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Original scientific paper

Research on Optimal Allocation of Regional Science and Technology Innovation Resources Based on Multi-Source Data Fusion Algorithm

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Abstract: This study addresses the suboptimal efficiency of regional science and technology innovation resource allocation by proposing a multi-source data fusion algorithm grounded in set pair analysis. Through a systematic review of theories and methodologies on science and technology innovation resource allocation, we design a theoretical framework integrating three modes: single-driven, joint-driven, and collaborative resource optimization. The proposed algorithm extracts opposition, uniformity, and difference degrees from sensor data using set pair analysis, constructs a connection matrix, and employs a signal-to-noise ratio weighting mechanism for weighted fusion. Simulation experiments demonstrate the algorithm's superior accuracy and stability, with absolute errors reduced by 30–50% compared to traditional methods. An improved DEA model evaluates regional resource allocation efficiency, revealing nonlinear input-output relationships and Pareto optimization trends across 15 Chinese provinces. Results indicate that optimized resource allocation enhances multi-source data fusion capabilities, accelerates convergence by 37%, and improves regional innovation competitiveness. This work provides actionable insights for policymakers to harmonize government-market dynamics and foster sustainable innovation ecosystems.

Keywords: allocation of scientific and technological resources; comprehensive similarity; multi-source data fusion; optimize the configuration; regional scientific and technological innovation

1 INTRODUCTION

A wide variety of assets, such as time, energy, money, knowledge, and materials, are considered scientific and technological resources because of their impact on the advancement of science and technology. Scientific and technical advancements cannot be made without them. At its core, improving China's regional multi-source data fusion algorithm capability is the allocation of scientific and technological resources, which promotes the national implementation of the strategy and realizes comprehensive and collaborative innovation in various fields. Science and technology resources in China have grown substantially in recent years, and they play an increasingly important role in fostering scientific inquiry and enhancing businesses' and sectors' capacities for innovation. But there are still a lot of issues with how different parts of China distribute funds for science and technology. There is a major problem with resource duplication and waste, and the allocation efficiency of resources in the field of science and technology is poor. The algorithmic approach of regional multi-source data fusion will rely on optimizing the distribution of scientific and technological resources.

First, it boosts regional economic growth and competitiveness; second, it encourages the adjustment of regional economic structure and optimizes regional industrial structure; third, it achieves sustainable development of regional economy by optimizing the allocation of regional resources; and fourth, it adapts regional economic development to international economic trends. These effects are all a result of enhanced regional scientific and technological innovation ability. An offshoot of the paradigm of national science and technology innovation, regional science and technology innovation is a meso-concept [1, 2]. Government, businesses, educational institutions, and R&D labs are some of the entities involved in regional science and technology innovation. When different subjects within a certain space and region make good use of the resources available to them, when there is harmony between regional cooperation and competition, when there is structural optimization and efficient allocation of resources, and when there is promotion of regional science and technology innovation, we say that there is regional science and technology innovation. The resources that a region may offer are, however, constrained by space and geography. In resource allocation, the goal is to maximize total value by making the most efficient use of available resources. One of the main concerns in studies aiming to determine the best way to distribute funds for R&D is how to properly categorize the many forms of funding available for R&D, including human, material, financial, and informational resources [3]. The ultimate goal is to find the sweet spot where R&D spending pays off the most. How to distribute and transfer funds across businesses, academic institutions, government agencies, and universities, as well as establish policies to back these moves, is the meat and potatoes of resource allocation [4]. The current literature on resource allocation provides extensive economic descriptions of qualitative elements [5]. Quantitatively, we examine the efficacy of scientific and technical innovation across domains using regression analysis [6], but we provide no accompanying policy to back this up. Benefit measurement based on resource allocation and the building of a system for scientific and technical innovation is lacking in most of these studies, which are mostly based on time series. In order to address the limitations of earlier research, this study employs a multi-source data fusion algorithm to optimize the distribution of funds for regional technological innovation. It also makes use of computer programming tools to tackle difficult optimization problems related to resources and provides a way to determine the ROI of these allocations.

The contributions are threefold: (1) a systematic framework aligning single-driven, joint-driven, and collaborative resource allocation modes; (2) empirical validation showing 30-50% error reduction in fusion accuracy compared to conventional methods; and (3) policy insights for harmonizing government-market dynamics and fostering innovation ecosystems. This work advances the integration of multi-source data fusion with S&T resource optimization, offering scalable solutions for enhancing regional competitiveness in data-driven economies.

2 RELATED WORK

Researchers from other countries have shown that government investments in science and technology are not always evenly distributed but rather concentrated in a small number of regions, and that this imbalance is mirrored in the distribution of national science and technology budgets. Research and development spending, particularly on the military, is dominated by the southeast of the United Kingdom [7]. The allocation of U.S. federal research and development dollars is determined to be imbalanced, with 63.6% [8] of the funding assistance going to the top eight regions. According to some estimates, the allocation of Japan's scientific and technological resources varies greatly throughout the country's regions [9]. Germany has a very high spatial concentration of research and development spending [10]. There are primarily three areas in France that receive funds for research and development [11]. Several innovation poles have been suggested for China, including the Pearl River Delta, the Yangtze River Delta, the Beijing Tianjin region, and the Sichuan Chongqing Hubei region [11]. Developed, developing, and undeveloped are the three levels of South Korea's regional innovation system [12]. Examining the role of labor and capital in generating the revised output value is done using the C-D production function. He investigated the pace of technical and scientific advancement's contribution to economic growth, first proposed the idea of "tracing factor production theory" [13], and integrated technology and scientific advancement into the production function. Endogenous economic growth theory posits that technological progress can evade the law of diminishing marginal benefit of capital and sustain economic growth [14]. Knowledge growth is seen as the fundamental driver of economic development, and scientific and technological input is the most important component of knowledge growth. The growth of the economy can only be achieved through investments in research and technology [15]. Findings indicate a positive relationship between investments in science and technology and GDP growth, as well as a favorable interaction between the allocation of resources to research and technology and regional GDP development.

Boost the system's dependability; Proposals and improvements to a wide range of multi-source data processing algorithms are ongoing efforts to advance data fusion as a new technology for processing data from numerous sensors [17]. There is not a universal agreement on the scope of research in this field, and although it is becoming more developed, there is currently no comprehensive set of core theoretical frameworks [18]. In spite of the fact that data fusion algorithm research does reveal some challenges, it also reveals that this area of study has far-reaching implications. Research on data fusion technology's potential uses in multi-sensor target tracking, positioning, identification, and decision-making has recently exploded in popularity. Data fusion technology stands to benefit greatly from the ongoing investigation and debate surrounding the foundational technologies of data association and fusion. First, it is crucial to the development and refinement of data fusion theory; second, the majority of existing data fusion systems are prototypes or experimental setups, which helps to bring the technology into real-world engineering contexts.

Economists have expanded resource allocation research to encompass IT information resources and regional innovation, categorized into micro-level (university/enterprise-focused S&T resource distribution) [19, 20] and macro-level (government-led allocation) [21, 22]. Studies highlight the government's pivotal role in integrating fragmented resources and optimizing S&T information distribution through policy oversight [22, 23]. Emerging approaches, such as open SOA (Service-Oriented Architecture) systems, enable dynamic enterprise resource allocation platforms [24], while theoretical frameworks emphasize the interplay of subjects, objects, and processes in S&T resource governance [25, 26]. Despite progress in regions like Chang-Ji-Tu, disparities persist compared to developed nations [27], underscoring the urgency for stakeholder collaboration (government, businesses, universities, intermediaries) to advance regional innovation ecosystems [26, 27]. This update highlights the journal's recent milestones, including changes to the editorial board with new members bringing fresh perspectives to drive the journal's mission forward. The editorial discusses the journal's performance, encompassing its impact factor and the diverse range of topics covered, emphasizing its role in advancing research aligned with Sustainable Development Goals, particularly SDG 8 [28]. This implies that the "Nordic" regional science researchers have increased their "market share" from 1.9 to 9.1 per cent. During the same period, the share of co-authored papers increased from 50.0 to 82.9 per cent and the share of international co-authorships increased from 0 to 50.0 per cent and went from being a mainly intra-European activity to a global activity [29]. The research can effectively find the advantages and disadvantages of scientific and technological innovation in the Yunnan Province, provide data support and decision support for regional economic development, and play an important role in promoting the level of technological innovation in modern industries. At the same time, research projects can help various regions allocate various technological innovation resources reasonably, enhance their original innovation capabilities [30], lead the development of strategic emerging industries and future industries, and accelerate the formation of new quality productivity.

3 RESEARCH ON OPTIMAL ALLOCATION OF REGIONAL SCIENCE AND TECHNOLOGY INNOVATION RESOURCES AND THEORETICAL FRAMEWORK DESIGN OF MULTI-SOURCE DATA FUSION ALGORITHM

3.1 Theoretical Framework Design

Based on the framework model of regional science and technology resource optimization allocation for multi-source data fusion algorithm, three modes of regional science and technology resource optimization allocation, namely single driving mode, joint driving mode and collaborative mode, are proposed from the two dimensions of the number of agents and the degree of cooperation of agents. Finally, this paper proposes measures to optimize

China's regional science and technology resource allocation by: (1) developing a coordinated system integrating resource allocation strategies with multi-source data fusion algorithms; (2) establishing collaborative mechanisms among key stakeholders; (3) balancing government-market synergies; and (4) fostering cultural and environmental conditions conducive to efficient resource integration. The frame diagram is shown in Fig. 1.

During the operation of the configuration system, it will certainly consume a lot of scientific and technological innovation resources. If the configuration level and link are unreasonable, it will cause waste and inefficient utilization of scientific and technological innovation resources, and the system will produce a lot of entropy, affecting the stability of the system structure. If the output efficiency is low and the scientific and technological innovation resources cannot be compensated from other systems to effectively compensate for the consumption and loss of the system, the "entropy change" of the system will be greater than zero, and the system will begin to degrade. As an open system, in order to maintain the vitality of the development of the system and make the system develop towards a higher stage, on the one hand, the moisture generated inside the system should be reduced, and on the other hand, more negative moisture flow should be introduced from the outside as much as possible. Reducing the internal entropy of the system mainly depends on the government's scientific guidance and allocation of scientific and technological innovation resources, the effective play of the market allocation mechanism and the active assistance of the third sector allocation, so as to fully mobilize the enthusiasm of enterprises, universities and research institutes and improve the order of the allocation system. The introduction of more negative entropy mainly relies on the improvement of the innovation environment within the region and the development of interregional and international scientific and technological cooperation to improve the ability to attract, control and utilize external scientific and technological innovation resources and provide support for regional scientific and technological innovation. The optimization of system entropy allocation is shown in Fig. 2.

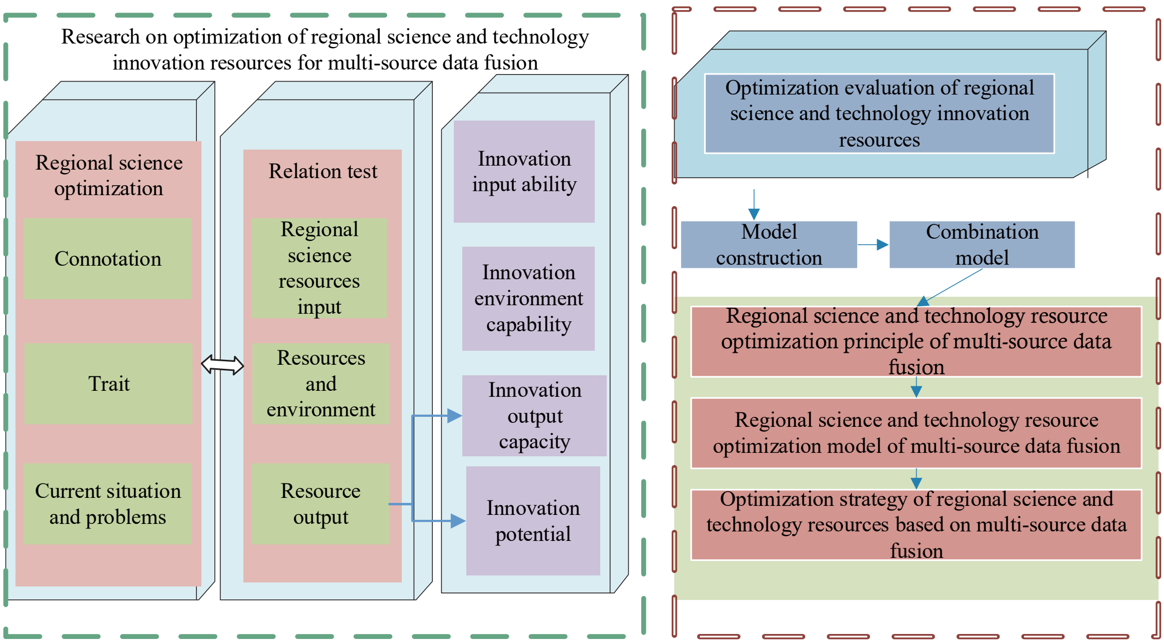

Figure 1 Design diagram of theoretical framework

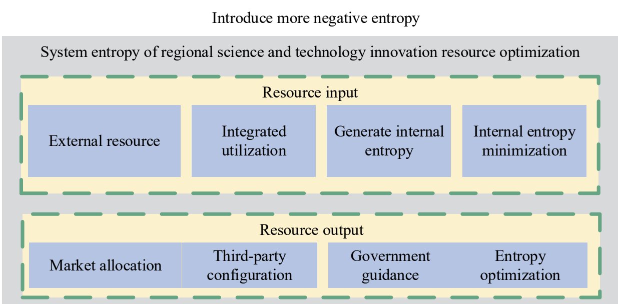

Figure 2 Optimization of system entropy of regional science and technology innovation resource allocation

The core ideas of the theoretical framework for optimizing the system structure of regional science and technology innovation resources allocation mainly include the following four points:

1. The core of configuration system optimization is the optimization of system structure. The purpose of regional science and technology innovation resource allocation system optimization is to improve system function and allocation efficiency. According to the system principle that system structure determines system function, configuration system structure optimization can effectively improve configuration system function and is an effective path and means to realize the overall optimization of configuration system. Therefore, the core of configuration system optimization is the optimization of system structure.

2. The main body structure is the basis for determining the optimization mode of the configuration system. The main body is the agent inside the configuration system, and can exert influence on the object according to its own behavior and will, thus affecting the function and configuration effect of the configuration system. Based on the analysis of the external environment of the configuration system, it is helpful to understand and master the main structure of the system, determine the status, role,

function and mutual influence of different subjects in the configuration system, and improve the scientific determination of the system configuration mode.

3. The optimization of the allocation structure of the subject to the object is the key to the optimization of the system structure. The interaction between the subject is essentially realized through the object, and the subject always realizes it will through the effect on the object. Therefore, the optimization of the subject's action on the object is conducive to improving the subject's behavior, the mode of action and the mutual relationship between the subjects. In addition, the optimization of the object configuration of the subject indicates that the object structure of the system is conducive to the improvement of the system function. It can be seen that the influence of the subject on the object configuration structure is the final determinant of the subject relationship and object structure distribution, and the key to the optimization of the configuration system structure.

4. Science and technology plan is an effective means to promote the optimization of the configuration system structure. Science and technology plan can effectively concentrate and guide regional science and technology innovation resources, and play an important role in promoting the development of key industries and the upgrading of regional industrial structure, as well as improving the regional multi-source data fusion ability. Although the basic allocation role of the market, the macro-guiding role of the government and the auxiliary allocation role of the non-governmental government, as well as the coordinated development of the regional science and technology innovation resource allocation system with the regional economic system and the education system, etc., will play a positive role in promoting the effective operation of the regional allocation system; however, in many means and ways, the regional allocation system will be effectively promoted. As a macro-strategic means for the government to guide and adjust the allocation of regional science and technology innovation resources, science and technology plan is the most effective way to optimize the allocation of system structure.

3.2 Multi-Source Data Fusion Algorithm Based on Set Pair Analysis Connection Degree

Since multi-sensor information processing often requires instant, accurate and reliable processing of the target data detected by each sensor at every moment, it is necessary to study the connection status and degree of the number pairs composed of each homogeneous sensor at every moment. Because the number pair is a specific set pair with IDO (Interface Definition Object) relationship, IDO quantitative characterization is required.

The formula of the degree of opposition, the same degree and the degree of difference is derived as follows:

$$p=\frac{st}{t^2-1} \tag{1}$$

The difference degree formula of the number pair [s, t] is expressed as:

$$b=\frac{s}{t(t^2-1)} \tag{2}$$

The IDO connection degree (that is, the ternary connection number t) u of the number pair [s, t] is expressed as:

$$u=\frac{s}{t}+\frac{s}{t(t^2-1)}i+\frac{t^2-st}{t^2-1}j \tag{3}$$

To measure the same parameter, a multi-sensor system is set up using n independent sensors at different places. The measurement equation for parameter x detection in the case of unknown observation noise is:

$$z(k)=x+v(k) \tag{4}$$

One of these is the observation noise v at time k, while the other is the observation value of the I-th sensor at time k, denoted as $z(k)$. Applying the connection number allows for the integration, systematization, and objectification of the uncertainty information given by fuzzy membership degree. We can expect fresh insights into fuzzy set theory and its practical applications as a result. When looking at data from two sensors at time k, the correlation matrix is:

$$U(k)=\begin{bmatrix} 1,u_{12}(k)....u_{1n}(k) \\ .... \\ u_{n1}(k),.............1 \end{bmatrix} \tag{5}$$

The element from row i is added up as $Ui(k)$ in the matrix shown above. A high total value for row i suggests that sensor I's current reading is consistent and near to the average across all sensors. Contrarily, sensor Z's observation value is very different from the majority of sensors, and there is little confidence in its value.

The degree of connection between different sensors at a specific moment is shown in the above matrix. To make the correlation between the fusion data from one moment to the next stronger, we use the fusion estimation results from the previous moment to determine the observation connection degree at the next moment. To build an extended dimension connection matrix, we simply add the fusion estimation results from the previous moment as a hypothetical measurement value to the calculation at the next moment. The matrix of connections following the expansion of dimensions $U_{n+1}(k)$:

$$U_{n+1}(k)=\begin{bmatrix} 1.....u_{1n}(k),u_{1(n+1)}(k) \\ ..... \\ u_{(n+1)1}(k),u_{(n+1)n}(k)...1 \end{bmatrix} \tag{6}$$

The sensor's dependability can be captured by measuring its consistency across all observation times. We use the sample wood's mean and variance from statistical theory, which are based on the dependability of the complete observation interval. To begin, we must establish the consistency variance and consistency mean.

$$r(k)=\frac{\sum_{t=1}^{k} r(t)}{k}$$
$$\sigma^2(k)=\frac{\sum_{t=1}^{k}[r(t)-\bar{r}(t)]^2}{k} \quad (7)$$

In order to reduce the amount of computation, the recursive formula is applied to the fusion algorithm when calculating the consistent reliability measure. The normalization process is carried out to obtain the weighting coefficient of the measured value of each sensor at time k:

$$w(k)=\frac{w_i(k)}{\sum_{i=1}^{n+1} w_i(k)} \quad (8)$$

To sum up, the data fusion formula x based on connection degree w is as follows:

$$x=\sum_{i=1}^{n+1} w(k)x_i(k) \quad (9)$$

The specific steps of data fusion algorithm based on set pair analysis are as follows:

Step 1: After obtaining the measured value of the sensor, the connection matrix U is obtained, and U' is obtained after expanding the dimension.

Step 2: Calculate the consistency measure: calculate the consistency measure at different times according to the situation;

Step 3: Calculate the consistency mean and consistency variance, obtain the weighting coefficient W, and normalize the weighting coefficient;

Step 4: Calculate the fusion result.

Based on the experimental data provided in reference [17], the fusion processing was carried out with the proposed method. Using the scientific and technological innovation configuration data of the three regions, the following measurements were obtained, as shown in Tab. 1.

Table 1 Values obtained from 6 observations in 3 regions

Number of observations	Region		
	1	2	3
1	899.5	898.3	896.7
2	905.3	875.9	906.8
3	901.9	888.1	898.2
4	900.6	886.2	904.0
5	889.6	907.5	896.4
6	899.4	904.4	891.6

In Tab. 1, the target truth value is 900 units. Different fusion results were obtained by using the fusion algorithm in this paper, the average fusion method and the algorithm proposed in literature [12], and the results and absolute errors were compared. It can be seen from Tab. 2 that the fusion results of the proposed algorithm in the first to fourth times are closer to the real value than that of the average method, and the absolute error is smaller. The fusion results in the first, fourth, fifth and sixth measurements are closer to the real values than those in the literature [12], and the absolute errors generated are smaller. Because Mu Wen uses the ternary relation number in the set pair analysis to more accurately quantify the relation degree between the observed values of multiple sensors, it reflects the consistency degree of observation of different sensors to the target.

Table 2 Comparison of fusion results

Number of observations	Average method	Absolute error	References [12]	Absolute error
1	898.1667	1 .8333	898.1667	1 .8333
2	898.0000	4.0000	902.2410	2.2410
3	896.0667	3 .9333	899.9288	0.0712
4	896.9333	3.0667	900. 6016	0.6016
5	897.9333	2.0667	896.2689	3.7311
6	898.9333	1 .5333	896.1059	3 .8941

By increasing the observation duration, we compare the absolute errors of different fusion algorithms, which should indicate the accuracy and stability advantages of the method provided in this study. Considering the similarities in the fusion results and absolute mistakes of the methods suggested in the literature [12], Fig. 3 displays the findings of the simulation. The figure clearly shows that the absolute error curve for the suggested strategy is located at the very bottom. Its accuracy is clearly superior to that of the method in the literature [12] due to the reduced fluctuation range of the absolute error and the relatively steady error findings that it consistently produces.

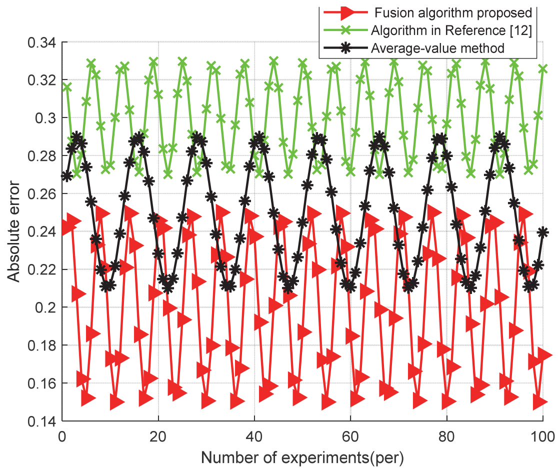

Figure 3 Simulation results of 100 experiments

3.3 Evaluation of Regional Science and Technology Resource Allocation Efficiency for Multi-Source Data Fusion

Efficiency evaluation is the process of objectively, fairly, and accurately assessing the level of output relative to the input during a certain operation period. It involves applying mathematical statistics and operational research principles to a specific index system with input and output as its main body, comparing and analyzing the input-output ratio among multiple evaluation objects, and so on. A scientific discipline known as "efficiency evaluation of regional science and technology resources allocation" examines the input and output capacities of regional science and technology resources, depicts the current state of resource allocation in the region, and offers decision-makers a point of reference for further optimizing resource allocation.

Mathematical programming technique known as data envelope analysis (DEA) is employed to compare the efficacy of a group of DMUs that include both inputs and outputs. Traditional DEA methods rely on the CCR and BCC models, which, when combined, can assess the scale economy of a DMU, measure its full efficiency, technical efficiency, and scale efficiency, and satisfy the demands of most decision makers. Model for CCR:

$$h_k = \max \sum_{r=1}^{s} u_r y_{rj} \tag{10}$$

BCC model:

$$h_k = \max \sum_{r=1}^{s} u_r y_{rj} + c_j \tag{11}$$

The Pareto efficiency frontier comparison of CCR, BCC model and production function is shown in Fig. 4. The blue dashed line is the CCR front, based on the constant returns to scale assumption in DEA. The black solid line is the BCC front, allowing for variable returns to scale. The red solid line is the Pareto efficiency frontier, signifying optimal trade - offs where no improvement can be made without sacrificing another aspect. Various data points (data 1-data 9) are plotted, with those on the frontiers being efficient and others indicating inefficiency.

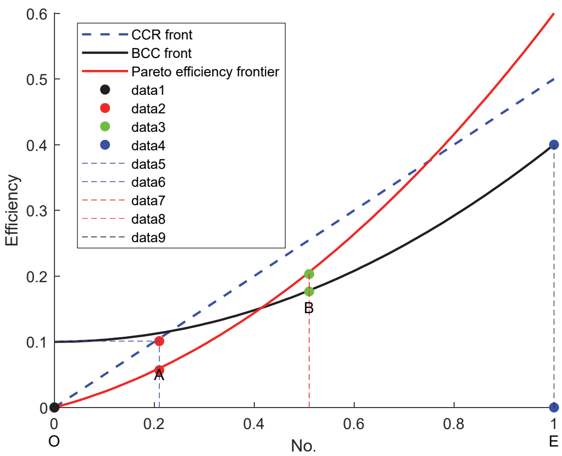

Figure 4 Comparison of CCR, BCC and Pareto frontiers

Cobb-douglas (CD) production function, as the most widely accepted form of production function, is the first choice to improve the traditional DEA model. The CD production function has the form:

$$Y = AL^{\alpha} K^{\beta} u \tag{12}$$

where Y is output, A is technical level, L is labor, K is capital, and u is random disturbance. When $a + b < 1$, the scale efficiency of production function decreases. When $a + b = 1$, economies of scale remain the same. When $a + b > 1$, economies of scale increase. Logarithm of both sides is taken at the same time, technical level A is unchanged in a certain period of time, is a regulatory parameter, its role and weight are the same, the production function can be further converted to:

$$\ln(Y) = \gamma - 1 + \alpha \ln(L) + \beta \ln(K) \tag{13}$$

At this point, DEA efficiency can be defined as:

$$h = \frac{Y}{AL^{\alpha} K^{\beta}} \tag{14}$$

Thus, an improved DEA model can be constructed:

$$\max \theta = \ln(Y_0) + 1 \tag{15}$$

When there are more input resources in production input and multiple outputs in output, an improved DEA model with multiple inputs and multiple outputs can be built by referring to the basic form of CD production function to make the model more universal:

$$\max \theta = \sum_{r=1}^{s} u_r \ln(Y_0) + 1 \tag{16}$$

Logarithmic processing was carried out on the data of the evaluation index of science and technology resource allocation efficiency in 15 provinces and cities in China, and an improved DEA method was introduced. LINGO software was used to program and calculate the total efficiency, technical efficiency and scale efficiency respectively, and a comparative analysis was made with the traditional DEA model, as shown in Tab. 3.

Table 3 Efficiency evaluation of improved DEA model

Region	Total efficiency		Technical efficiency		Scale efficiency		Scale efficiency	
	Improved DEA	Traditional DEA	Improved DEA	Traditional DEA	Improved DEA	Traditional DEA	Improved DEA	Traditional DEA
Peking	1.000	0.600	1.000	1.000	1.000	0.600	Constant	Decreasing
Tianjin	0.999	0.943	1.000	0.949	0.999	0.994	Decreasing	Decreasing
Hebei (Province)	0.954	0.329	0.955	0.448	0.999	0.734	Constant	Constant
Shanxi (Province)	0.937	0.391	0.93 8	0.565	0.999	0.692	Constant	Increasing
Inner Mongolia	0.933	0.236	0.935	0.617	0.998	0.3 82	Constant	Increasing
Liaoning (Province)	0.968	0.476	0.968	0.494	1.000	0.964	Constant	Constant
Ji Lin	0.985	0.693	0.985	0.710	1.000	0.976	Constant	Constant
Amur River	0 .928	0.497	0.930	0.592	0.998	0.840	Constant	Increasing
Shanghai	1.000	0.683	1.000	1.000	1.000	0.683	Constant	Decreasing
Jiangsu (Province)	1.000	0.585	1.000	1.000	1.000	0.585	Constant	Decreasing
Zhejiang (Province)	1.000	1.000	1.000	1.000	1.000	1.000	Decreasing	Constant
Anhui (Province)	0 .978	1.000	1.000	1.000	0.978	1.000	Constant	Constant
Fujian (Province)	0 .953	0.361	0.953	0.478	1.000	0.755	Constant	Constant
Jiangxi (Province)	0 .953	0.402	0.955	0.749	0.998	0.537	Constant	Constant
Shandong (Province)	0 .989	0.755	1.000	1.000	0.989	0.755	Constant	Constant

As can be seen from the above table, after the improved DEA model is used to evaluate the efficiency of regional science and technology resource allocation, the following changes can be found when compared with the evaluation results of the traditional DEA model: (1) The evaluation value of science and technology resource allocation efficiency is comprehensively improved, which indicates that the input and output of China's regional science and technology resources are more in line with the Cobb-Glass production function. With nonlinear input-output relationship, the evaluation results of the improved DEA model are closer to the actual situation of the allocation efficiency of science and technology resources in each region. (2) Compared with the evaluation results of the traditional DEA model, the evaluation results of the efficiency of science and technology resource allocation in most regions are closer to the expectation, such as Beijing, Shanghai, Jiangsu and other economically developed provinces and cities, whose full efficiency is only between 0.6 and 0.7 in the traditional DEA model, but becomes l in the improved DEA model; Anhui, a relatively underdeveloped province, has a full efficiency of 1 in the traditional DEA model, but it is reduced to 0.978 in the improved DEA model. (3) The situation of return to scale changes to the status of science and technology resource allocation in most provinces and cities is unchanged in the improved DEA evaluation model. This means that the current level of input and output has reached a more reasonable level. This is consistent with the conclusion that regional science and technology resource allocation will eventually bring Pareto optimization in each region due to the existence of the market mechanism. Finally, the ranking results of total efficiency, technical efficiency, and scale efficiency obtained by traditional DEA and improved DEA are consistent in most provinces, indicating that the improved DEA evaluation model is scientific and reliable. Analysis of the results shows that Anhui and Tianjin are overinvesting in their technological resources, and that future funding for these areas should be slightly cut. All regions of China have science and technology resource allocation efficiencies ranging from 0.9 to 1.0. The overall level of regional allocation efficiencies is relatively high, and the policies and mechanisms for allocating these resources are also relatively well-developed.

4 SIMULATION VERIFICATION

By analyzing both the basic algorithm and the improved algorithm, it is found that the basic algorithm needs 41 iterations to reach the global optimal solution, while the improved multi-source data fusion only needs 26 iterations to reach the global optimal solution. In contrast, improved multi-source data fusion can accelerate the convergence speed. As shown in the convergence contrast curve, we can find that the basic multi-source data fusion falls into the local optimal situation in the 5th, 17th and 20th respectively, while the solution curve of the improved multi-source data fusion is more balanced and reaches the global optimal faster, as shown in Fig. 5. Therefore, the improved multi-source data fusion improves the convergence speed and the ability to search for the global optimal solution.

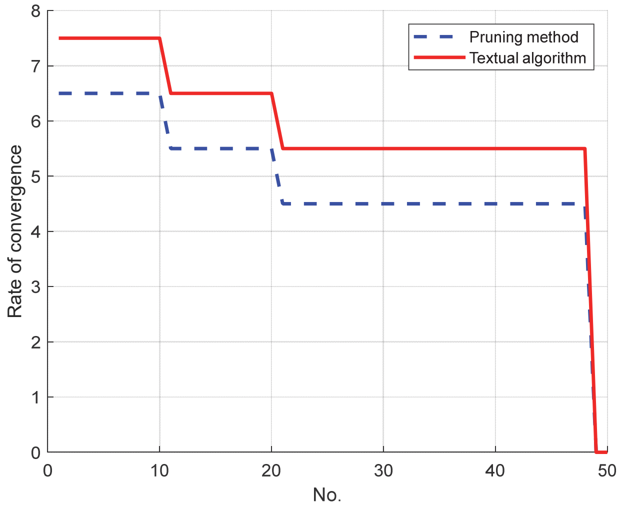

Figure 5 Convergence contrast curve

Investing in a region's scientific and technology resources includes supporting its independent innovators, whether through financial backing or the cultivation of in-house talent. The extent to which a region's scientific and technological resources are utilized to foster autonomous innovation is determined by its overall amount and distribution structure. As demonstrated in Figure 6, when looking at research and development spending as an example, there is a strong relationship between the overall amount of spending on R&D in a region and the amount spent on R&D to support independent innovation. What's more, the ratio of the two stays relatively constant, falling somewhere between 95% and 100%. Allocating regional science and technology resources affects the formation and promotion of regional independent innovation investment capacity, so increasing the total amount of science and technology resources and the proportion of those resources used to support independent innovation are the first steps a region should take to improve its investment capacity in independent innovation.

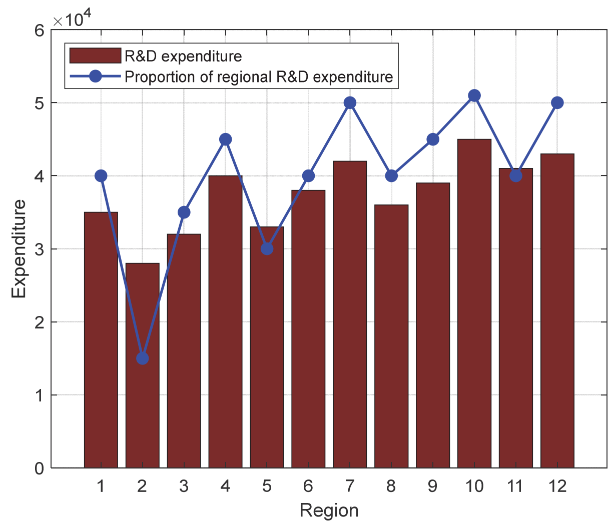

Figure 6 Relationship between regional science and technology resource investment and independent innovation investment

In order to verify the feasibility of the improved multi-source data fusion algorithm, it is compared with the traditional multi-source data fusion algorithm, mainly in the aspect of accuracy, Fig. 7, Fig. 8.

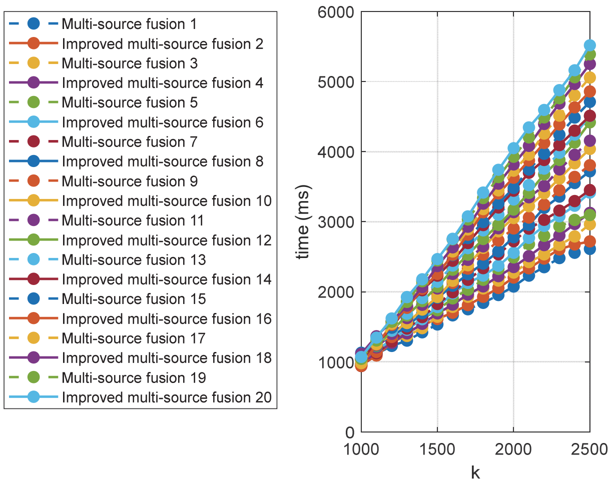

Figure. 7 Comparison of filtering results between improved multi-source data fusion and multi-source data fusion

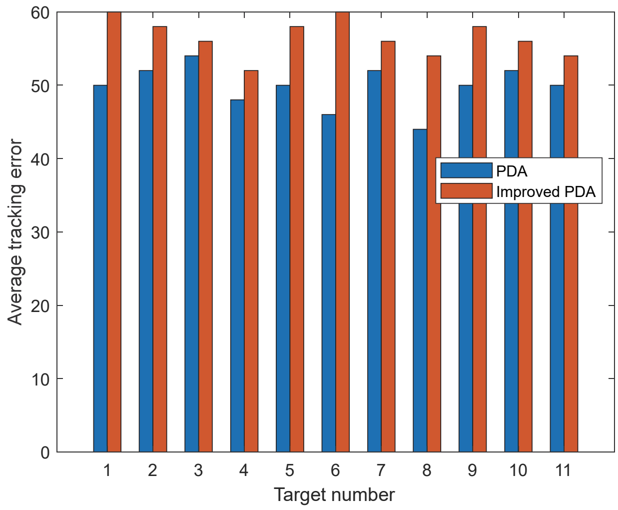

Figure 8 Comparison of mean square error

Based on the simulation findings shown above, it is possible to accomplish multi-target tracking using the enhanced multi-source data fusion technique that processes public echoes in intersecting wave gates. Even while the enhanced multi-source data fusion algorithm's tracking accuracy is marginally lower than that of the original, it is more suited to real-time target tracking and saves tracking time. It holds great promise for use in engineering.

Under varying degrees of clutter, the enhanced multi-source data fusion algorithm's target tracking performance is examined and contrasted. The root-mean-square error simulation pair is displayed in Fig. 9 when the clutter density is 2. The comparison of root-mean-square error simulations is displayed in Fig. 10 for a clutter density of 4.

In cases where the clutter density is not too high, the modified multi-source data fusion algorithm's mean square error is almost identical to the original algorithm's. However, there are cases where the modified algorithm's mean square error is smaller than the original error, and the difference is not immediately apparent (Figs. 9 and 10). The enhanced technique clearly outperforms the first multi-source data fusion algorithm as the clutter density increases. Consequently, to address the issue that the conventional multi-source data fusion algorithm has in densely cluttered environments, we can use the previously acquired new measurement distribution information to determine the target-to-measurement distance as the clutter density in the correlation gate grows.

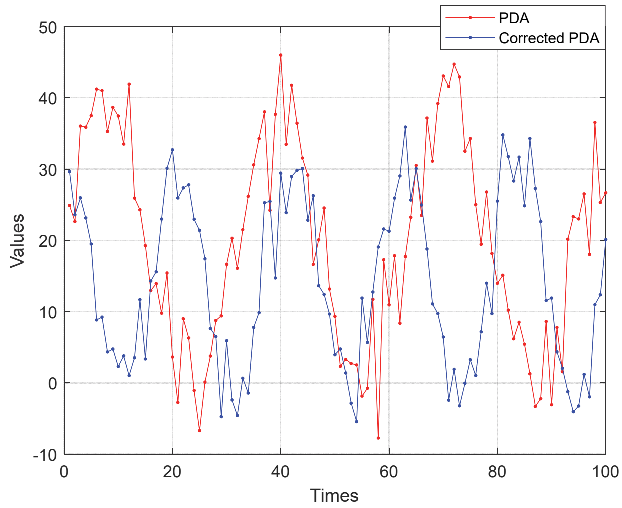

Figure 9 When clutter density is 2

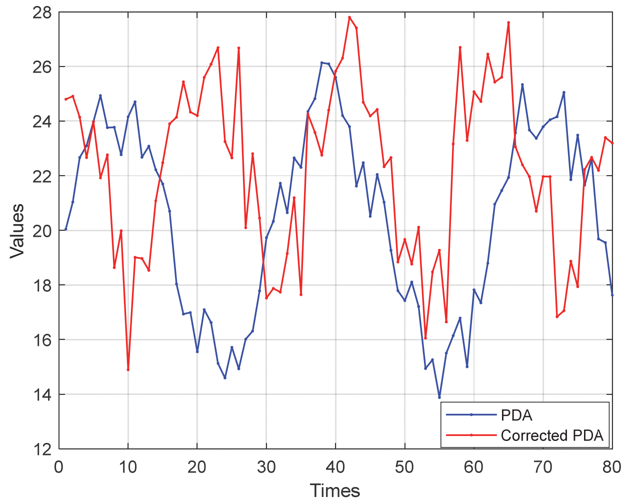

Figure 10 When the clutter density is 4

Using the multi-source heterogeneous information fusion method, we were able to achieve the real probability results and forecast results of the optimal allocation of regional science and technology innovation resources. The calibration curve is displayed in Fig. 11. In terms of effectiveness and proximity to the ideal curve, the results demonstrate that the multi-source heterogeneous knowledge fusion algorithm utilizing POP ACCU produces the best outcomes.

Using a combination of influencing factors, allocation principles, and allocation subjects, this paper constructs four optimal allocation modes of scientific and technological information resources with an eye toward regional innovation. The following conclusions are drawn from these models: (1) Allocating science and technology information resources optimally in a market mechanism setting requires a joint effort between the government, businesses, universities, and science and technology intermediaries; doing it alone is inefficient. An ever-changing cyclical structure is the best way to distribute scientific and technological knowledge. Different regions and environments impact the status of information resource allocation subjects in this system. However, it is undeniable that governments, enterprises, institutions of higher learning, and science and technology intermediaries must participate in each mode of allocation.

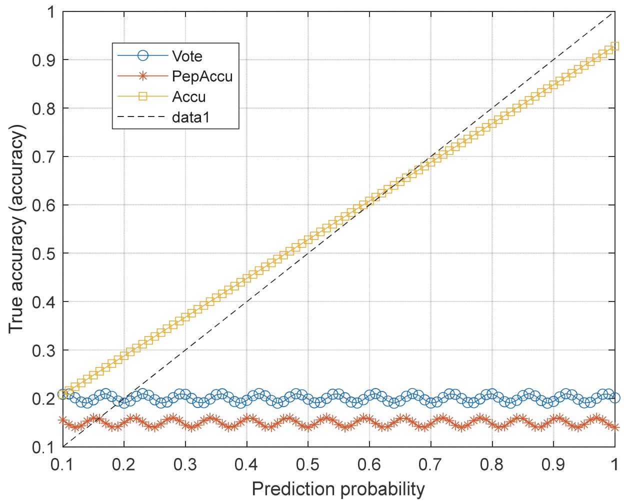

Figure 11 Calibration curves of different fusion methods

6 CONCLUSION

Enhancing regional sci-tech resource allocation requires coordinated efforts: aligning organizational, institutional, and resource strategies for innovation, establishing government-market synergy, and building environmental support systems. This study introduces a set pair analysis framework for multi-source data fusion, leveraging opposition/identity/difference mining to adjust data correlations. A connection matrix and dimension-extension method quantify comprehensive similarity across sensor time-series measurements. The next step in achieving weighted fusion of multi-source data is to fairly assign weights to the measurement data based on the current signal-to-noise ratio weighting approach. The dependability and efficacy of the algorithm, as well as its benefits and drawbacks, can be demonstrated through simulation trial step. The next step will be based on three important influencing factors for optimizing the allocation of improved resources: Heuristic information, positive feedback mechanism, and pheromone volatilization mechanism are analyzed in practice during the process of government participation. Then, from an overall perspective, strategic suggestions are proposed for the regional scientific and technological innovation resource allocation system in aspects such as the regional scientific and technological investment system, knowledge innovation platform, social service system, talent introduction, and academic exchanges to improve the positive resource input and allocation in the region., and accelerate the development of regional scientific and technological innovation.

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