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An adaptive frequency optimization method for credibility assessment of equipment digital twins in intelligent manufacturing

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Abstract

To guarantee the effective equipment digital twin (DT) applications in intelligent manufacturing, the DT's credibility must be properly assessed continuously. Pursuing a rather high assessment frequency would guarantee the accuracy of the credibility but would slow down the quantification process or consume too much computational resources. The dynamic credibility assessment of the real-time evolving DTs has comprehensive requirements for accuracy, rapidity, and cost. To achieve the dynamic balance, an adaptive assessment frequency optimization method is proposed. The optimal assessment frequency can be adjusted in real time using particle swarm optimization algorithms according to variable application requirements and working conditions. The influence of different frequency on the credibility of digital twins are analyzed based on experience from VV&A (Verification, Validation and Accreditation) methods in M&S (Modeling and Simulation). The method not only guarantees the accuracy and effectiveness of the assessment results, but also meets the assessment rapidity requirements and is relatively more economical.

Keywords: credibility assessment; digital twin; intelligent manufacturing; adaptive optimization; modeling and simulation

1. Introduction

The Digital Twin (DT) has become a research hotspot in recent years. A digital twin is a digital model of a physical object, which can evolve in real time by receiving data from the physical object so as to keep it consistent with the physical object throughout its whole life cycle (Zhang, Zhou & Horn, 2021). The evolution and interactivity are two prominent features of current digital twins, which enable the DT users to obtain intrinsic information of the specific real-world object from virtual simulation tests. Based on the realistic simulation results, the digital twins can feedback effective optimization strategies on the physical system. By conducting the strategies, the current problems of the physical system would be solved, hidden risks would be avoided, and the overall efficiency would be improved (Liu, Ong & Nee, 2022).

In the field of M&S, if the credibility of a model has not been evaluated according to the user requirements, the model cannot play its value in practice (Oberkampf & Trucano, 2008). Similarly, an equipment digital twin also needs a set of credibility evaluation methods. Only by ensuring that the credibility of the digital twin is higher than the use threshold can the digital twin have practical applications.

The credibility evaluation of equipment digital twins is necessary, but difficult, because equipment digital twins are highly dynamic and complex. On the one hand, equipment is a multi-granularity object involving multi-disciplinary fields, so the corresponding digital twin model has the characteristics of multi-physical domains, multi scales, and multi resolutions. The process of evaluating the credibility of such a complicated model is a system engineering project. On the other hand, the digital twins continuously evolve and interact with the physical objects during their entire lifecycles. Therefore, a digital twin is highly dynamic, which also leads to high uncertainty (Barkanyi, Chovan, Nemeth & Abonyi, 2021). These features put forward higher standards for the credibility evaluation methods of equipment digital twins.

In intelligent manufacturing, large numbers of processing equipment are connected to the scheduling center in the form of digital twins (Wu, Mao, Chen & Wang, 2021). The digital twins perform simulation predictions based on actual production conditions. The scheduling center generates control signals to the manufacturing process for real-time capacity optimization. To guarantee the effectiveness of the DT applications, the DTs are supposed to be assessed in a high frequency. The digital twins need to be corrected based on the real-time status data of the processing equipment so as to stay within an acceptable credibility level. The dynamic credibility assessment of the real-time evolving digital twins has comprehensive requirements for accuracy, rapidity, and cost. Pursuing a rather high assessment frequency would guarantee the accuracy of the credibility but would slow down the quantification of overall credibility or consume too much computational resources.

In this paper, we propose an adaptive assessment frequency optimization method. The optimal assessment frequency can be adjusted in real time using particle swarm optimization algorithms according to variable application requirements and working conditions. The influence of different frequency on the credibility of digital twins are analyzed according to VV&A (Verification, Validation and Accreditation) methods from M&S (Modeling and Simulation). The method not only guarantees the accuracy and effectiveness of the assessment results, but also meets the assessment rapidity requirements and is relatively more economical.

2. State of the art

During the ten years of DT concept development, most of the literature focused on discussing its concept and connotation (Lim, Zheng & Chen, 2020; Liu et al., 2021; Lu et al., 2020; Zhou et al., 2020; Tao et al., 2019). There still lacks a systematic credibility evaluation framework for reference in the field. The evaluation of a DT will include the evaluation of the DT model itself and the evaluation of real-time data used for the construction and evolution of the model. Theoretically, changes of data will be incorporated and reflected in the model, nevertheless, a separate evaluation of the credibility of data can prevent untrusted data from entering the DT, so as to better ensure the credibility of DT. Although there are few literatures on credibility evaluation for DTs, there are lot of research on the credibility evaluation in the field of M&S that will be helpful to develop credibility evaluation methods for DTs and equipment DTs.

2.1 Data credibility evaluation

Credibility of data used by a DT will influence the credibility of the DT. These data include a large number of sensor data, human related non-sensor data, and data from software.

If the sensor is damaged or fails (Sun, Luo & Das, 2019), or the sensor is unwilling to play a normal role in the sensor network (Jiang et al., 2014), the sensor data of the abnormal node is unreliable. Even if the data sources are normal, they are still inevitably affected by the working environment (Miao, 2014) or the installation distance and angle of the sensor (Mao, 2016). For the credibility evaluation of sensor data itself, The authors (Liao et al., 2021) used the cumulative residual chi square check to evaluate the credibility of the data by comparing the current data with the historical data.

Digital twin is inseparable from human participation in the construction stage and operation decision-making stage. The author (Levelt & Caramazza, 2007) evaluated the influence of ambiguity and authority on this kind of data by studying psychology. Brown et al. (Barber & Robert, 2010) evaluated the credibility of human related propositions from the perspective of a priori knowledge and a posteriori knowledge.

2.2 Model credibility evaluation

The concept of VV & A (Verification, Validation and Accreditation) proposed by the U.S. Department of defense (DoD) is a series of methods and processes recognized in the field to improve the credibility of modeling and simulation. The research team of system simulation of National University of Defense Technology has carried out long-term research on VV & A of weapon equipment system simulation (Tang, 2009; Liao et al., 2003; Wang, 2018). The teams of Harbin Institute of Technology have carried out VV & A and credibility evaluation research on the distributed interactive simulation system and made great achievements in this regard (Yang et al., 1999). For aerospace simulation system, reference (Kim et al., 2017) puts forward a trust evaluation framework for the whole life cycle of modeling and simulation development. Reference (Zhou et al., 2020; Zhang & Ye, 2006; Zhen & Hu, 2015; Sim & Lee, 2014) combs and expounds the trust evaluation theory of complex weapon equipment model.

Further, the specific methods of model credibility evaluation can be summarized into three categories: qualitative analysis methods, quantitative analysis methods and comprehensive analysis methods. Document (Zhang et al., 2021) proposed a d-digital target programming method suitable for complex simulation systems. The authors (Beydoun, Low & Bogg, 2013) proposed a set of model evaluation methods based on expert scoring, simulation requirements and simulation environment. Acar (2015) pointed out that the prediction ability of meta modeling can be improved by combining various types of models in the form of weighted average integration. Li et al. (2021) studies the credibility evaluation technology of complex simulation models by using the multi-agent interactive network method. Aiming at the problem of high complexity of simulation model, Ferson & Oberkampf (2009) designed the u-pooling region indicator. Li et al. (2014) proposed multivariate probability integral transformation (PIT). Dornheim & Brazauskas (2011) proposed a hybrid linear expectation model to automatically and efficiently calculate the credibility of complex systems. Liang et al. (2013) proposed a credibility measurement method based on dynamic Bayesian network. Hu (2011) proposed a framework of dynamic data-driven simulation method, which uses Monte Carlo method to conduct real-time simulation of wild fire.

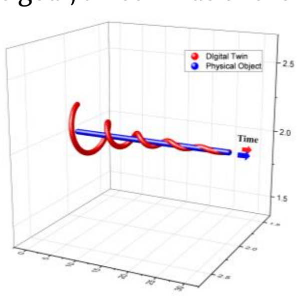
Traditional M&S pays more attention to offline simulation, and its credibility evaluation method is mainly Verification, Validation, and Accreditation. DT specifically aims at online simulation, expanding interactive and evolutionary characteristics based on traditional offline simulation. Therefore, a number of credibility concepts and evaluation methods from in M&S domain can be used for references. Considering the unique features of equipment DTs, new principles and methods need to be applied to conduct the credibility evaluation of DTs.

3. Materials and Methods

3.1. Features of the digital twin system

1) Evolution

Evolution is the most iconic feature of a DT as well as an equipment DT. The aim of DT evolution is to mirror the physical object throughout its lifecycle. To achieve the goal, three kinds of evolution are applied.



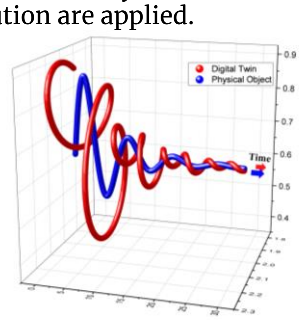


Fig. 1(a) Evolution without input **Fig. 1(b) Evolution with input**

The first is the internal circulation evolution. This form exists because the DT needs to be initialized and the mechanism of the physical object needs to be refined. On the one hand, when a digital twin is constructed, there still exists a structure and parameter gap between the digital model and the physical object. Therefore, the real-time data are collected to adjust the digital model according to the real state of the physical object. On the other hand, due to the incomplete recognition of the intrinsic mechanism of the physical world, a flow of continuous data are collected to constantly adjust and improve the inner mechanism of DT. As shown in Fig.1(a), each circular cross-section is one attempt to refine the mechanism. For compensation of the intrinsic error caused by unmatured mechanism, the initialization-like adjustment of the DT structure and parameter need to be conducted periodically. However, the value of DT depends on the effective simulation supported by real mechanism, rather than high similarity caused by high frequency calibration. Therefore, how well does the mechanism refinement work strongly affects the DT credibility, and needs to be evaluated. This makes the evaluation quite different from those only compare the outputs obtained from both DT and the physical object.

The second is the execution of the digital twin model. Considering the physical object as an isolated system. If not influenced by the outside, including the environment and manual intervention, the physical object changes only according to its own laws. In this case, once perfectly initialized, the digital twin will act the same as the physical object according to the fully refined mechanism.

The last is the external circulation evolution. Because the isolated system is bound to be used by human and affected by the environment, it is essential to gather the intervention information from the outside. This kind of data are collected and transformed into the input of DT, which will motivate the corresponding reaction of DT according to its inner mechanism. Theoretically, possessed with the perfect initialization and mechanism, the DT will present the same state as the physical object based on the impact data from outside the isolated system. But as shown in Fig.1(b), in the real situation, the DT would try to consume the input and fulfill the internal circulation refinement at the same time. Although the difference between the DT and the physical object seems large at first, the error would shrink afterwards. In the case of constant input flow, it would take a long time to distinguish the external disturbance from the error caused by immature mechanism. Therefore, the credibility evaluation should evaluate the DT through a period of time, and the credibility value would change continuously throughout the whole lifecycle.

2) Interactivity

There are two directions of interactivity. One is from the equipment to the DT. The transmission content includes the real-time acquisition of the status information of the equipment through distributed sensors, the data automatically generated by various built-in software of the equipment, and manually updated information like text drawings. The other direction is from the digital twin to the equipment. The optimization adjustment strategy, scheduling and other decisions on the equipment can be made according to the testing, prediction, and simulation based on the digital twin. The equipment will be updated iteratively according to the feedback information.

The interaction between the two equally essential directions is relatively independent and occurs according to the needs. The interaction pointing to the digital twin is the basis. The quality of this step will determine the credibility of subsequent prediction and simulation. It is necessary to shorten the information iteration cycle as much as possible on the premise of ensuring the information quality. The interaction pointing to the equipment is the purpose. If the performance is reduced in this step, it may lead to a vicious circle in the follow-up. Therefore, sufficient arguments and risk prevention measures are necessary when implementing the feedback suggestions.

3.2. problem analysis

The analysis of the target problem considered both the experience from VV&A process in M&S and the dynamic evolution feature of DT. The analysis consists of the meaning of DT credibility and its assessment, credibility assessment in intelligent manufacturing scenarios, trigger modes of the assessment, impact of assessments with different trigger frequency and important factors for assessment frequency adaptation.

1）The meaning of DT credibility and its assessment

The credibility of an equipment digital twin is the degree of correctness and timeliness of the given DT, simulation process and simulation results, when DT continuously interacts and evolves in each stage of the equipment life cycle, under the requirements defined by Lu et al. (2023).

Credibility assessment requires evaluation of the model building process, the application process, and the simulation results. For the digital twins, this evaluation process is too time-consuming to be feasible, and therefore requires significant simplification, such as separating the basic evaluation from the dynamic evaluation. For parts that remain constant over time or change very slowly, a thorough and detailed basic evaluation is performed at long intervals. While for parts that change rapidly, a fast dynamic evaluation is performed using algorithms based on real-time data.

2) Credibility assessment in intelligent manufacturing scenarios

In the intelligent manufacturing scenario, due to the flexibility of the manufacturing process, the correlation between multiple types of manufacturing equipment is not fixed. The equipment faces more possibilities of working environment and work content. So the change of equipment and the changing frequency are unpredictable. Therefore effective credibility assessment is needed to confirm the real-time consistency of the twin model of each equipment and its physical object. Otherwise the planning of the manufacturing process could hardly have practical effect due to a large number of errors that cannot be predicted in advance.

3) Trigger analysis for credibility assessment

There are three main trigger modes for the credibility assessment process.

The first is the time-triggered mode, i.e., setting the frequency of the interval to trigger the evaluation process fixedly. This approach is more effective for demand scenarios with fewer change possibilities, and once the device has a rapid and complex change, the assessment frequency needs to be set to a fixed higher value, which is a waste of resources.

The second is the event-triggered mode, i.e., the corresponding evaluation is triggered based on detected events such as device state changes or end-of-evolution process flags. This approach is more effective for scenarios with apparent change states and simple interaction processes. If the device interaction is complex and the change situations are diverse, it is difficult to preset the detection parameters or methods in advance.

The third is a mixed event and time trigger mode, that is, set a fixed lower interval time, while also responding to the received event trigger signal. This mode can play the advantages of both modes to a certain extent, but does not compensate enough for the disadvantages of both. There is an actual need for an adaptive interval frequency trigger mode. It can not only automatically calculate the appropriate high frequency trigger signal in the changing complex working conditions, but can also adjust to a lower frequency trigger signal in the low period of the scene events.

4) Analysis of the impact of high and low trigger frequency on credibility assessment

The frequency of the credibility assessment trigger is compared to the states change speed of the physical objects. When the credibility assessment trigger frequency is high, the data related to the changing physical objects can be collected more comprehensively. However, when the evaluation frequency is much larger than the change rate of physical objects, it will generate a large amount of unnecessary sampling data, trigger lots of evaluation process. This further increases the computational workload of the evolution process trigger, which will cause a lot of waste of system physical and computational resources, and even cause repeated conflicts before and after the evolution process. When the evaluation frequency is low, the change states of some physical objects will be missed, which causes inconsistency between the DTs and physical objects fundamentally. If the change states of physical objects have little impact on the application requirements of the DTs, this relatively low evaluation frequency can be accepted to obtain a better balance considering the resource efficiency.

5) Analysis of important factors for assessment frequency adaptation

a. The effect of working conditions

From the analysis of the trigger frequency impacts, it is clear that the change speed of the working condition will affect the change speed of the equipment. Thus the optimal frequency of the assessment will be affected. The understanding of the working conditions comes from the environmental perception, so it is necessary to collect data, analyze and model the environment factors that can affect the change of the equipment. So that the change of the working condition and the change of the equipment can be deduced in turn. Due to the high uncertainty of the environment and the ambiguity of the influence mechanism between the working conditions and the equipment, it is difficult to make accurate analyses and predictions. Considering that this factor is an indirect influence, a qualitative analysis can be performed to give a rough estimate, and further frequency adjustment can be used to find the optimal frequency value.

b. The effect of user requirements

The user requirements refer to the requirements for the application of DTs. In this context, it refers to the optimality or planning requirements for the manufacturing capability of each device in a intelligent manufacturing scenario. This type of requirements will determine the credibility requirements for each assessment indicator of the manufacturing equipment DTs. The credibility requirements determine the acceptable range of variance between the falsity and reality indicated by each indicator. According to the analysis of the impact of evaluation frequency on plausibility, when the frequency is lower, the clarity of the physical objects variation will be lower. So the lower limit of the assessment frequency for each indicator will be determined by the acceptable error range given by the user requirements.

c. The effect of evolution methods

The evolution methods are methods that adjust the existing model in the direction of error reduction. Different evolution methods have various sensitivity to errors. When the error changes are small, some methods can target evolution for each tiny change, some methods will be fuzzy and unify the changes as one, and some methods will not be able to identify the changes and do not evolve. There is no absolute superiority or inferiority of each type of method itself. It is necessary to comprehensively consider the specific demand scenario with the corresponding evolution method and configure the appropriate evaluation frequency. For example, for evolution methods with high sensitivity, in high precision manufacturing, the credibility requirement for the DT is rather high. The DT needs to be evolved immediately for any small errors. So that a high frequency should be configured for the assessment. However, in toy-like manufacturing with low precision requirements, high-frequency evaluation will trigger high-frequency evolution, resulting in unnecessary waste of computational resources. In such cases, a low frequency should be configured for the assessment.

d. The effect of assessment time consumption

In different scenarios, with different devices, different assessment methods will consume different periods of time. If the assessment time is too long, it is not suitable to use a higher assessment frequency, otherwise more and more assessment processes will linger in the system and the resource cost effectiveness will be low. From another perspective, assessment methods with longer assessment time cost are inherently unsuitable for physical objects that change fast. This inherent constraint enables assessment time consumption to be an important reference factor for assessment frequency, and the two should be kept within a certain ratio.

e. The effect of resource costs

Resource costs include the costs of data acquisition, transmission, and storage, and the cost of assessment computation resources, which is an important factor limiting the upper limit of assessment frequency. When the assessment cost is relatively high, the grasp of the dynamics of physical object changes is limited to a certain extent and thus is not applicable to physical objects that change too rapidly. This is similar to the analysis of time consumption described above. However, there is no necessary correlation between time consumption and resource costs. Only if one part of the assessment process is particularly slow, the overall time spent will be long, while the resource costs may still be low. Therefore, the impact of time consumption and resource costs on the frequency of assessment should be viewed together.

The analysis above is referred to the VV&A experience and the prominent evolution feature of DT. To balance the performance and cost of the DT credibility assessment, the PSO algorithm is reconfigured by optimizing five important factors raised by the analysis.

3.3. methodology

In this paragraph, the PSO (Particle Swarm Optimization) algorithm is introduced firstly, then the acquisition methods of each frequency influencing factors are briefly analyzed, and the total method including data acquisition, factors calculation and the adjusted PSO algorithm is given in the end.

1) PSO algorithm

In 1995, inspired by the regularity of bird flock foraging behavior, James Kennedy and Russell Eberhart developed a simplified algorithmic model that was eventually improved over the years to form the PSO algorithm, which can also be called the particle swarm algorithm.

Particle swarm algorithms have the advantages of fast convergence, few parameters, and simple implementation of the algorithm (for high-dimensional optimization problems, convergence to the optimal solution is faster than genetic algorithms), but there is also the problem of falling into a local optimal solution.

The idea of the particle swarm algorithm originated from the study of the foraging behavior of a flock of birds, where the flock finds the optimal destination by sharing information collectively. In the figure below, imagine a scenario in which a flock of birds is searching for food randomly in a forest, and they want to find the location with the largest amount of food. However, none of the birds know exactly where the food is, but only have a sense of where it is in the general direction. Each bird searches in the direction it decides, and during the search it records the location where it has found the most food and the amount of food. During the search process, each bird adjusts its search direction according to the location with the most food in its memory and the location with the most food recorded by the current flock. After a period of searching, the flock can find out where the most food is in the forest.

2) The obtainment of frequency influencing factors

The adaptive assessment frequency is composed of a weighted sum of 5 influencing factors in Eq.1.

$$\mathrm{F} = A_1 * S + A_2 * L + A_3 * E + A_4 * C + A_5 * R \tag{1}$$

Where F is the adaptive assessment frequency, S is the change rate of the equipment, L is the lower limit given by user requirements, E is the sensitivity of the evolution method, C is the assessment time consumption, R is the resource costs, $A_1 \sim A_5$ are the parameters to be optimized by PSO.

To obtain S, the data that can be collected from the working environment should be analyzed. Appropriate acquisition points should be selected for the environmental data $x(t)$. Use the batch of data to construct the working condition change rate formula $f(x(t))$. Based on the experience and data $y(t)$ collected from the field tests, the working condition change rate is transformed into the equipment change rate by $g(\cdot,\cdot)$, which becomes one of the particle parameters.

$$S = g(f(x(t)), y(t)) \tag{2}$$

To obtain L, an analysis on user requirements is conducted to quantify the range of plausible values for the hierarchical indicators. The indicators are from multidimensional perspectives of the characterized manufacturing equipment DT. The value range is further analyzed to derive the lower limit of the assessment frequency of each indicator, which is denoted as $(l_1, l_2, \dots, l_n)$. The assessment frequency is supposed to be the maximum of each lower limit, so that the physical state can be always fetched properly. The lower limit is not necessarily the lowest value of the actual assessment frequency, and sometimes the assessment accuracy needs to be sacrificed for the needs of lower resource costs or timeliness.

$$L = \max\,(l_1, l_2, \dots, l_n) \tag{3}$$

To obtain E, the sensitivities of different evolution methods are quantified based on the concerning errors. The sensitivity E_s is calculated by Eq.4. The impact of evolution methods on the assessment frequency should be analyzed to initially establish suitable evolution methods under different scenario requirements. The corresponding sensitivity of the chosen evolution method is denoted as E.

$$E_s = \frac{\varepsilon_{min}}{\varepsilon_{average}} \tag{4}$$

Where the ε_{min} refers to the minimum error which can trigger the evolution process, the $\varepsilon_{average}$ means the average of the error detected by the assessment.

To obtain C, the theoretical analysis of time consumption of each assessment process should be combined with actual measured data to get the average assessment time consumption C under certain scenario conditions。

To obtain R, the cost of data acquisition, transmission and storage, and the cost of evaluation computing resources should be quantified one by one. Thus the average cost to be spent for one assessment process could be given.

Considering the proposed influencing factors, the main processes of PSO algorithm is adapted and shown in fig.2 .

3) Adaptive algorithm

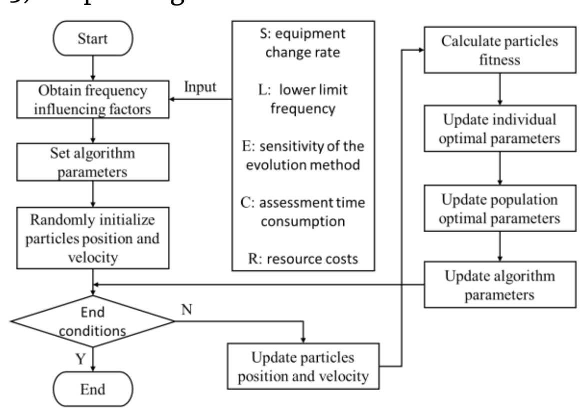


Fig. 2 Algorithm flow chart

Table 1. Algorithm pseudo-code.

Algorithm: PSO for adaptive assessment frequency
FOR each influencing factors
Obtain factor value
FOR each particle i
FOR each factor parameter A
Initialize position x_{iA} randomly within acceptable range
Initialize velocity v_{iA} randomly within acceptable range
END FOR
END FOR
Iteration $j = 1$
DO
FOR each particle i
Update frequency F according to the equation
$F = A_1 * S + A_2 * L + A_3 * E + A_4 * C + A_5 * R$
Calculate fitness value
IF the fitness value is better than $p_{iA,pb}^j$ in history
Set current fitness value as $p_{iA,pb}^j$
END IF
END FOR
Choose the particle with the best fitness value as the $p_{A,gb}^j$
FOR each particle i
FOR each factor parameter A
Calculate velocity according to the equation
$v_{iA}^{j+1} = \omega v_{iA}^j + c_1 r_1 (p_{iA,pb}^j - x_{iA}^j) + c_2 r_2 (p_{A,gb}^j - x_{iA}^j)$
Update particle position according to the equation
$x_{iA}^{j+1} = x_{iA}^j + v_{iA}^{j+1}$
END FOR
END FOR
$j = j + 1$
WHILE maximum iterations or minimum error criteria are not attained

In the pseudo-code given in table 1, i is the particle number, A is a certain parameter to be optimized in Eq.1, x_{iA} is the position value of parameter A of the particle i, v_{iA} is the velocity value of parameter A of the particle i, j is the iteration number, $p_{iA,pb}^j$ is the individual optimized value of parameter A of particle i in iteration j, $p_{A,gb}^j$ is the population optimized value of parameter A in iteration j, v_{iA}^j is the velocity value of parameter A of the particle i in iteration j, x_{iA}^j is the position value of parameter A of the particle i in iteration j.

The velocity updating equation is as follows:

$$v_{iA}^{j+1} = \omega v_{iA}^j + c_1 r_1 (p_{iA,pb}^j - x_{iA}^j) + c_2 r_2 (p_{A,gb}^j - x_{iA}^j) \quad (5)$$

Where ω is the inertia weight of a certain particle, c_1 is the individual learning rate, c_2 is the population learning rate , r_1, r_2 are randomized among [0,1] to increase the randomness of the search.

There are three parts in the velocity updating equation. The first is ωv_{iA}^j, which is the inertia part. This part represents the confidence in the previous motion state of the particle itself. Larger ω is good for global search, jumping out of local extremes and not falling into local optimums, while a smaller ω is beneficial to local search, allowing the algorithm to converge to the optimal solution quickly. When the problem space is large, in order to achieve a balance between search speed and search accuracy, it is a common practice to make the algorithm have a high global search capability in the early stage to get a suitable seed, and a high local search capability in the later stage to improve the convergence accuracy, so It is not desirable to have a fixed constant. In the manufacturing scenario, the working condition would not change too fast, so the inertia weight should pick a relatively high number, like 1.5 or 1.8.

The second is $c_1 r_1 (p_{iA,pb}^j - x_{iA}^j)$, which is the cognitive part. It represents the part of the particle's own experience, which can be understood as the distance and direction between the particle's current position and its own historical optimal position. When the working condition is relatively stable, it is recommended to choose a higher value of c_1 than c_2 to obtain the optimized solutions more precisely, like $c_1 = 2.2$, $c_2 = 1.8$.

The third is $c_2 r_2 (p_{A,gb}^j - x_{iA}^j)$, which is the social part. It denotes the information sharing and cooperation between particles, especially from the experience of other good particles in the population, which can be understood as the distance and direction between the current position of a particle and the historical optimal position of the population.

4. Results and Discussion

With the analysis of DT characteristics and the understanding of the connotation of DT credibility, this paper proposes the meaning and importance of DT credibility assessment in intelligent manufacturing scenarios. Further, with respect to the frequency of credibility assessment, the patterns of assessment triggers in intelligent manufacturing are analyzed, and the impact of different assessment frequency on the assessment effect is discussed. The impact on the effectiveness of assessment frequency is analyzed from five main aspects: working conditions, user requirements, evolution methods, assessment time consumption, and resource costs. The quantitative acquisition methods of each factor are briefly introduced.

The optimization function of the assessment frequency is organized according to the idea of multi-objective optimization, and the PSO algorithm is modified to adapt it to the requirements of this scenario. The preferential settings of some parameters in the algorithm are initially discussed for the characteristics of the intelligent manufacturing scenario. Finally, the whole process including data collection, influence factors acquisition, parameter optimization and the pseudo-code of the core algorithm are formed. The method can solve the problem of DT credibility assessment frequency adaptation in the intelligent manufacturing scenario.

The analysis of assessment frequency in this paper is a major missing point in the current research on digital twin trusted assessment. Most of the research has not yet focused on the profound impact on assessment brought by the automatic cycle of rapid construction, real-time assessment, and dynamic use of digital twins. This paper provides a preliminary analysis of the issue, and the relevant assessment elements, access methods, and overall self-optimizing adjustments are of high value to the effectiveness of DT credibility assessment.

5. Conclusions

In this paper, an adaptive assessment frequency optimization method is proposed. The optimal assessment frequency can be adjusted in real time using particle swarm optimization algorithms according to five influencing factors: working conditions, user requirements, evolution methods, assessment time consumption, and resource costs. The method is of high value to the effectiveness of DT credibility assessment in intelligent manufacturing scenario. The DT credibility can be assessed properly by adjusting the assessment frequency to balance the accuracy, time consumption and cost. For the efficiency limitation of the PSO algorithm, the working condition could not change too rapidly. Otherwise, it would be difficult to converge at the optimal frequency. Optimization algorithms that balance global optimum search power and convergence efficiency need to be carried out. More detailed parameterization and fuller experimental validation also need to be done in the future.

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