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Article

Innovative application of deep learning and genetic algorithm based on biomechanics in enterprise economics and audit management

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Abstract: With the increasing demand for enterprise economic management in complex and dynamic environments, the interdisciplinary application of biomechanics has shown significant potential. This article explores the innovative practices of genetic algorithms and deep learning in optimizing enterprise economic management. Genetic algorithm simulates biological evolution mechanisms such as natural selection and genetic variation to achieve multi-dimensional and multi-level optimization of enterprise economic models, improving decision-making efficiency and adaptability. Deep learning draws on the structural characteristics of biological neural networks to solve problems such as insufficient data and model overfitting, optimizing the intelligence level of resource allocation, performance evaluation, and strategic planning in enterprise management. On this basis, this paper introduces the concept of biomechanics to further improve the adaptability and efficiency of the model. Biomechanics emphasizes the movement and adaptability of organisms in complex environments, which provides a new perspective for corporate economic management. By simulating the dynamic adjustment mechanism of organisms in the face of external pressure, enterprises can respond to market changes more flexibly and optimize resource allocation and decision-making processes. In addition, this article proposes a comprehensive framework that combines multi-level genetic algorithms and deep learning, and verifies its effectiveness in dynamic market environments through case studies. Research has shown that biomechanics not only provides theoretical support for enterprise economic management, but also offers efficient and sustainable pathways for solving complex economic problems. By incorporating the inspiration of biomechanics into the optimization practice of corporate economic management, enterprises can better adapt to market changes, improve the flexibility and efficiency of decision-making, and point the way for future economic management innovation.

Keywords: new situation; enterprise model management; deep learning; model driven; biomechanics

1. Introduction

In the complex and ever-changing economic environment, innovation and optimization of enterprise economic management have become increasingly important. The traditional management model is difficult to cope with the challenges of resource allocation, decision-making efficiency, and sustainable development in today's dynamic market [1–4]. In terms of resource allocation, it often fails to distribute assets optimally, leading to waste and inefficiency. When it comes to decision-making efficiency, slow and cumbersome processes delay crucial choices, causing missed opportunities. And with regard to sustainable development, the old ways lack the foresight to balance short-term gains with long-term ecological and social responsibilities. This makes it extremely difficult for enterprises relying on such models to thrive and remain competitive in today's dynamic market. Therefore, finding new technological means to enhance the intelligence level of enterprise economic management has become the key. In the current business landscape, enterprises are constantly striving to gain an edge, and technological augmentation of management practices is no longer a luxury but a necessity. In recent years, biomechanics has been widely applied in multiple fields due to its unique adaptability and evolution, among which genetic algorithms and deep learning are particularly prominent [5,6]. Genetic algorithms, inspired by the principles of natural selection and evolution, can sift through vast amounts of data to find optimal solutions for resource allocation and decision-making. Deep learning, on the other hand, mimics the complex neural networks of living organisms to analyze patterns and predict future trends, providing invaluable insights for strategic planning and performance evaluation within enterprises.

Genetic algorithm simulates the mechanisms of natural selection, genetic variation, and survival of the fittest in biological evolution, and can efficiently find the optimal solution in a multidimensional search space. It acts like a highly efficient navigator in the vast sea of enterprise data, meticulously sifting through countless possibilities. This technology can be used in enterprise economic management to optimize complex decision models, such as resource allocation, cost control, and risk assessment. For instance, in resource allocation, it ensures that every asset is put to its most productive use, minimizing waste. On the other hand, deep learning, by simulating the structure and function of biological neural networks, has significant advantages in processing large-scale data with nonlinear modeling capabilities, especially when faced with insufficient data and complex relationships. It's as if it has an innate ability to fill in the gaps and make sense of chaos. Combining weakly supervised learning and meta learning technologies, deep learning provides more intelligent solutions for enterprises in situations of data scarcity [7–10]. When dealing with sporadic customer demand data or fluctuating market trend information, it can still extract valuable insights, guiding enterprises to make shrewd decisions and stay ahead in the competitive market.

In today's digital age, the role of algorithms in corporate operations has expanded exponentially. This algorithmic methodology, leveraging the power of advanced technologies, delves deep into the analysis of the motivation expressed by applicants. When it comes to written applications, through natural language processing [11], it can dissect the text, picking up on nuances, intentions, and underlying drives that might otherwise go unnoticed. During video interviews, it extends its reach to scrutinize facial expressions, capturing micro-expressions and emotional cues that could reveal an applicant's true enthusiasm or hesitation. Moreover, this algorithm doesn't stop at candidate evaluation. It also takes on the task of providing managers and staff with performance comments. By crunching through vast amounts of data related to work outputs, deadlines met, and collaborative efforts, it formulates feedback that is meant to be objective and constructive. However, as algorithms increasingly permeate corporate decision-making, a critical question looms large: is algorithm-based decision-making truly as accurate and objective as we expect it to be? Algorithmic decision-making, despite its seeming efficiency, is not without flaws, just like any other human-devised method. Consider the perspective of job seekers. What must they think when they encounter a corporation that resorts to technology to automate a significant portion of the interview and personnel selection process? It could potentially make them feel like just another data point, devoid of the human touch that a traditional interview might offer. For employees, when they receive performance reviews generated automatically rather than directly from supervisors, their reactions could vary widely. Some might question the authenticity and fairness of the feedback, while others might struggle to connect with the impersonal nature of it. And then there's the issue of tolerance. How much will workers put up with this kind of automated feedback before they start to disengage? Equally important is understanding how much managers truly rely on algorithms when making crucial choices. These complex and intertwined issues form the crux of what this paper must meticulously address [12].

During the early stages of statistical science's growth, a time when technological advancements were still in their infancy, handling large amounts of data was an insurmountable challenge due to the lack of computers [13]. Researchers and practitioners were confined to a world of limited computational resources, forcing them to adopt rather rudimentary yet ingenious methods. We can only create hypothetical mathematical models, painstakingly constructing frameworks that aimed to approximate the real-world phenomena as closely as possible. Then came the arduous task of performing manual calculations, often spending hours, if not days, crunching numbers with pen and paper. After making mathematical assumptions, such as independent and normal distribution for the background distribution of a small amount of data, they would infer certain properties of the results derived from these models. This involved meticulously calculating the confidence interval, a range within which the true value was likely to lie, and assessing the unbiased and consistency of the value of the hypothesis test, crucial aspects for validating the reliability of the findings. However, reality seldom adheres strictly to our assumptions. When the data is far from the mathematical assumption, a new set of strategies came into play. People resorted to the central limit theorem or various large sample theorems, leveraging these theoretical tools to obtain some similar properties when the sample size tends to infinity. It was a race against the odds, as statisticians strived to extract meaningful insights from data that was often messy and unruly, laying the foundation for the evolution of statistical science and its ever-expanding role in diverse fields, much like the parallel development of algorithms in corporate decision-making.

With the progress of the times, researchers gradually set up courses such as data mining and machine learning, and statistical magazines began to pay more attention to these studies. Many of these algorithm models are not described by closed mathematical formulas, but reflected in computer algorithms or programs, as shown in **Figure 1** that the risk of results is not the *p* value obtained by assuming distribution, it is described by the error of cross validation of test sets that do not participate in modeling training.

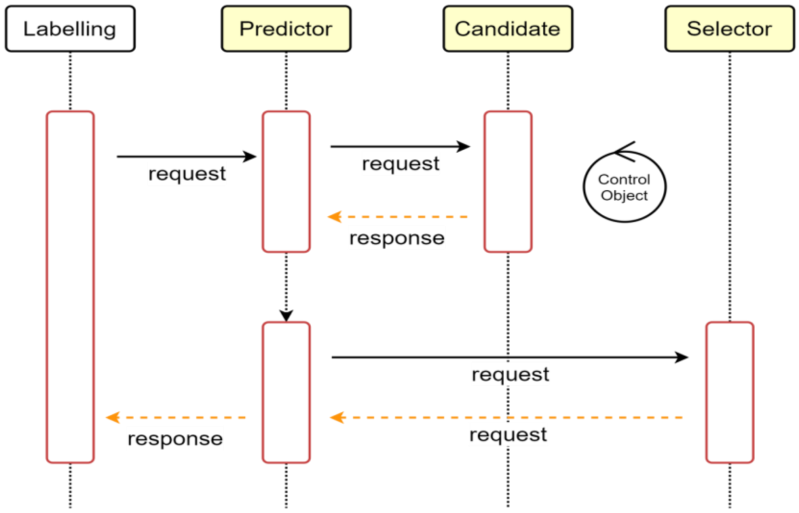

Figure 1. Active deep learning and algorithm allocation.

By flowcharting or demonstrating how active deep learning dynamically chooses data and techniques to enhance model performance while avoiding overfitting through cross-validation, **Figure 1** may offer a more dependable mechanism for model evaluation than conventional statistical methods.

In this context, the rise of model driven and algorithm allocation is also accompanied by solutions to the lack of deep learning label samples. At present, the field of deep learning has conducted in-depth and extensive research on the problem of insufficient labeled samples mainly from four aspects: sample utilization, network structure, optimization process, activation function and so on [14,15]. Improving the use of samples is one of the most common methods for the shortage of labeled samples, mainly including meta learning, weak supervised learning, data enhancement and so on. The active deep learning described in this paper is often classified as weak supervised learning or semi supervised learning. It is worth noting that although many research results such as small samples or meta learning have emerged at present, because of the opposition between small samples and a large number of parameters of neural networks, many studies may still need a very difficult way to be practical. Therefore, how to label samples is also a bottleneck problem for the continued prosperity of current deep learning. Relatively speaking, the research of annotation strategy is closer to reality and easier to implement than the direct realization of small sample learning.

2. Methods

Currently, the innovation and practice of enterprise economic management revolve around model change. Through a number of model transformations, the abstract model can be transformed into the object code or specific model. Create a model initialization first, then convert it using specific conversion rules as part of the model-driven software development process. After that, refine it according to the particular platform before turning it into code. This chapter suggests a hybrid model transformation approach, which is based on the one and one suggested in the prior two chapters. A one-to-one relational model transformation method is suggested based on the theory of specification and first-order predicate logic in order to address the heterogeneity of model transformation. A model transformation method from one to the target language is proposed based on the text template evolution method. In addition, this paper also provides a model synchronization mechanism based on model version for the above model transformation methods [16,17].

2.1. Model transformation principle

After the training, the deployment and application of the deep learning model in the production environment is very important. As shown in **Figure 2** that the trained model can not only accept the test of some public data sets and lists, but also need to create value in the real business scenario, not just lie on the experimental machine for pr.

In addition, the binary relationship described by relationships should meet the following properties:

1) The source model is the definition domain of the relationship, and the target model is the value domain of the relationship;
2) The non redundant nature of the relationship. $\forall e \in R, f \in R$, if $dom(e) = dom(f)$, and $ran(e) = ran(f)$, be e=f.

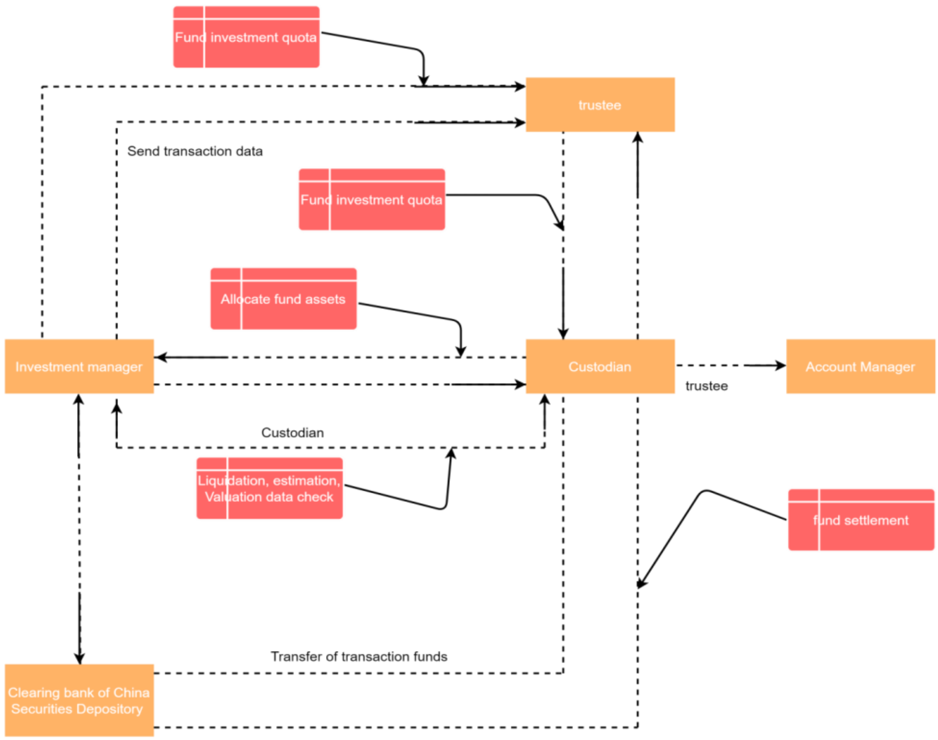

Figure 2. Model transformation principle from platform independent business model to platform related business component model.

2.2. Model transformation principle

Onnx data types have two formal variables, which are different in the supported data types and supported calculation units. For the supported data types, the onnx tensor is defined as input and output types only [18,19]. The classic automatic learning extension onnx ml can also recognize sequences and maps [20,21]. For the enterprise economic management model, the transformation rules from business entity to business model are very important. As shown in the **Figure 3**:

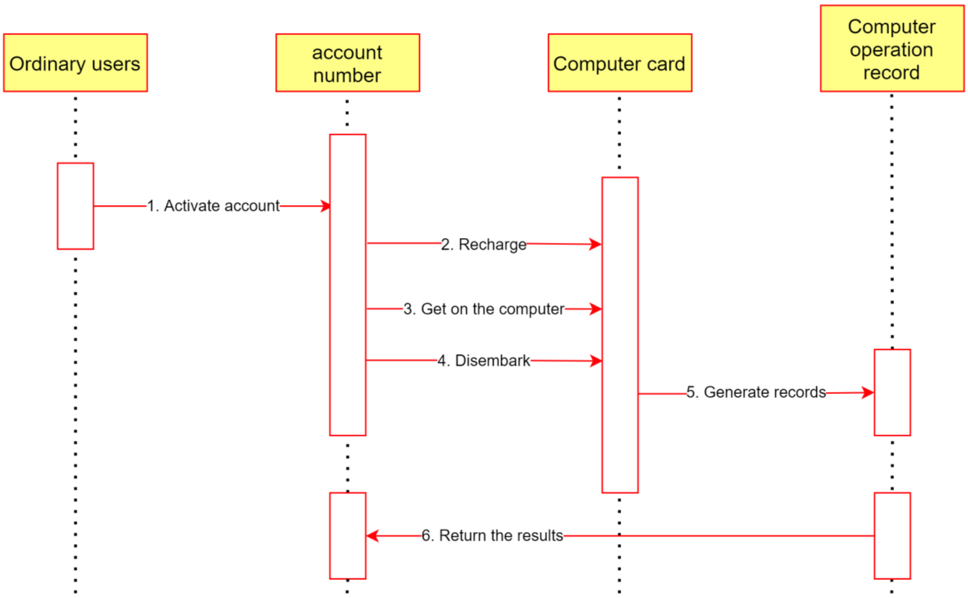

Figure 3. Model transformation relationship from business entity in pm bm to Bo in psm-bc.

Its conversion methods mainly include the following two types:

1) Conversion of entity type

Each entity type is converted to a relational schema. Entity attribute is the attribute of relationship, and entity knowledge is the key of relationship.

2) Transformation of contact point type

A. The relationship between entities is 1:1. You can add the attributes of keys and connection types of other relational schemas to the attributes of any relational schema that converts two entities into a relational schema.

B. If the relationship between entities is 1:n, the relationship mode key and relationship type attribute of the n-side entity type conversion are added to the relationship mode of the first side entity type conversion.

If the connection between entities is m:n, the connection type is also converted to relational mode. Its characteristics are: in addition to the characteristics of communication type, it also has two-way entity type keys and key insertion composed of two ends of entity keys. Its technical structure is as follows.

3. Case study

Under the new situation, the overall design goal of model driven enterprise economic management model algorithm is to provide a model driven software rapid development platform, take pim-bm as the output and target language as the output, and realize the method of model conversion and model synchronization between pim-bm and psm-bc codes [2,3].

3.1. Platform architecture

As shown in **Figure 4**, the MD Insider platform is divided into model data storage layer, model access layer, model definition layer model transformation layer, transformation rule layer [4].

1) The model data storage layer uses content warehouse to store the model;
2) The model access layer realizes the management of models, including basic operations such as model check-in and check-out;
3) The definition layer of the model gives the meta models of pim-bm and psm-bc;
4) The model transformation layer realizes the model transformation and model synchronization between pmbm, psm-bc and code;
5) The transformation rule layer realizes the parsing and execution of transformation rules described in QVT relations language, and the parsing and execution of template statements in template files.

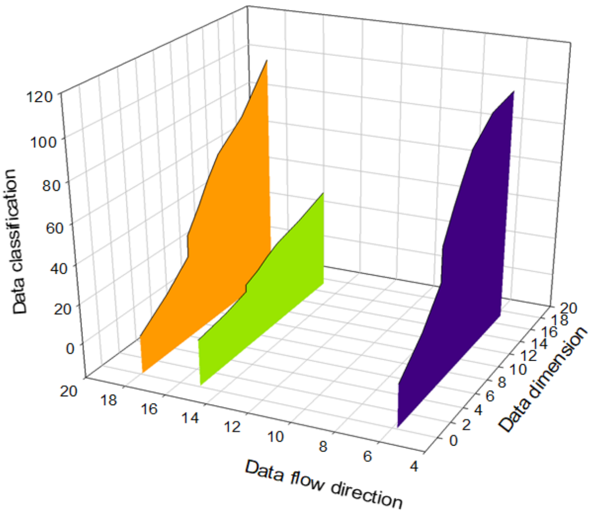

Figure 4. MD Insider platform architecture.

Furthermore, in the platform model, forwarding the task and asking other edge clouds to process the user's tasks is necessary if the service capacity of the edge cloud closest to the user is saturated and there is no way to meet the user's needs. Additionally, when data sharing and information interaction between the edge clouds are necessary, multi-hopping in the platform is also required to meet the needs. In order to centralize management and distribution, SDN technology divides the platform network's control layer from its data layer, merges different resources, and increases the network's flexibility. Its business flow scheduling method is shown in the **Table 1**:

Table 1. Schematic diagram of business flow scheduling method.

Input: TT traffic set s, link set E, time slot set and path set
Output: unscheduled rate of TT business flow
1: sum = 0
2: for $\forall \lambda_k \in S$ do
3: for $\forall \varepsilon_{i,j} \in R'_{\lambda_k}$

Table 1. (*Continued*).

Input: TT traffic set s, link set E, time slot set and path set
Output: unscheduled rate of TT business flow
4: Follow the constraint formula (41) to formula (43) to search the business flow λ K transmission time on the link t
5: Change the time limit status of the corresponding link, change the value to 1, record the time limit and link number used, and add them to the set of Linxia and otld
6: if $t \leq$ deadine $- \Delta t_{in} - \Delta t_x$
7: continue
8: else
9: Restore the link slot state changed during the scheduling of this service flow to the unused state
10: sum++
11: re tum sum

3.2. Functional components

By calculating the degree of acquaintance between samples, the ones with high degree of acquaintance are divided into one category. There are several ways to measure the degree of familiarity between samples:

1) Minkowski distance is the normal form distance mentioned above

When $p = 1$ is Manhattan distance, the formula is as follows (take two-dimensional space as an example):

$$d = |x_1 - x_2| + |y_1 - y_2| \quad (1)$$

2) When $p = 2$, it is Euclidean distance, and the formula is as follows:

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (2)$$

3) When $p =$ is infinite, it is the Chebyshev distance, and the formula is as follows:

$$d = max(|x_1 - x_2|, |y_1 - y_2| \quad (3)$$

Generally, Euclidean distance is used more. When the data volume is flattened, cheff snow distance is generally used. After selecting the optimization distance of genetic algorithm, the quantity and quality of its data flow have been significantly improved, as shown in the **Figure 5**:

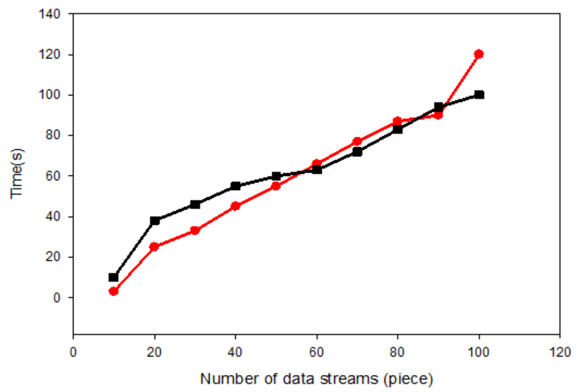

Figure 5. Schematic diagram of data flow quantity under genetic algorithm optimization.

Multiple network elements, such as terminals, routers, access devices, etc., can send data through the functional unit traffic scenario. Each of these elements corresponds to a node. Any two nodes can communicate with one another via a single hop or several hops. Every routing node has multiple neighboring nodes. It is capable of mutual communication as long as it is within the transmission range. This research uses Secure Network Communications (SNC) to determine the upper bound of the business flow's backlog length and random delay based on an analysis of the basic series network topology. **Figure 6** depicts the functional components research scenario:

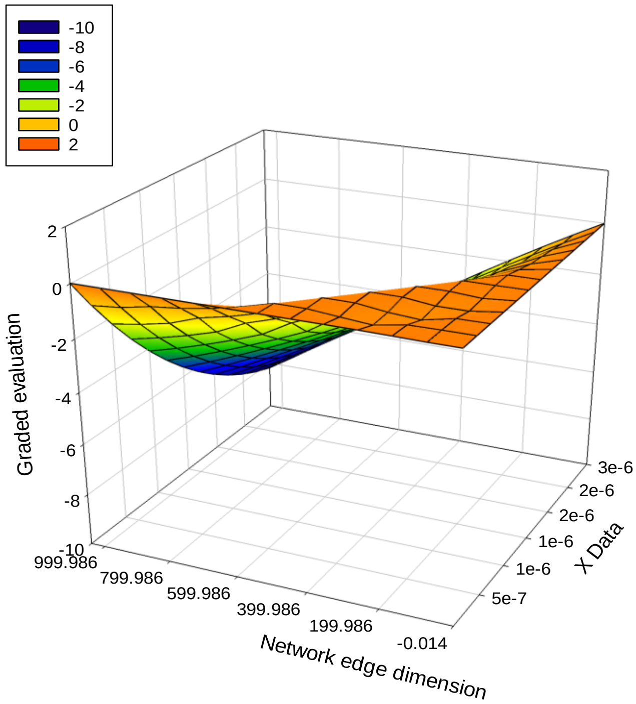

Figure 6. Schematic diagram of mobile edge cloud network structure.

The arrival process of business flow and the service process of agents in the model platform network are mathematically modeled in this article using SNC as a tool. The path through the flow into the service chain is abstracted in this work using a mathematical model, and the agents on the path are abstracted into the service chain nodes. The remaining two service data flows are considered the interference data flow if in this study, whereas the three services mentioned above are considered the through flow TF. The arrival process and the received service process are examined when they are considered to be the through flow.

3.3. Mathematical model

In this section, MGF in SNC is used as an analysis tool. The analysis process of a single business flow is shown in the figure below. In the **Figure 7**, z-flow represents the through flow TF, and X-Flow and y-flow represent the interference flow if. The solution idea of this paper is as follows. Firstly, this paper obtains the cumulative interference data that affects TF on a single node, and uses the aggregation flow theorem in SNC to merge the cumulative interference data of if; Then, using the residual service theorem in SNC, the service process obtained by TF on a single node is obtained; Then, using the concatenation property in SNC, all single node service processes in the service chain are equivalent to a whole.

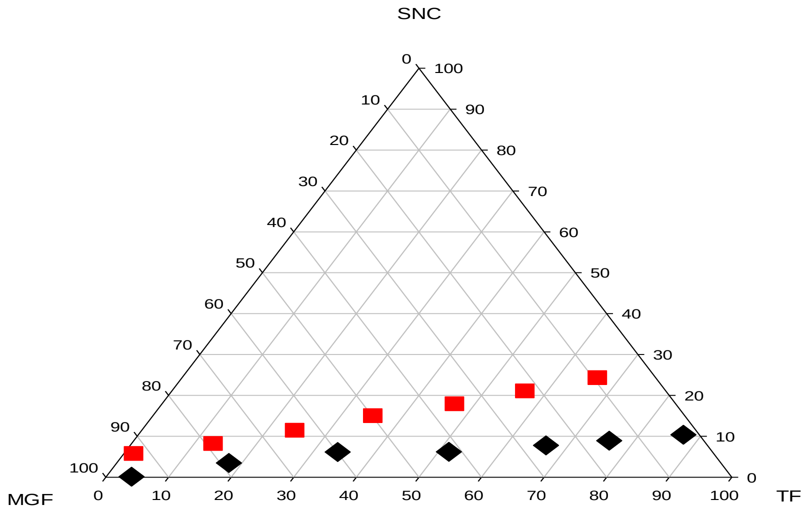

Figure 7. Schematic diagram of mathematical model when economic data flow is used as through flow.

4. Discussion

In today's rapidly evolving business landscape, enterprises face increasing complexity and dynamic challenges. The demand for effective economic management strategies has never been greater. Traditional approaches often struggle to keep pace with the speed of change, leading to a growing interest in interdisciplinary applications that can enhance decision-making and operational efficiency. Among these, the integration of biomechanics into enterprise economic management presents a compelling opportunity. By leveraging insights from biological systems, businesses can develop more adaptable and efficient management practices.

Biomechanics, the study of the mechanical principles of living organisms, offers valuable insights into how entities adapt and respond to their environments. In nature, organisms continuously adjust their movements and strategies to survive and thrive amidst external pressures. This adaptability is crucial for success in complex environments, and it serves as a powerful metaphor for the challenges faced by modern enterprises. By applying the principles of biomechanics, businesses can emulate the dynamic adjustment mechanisms observed in biological systems. For instance, just as animals alter their behavior in response to changes in their surroundings, organizations can enhance their responsiveness to market fluctuations. This perspective encourages a shift from static, rigid management approaches to more fluid, flexible strategies that prioritize adaptability. The innovative practices of genetic algorithms and deep learning are at the forefront of this interdisciplinary exploration. Genetic algorithms, inspired by the process of natural selection, allow organizations to optimize economic models by simulating evolutionary processes. This method enables enterprises to explore a vast solution space, identifying optimal strategies through iterative improvements. By mimicking biological evolution, companies can achieve multidimensional optimization, enhancing decision-making efficiency and adaptability. Similarly, deep learning draws on the structural characteristics of biological neural networks. These advanced algorithms excel at processing large datasets and identifying patterns, making them invaluable for resource allocation, performance evaluation, and strategic planning. However, one of the significant challenges in using deep learning is the risk of overfitting, particularly when data is limited. Here, the principles of biomechanics can inform the design of more robust models that maintain flexibility while minimizing the risk of overfitting [6].

The introduction of biomechanics into enterprise economic management can significantly enhance adaptability. Organizations can implement dynamic adjustment mechanisms similar to those found in biological systems. For example, businesses can develop feedback loops that allow for real-time adjustments based on market conditions. This approach mirrors how organisms continuously assess their environment and modify their behavior accordingly. Moreover, the concept of resilience, a key aspect of biomechanics, can be applied to organizational structures. Resilient organizations are those that can withstand shocks and adapt to changes without losing their core functionality. By fostering a culture of resilience, companies can better navigate uncertainties and maintain stability in the face of challenges. Several case studies illustrate the effectiveness of integrating biomechanics with genetic algorithms and deep learning in enterprise economic management. For instance, a manufacturing company adopted a genetic algorithm to optimize its supply chain operations. By simulating various scenarios and adjusting parameters dynamically, the company improved its inventory management and reduced costs. The ability to adapt to changing demand patterns was crucial in maintaining competitiveness. In another example, a tech startup utilized deep learning to analyze customer behavior and preferences. By incorporating feedback mechanisms akin to those observed in biological systems, the startup was able to refine its product offerings and enhance customer satisfaction. This adaptability not only improved sales but also fostered customer loyalty, demonstrating the practical benefits of biomechanical insights.

The proposed comprehensive framework that combines multi-level genetic algorithms and deep learning is a significant advancement in this field. By integrating these methodologies, organizations can create a synergistic approach that enhances both optimization and adaptability. This framework enables businesses to leverage the strengths of each technique while mitigating their weaknesses. For instance, genetic algorithms can guide the overall optimization process, while deep learning models provide the necessary intelligence for real-time decision-making. This combination allows enterprises to remain agile in dynamic market environments, responding swiftly to changes and capitalizing on new opportunities. While the integration of biomechanics into enterprise economic management offers promising avenues for innovation, it is not without challenges. One significant hurdle is the need for interdisciplinary collaboration. Effective implementation requires expertise from both biological sciences and business management. Organizations must foster an environment that encourages collaboration across disciplines to fully realize the potential of these innovative practices. Additionally, data availability and quality remain critical factors. For deep learning models to be effective, they require large, high-quality datasets. Organizations must invest in data collection and management to ensure that their models are well-informed and capable of making accurate predictions.

Incorporating biomechanics into enterprise economic management represents a paradigm shift in how organizations approach decision-making and adaptability. By drawing on the principles of biological systems, businesses can enhance their resilience, optimize their operations, and respond more effectively to the complexities of the modern market. The innovative practices of genetic algorithms and deep learning, when combined with biomechanical insights, offer a powerful framework for navigating the challenges of today's dynamic environments. As enterprises continue to seek sustainable pathways for solving complex economic problems, the lessons learned from biomechanics will become increasingly relevant. By embracing this interdisciplinary approach, organizations can not only improve their performance but also pave the way for future innovations in economic management. The journey toward a more adaptable and efficient business landscape is just beginning, and the potential for growth and transformation is immense.

5. Conclusion

In the current scenario, it is more crucial to optimize enterprise economic models and algorithms in order to increase the overall strength of businesses. In light of this, this paper primarily uses current market businesses as its research object, business management as its primary research topic, algorithm model reform and mathematical model innovation as its research directions, and conducts a number of analyses and investigations. First, a model for the economic model platform network that introduces TSN technology is built using graph theory. Next, the data model of TT business flow is established based on the certainty needs of TT business flow in the economic model platform network. Together with the TSN switch and TT business flow characteristics, the restrictions in four areas are determined, and the optimization objective of this study is to minimize the unplanned rate of TT business flow. Due to the complexity of the aforementioned problem, this work splits it into two pieces, scheduling and routing, each of which is optimized. In terms of routing, this paper suggests taking into account both the route's length and the link's remaining bandwidth in detail. It also calculates the weights of these two factors and illustrates how network size affects the enterprise economic model's unscheduled business flow rate and the laborious algorithm optimization.

Ethical approval: Not applicable.

Data availability: The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflict of interest: The author declares no conflict of interest.

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