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RESEARCH

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Material product life cycle analysis driven by industrial internet of things

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Abstract

With the fast expansion of the industrial Internet of Things (IIoT) in recent years, the requirement for high-speed, dependable, low-latency, and full-coverage IIoT has grown more pressing. Because of the complexities of the industrial environment and the distance of the specific plant site, communication quality is severely hampered. To overcome these challenges, the space-air-ground integrated network (SAGIN) is seen as a viable solution for the IIoT. This article examines SAGIN, IIoT, product life cycle management, and how to handle these difficulties using three methodologies. This paper explores SAGIN, IIoT, product life cycle management, and how three approaches can be used to deal with these difficulties. We first introduce the overall architecture of SAGIN and then use illustrations to explain the concept of product cycle data. The final experimental results demonstrate the effectiveness of our proposed method.

Keywords: Air-space-ground integrated networks, Internet of Things, Improved BASS model, Annealing simulation algorithm, Bayesian model

1 Introduction

The Internet of Things (IoT) is a computing concept that portrays ubiquitous Internet connectivity, which transforms common objects into connected devices. Machine-to-machine (M2M) and industrial communication technology are combined with automation applications in the Industrial IIoT, which is a subset of the Internet of Things. The IIoT allows for a better understanding of industrial processes, resulting in more efficient and sustainable manufacturing. Wireless networks are frequently employed to provide the flexibility and scalability that IIoT communications require. Prior to now, most wireless technologies in industrial applications relied on ad hoc solutions. They do, however, have limitations in terms of scalability and coverage when covering extremely large areas. While cellular technologies have the ability to connect large devices across long distances, they require both infrastructure and controlled frequency bands [4]. Because IIoT applications often require minimal throughput per node, capacity is not a major concern. Instead, a large number of low-cost devices with limited hardware capabilities and energy must be connected to the Internet.

Networking has become closely tied to industrial production since the introduction and growth of the IIoT. All of the sensors in a factory may interact with one another thanks to the IIoT, resulting in a myriad of applications. Terrestrial networks, on the other hand, have a restricted service range, and certain areas, such as industries in remote deserts and offshore oil wells, are not covered by current networks. To expand the range of human activities into new areas, the space-air-ground integrated networks (SAGIN) are viewed as a feasible alternative for the IIoT to solve these issues. The IIoT will have considerably more potential in the SAGIN IIoT scenario because of the omnipresent network.

This paper endeavors to employ SAGIN IoT to build an enterprise information system. The key is how to realize the mutual exchange and sharing of information between different systems of an enterprise. Through continuous research and exploration of this problem, people began to develop and excavate in the direction of enterprise data integration, with the enterprise's product life cycle data as the core, to study the solution to this problem. The rapid development of the global manufacturing industry makes the integration of enterprise information no longer limited to data integration within the enterprise. Enterprises need to face more angles and levels to integrate data, such as between different systems, between different enterprises, between different industries, etc., to exchange data in these dimensions.

Under today's new situation, there are also new requirements for product data management. Based on this, companies need to exchange and share product data between networks with different structures. The existing traditional product data management is prone to various problems, such as missing product data, product data mismatch, and data incompleteness. The traditional method of product data management is mainly achieved by mapping between product data and relational data, and with the cooperation of the file system. Once faced with complex types of data, traditional product data management based on relational data management systems will have the above problems. Therefore, ensuring that the product data are safe and correct, while being able to store the product data effectively, is the primary problem faced by the new product data management system.

In today's market conditions, the overall life cycle of products is constantly shortening, and consumers' demand for products is also highly uncertain, causing companies to face more difficulties and uncertainties in the process of R&D and production. Therefore, demand forecasting for products has become a big rigid demand now. If the product demand can be predicted accurately, the company can carry out timely and effective control during the design and production stage of the product, which has important reference value for the entire process of the product from scratch. The existing methods do not comprehensively consider products with different life cycles, so the accuracy of the final results is not good and will lead to more concurrent adverse consequences, such as decreased corporate reputation and decreased product sales. Therefore, it is necessary to improve the existing imperfect forecasting methods, to provide enterprises with more effective and practical reference, and to improve the design level and production level of the entire product launch process, so that the company and its products have more attention and competitiveness in the market.

Material plays an important role in promoting the continuous development of social economy at all levels and is also an important material basis for economic development. Polymer material products include, for example, rubber, plastics, fibers, coatings, adhesives, and polymer matrix composites. A large number of atoms are covalently bonded to each other to form organic compounds with particularly large molecular weights and repeating structural units. Throughout the development of human society, the production and use of materials has existed and played a vital role throughout. Improving the product life cycle evaluation system and improving the accuracy of evaluation forecasts can well predict the sales volume of new products in the business. Database systems can also be used to determine which products will bring the greatest benefit based on product similarity. And to a certain extent, the evaluation of materials and products can positively guide the ecological environment, which has greater practical significance.

This paper proposes an improved BASS algorithm, which combines annealing simulation algorithm, Bayesian model and similarity measurement, and considers aspects such as seasonal effects. And the data are constantly updated, and more accurate forecasting results are obtained, which has certain guidance and feasibility.

2 Related work

2.1 IOT, IIOT, and Industry 4.0

IoT, IIoT, and Industry 4.0 are all similar ideas, but they are not synonymous. We present a preliminary taxonomy of these terms in this section. There are a variety of definitions for the Internet of Things, each attempting to encapsulate one of its key qualities. It is commonly referred to as a "machine network," emphasizing the goal of allowing devices to communicate with one another. The Consumer Internet of Things, rather than the Industrial Internet of Things, is a better name for what is commonly referred to as the Internet of Things [6, 7]. Consumer IoT is centered on people; "things" are connected smart consumer electronic gadgets that boost human awareness of their surroundings while saving time and money. Machine-to-user and machine-to-consumer communication are the two types of Consumer IoT communication. Consumer IoT communication can be classified into two categories: machine-to-user and client–server interactions.

On the other hand, in industry, we are aiding the emergence of digitalization and smart manufacturing, which strives to combine operational and information technology (IT) [8]. Simply described, the Industrial Internet of Things (IIoT) is the process of connecting all industrial assets to information systems and commercial processes. As a result, the massive volume of data gathered can lead to analytical solutions and improved industrial operations. Smart manufacturing, on the other hand, places a strong emphasis on the manufacturing portion of the product life cycle, with the purpose of responding rapidly and dynamically to demand changes. As a result, the Industrial Internet of Things has a significant impact on the entire industrial value chain and is a prerequisite for intelligent production.

2.2 Industry: SAGIN

The space-air-ground integrated network (SAGIN) has gained a lot of interest from academics and industry because it uses modern information network technology to connect space, air, and ground network elements. More and more organizations, such as the global information grid (GIG) [4, 5], One Web [6], SpaceX [7], and others, have started projects using SAGIN in recent years. SAGIN can be employed in a variety of practical domains, including earth observation and mapping, intelligent transportation systems (ITS) [8], military missions, disaster relief [9], and so on, due to its inherent advantages in terms of vast coverage, high throughput, and great resilience. Satellites, in particular, can provide seamless connectivity to rural, ocean, and mountain areas, while air segment networks can boost capacity in covered areas with high service demands and densely distributed ground segment systems can provide high data rate access. The combination of these network segments would have numerous advantages for future 5G wireless communications.

To achieve high-throughput and high-reliability data delivery, SAGIN uses distinct communication protocols in each segment or the integration of different segments as a multidimensional network. Unlike typical ground or satellite networks, SAGIN is constrained in all three segments at the same time, including traffic distribution, spectrum allocation, load balancing, mobility management, power control, route scheduling, and end-to-end (E2E) QoS requirements. Given the varied practical network resource limits from each segment, it is vital for network designers to achieve optimal performance in E2E data transfer.

2.3 Previous work on material product life cycle assessment

Material product life cycle assessment has research significance in both environmental and commercial fields. It often appears in many fields such as politics, economy, environment, technology, society, and so on. ChesalinAN studied the use of qualitative and quantitative methods for risk assessment in the product life cycle stage and proposed a general algorithm for selecting fuzzy risk assessment models with different input data and system requirements to effectively utilize statistical information and expert assessment. The "risk-based approach" can reduce the cost of correcting possible errors in the future and reduce the uncertainty in the implementation of follow-up actions [1]. HedbergTD introduced a method of using graphics to link and track data throughout the product life cycle to form a digital thread. It also describes the prototype implementation and case studies of this method to show the round trip of product assembly information between the design, manufacturing, and quality areas of the product life cycle [2]. Satoh proposed a discrete bass model, which is a discrete simulation of the bass model. The discrete Bass model is defined as a difference formula with exact solutions. The difference formula and solution, respectively, approach the differential formula defined by the Bass model and the solution when the time interval approaches zero. The discrete Bass model retains the characteristics of the Bass model because the difference formula has an exact solution [3]. In order to solve the inherent problems of the existing Bass model, YWang uses the nonlinear least squares (NLS) method to develop the gray Bass model and provides the whitened solution of the differential formula. The Bass model takes advantage of the specific advantages of simulating and predicting the spread of new products [4]. PengX proposed a new axiomatic definition of a single-valued neutrosophic similarity measure, which is represented by a single-valued neutrosophic number (SVNN), which will reduce information loss and retain more original information. Then the objective weight of each parameter is determined by the grey system theory. Subsequently, a combination weight is proposed, which can reflect the subjective considerations of decision-makers as well as objective information. Finally, the two algorithms are combined to solve the decision-making problem based on average solution distance assessment (EDAS) and similarity measurement [5]. MandalK introduces two new simple similarity measures to overcome some shortcomings of the existing Jaccard, Dice, and Cosine similarity measures of SVNS, which are used to rank alternatives. Based on the similarity measurement, two entropy measurement formulas have been developed to prove the basic relationship between the similarity measurement and the entropy measurement [6]. These studies have a certain degree of guidance, but there are insufficient arguments or insufficient precision, which can be further improved.

2.4 Previously on the use of IoT in relevant models

Sensor, Embedded, Computing, and Communication technologies are all part of the Internet of Things (IoT). The goal of the Internet of Things is to give seamless services to anything, at any time and in any location. The impact of IoT on society will be greater than that of the internet and ICT, according to the research and development community, which will benefit society and industries' well-being.

Augmented reality, high-resolution video streaming, self-driving vehicles, smart environments, e-health care, and other IoT-centric concepts are becoming commonplace. For these applications, higher data rates, large bandwidth, extended capacity, low latency, and high throughput are required. In light of these evolving conceptions, IoT has changed the world by offering seamless communication across heterogeneous networks (HetNets). The ultimate goal of IoT is to give end-users with plug-and-play technology that allows for ease of use, remote access control, and configurability. Cellular networks in the fifth generation (5G) are essential facilitators for wider adoption of IoT technology.

The utilization of a possible IoT system is based on addressing the most important system-level design characteristics such as energy efficiency, resilience, scalability, interoperability, and security concerns. Because IoT devices are resource constrained and pose numerous issues, both compute and communication resources must be used wisely and cautiously.

3 Methods

3.1 Life cycle assessment data model analysis system model

The structure design of the database is based on the storage requirements of the analysis data. To build a complete database, the structure of the database must first be designed and established. If the corresponding database structure has been established, the next step is to collect the data and store it according to the corresponding structure of the data. This basically completes the establishment of the database [7]. However, this type of database is still relatively rudimentary and not suitable for general users. A complete and easy-to-use database requires sufficient interactivity and intelligence. The user initiates operations such as accessing, searching, and querying the database through a terminal with a built-in application program. The premise of these operations is to set different preconditions. The simplest and most direct method is to use the database management system as a medium to provide users with interactive and structured operation communication methods, so that various practical operations are possible, such as adding, deleting, etc. [8]. However, the above methods are more professional, and the target groups are mainly database-related staff. For ordinary users, the interface of the program, the difficulty of operation, etc., need to be optimized and simplified [9]. The concept of product cycle data is shown in Fig. 1.

The product life cycle is the entire process from the idea of a new product until it disappears. Most product life cycles are S-shaped, and product life cycles generally refer to new types of products on the market, not just a single brand. The core data required for LCA analysis is the system data of the product, and the system data of the product contain two kinds of data, namely exchange flow data and unit process data. The system data of the product have specific values. If subdivide the product system data, it can see: product system, process connection, exchange flow, etc. Project management data are different from product system data. It mainly stores the process management of the storage unit and related modeling and verification data, such as project time and personnel information. These data are only used to express the transparency of the data in the unit process [10]. The data of LCIA method are mainly composed of LCIA factor, LCIA classification, LCIA method, and so on. It mainly affects the evaluation process and at the same time provides certain support for environmental impact evaluation. The result obtained after the LCIA analysis is the evaluation result data, which serves as a basis to provide practical support for the explanation stage [11].

In the process of establishing the LCA database, the basic data set will not directly participate in the whole process. After the data are collected, the LCIA method and other related data are established uniformly. This sequence of operations can ensure the consistency of the final data [12].

In addition to the above-mentioned related issues, LCA analysis will also face the impact of comparing multiple different products with similar functions in various aspects [13]. This type of problem is usually referred to as a project, and it is applied to a system with similar functions and different products. And to manage and collect these data in the mode of engineering table, the details are described in Fig. 2.

Usually, many parts or many products are assembled together to form a complete and effective product, and at the same time, a product-centric system is produced. The system is the sum of the product flow and the basic flow. Therefore, the system not only has a certain feature or function, but can also have multiple features or functions at the same time. Because of its complete product composition system, it can well simulate the unit

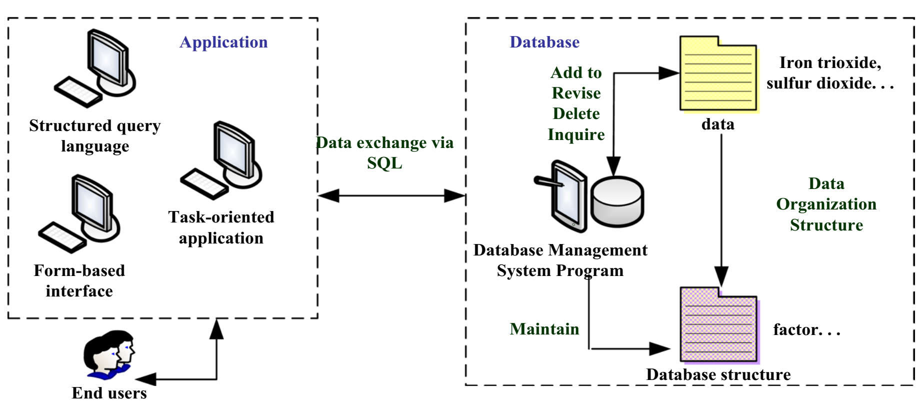

Fig. 1 Product cycle data concept

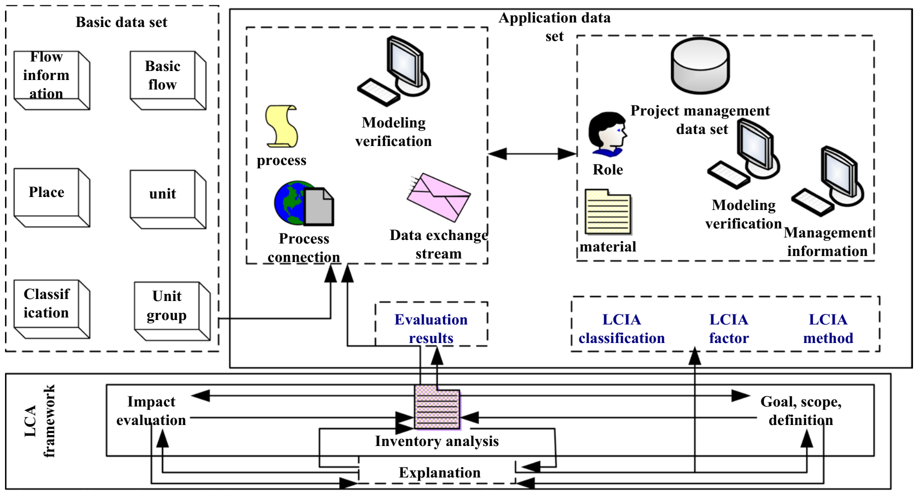

Fig. 2 The overall structure of the LCA database

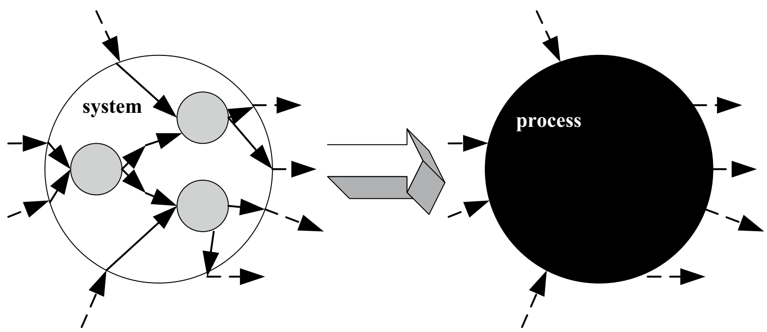

Fig. 3 Simplification of complex material product system

process of the entire product life cycle [14]. If we refine a product, the parts or products that make up the product can be regarded as a product system. Therefore, the product system can be subdivided almost continuously. As shown in Fig. 3, the product system contains three sub-product systems, and the three sub-product systems are subdivided and analyzed to get the system inventory result [15].

3.2 Product life cycle design and multi-objective reliability algorithm

In the process of designing the life cycle of a product, it is actually to analyze, review, improve, and finally shape all the links and factors before the product is launched [16]. Therefore, in the process of product life cycle design, knowledge and technology in various fields are covered, and the requirements for talents are also harsh. Every link and every factor in the design process, their final conclusions are based on professional knowledge and strong technical capabilities [17]. With the continuous replacement and upgrading of technology, for judging whether the life cycle of the product meets the design requirements and actual needs, relevant analysis and simulation systems can be used to conduct detailed experimental reviews, find out the problems in the design process in time, and discuss relevant improvement suggestions and schemes. From a more rigorous point of view, the process of designing the life cycle of a product is comprehensive and diversified [18]. It not only integrates the massive knowledge of multiple disciplines and puts it into practical application, but also adopts the mode of multi-technology co-operation. The former and the latter are integrated with each other based on the existing national background, social capabilities, etc. [19]. The levels involved are: 1. The functional design of the product. 2. The raw material and processing technology of the product. 3. The service life of the product under normal and severe conditions. 4. Product processing equipment and assembly process. 5. Whether the product complies with national environmental protection standards. 6. Emergency plan reserved for unexpected situations. Figure 4 shows the product life cycle design link.

The product life cycle is mainly determined by the changes of consumers' consumption patterns, consumption levels, consumption structure, and consumption psychology. It is generally divided into four stages: introduction (entry), growth, maturity (saturation), and decline (decline).Obviously, the overall cost of a product increases as its reliability increases. Therefore, $k(w)$ is a monotonically increasing function. The improvement of reliability is accompanied by changes in various links, such as materials and processes. At the same time, through specific analysis, it can be seen that when the reliability of the product is low, the cost required to improve the reliability of the product at this time is significantly lower than the cost when the reliability is high. Let $g(\mu \leq k)$ represent the probability that the working cost μ is not greater than k under a certain environment and within the normal service life of the product. That is, when the cost of the product is k, its corresponding reliability is $w(k) = g(\mu \leq k)$. The corresponding probability that the cost of the product μ is greater than k is $g(\mu \leq k) = 1 - w(k)$. The specific expression of function $g(\mu \leq k)$ is not easy to write, but according to the data and graphs, it is not difficult to analyze: when the cost of the product is k, increase the cost Δk at this time, and the corresponding ratio to improve its reliability can be obtained.

$$\frac{\Delta w(k)}{\Delta k} = \frac{\Delta g(\mu \leq k)}{\Delta k} \tag{1}$$

The ratio of this ratio to $\Delta g(\mu \leq k)$ is regarded as the product cost-return ratio, as shown in the following formula:

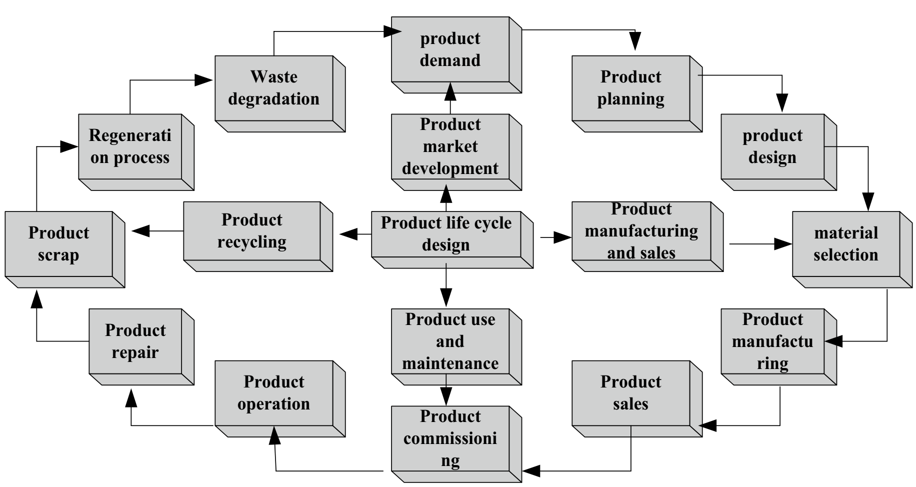

Fig. 4 Product life cycle design

$$x(k) = \frac{\Delta g(\mu \leq k)}{\Delta k} \cdot \frac{1}{g(\mu \leq k)} = \frac{\Delta g(\mu \leq k + \Delta k) - g(\mu \leq k)}{g(\mu >)\Delta k} = \frac{g(k + \Delta k) - \nu(k)}{\Delta k[1 - \nu(k)]} \tag{2}$$

Let there be no additional cost at this time, and transform the above formula into a differential formula, we can get:

$$\frac{\mathrm{d}w}{\mathrm{d}k} = [1 - w]x(k) \tag{3}$$

Supposing $w(k_1) = w_1$, and there is a constant $x(k) = s$, then the differential formula can be solved:

$$w(k) = 1 - (1 - w_1) - e^{-s(k-k_1)} \tag{4}$$

It can be seen that if another value of $w(k_2) = w_2$ can be obtained at this time, the value of parameter s can be solved. At this time, the initial value $w(k_0)$ wirelessly approaches 0, and the inverse function of $w(k)$ can be obtained as:

$$w(k) = 1 - e^{-s(k-k_0)} \tag{5}$$

For each parameter in the analysis formula, when the product reliability w is close to 0, the parameter k_0 can be expressed as the product cost at this time, which is equivalent to the cost required when a product design scheme fails. At the same time, it is obviously different from the product design scheme when the reliability $R=0$. Even if $w = 0$, there are big differences between each design scheme of the product. For further analysis of the formula, the parameter m affects the trend of the curve at all times, that is, when the value of the parameter m is larger, the curve trend in the early period is relatively flat, and the curve trend in the later period is more steep. This shows that when the value of the reliability w is not large enough, the cost that needs to be increased to improve the reliability of the product is small. When the value of the product reliability w is larger, it means that if the reliability of the product is continuously improved, the required cost will be greater. Therefore, through specific analysis of the actual situation of the product, past experience and professional knowledge and other means of evaluation, the values of the parameter m and the parameter k_0 can be estimated more accurately, and the specific expression of the function $k(w)$ can be finally obtained. Among them, it should be noted that, according to the actual situation of the product, the product reliability taken in the function $k(w)$ should come from the dynamic reliability $w(0, R)$ of the product during initial use or the reliability $w_0(R)$ during its design. Because $w_0(R)$ is a special case of $w(0, R)$, the cost function can be expressed as $k[w(0, R)]$:

$$k[w(0,R)] = \left[1 - \frac{1}{m}Ln[1 - w(0,R)]\right]k_0 \tag{6}$$

When a product fails, the loss it brings at this time is expressed as D, and the loss D consists of three parts: first, the economic loss $S_{(1)}$ caused by the product itself when the product fails. Second, the initiating loss $S_{(2)}$ caused to other aspects when the product fails. This loss includes the internal and overall loss of the product and is indirect. Third, when the product fails, it will cause the phenomenon of production stoppage, which leads to related losses, that is, the loss of production stoppage $S_{(3)}$. Regardless of the above loss, its occurrence is closely related to the degree of failure of the product, that is, different degrees of failure will produce different types of losses, and the degree of loss is also different. The specific value of the loss S cannot be accurately calculated, but the previous accumulated product experience and related data can be used to estimate the loss. During the life cycle of mechanical products, the cost of materials required for production and market changes is constantly changing with time, so these can be called functions of time.

$$S(t) = S_{(1)}(t) + S_{(2)}(t) + S_{(3)}(t) \tag{7}$$

Because the material product will gradually fatigue and the surrounding environmental factors will change at any time, so the dynamic reliability $w(r, R - r)$ will continue to decay, and the loss expectation at this time is a function of time, namely:

$$F(r) = [1 - w(r, R - r)]S(r) \tag{8}$$

At this time, the expected failure loss for the entire life cycle of the material product is:

$$F = \frac{1}{R}\int_0^{\mu} [1 - w(r, R - r)]S(r)s(r) \tag{9}$$

The optimization model of the entire life cycle of the material product is:

$$Q(r) = \left[1 - \frac{1}{m}Ln[1 - w(0, R)]\right]k_0 + \frac{1}{R}\int_0^{\mu} [1 - w(r, R - r)]S(r)sr \rightarrow \min \tag{10}$$

Taking the previous research on the attenuation of product reliability and the related dynamic reliability function $w(r, R - r)$ as a reference, the above model is solved. It can be concluded that when the design life of the product is T, the most suitable design reliability $w(0, R)$ value for the product at this time. According to the value of the most suitable design reliability $w(0, R)$, the product can be designed more reliably. The solution process of multi-objective decision-making is shown in Fig. 5:

The so-called multi-objective decision-making theory refers to when a problem has multiple conflicting decisions at the same time, and the comprehensive design of these decisions is carried out to find the best one in the relative situation. By optimizing multiple goals by weighting, multiple and complex optimization problems can be converted into single optimization problems.

$$Minh(n) = h(H) + h(R) + h(V) + h(k) + h(D) + h(w) \tag{11}$$

In the formula, a certain function or performance of the optimized product is expressed as H, the quality of the product is expressed as V, and the economic efficiency of the product is expressed as k. The production efficiency of the product is represented as R, the resource utilization rate during the production of the product is represented as w, and the environmental protection and energy in the production process of the product is represented as D. Based on the corresponding mathematical model, the problem with multiple goals is optimized to obtain a suitable single

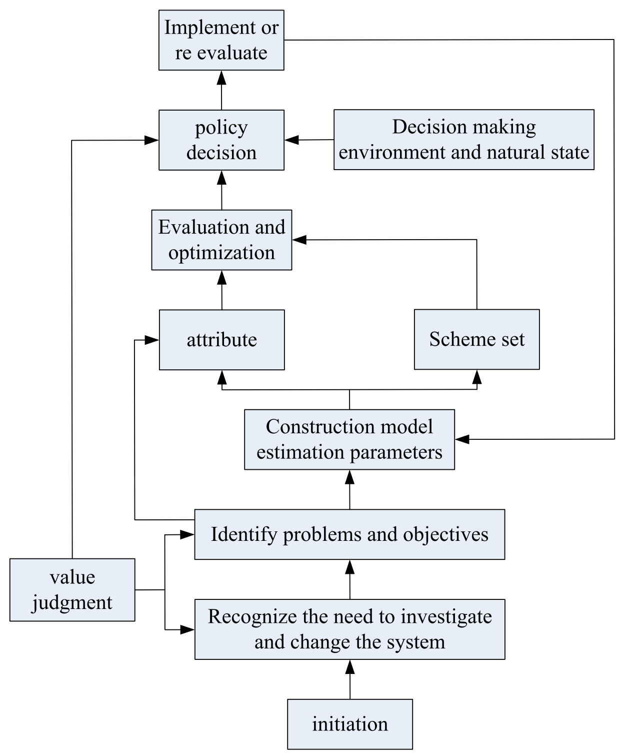

Fig. 5 The solution process diagram of multi-objective decision-making

problem, and then it is solved. Mathematical models that can optimize multi-objective problems into single-objective problems include ① optimization method, ② linear weighting, ③ square sum weighting, ④ multiplication and division, ⑤ hierarchical sequence method.

3.3 Material product preview similarity model

Before material products are launched, new products need to be predicted, and the promotion direction must be determined based on the predicted data. However, due to the complex attributes of the product, it is difficult to perform an effective similarity measurement on the material products, so at this time, the database will be feature extraction, and then the similarity measurement after decomposition [20].

Let I be a non-empty set, any pair of a, b in this set corresponds to a real number $s(a, b)$ and is greater than or equal to 0. When $a = b$, the real number is 0, and the real number has symmetry. $s(a, b) \leq s(a, c) + s(c, b), c \in I$, that is, the direct distance between the objects in the set is less than or equal to the distance of other objects in the path, we can get:

1. Euclidean distance

$$S(a_i, a_1) = \left[\sum_{k=1}^{s} (a_{ik} - a_{1k})^2\right]^{1/2} \tag{12}$$

The Euclidean distance can calculate the straight-line distance between two vectors, and according to the attribute weight, Euclidean distance transform has a wide range of applications in digital image processing, especially for image skeleton extraction, it is a good reference. The above formula can be converted into a weighted Euclidean distance:

$$S(a_i, a_1) = \left[\sum_{k=1}^{s} w_k (a_{ik} - a_{1k})^2\right]^{1/2} \tag{13}$$

Each dimension of Euclidean distance has different influencing factors, and its weight value has been verified in practice. Euclidean distance is equal to the difference between different attributes of the sample (that is, each indicator or each variable), and sometimes it cannot meet the actual requirements. The effect of overall variability on distance is not considered.

2. Squared Euclidean

$$S(a_i, a_1) = \sum_{k=1}^{s} (a_{ik} - a_{1k})^2 \tag{14}$$

The importance of each attribute in this formula can be given weight.

3. Manchester distance

$$S(a_i, a_1) = \sum_{k=1}^{s} |a_{ik} - a_{1k}| \tag{15}$$

This is mainly used to calculate the absolute distance between vectors, which can be transformed into:

$$S(a_i, a_1) = \sum_{k=1}^{s} w_k |a_{ik} - a_{1k}| \tag{16}$$

4. Minkowski distance

$$S(a_i, a_1) = \left[\sum_{k=1}^{s} |a_{ij} - a_{1j}|^n\right]^{1/n} \tag{17}$$

The $a_u = (a_{u1}, a_{u2}, ..., a_{us})$ in the Minkowski distance is the sample point in the s-dimensional data sample space. And when $N = 1$, it will be converted into Manchester distance, when $N = 2$, it will be converted into Euclidean distance.

5. Chebyshev distance

$$S(a_i, a_1) = \max_k |a_{ik} - a_{1k}| \tag{18}$$

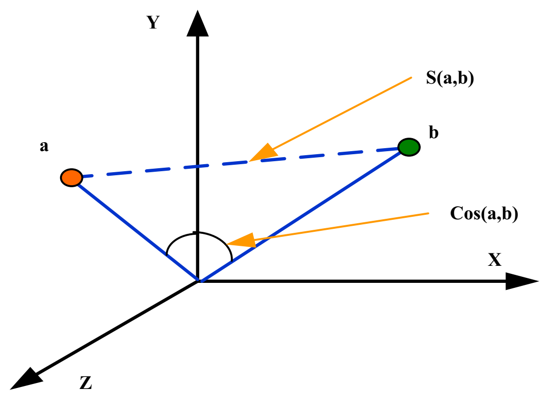

Fig. 6 Cosine angle similarity

6. Pearson correlation coefficient.

The Pearson correlation coefficient is used to measure the degree of linear correlation between two variables, and its value is between -1 and 1. The intuitive expression for this linear correlation is that as one variable increases, the other increases at the same time. When the two are distributed on a straight line, the Pearson correlation coefficient is equal to 1 or -1. There is no linear relationship between the two variables and the Pearson correlation coefficient is 0.

$$S(a_i, a_1) = (1 - r_{ij})/2, r_{ij} = \sum_{v=1}^{s} (a_{iv} - \mathrm{avg}a_i)(a_{kv} - \mathrm{avg}a_k) \Big/ \sqrt{\sum_{v=1}^{s} (a_{iv} - \mathrm{avg}a_i)^2 \sum_{v=1}^{s} (a_{kv} - \mathrm{avg}a_k)^2} \tag{19}$$

7. Percent Disagreement distance

$$S(a_i, a_1) = (\mathrm{Num}(a_{ik} \neq a_{1k})/s) \tag{20}$$

8. Point symmetry distance

$$S(a_i, a_1) = \min_{\substack{k-1,\ldots,M \\ k\neq i}} \frac{\|(a_i - a_1) + (a_k - a_1)\|}{\|(a_i - a_1)\| + \|(a_k - a_1)\|} \tag{21}$$

Rotates the graph 180° around a point. If it can overlap another figure, the two figures are said to be symmetrical about the center of that point. This point is called the point of symmetry. The symmetry of two figures about a point is also called centrosymmetric. Symmetry points in these two figures are called symmetry points about the center.

9. Cosine of included angle.

The principle of angle cosine similarity is shown in Fig. 6:

$$\cos(a_d, a_1) = \cos(a_i, a_1) = \frac{\sum_k (a_{ik} - a_{1k})}{\sqrt{\sum_k a_{ik} \cdot \sum_k a_{1k}}} \tag{22}$$

When the included angle is 90°, the similarity is 0, and when the included angle is 0, it means that it is very similar.

10. Custom distance

$$S_q(a_d, a_1) = S_q(a_i, a_1) = \left[\sum_k |a_{ik} - a_{1k}|^q\right]^{1/t} \tag{23}$$

All the above similarity measures satisfy non-negativity, reflexivity, symmetry, and triangle inequality. Reflexivity in a broad sense refers to the application of a theory's assumptions to the theory itself, and more broadly it refers to the self-monitoring (or self-discipline) of an expert system and interrogating itself against the assumptions. Set by yourself.

4 Results

4.1 Improved BASS model product life cycle prediction model design

This article makes a detailed analysis of the original BASS model. It can be seen that although the BASS model takes the product life cycle into consideration, its analysis of the impact of product demand is not complete, and the model has not made sufficient preparations for its adaptability. Therefore, this article makes a more complete improvement on the original BASS model and uses the improved BASS model to evaluate the similarity of products through the system similarity measurement method. At the same time, certain data-based forecasts are given to the required products. The improved BASS model also supplements the considerations of consumers' preferences, demand, and other aspects that are lacking in the original model, which are affected by external factors and product-related factors, thereby improving the accuracy of product prediction. The product price, consumer preferences, seasonal climate, and other aspects are comprehensively analyzed and considered. The

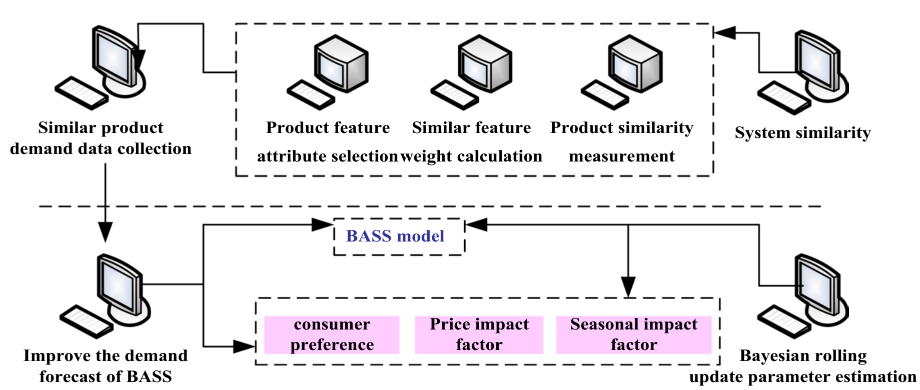

Fig. 7 The construction of a short life cycle product demand model system based on the improved BASS model

short-life cycle product demand model system based on the improved BASS model is shown in Fig. 7.

In this paper, the original BASS model has been improved in many ways. The BASS model was originally a model used to predict the sales of durable consumer goods. Because the application was very successful, it was gradually used in various fields, especially for high-tech fields such as broadband. At the same time, Bayes is used as an aid to estimate the relevant parameters, so that the BASS model can predict and analyze sales data with higher accuracy.

4.2 Product case analysis based on the improved BASS model

This experiment uses six products of company A as examples to extract data. It should be noted that five of the products were launched a year earlier than the other one, but the six products have similar or identical characteristics, such as corresponding seasonal weather and sales markets. For the universality and authenticity of the experiment, a questionnaire survey was conducted to 100 randomly selected consumers in the form of a questionnaire survey. Synthesizing their evaluations and ideas on five of the products, the average utility value of the above five products in the consumer's consumption concept is obtained. At the same time, excluding the case where the six products have different time to market, the calculation is based on the seasonal climate conditions; starting from the time to market of each product, because many products are affected by temperature and the surrounding environment, the sales volume will vary, as shown in Fig. 8.

It can be seen from Fig. 8 that the six products have a high degree of similarity in the demand distribution. At the same time, the demand curve of the six products is the same as the conceptual structure mentioned in the BASS model. Some data in Fig. 8 are abnormal due to the influence of seasonal climate, so the influence of such factors as seasonal climate should be excluded in the relevant analysis. Selecting the top 5 products that were sold in the same year, take their 12-month sales data, and set the weight to S. The seasonal coefficient of each similar product can be calculated as Table 1.

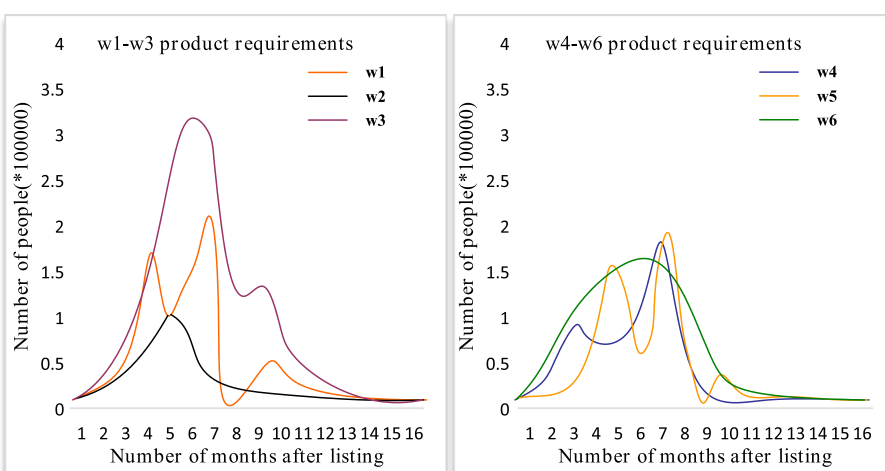

Fig. 8 Product demand data situation

Table 1 Seasonal impact factors of five products

Month/season coefficient	$S(w1)$	$S(w2)$	$S(w3)$	$S(w4)$	$S(w5)$
1	0.773174	0.686836	0.651691	0.355131	1.247094
2	0.672492	0.56066	0.35912	0.251499	0.349567
3	0.587297	0.744896	0.540004	0.25159	0.177394
4	0.758173	0.592848	0.115021	1.613155	0.096145
5	0.568654	0.668083	0.810622	1.252027	0.242177
6	0.650443	0.646095	0.593017	1.257241	0.871133
7	0.943826	0.935883	1.158385	1.382376	3.168278
8	1.032712	0.737444	1.774132	1.788793	1.72654
9	1.469133	2.335874	2.361638	2.540968	3.253389
10	2.498147	1.805421	1.803175	1.171413	0.781193
11	1.284655	1.063731	0.948811	0.774244	0.0830949
12	0.775062	1.045804	1.015767	0.860135	0.344592

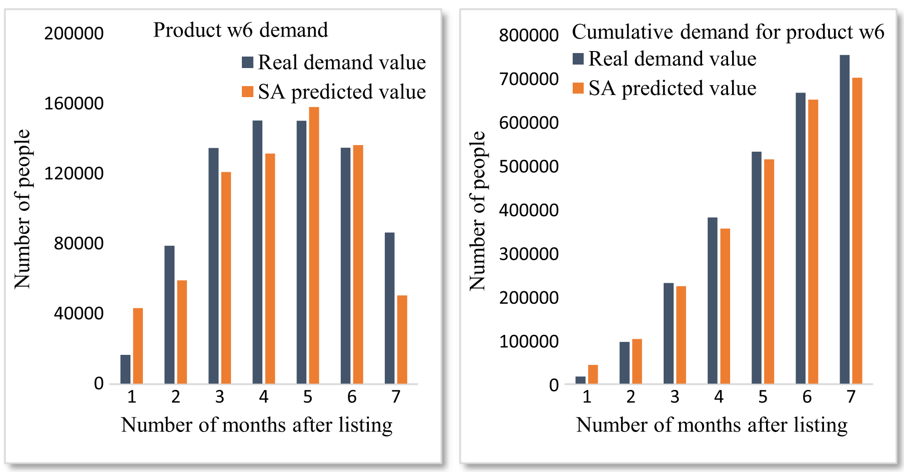

Fig. 9 The first month demand forecast value and real value compared with the cumulative demand value and real value

As can be seen from Table 1, $S(w1)$ was most affected in October, $S(w2)$, $S(w3)$, and $S(w4)$ were all affected the most in September, and $S(w5)$ was most affected in July and September was the most affected. Then, according to the weights of similar products, the weights are expressed as, and the seasonal impact factor of product $w6$ is known as:

$$S(w6) = S(w1) \times Q(w1) + S(w2) \times Q(w2) + S(w3) \times Q(w3) + S(w4) \times Q(w4) + S(w5) \times Q(w5) \tag{24}$$

Based on the annealing simulation algorithm, it is assumed that the introduction time of the company's product $W6$ is the month of its sale. At this time, the demand value of the product in the first month and the accumulated demand value are more accurately predicted and estimated, and the data are compared with the actual data. Figure 9 shows the comparison between the forecasted demand value and the true value of the first month and the cumulative demand value and the true value.

Table 2 The posterior probability of the demand mode of the first 5 products

Posterior probability/ product	*w*1	*w*2	*w*3	*w*4	*w*5
1	0.198	0.216	0.204	0.202	0.2
2	0.191	0.225	0.212	0.196	0.194
3	0.185	0.235	0.22	0.191	0.189
4	0.178	0.244	0.228	0.185	0.183
5	0.171	0.253	0.236	0.179	0.177
6	0.165	0.263	0.244	0.174	0.172
7	0.158	0.272	0.252	0.168	0.166

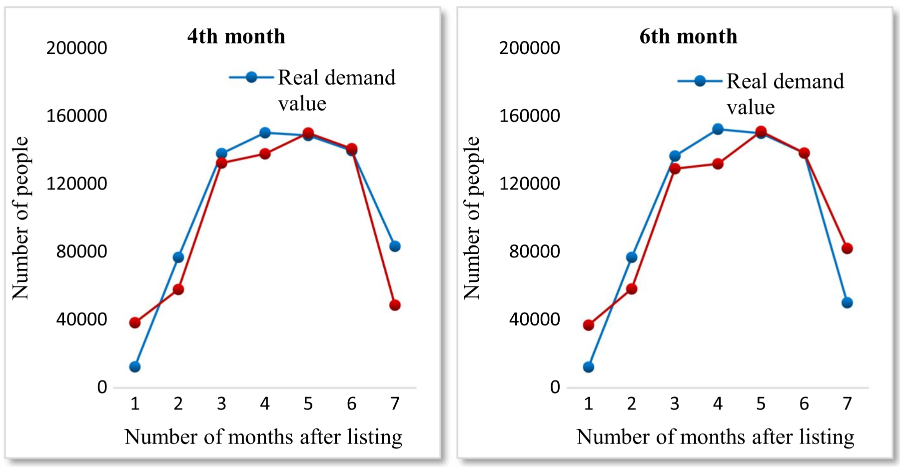

Fig. 10 Comparison of forecasted and true demand values in the 4th and 6th months

Comparing the estimated product cumulative demand budget and the actual sales value of the product in Fig. 9, it can be clearly seen that at the beginning of the product's life cycle, the predicted demand value differs greatly from the actual product demand. The product life cycle can generally be divided into four stages, namely the introduction stage, the growth stage, the maturity stage, and the decline stage. The main reason for this is that the data used in the prediction are not the data of product *w*6 itself, but is derived from the data of products similar to product *w*6. When the product *w*6 starts to be sold, there will be corresponding phase data generated. According to Bayesian thinking, after detailed analysis of these data, the parameter distribution of the corresponding model of the product will be adjusted and updated in time. The first task is to find the posterior probability of each product distribution according to the demand mode of all similar products, as shown in Table 2.

At the end of each month, the posterior probability of the demand distribution of product *w*2 according to the demand pattern of the other five products is shown in Table 2. The detailed data of the posterior probability show how the obtained posterior probability is updated with the actual sales data as a reference. It can be concluded that product *w*2 is more similar to product *w*6 that has not been predicted in terms of sales and its own characteristics. In the following process, according to the actual sales data of the product, the parameter distribution of the product is

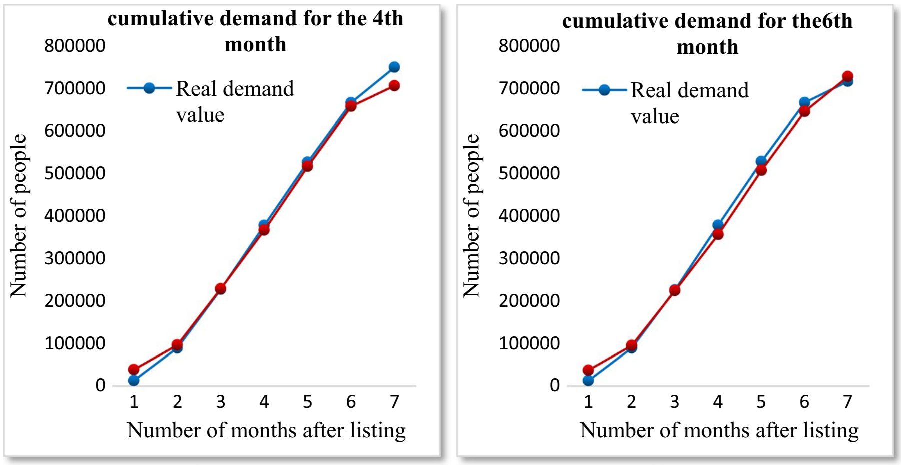

Fig. 11 Comparison of cumulative demand forecast and true value in the 4th and 6th months

Table 3 Improved BASS algorithm and analysis of the accuracy of the prediction value of the BASS algorithm

Month after listing	1	2	3	4	5	6	7	Prediction accuracy
BASS predicted value	57,216	110,467	139,020	141,268	142,076	104,317	42,932	0.22874
Improved BASS prediction value	42,317	59,721	122,499	141,833	159,888	138,257	40,002	0.14056
Real sales	15,021	78,125	130,002	156,698	153,246	137,625	68,576	

continuously updated, while the product is still in the sales stage, so as to realize the dynamic update of the entire prediction process of the product. This article will calculate the estimated value of the single-month demand of the products corresponding to the 4th and 6th months and the estimated value of the cumulative demand for comparison with the actual data, as shown in Fig. 10.

Then calculate the value to more accurately and intuitively describe the specific situation of the predicted value and the true value, as shown in Fig. 11.

It can be seen from Fig. 11 that the monthly demand value of the product calculated by the method used in the article and its accumulated demand value are very close to the actual value of product *w*6. Because in each stage of the later stage, its parameters are constantly updated based on the actual value of the previous period, which significantly improves the accuracy of the overall forecast.

4.3 Improved BASS model prediction results

The estimated value obtained by the original BASS model and the estimated value obtained by the improved BASS model in the article are compared with the actual sales value of product *w*5 to verify the effectiveness and feasibility of the method mentioned in the article, as shown in Table 3.

It can be seen that the improved BASS algorithm has excellent prediction accuracy for product life cycle and sales, with an error of only 14.06%, which is 8.81% lower than the original BASS model.

5 Discussions

This experiment uses six products of company A as examples to extract data. A questionnaire survey was conducted with 100 randomly selected consumers in the form of a questionnaire, and their evaluations and ideas on five of the products were combined to obtain the average utility value of the above five products in the consumer's consumption concept. Then use the data of these five products to predict the sales volume of the sixth product. According to the above example, it can be seen that the improved BASS model has the following characteristics. The improved BASS model uses a more objective method to distinguish the similarity of products, and the results obtained have more reference value. The improved BASS model is established according to the price factor of the product, and the initial value can be found from the data of the product similar to the product that has not been predicted, so that the initial demand of the product can be calculated. After that, the parameters of the improved model when the product is sold are updated by using Bayesian ideas. According to the above examples, it can be concluded that the improved BASS model proposed in the article has a significant improvement in accuracy compared with the original BASS model. At the same time, it has extremely high reference significance for product development, design, sales, and other aspects.

As a result, the Internet of Things has a substantial impact on the upgraded BASS model. Augmented reality, high-resolution video streaming, self-driving cars, smart environments, e-health care, and other Internet of Things (IoT)-centric concepts are now widespread. IoT has altered the globe by delivering seamless connectivity between diverse networks in light of these developing notions (HetNets). The ultimate goal of IoT is to bring plug-and-play technology that provides end-users with simplicity of use, remote access control, and configurability.

6 Conclusions

Due to the complexity of the industrial environment and the distance from a specific location, the quality of communication is severely compromised. SAGIN is seen as a viable solution to these problems for the IIoT. This paper discusses SAGIN, IIoT, product lifecycle management. Based on SAGIN's in-depth research on these data, Bayesian theory and annealing simulation process are used to change and update the parameter distribution of related product models in real time to improve prediction accuracy. Finally, with an error of 14.06%, the modified architecture has very strong prediction accuracy for product life cycle and sales, which is 8.81% lower than the BASS model.

Abbreviations

IIoT	Industrial Internet of Things
SAGIN	Space-air-ground integrated networks
M2M	Machine-to-machine
IoT	Internet of Things
R&D	Research and development
IT	Information technology
GIG	Global information grid
E2E	End-to-end
QoS	Quality of service
NLS	Nonlinear least squares
SVNN	Single-valued neutrosophic number
SVNS	Single-valued neutrosophic sets

EDAS	Evaluation based on distance from average solution
ICT	Information and communications technology
HetNets	Heterogeneous networks
5G	Fifth generation
LCA	Life cycle assessment
LCIA	Life cycle impact assessment

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Author contributions
QWH has completed all the work related to this paper. HY, JJW, HF, and LZ participated in the simulation verification. All authors read and approved the final manuscript.

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Availability of data and materials
Data are confidential and not public.

Declarations

Competing interests
The authors declare that they have no competing interests.

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