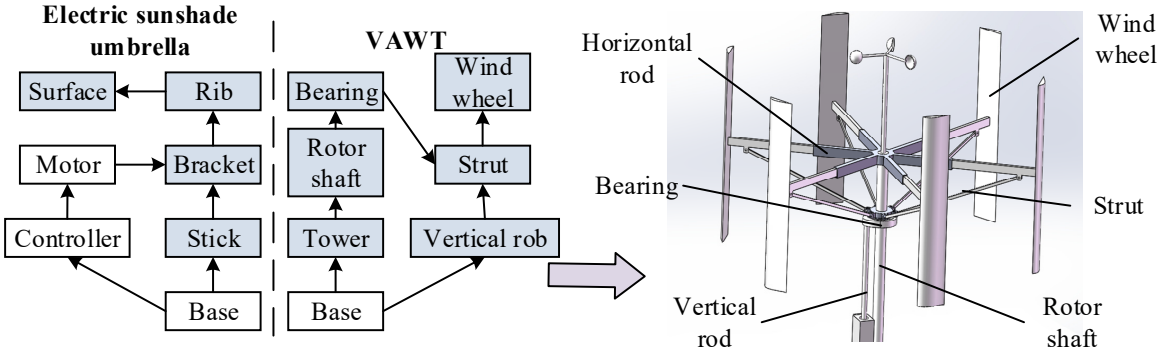


Figure 10. The formation process of conceptual scheme 1.

The structural mapping process of the remote-control blinds is shown in Figure 11, forming conceptual scheme 2. The VAWT's tower frame is a modular structure that can be adjusted to different heights to suit the working environment. The VAWT blades transition from a single-piece to a louvre-style assembly. When airflow passes through, the windward blades close, driving the wind turbine to rotate and generate electricity. The leeward blades open, reducing resistance to the wind turbine's rotation, and the process repeats.

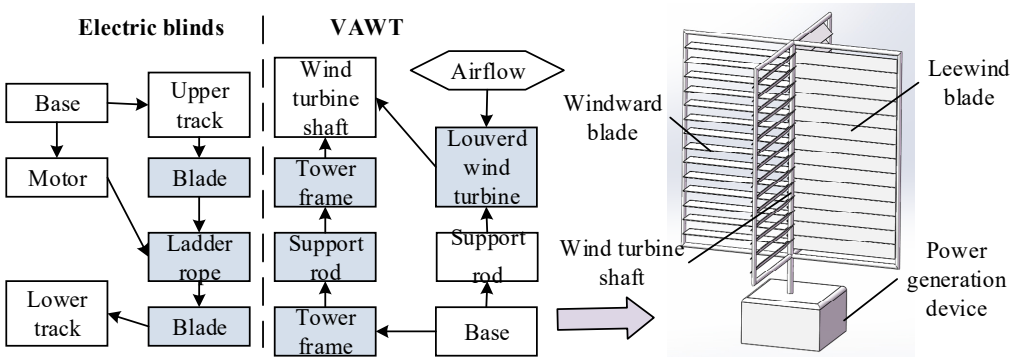


Figure 11. The formation process of conceptual scheme 2.

The structural mapping process of the magnetic levitation blower is shown in Figure 12, forming conceptual scheme 3. One end of the impeller shaft is connected to the blades, while the other end is connected to the central rotating magnet. The central rotating magnet is flanked by circular levitation magnets of opposite polarity, each supported by a corresponding annular fixed magnet. An induction coil is installed around the central rotating magnet, which generates electrical energy as the magnet rotates rapidly. Friction between the impeller shaft and other components is reduced, thereby improving the overall efficiency of the VAWT.

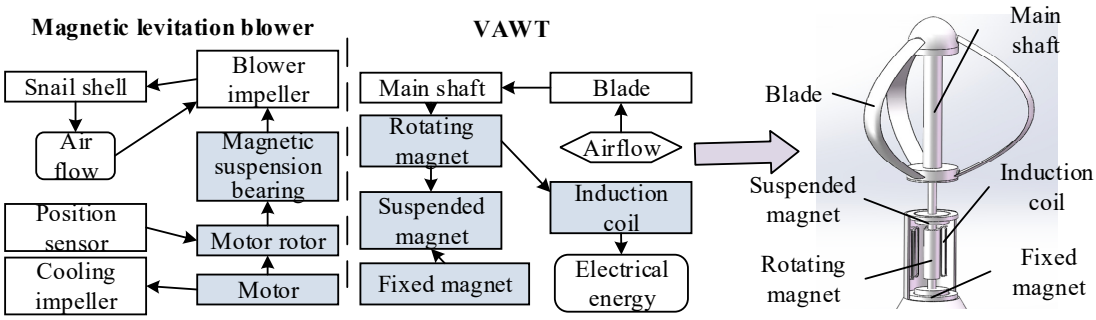


Figure 12. The formation process of conceptual scheme 3.

The structural mapping process of the liquid flow meter is shown in Figure 13, forming conceptual scheme 4. The wind-gathering structure is designed in a bell shape, with the larger opening at the end to collect as much wind energy as possible. As air flow passes through the fan, the cross-sectional area decreases, increasing the flow velocity. The accelerated airflow drives the generator blades in the ventilation duct, thereby converting wind energy into electrical energy. To fully capture wind energy, two wind-collection devices can be stacked to achieve a secondary acceleration effect.

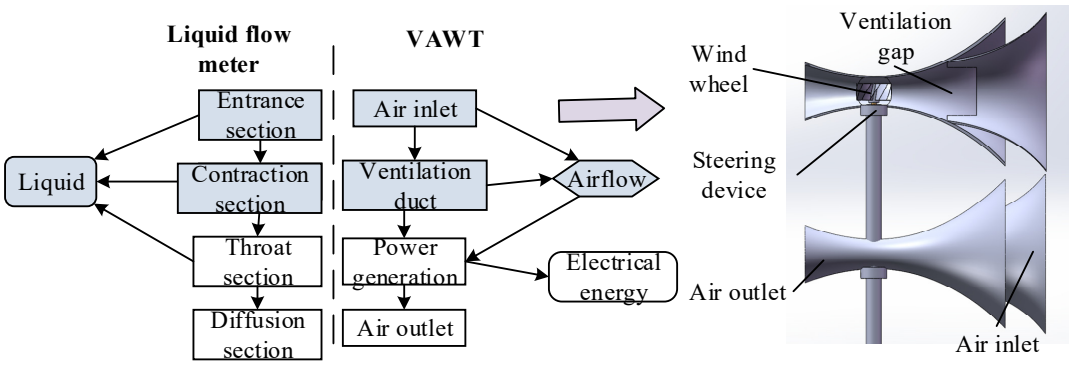


Figure 13. The formation process of conceptual scheme 4.

The analogy process for variable-wing aircraft is shown in Figure 14, which forms conceptual scheme 5. The tower is equipped with a variable-direction air deflector and a wind direction sensor. The sensor collects airflow data and transmits it to the microcontroller installed on the base. The blades of the variable-direction air deflector are controlled by the microcontroller and rotate around the axis to always maintain the most suitable air intake angle. The variable-direction air deflector must be made of high-strength materials to withstand complex stress conditions.

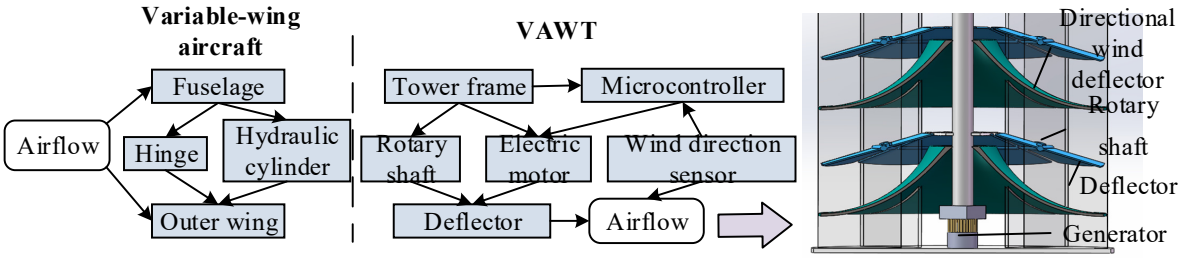


Figure 14. The formation process of conceptual scheme 5.

The electric spoiler, ranked 5th in parallel, cannot form a standalone scheme but can be structurally mapped to the counter-rotating helicopter, ranked 6th. As shown in Figure 15, it forms conceptual scheme 6. The wind collection device consists of inner and outer wind turbines whose main shafts are connected by a shaft sleeve and simultaneously driven into a gearbox for power generation. To fully utilize wind energy resources, an adjustable flap system is added. Through computational fluid dynamics research, the airflow velocity through the deflector increases, driving the inner and outer wind turbines to rotate faster.

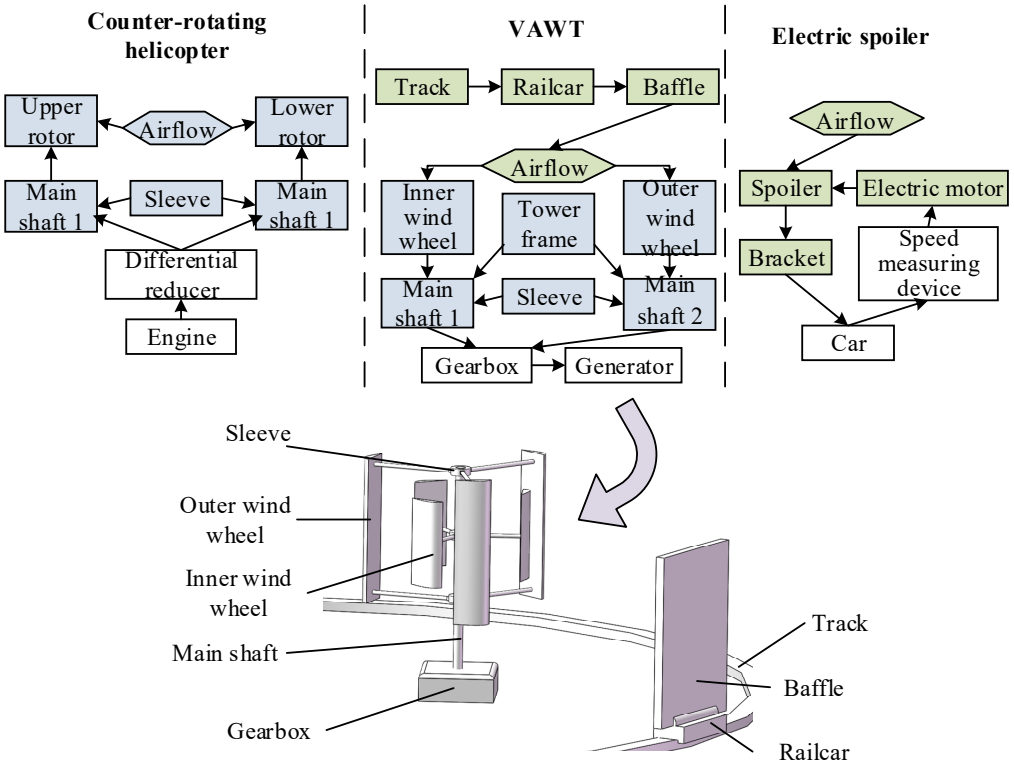


Figure 15. The formation process of conceptual scheme 6.

The structural mapping process of the boiler exhaust device is shown in Figure 16, forming conceptual scheme 7. Solar collectors are installed on the tower to generate

auxiliary power and heat the air in the tower's central channel. As the air density decreases, a density difference with the external environment forms, creating an upward airflow that drives the VAWT at the top. Additionally, the generator produces harmful high temperatures during operation. Installing a waste-heat conduction structure harnesses waste heat to enhance the chimney effect, turning what was previously harmful into a beneficial outcome.

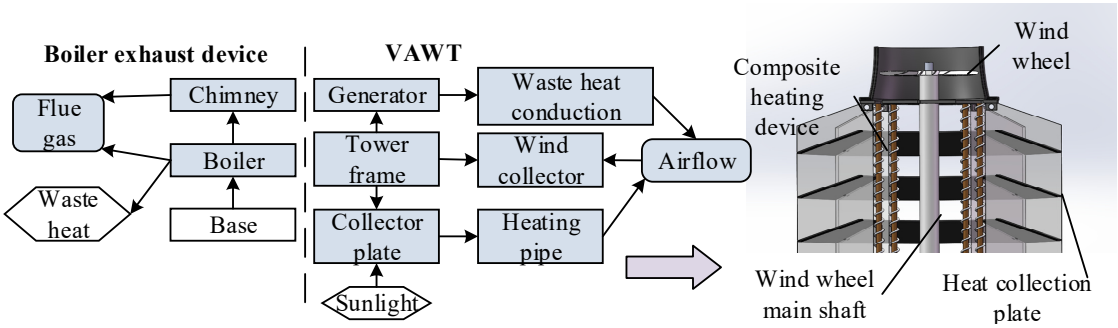


Figure 16. The formation process of conceptual scheme 7.

4.3. Scheme Evaluation of the VAWT

Following the sorting criteria and assignment ranges introduced in Section 3.3, the seven conceptual schemes of VAWT are evaluated. The theta reliability coefficient for the evaluation results was 0.905, exceeding the benchmark of 0.8, indicating that the data meet the research requirements. Using these data, an evaluation decision matrix **X** is constructed, and the TOPSIS ranking results of the conceptual schemes are shown in Table 11. Conceptual scheme 4 has the largest C_i value. Combined with the sensitivity analysis results in Table 12, Schemes 4 and 5 are the closest to the ideal optimal alternative.

Table 11. TOPSIS results for the conceptual scheme.

Scheme	SA	SD	SS	D^+	D^-	C_i	Rank
1	0.6	0.3	0.7	0.106	0.092	0.466	7
2	0.5	0.5	0.6	0.080	0.084	0.510	5
3	0.6	0.4	0.7	0.084	0.096	0.534	3
4	0.6	0.6	0.5	0.065	0.088	0.576	1
5	0.8	0.7	0.3	0.090	0.115	0.560	2
6	0.6	0.5	0.5	0.078	0.069	0.472	6
7	0.7	0.5	0.5	0.070	0.077	0.527	4

Table 12. Sensitivity analysis results.

Scheme	SA-Oriented	SD-Oriented	SS-Oriented
1	0.439/1	0.316/7	0.632/2
2	0.390/7	0.505/4	0.617/3
3	0.484/4	0.407/6	0.687/1
4	0.501/3	0.666/2	0.536/4
5	0.631/1	0.694/1	0.389/7
6	0.428/6	0.488/5	0.486/6
7	0.572/2	0.511/3	0.512/5

To further enhance the design's agility and innovation, the final scheme, as shown in Figure 17, is developed by taking schemes 4 and 5 as the core and integrating the unique advantages of the other schemes. Its operating principle involves sensors on

the tower frame that continuously collect natural wind data, which is transmitted to the microcontroller installed at the base. The microcontroller then controls the deflecting airflow device to maintain an appropriate angle. While airflow speeds at lower elevations are relatively low, they can be accelerated through multiple directional wind concentrators, making it easier to reach the wind turbine's startup speed and even its rated operating speed. The double-layer wind turbine can more effectively capture wind energy resources, transmitting torque through the wind turbine shaft to the generator at the base. During operation, the generator produces harmful heat, which is conducted through the conduction structure to warm the air in the gaps between the tower frames, enhancing the chimney effect. The solar thermal panels at the top not only provide additional electricity but also help heat the local air. In the future, when flexible solar panels become more affordable, they can be fully installed on the upper surfaces of the directional wind concentrators and variable-angle wind deflectors.

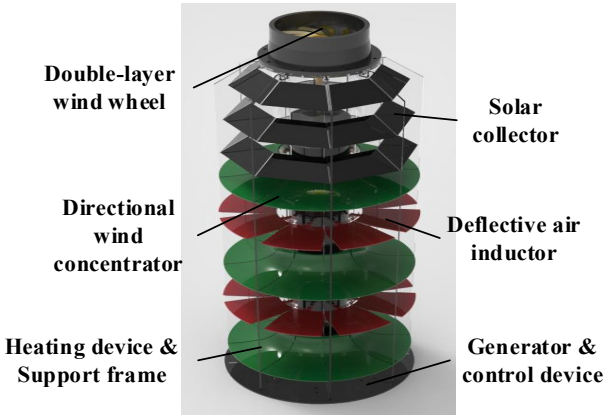


Figure 17. Rendering of the final scheme.

Figure 18 presents the CFD simulation results of the directional wind concentrator. Under preset wind conditions, the directional wind concentrator can effectively increase the wind speed at the outlet and fully utilize the available wind resources. Future work will conduct comprehensive simulations of the overall structure to investigate power-generation efficiency under coupled wind, solar, and thermal conditions.

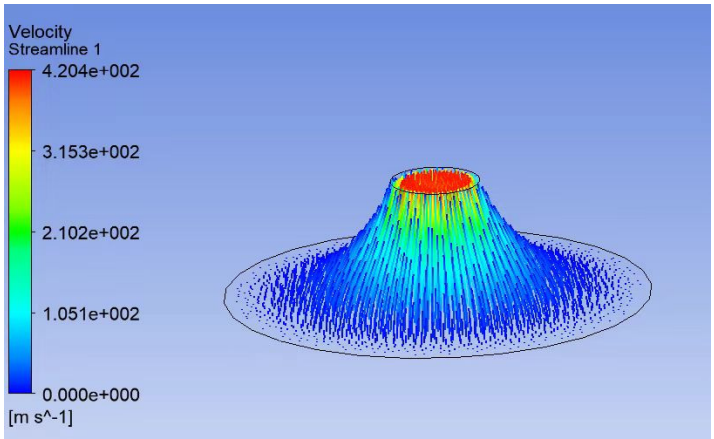


Figure 18. Simulation results of the directional wind concentrator.

The detachable nature of virtual code is the foundation of successful software agile development. Similarly, from the perspective of subsystem composition, the technical differences between the final scheme and existing products were compared. Results are

shown in Table 13. Based on the initial analysis of the shortcomings of VAWT, the agile innovation of the final solution is reflected in the following two aspects: (1) the directional wind collector and chimney structure actively accelerate the natural wind, fully utilizing the low-wind-speed resources near the ground. This helps achieve the fan's starting wind speed, thus extending working time. (2) The directional draft fan can not only adjust the longitudinal inlet angle but also reduce air leakage in the leeward direction.

Table 13. Technical advantages of the final scheme.

System	Existing Product	Final Scheme
Energy sub-system	Unable to perform wind and yaw control, resulting in low wind energy utilization efficiency.	The wind-gathering structure accelerates airflow, with low start-up wind speeds and high safe operating speeds.
Transmission sub-system	The generator is installed on the base, resulting in a longer mechanical transmission path.	Magnetic levitation technology is used in components such as generators and bearings to reduce friction and energy loss.
Working sub-system	Poor self-starting performance and difficult overspeed control.	Equipped with double-layer wind turbines and utilizing solar energy for auxiliary power generation.
Control sub-system	Manual control and information transmission are required.	The variable-direction air deflector's angle can be adjusted in real time, and intelligent algorithms help the fan maintain its ideal operating state.

5. Discussion

5.1. Theoretical Implications

The main theoretical implication of this study is the development of a conceptual design chain linking agile user feedback to TRIZ-based technological evolution through the LT dimension. Previous agile innovation studies mainly emphasized process flexibility, team communication, and rapid iteration. Previous TRIZ studies have provided powerful tools for contradiction analysis and inventive problem solving. LT-dimensional studies have shown that heterogeneous engineering quantities can be represented in a compact physical space. The present study links these streams by treating the LT dimension as a translation layer between informal user language and structured reasoning about technological evolution.

This connection is more than a simple combination of methods. The proposed workflow defines how one method supplies structured input to the next. Fishbone analysis produces a core physical problem; NLP-assisted rules transform this problem into LT dimensions; the BP neural network recommends a technological evolution law; LT similarity retrieves physically relevant cases; structural mapping converts source-case relations into conceptual schemes; and TOPSIS ranks these schemes with a reproducible decision logic. The theoretical contribution, therefore, lies in the coupling mechanism among these tools, rather than in claiming that any single tool is newly invented.

Another theoretical implication is the repositioning of AI in early-stage engineering design. In many AI-assisted design studies, the predictive model is expected to produce highly accurate outputs. This expectation is reasonable in tasks with large datasets and clearly labelled outcomes, but it is often unrealistic in conceptual innovation, where data are scarce, labels are ambiguous, and expert reasoning remains indispensable. This paper, therefore, treats the BP neural network as an auxiliary recommendation mechanism. Its output is useful only when it is consistent with the problem's physical interpretation. This modest positioning makes AI more compatible with engineering reasoning and reduces the risk of black-box design decisions.

The proposed LT mapping mechanism also contributes to conceptual design theory by formalizing the transition from language to physical abstraction. User feedback is usually expressed in natural, sometimes imprecise, language. Designers must interpret this language before any formal method can be applied. The result is not a fully automated semantic understanding system, but a transparent classification procedure that can be inspected and repeated by other design teams.

Finally, the study clarifies the theoretical boundary between concept generation and engineering verification. Conceptual design methods are sometimes criticized for not immediately demonstrating performance improvement. This criticism is understandable, but it overlooks the role of conceptual design in opening promising solution spaces before detailed analysis. The proposed method does not claim to replace simulation or experiment. Instead, it provides a structured front-end process that can feed better-defined candidates into later verification stages. This boundary is essential for a fair evaluation of the paper's contribution. To clearly demonstrate the differences in theoretical emphasis between this paper and other team members' works, Table 14 compares their respective contributions and research limitations.

Table 14. Comparison of works from the same team.

Author and Year	Research Theme	Unique Contributions	Limitations and Gaps
Liu 2019 [69]	Creative design via knowledge clustering and CBR	Integrates C-K theory with CBR to expand search boundaries and handle early-stage design uncertainty.	Innovation is bounded by the existing case library, tending towards incremental rather than radical changes.
Zhang 2023 [68]	Radical concept generation based on tech evolution.	Proactively identifies radical opportunities by using ANN to predict the shift from parasitic to symbiotic technologies.	The extraction of NCF remains subjective, and the model's generalization to highly customized products is untested.
Wang 2024 [56]	Innovative design via radical problem solving.	Uses IFR to transform parameter issues into system-level Radical Problems, significantly enriching the solution space.	The "analogy" step still relies heavily on the designer's intuition and experience to bridge the gap between abstraction and reality.
He 2025 [41]	Rainflow evolution model for complex systems.	Introduces the Fc-Fo-Fa field matrix and energy-based retrieval to de-couple complex system functions.	The rigorous modeling process is time-consuming, making it difficult to meet ultra-fast market response demands.
Proposed method 2026	Agile innovation via LT Dimension and TRIZ.	Bridges user feedback to structural design via NLP-assisted LT mapping, emphasizing rapid iteration and agility.	As an agile approach, it excels in ideation but needs deeper multi-physics simulation to verify concept reliability.

5.2. Practical Implications

From a practical perspective, the proposed method can help design teams respond to user feedback more systematically. In many mechanical product development projects, user complaints are collected continuously, but they are not always systematically converted into engineering problems. Some teams rely heavily on senior designers' experience, while others proceed directly to CAD modifications without clarifying the underlying physical bottleneck. The proposed method provides an intermediate path. It encourages teams to organize feedback, identify physical actions, map them to LT dimensions, and search for structurally relevant analogies before committing to detailed modelling.

The method is especially useful for small and medium-sized manufacturing enterprises that need rapid product iteration but lack large simulation teams or mature digital twin platforms. These enterprises often cannot afford to run detailed simulations for every early-stage idea. A transparent conceptual screening method can help them reduce the number of weak alternatives and focus limited resources on more promising candidates. For larger enterprises, the method can be integrated into existing stage-gate, agile, or digital-twin-based development systems as a front-end concept-generation module.

The required computational resources are modest. The NLP component only needs basic segmentation, keyword extraction, and rule matching. The BP neural network used in this study is small and can be trained on a general personal computer. The TOPSIS calculation can be completed using spreadsheet software or standard numerical tools. Therefore, the barrier to implementation is not mainly computational. The more important requirement is knowledge organization: teams need a curated case base, a clear LT rule library, and evaluators who understand both the product domain and conceptual design criteria.

In practical deployment, the method can be used in three typical scenarios. The first scenario is rapid redesign, in which an existing product receives repeated user complaints and the design team needs several concept alternatives in a short time. The second scenario is cross-domain analogy, where designers hope to borrow solution logic from other mechanical, fluidic, thermal, or control systems. The third scenario is early design review, where several conceptual schemes already exist, but the team needs a transparent ranking procedure before deciding which scheme should enter simulation or prototyping. These scenarios match the strengths of the proposed method.

5.3. Limitations and Future Work

This study has several limitations. First, the BP neural network is trained on only 100 technological evolution cases. Although the manuscript reports the data split, evaluation protocol, and usage boundary, the dataset is still too small to support strong claims about general predictive performance. Future work should expand the case base, balance the distribution of evolution law labels, and compare the BP model with other classifiers such as support vector machines, random forests, and lightweight neural models. Such comparisons would help determine whether the current BP network is the most suitable predictor for LT-based evolution-law recommendation.

Second, the VAWT case remains at the conceptual design level. The selected scheme has not been verified through CFD simulation, wind-tunnel testing, field measurements, or prototype evaluation. This limitation is explicitly acknowledged because the purpose of the paper is to demonstrate a transparent concept-generation method rather than to validate a specific wind-turbine design. Future work should use CFD to examine airflow acceleration, pressure loss, turbulence distribution, and rotor torque. Structural analysis should also be conducted to check the strength and fatigue behavior of the guide shell, duct, and flexible inlet edge.

Despite these limitations, the proposed method provides a useful foundation for agile conceptual innovation in complex mechatronic systems. It is transparent enough to be inspected, lightweight enough to be implemented by ordinary design teams, and structured enough to reduce arbitrary brainstorming. Its main value lies in helping designers move from scattered user feedback to physically meaningful concept alternatives. Future research should strengthen the method through larger datasets, richer case bases, domain-specific verification, and integration with digital twin platforms.

6. Conclusions

This study proposed an LT–TRIZ agile innovation design method for early-stage conceptual design of complex mechatronic systems. The method was developed to address a practical gap in agile mechanical product innovation: user feedback can often be collected rapidly, but it is difficult to transform such feedback into physically meaningful conceptual structures in a transparent and repeatable way. To bridge this gap, the proposed method integrates fishbone-based functional modelling, NLP-assisted LT-dimension classification, BP neural network-based prediction of technological evolution laws, structural mapping, and TOPSIS-based scheme evaluation into a coherent concept-generation workflow.

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References

1. Guderian, C.C.; Bican, P.M.; Riar, F.J.; Chattopadhyay, S. Innovation management in crisis: Patent analytics as a response to the COVID-19 pandemic. *R&D Manag.* **2021**, *51*, 223–239. [CrossRef]
2. Vanpaemel, S.; Kutz, J.N.; Brunton, S.L. Physics-Inspired Data-Driven Modeling of Complex Mechanical Components in Mechatronic Systems. *Mech. Syst. Signal Process.* **2025**, *238*, 113259. [CrossRef]
3. Cano, E.L.; García-Camús, J.M.; Garzás, J.; Moguerza, J.M.; Sánchez, N. A Scrum-based framework for new product development in the non-software industry. *J. Eng. Technol. Manag.* **2021**, *61*, 101634. [CrossRef]
4. Vlăsceanu, A.; Avram, M.; Constantin, V.; Moraru, E. Research on Indoor Positioning Systems and Autonomous Mechatronic Systems for Surveillance of Intrabuilding Zones. *Appl. Sci.* **2025**, *15*, 918. [CrossRef]
5. Dihan, M.S.; Akash, A.I.; Tasneem, Z.; Das, P.; Das, S.K.; Islam, M.R.; Islam, M.; Badal, F.R.; Ali, F.; Ahamed, H.; et al. Digital Twin: Data Exploration, Architecture, Implementation and Future. *Heliyon* **2024**, *10*, e35216. [CrossRef]
6. Cooper, R.G.; Ingby, J.; Källrot, C.; Mott, P.; Vedsmand, T. Agile Innovation in a Manufacturing Company: How Tetra Pak Evolved Its Product Development Process. *Res. Technol. Manag.* **2025**, *68*, 42–51. [CrossRef]
7. Bianchi, M.; Marzi, G.; Guerini, M. Agile, Stage-Gate and their combination: Exploring how they relate to performance in software development. *J. Bus. Res.* **2020**, *110*, 538–553. [CrossRef]
8. Baxter, D.; Turner, N. Why Scrum works in new product development: The role of social capital in managing complexity. *Prod. Plan. Control* **2023**, *34*, 1248–1260. [CrossRef]
9. Andriyani, Y.; Yohanitas, W.A.; Kartika, R.S. Adaptive innovation model design: Integrating agile and open innovation in regional areas innovation. *J. Open Innov. Technol. Mark. Complex.* **2024**, *10*, 100197. [CrossRef]
10. Sharma, S.; Singh, G.; Jones, P.; Kraus, S.; Dwivedi, Y.K. Understanding agile innovation management adoption for SMEs. *IEEE Trans. Eng. Manag.* **2022**, *69*, 3546–3557. [CrossRef]
11. Beitz, W.; Pahl, G.; Grote, K. Engineering Design: A Systematic Approach. *MRS Bull.* **1996**, *71*, 3.

12. Borgianni, Y.; Maccioni, L. Applications of TRIZ in manufacturing environments: A review. *J. Manuf. Syst.* **2020**, *56*, 303–319. [CrossRef]
13. Luo, Y.; Ni, M.; Zhang, F. A design model of FBS based on interval-valued Pythagorean fuzzy sets. *Adv. Eng. Inform.* **2023**, *56*, 101957. [CrossRef]
14. Bushuev, A.; Kudriavtseva, V. Simulation of the block diagrams of the information energy converters. In Proceedings of the International Conference on Innovative Applied Energy (IAPE '19), Oxford, UK, 14–15 March 2019.
15. Zhong, R.Y.; Xu, X.; Klotz, E.; Newman, S.T. Intelligent manufacturing in the context of industry 4.0: A review. *Engineering* **2017**, *3*, 616–630. [CrossRef]
16. Liu, M.; Fang, S.; Dong, H.; Xu, C. Review of digital twin about concepts, technologies, and industrial applications. *J. Manuf. Syst.* **2021**, *58*, 346–361. [CrossRef]
17. Wan, Y.W.; Liao, X.M.; Chen, C.; Wang, Z.W.; Liu, Y. Empowering LLMs by Hybrid Retrieval-Augmented Generation for Domain-Centric Q&A in Smart Manufacturing. *Adv. Eng. Inform.* **2025**, *65*, 103212.
18. Alkhodair, M.; Alkhudhayr, H. Harnessing Industry 4.0 for SMEs: Advancing Smart Manufacturing and Logistics for Sustainable Supply Chains. *Sustainability* **2025**, *17*, 813. [CrossRef]
19. Danneels, E.; Colarelli-O'Connor, G. From New Venture Idea to Viable Business: Breakthrough Innovation Capability in Established Firms. *Technovation* **2025**, *141*, 103186. [CrossRef]
20. Ferrigno, G.; Barabuffi, L.; Marcazzan, D.; Piccaluga, A. What "V" of the Big Data Support Firms' Radical and Incremental Innovation? *Technovation* **2025**, *146*, 103295. [CrossRef]
21. Lichtenthaler, U. A conceptual framework for combining agile and structured innovation processes. *Res. Technol. Manag.* **2020**, *63*, 42–48. [CrossRef]
22. Endres, M.; Bican, P.M.; Wöllner, T. Sustainability meets agile: Using Scrum to develop frugal innovations. *J. Clean. Prod.* **2022**, *347*, 130871. [CrossRef]
23. Annosi, M.C.; Appio, F.P.; Martini, A. Institutional context and agile team innovation: A sensemaking approach to collective knowledge creation. *Technovation* **2024**, *129*, 102894. [CrossRef]
24. Suárez-Gómez, E.D.; Hoyos-Vallejo, C.A. Scalable agile frameworks in large enterprise project portfolio management. *IEEE Access* **2023**, *11*, 98666–98684. [CrossRef]
25. Cooper, R.G. The drivers of success in new-product development. *Ind. Mark. Manag.* **2019**, *76*, 36–47. [CrossRef]
26. Beaumont, M.; Thuriaux-Alemán, B.; Prasad, P.; Hatton, C. Using agile approaches for breakthrough product innovation. *Strategy Leadersh.* **2017**, *45*, 19–25. [CrossRef]
27. Cooper, R.G. Idea-to-Launch Gating Systems: Better, Faster, and More Agile. *Res. Technol. Manag.* **2017**, *60*, 48–52. [CrossRef]
28. Albers, A.; Heimicke, J.; Spadinger, M.; Reiss, N.; Breitschuh, J.; Richter, T.; Bursac, N.; Marthaler, F. A systematic approach to situation-adequate mechatronic system development by ASD-Agile Systems Design. *Procedia CIRP* **2019**, *84*, 1015–1022. [CrossRef]
29. Cubillos, J.; Aponte, J.; Gomez, D.; Rojas, E. Agile Effort Estimation in Colombia: An Assessment and Opportunities for Improvement. *Sci. Comput. Program.* **2024**, *236*, 103115. [CrossRef]
30. Valdés-Rodríguez, Y.; Hochstetter-Diez, J.; Díaz-Arancibia, J.; Cadena-Martínez, R. Towards the Integration of Security Practices in Agile Software Development: A Systematic Mapping Review. *Appl. Sci.* **2023**, *13*, 4578. [CrossRef]
31. Tomaselli, G.P.; Pinto, N.S.; Acuña, C. Requirements Management Methods and Practices for Improving the Quality of Agile Software Development Processes: A Review of the Literature. *Requir. Eng.* **2025**, *30*, 371–398. [CrossRef]
32. Gupta, M.; Digalwar, A.; Gupta, A.; Goyal, A. Integrating Theory of Constraints, Lean and Six Sigma: A Framework Development and Its Application. *Prod. Plan. Control* **2024**, *35*, 238–261. [CrossRef]
33. Fazeli, H.R.; Peng, Q. Generation and Evaluation of Product Concepts by Integrating Extended Axiomatic Design, Quality Function Deployment and Design Structure Matrix. *Adv. Eng. Inform.* **2022**, *54*, 101716. [CrossRef]
34. Leng, J.W.; Guo, J.; Xie, J.; Zhou, X.; Liu, A.; Gu, X.; Mourtzis, D.; Qi, Q.; Liu, Q.; Shen, W.; et al. Review of Manufacturing System Design in the Interplay of Industry 4.0 and Industry 5.0 (Part I): Design Thinking and Modeling Methods. *J. Manuf. Syst.* **2024**, *76*, 158–187. [CrossRef]
35. Hoenig, A.; Roy, K.; Acquaah, Y.T.; Yi, S.; Desai, S.S. Explainable AI for Cyber-Physical Systems: Issues and Challenges. *IEEE Access* **2024**, *12*, 73113–73140. [CrossRef]
36. Li, H.; He, X.; Wu, Y.; Liu, G.; Wang, H.; Wen, X.; Li, L. Digital twin and AI-driven robotic embodied control system: A novel adaptive learning and decision optimization method. *Rob. Comput.-Integr. Manuf.* **2026**, *98*, 103138. [CrossRef]
37. Jiang, S.; Li, W.; Qian, Y.; Zhang, Y.; Luo, J. AutoTRIZ: Automating engineering innovation with TRIZ and large language models. *Adv. Eng. Inform.* **2025**, *65*, 103312. [CrossRef]
38. Mohammadi, A.; Zeng, Y. Enhancing TRIZ through Environment-Based Design Methodology Supported by a Large Language Model. *AI EDAM* **2025**, *39*, e12. [CrossRef]

39. Chen, R.K.; Sheu, D.D.; Sheu, M.Y.; Shi, L. A 3-element structure mapping for enhanced TRIZ problem-solving based on substance-field analysis. *Comput. Ind. Eng.* **2025**, *206*, 111167. [CrossRef]
40. Ghane, M.; Ang, M.C.; Cavallucci, D.; Kadir, R.A.; Ng, K.W.; Sorooshian, S. TRIZ trend of engineering system evolution: A review on applications, benefits, challenges and enhancement with computer-aided aspects. *Comput. Ind. Eng.* **2022**, *174*, 108833. [CrossRef]
41. He, C.; Zhao, M.; Tan, R. Rainflow evolution model: A holistic method of complex product functional design. *Adv. Eng. Inform.* **2025**, *65*, 103162. [CrossRef]
42. Mao, J.; Zhu, Y.; Chen, M.; Chen, G.; Yan, C.; Liu, D. A contradiction solving method for complex product conceptual design based on deep learning and technological evolution patterns. *Adv. Eng. Inform.* **2023**, *55*, 101825. [CrossRef]
43. Cavallucci, D.; Rousselot, F.; Zanni, C. An ontology for TRIZ. *Comput. Ind.* **2021**, *9*, 251–260. [CrossRef]
44. Wei, L.; Yuanyuan, L. A systematic approach for business model innovation in RSWM product service systems by resolving multiple contradictions. *Expert Syst. Appl.* **2025**, *290*, 128367. [CrossRef]
45. Shie, A.-J.; Xu, E.-M.; Ye, Z.-Z.; Ruan, J.-Q.; Yang, G.; Lee, C.-H. Kansei-oriented and artificial intelligence-driven framework for mutual aid elderly care service optimization. *Adv. Eng. Inform.* **2025**, *67*, 103489. [CrossRef]
46. Liu, F.; Deng, Q.; Jing, Y.; Gao, J. Product innovation design methods based on multi-biological knowledge inspiration. *J. Eng. Des.* **2025**, *37*, 741–784. [CrossRef]
47. Wang, X.; Liu, Z. Knowledge graph-based conceptual design of complex mechanical products. *Adv. Eng. Inform.* **2021**, *49*, 101340. [CrossRef]
48. ElMaraghy, W.; ElMaraghy, H.; Tomiyama, T.; Monostori, L. Complexity in engineering design and manufacturing. *CIRP Ann.* **2012**, *61*, 793–814. [CrossRef]
49. Buisson, C.-A.; Cardou, P.; Fréchette, A. Quantitative comparison of cable models through dimensional analysis. *Mech. Mach. Theory* **2025**, *214*, 106130. [CrossRef]
50. Jurij, K. Estimation of transportation energy efficiency by Bartini criterion L6T-4. *Archit. Eng.* **2017**, *2*, 15–19.
51. Bushuev, A. Numerical Estimation of the Energy Information Circuits of Measurement Devices. *Meas. Tech.* **2017**, *60*, 857–862. [CrossRef]
52. Kotikov, J. Formation of a function series for estimates of transportation energy efficiency based on Bartini's LT-table entities. *Archit. Eng.* **2018**, *3*, 3–9.
53. Rajić, D. Innovative synergism as a result of TRIZ and LT-system synthesis. In Proceedings of the International Conference on TRIZ, Heilbronn, Germany, 11–14 September 2019; pp. 226–242.
54. Kuznetsov, O.; Bolshakov, B. Russian cosmism, global crisis, sustainable development. *Proj. Baikal* **2013**, *1*, 112–139.
55. Zheng, P.; Lin, T.J.; Chen, C.H.; Xu, X. A systematic design approach for service innovation of smart product-service systems. *J. Clean. Prod.* **2018**, *201*, 657–667. [CrossRef]
56. Wang, F.; Tan, R.; Wang, K.; Cen, S.; Peng, Q. Innovative product design based on radical problem solving. *Comput. Ind. Eng.* **2024**, *189*, 109941. [CrossRef]
57. Grieves, M.; Vickers, J. Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In *Transdisciplinary Perspectives on Complex Systems*; Springer: Cham, Switzerland, 2017; pp. 85–113. [CrossRef]
58. Leng, J.; Wang, D.; Shen, W.; Li, X.; Liu, Q.; Chen, X. Digital twins-based smart manufacturing system design in Industry 4.0: A review. *J. Manuf. Syst.* **2021**, *60*, 119–137. [CrossRef]
59. Luo, T.; Wu, C.; Duan, L. Fishbone diagram and risk matrix analysis method and its application in safety assessment of natural gas spherical tank. *J. Clean. Prod.* **2018**, *174*, 296–304. [CrossRef]
60. Wang, K.; Tan, R.; Peng, Q.; Zhang, L.; Wang, F. A systematic problem analysis network for product conceptual design. *Comput. Ind. Eng.* **2024**, *194*, 110382. [CrossRef]
61. Zhang, H.; Miao, J.; Liu, Z.; Wesson, I.L.; Shang, J. NLPIR-Parser: Making Chinese and English semantic analysis easier and complete. In Proceedings of the 15th International Conference on the Statistical Analysis of Textual Data, Toulouse, France, 16–19 June 2020.
62. Wang, K.; Tan, R.; Peng, Q.; Zhang, L. Evaluation of design innovation using the length-time dimension and regression analysis. *J. Mech. Sci. Technol.* **2022**, *36*, 5625–5637. [CrossRef]
63. Huang, J.; Wen, Z.; Xiao, X. Extended Levenberg-Marquardt method for composite function minimization. *J. Comput. Math.* **2017**, *35*, 529–546. [CrossRef]
64. Liu, H.; Li, Y.; Chen, J.; Tao, Y.; Xia, W. A structure mapping-based representation of knowledge transfer in conceptual design process. *Proc. Inst. Mech. Eng. Part B J. Eng. Manuf.* **2020**, *234*, 400–420.
65. Wang, K.; Tan, R.; Peng, Q. Product Improvement Using Knowledge Mining and Effect Analogy. *Appl. Sci.* **2024**, *14*, 3699. [CrossRef]
66. Sun, J.G.; Li, G.Q.; Zhang, K.X.; Zheng, Y.; Li, H.Y.; Wang, K. Collaborative innovation design process model based on OPM. *Comput. Integr. Manuf. Syst.* **2024**, *30*, 3019–3037. (In Chinese)

67. Han, F.; Alkhawaji, R.N.; Shafieezadeh, M.M. Evaluating sustainable water management strategies using TOPSIS and fuzzy TOPSIS methods. *Appl. Water Sci.* **2025**, *15*, 4. [CrossRef]
68. Zhang, L.; Tan, R.; Peng, Q.; Yang, W.; Zhang, J.; Wang, K. A holistic method for radical concept generation based on technological evolution: A case application of DC charging pile. *Comput. Ind. Eng.* **2023**, *179*, 109213. [CrossRef]
69. Liu, W.; Tan, R.; Cao, G.; Yu, F.; Li, H. Creative design through knowledge clustering and case-based reasoning. *Eng. Comput.* **2020**, *36*, 527–541. [CrossRef]
70. Metsämuuronen, J. Typology of deflation-corrected estimators of reliability. *Front. Psychol.* **2022**, *13*, 891959. [CrossRef]
71. Cazzaro, D.; Bedon, G.; Pisinger, D. Vertical axis wind turbine layout optimization. *Energies* **2023**, *16*, 2697. [CrossRef]
72. Azadani, L. Vertical axis wind turbines in cluster configurations. *Ocean Eng.* **2023**, *272*, 113855. [CrossRef]

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