An empirical learning-based validation procedure for simulation workflow

Zhuqing Liu, Liyuanjun Lai, Lin Zhang
School of Automation Science and Electrical Engineering
Beihang University (BUAA), Beijing, 100191 China
Email: zhuqingliu@buaa.edu.cn

Abstract—Simulation workflow is a top-level model for the design and control of simulation process. It connects multiple simulation components with time and interaction restrictions to form a complete simulation system. Before the construction and evaluation of the component models, the validation of upper-layer simulation workflow is of the most importance in a simulation system. However, the methods especially for validating simulation workflow is very limit. Many of the existing validation techniques are domain-dependent with cumbersome questionnaire design and expert scoring. Therefore, this paper present an empirical learning-based validation procedure to implement a semi-automated evaluation for simulation workflow. First, representative features of general simulation workflow and their relations with validation indices are proposed. The calculation process of workflow credibility based on Analytic Hierarchy Process (AHP) is then introduced. In order to make full use of the historical data and implement more efficient validation, four learning algorithms, including back propagation neural network (BPNN), extreme learning machine (ELM), evolving neuron (eNFN) and fast incremental gaussian mixture model (FIGMN), are introduced for constructing the empirical relation between the workflow credibility and its features. A case study on a landing process simulation workflow is established to test the feasibility of the proposed procedure. The experimental results also provide some useful overview of the state-of-the-art learning algorithms on the credibility evaluation of simulation models.

Keywords—model validation, simulation workflow, fast learning algorithms

I. INTRODUCTION

Simulation are increasingly used to study complex systems in real world, providing a faster, cheaper and more flexible alternative than physical experiments. With the expansion of simulation objects, it is more and more imperative to compose a number of domain-models to implement comprehensive system analysis. For such collaborative works, simulation workflow is introduced as a top-level model for the design and control of simulation process. It is used for representing the connection structure of under-layer component models, describing their temporal information and so as to managing their function transformation. A complete workflow specification requires careful integration of many different process characteristics. It contains the definitions of individual activities, their scope, the order of execution that maintains the overall simulation process logic, the rules governing the discipline of work list scheduling to models, identification of time constraints and more. Before the construction and evaluation of the component models, the validation of upper-layer simulation workflow is of the most importance in a simulation system.

At present, most of the existing validation techniques are customized for various under-layer component models. They focus mainly on the output consistency between simulation model and the real-world object. However, the output of a simulation workflow is not a single group of data related to one basic model, but a number of combined states related to multiple component models. Validating all possible states of a composed simulation system with the real-world objects is clearly unrealistic. Therefore, a more systematic method is required to comprehensively evaluate how does the simulation workflow work and whether they can be trusted.

The credibility of the simulation workflow is a key aspect to verify whether the corresponding system could operate normally. Currently, the validation method especially designed for upper-layer simulation workflow is rare.

There are three main methods to evaluate the credibility of simulation models: quantitative analysis, qualitative analysis and combined analysis. Existing qualitative methods for validating complex simulation systems are based on cumbersome questionnaire design and expert scoring. On one hand, questionnaire is generally designed for a specific model, which is subjective and hard to extend. On the other hand, experts scoring requires high personnel ability. Therefore, most of the qualitative methods are time-consuming and inextensible.

Quantitative analysis refers mainly to the consistency validation of simulation results with the real-world objects. The measurement of accuracy between model outputs and real data is made according to different sorts of performance criteria. It has high accuracy and strong objectiveness. However, Quantitative analysis usually requires a large number of reference data from real world, which is rare or even unavailable for most simulation objects. Moreover, many important internal features other than the simulation results have yet been considered.

In combined analysis, some intelligent algorithms, such as bayesian algorithms and neural networks and so on, are introduced with a large amount of historical simulation data to mapping the non-linear relationships between model validation metrics and subject matter expert scores. However, researches on mining model internal factors account for its overall credibility are still limited.

According to the above-mentioned problems, this paper present an empirical learning-based validation procedure to implement a semi-automated evaluation for simulation workflow. First, a three step framework which provides a guidance as to the suitability of evaluating the simulation workflow credibility is summarized. Second, four algorithms (back propagation neural network (BPNN), extreme learning machine (ELM), evolving neuron (eNFN) and fast incremental gaussian mixture model (FIGMN)) are introduced and compared to learn the non-linear relations between the model internal factors and its credibility. Finally, a case study is established to shows the feasibility of proposed
procedure as well as the superiority and inferiority of the four algorithms in the validation of simulation workflow.

The paper is structured as follows: Related works on simulation model validation is discussed in section 2. In section 3, a general representation of simulation workflow is shown. The procedure for simulation workflow validation is elaborated in section 4. In section 5, Four algorithms are briefly introduced, giving a general overview of their application ways on learning the empirical relationships between the model internal factors and its credibility. A case study is also provided. Section 6 gives the conclusions obtained from the experiments.

II. RELATED WORKS

Quantitative analysis, qualitative analysis and combined analysis are widely used to validate the credibility of simulation models. Quantitative analysis is to establish a mathematical model to represent the relationships between the simulation results and the evaluation indicators. Qualitative analysis is a kind of method which depends on rigorous techniques for gathering high-quality data and the credibility of the experts. Combined analysis research is set up by using different learning algorithms. There is a great debate between those evaluation methods in early literatures [8][9]. In practice, these three methods have their own advantages and disadvantages. In recent years the debate has softened [10]. A consensus has gradually emerged that the important challenge is to match appropriately the methods to empirical questions and issues, and not to universally advocate any single methodological approach for all problems. Thus, they should be replenished by each other and used alternately.

In qualitative analysis research, most of the researches are based on questionnaire design and expert scoring. For example, Schruben proposed Turing test method which is based on relevant experts to process output data from simulation model [11]. Beydoun developed a set of evaluation methods for models based on experts scoring, simulation requirements and simulation environment [12]. Buchmann analyzed the relationship between agent heterogeneity, model structure and the detailed data used to represent model performance [13]. In terms of the mutual trust of agents, Schreiber designed a multi-agent network model for the coevolution of agents [14]. Schmidt established a method of calculating the credibility of a certain model based on fuzzy theory [15]. However, Velayas indicates that this method has a strong subjectivity, qualitative aspects of the evaluation, and the actual use of emptied weight may lack the expert scoring [16]. In addition, most of the qualitative methods are time-consuming and inextensible. Therefore, qualitative analysis is not widely used in isolation.

Currently, quantitative analysis research on evaluating credibility of simulation model is based on the traditional evaluation method and the comparison between the simulation data and the truthful data [17]. For example, Acat indicates that the prediction capability of metamodelling can be improved by combining various types of models in the form of a weighted average ensemble in order to minimize the root mean square cross validation error (RMSE-CV) and root mean square error (RMSE) [18]. To ensure the performance, stability and security of simulation models, researchers provide a set of general indices used for credibility evaluation of simulation model by using mathematical error, information theory, parameter estimation, non-parametric test, and distance judgments [19][20]. These indices can be used not only for the multi-agent simulation model evaluation in the fields of transportation, manufacturing, economy, etc. [21][22][23], but also for the evaluation of machine learning algorithms, such as fitting neural networks and clustering algorithms [24][25][26]. However, in these researches, the opinions of experts in the relevant scientific research are ignored. So it can only be used for models with a high level of data integrity and consistency. In some models, such as the simulation workflow, quantifiable indices are in a small scale [27]. It is hard for quantitative analysis to evaluate the simulation credibility, especially in the strategic analysis of a composed model with insufficient simulation data.

Combined analysis is a new emerging methods for the validation of simulation models. It combines the subjective expert scoring and the objective calculation of model performances by using historical training data. Typical examples include the credibility evaluation theory based on probability and evidence [28], fuzzy set theory [29], multiple attribute decision making theory [30] and so on. Considering the frequent changes in simulation requirements and the complex mechanism of real objects, a number of methods on evaluating the credibility of simulation model based on stochastic probability distributions have been proposed in recent years, such as validation based on cumulative density function comparison [31]. Scott Ferson [32] designed the u-pooling region index. Wei Li [33] proposed multivariate probability integral transformation (PI) [34]. Chan [35][36] investigates the use of interaction statistics as a metric for detecting emergent behaviors from agent-based simulation. Harald Dornheim proposed a hybrid linear expectation model to calculate the reliability of complex system automatically and efficiently [37]. Liang Hongquan [38] proposed a new method of reliability measurement which is based on dynamic Bayesian network. However, researches on the impact of internal factors of using comprehensive analysis are still limit.

In general, the research on validation technology of simulation system has matured. Many standards and documents are formed while the study of model credibility evaluation is also in progress. However, the research on evaluating the reliability of the simulation workflow is still very limited. None of the existing methods has considered the relationship construction between the model credibility and its internal factors other than its simulation results. To solve those mentioned problems, this paper present an empirical learning-based validation procedure to find the inside connection between the credibility of simulation workflow and its internal features and so as to implement a semi-automated evaluation for simulation workflow.

III. A GENERAL REPRESENTATION OF SIMULATION WORKFLOW

Simulation workflow is a top-level model for the design and analysis of complex system. It can be seen as a blueprint of collaborative simulation system. For a specific requirement, a complete simulation workflow is designed to guide the execution of distributed under-layer models, supervise the states of them and designate the logical relationships among different sub-processes. It can be generally constructed in XML scheme. In this paper, it is represented as a directed graph S=(N, E). The node set N of the directed graph consists of three types, active node Na, logical node Nl and event node Ne.

The active node is a detailed description of a short simulation sub-process with a specific environment. It specifies the simulation parameters, interfaces and prerequisites of the related under-layer model with a group of events.

The logical node is defined as the AND/OR/NOR conditions among different active nodes. It is designed as a compensation of the edges to clearly describe the execution conditions of each active node and make them cooperated in a strict order.

Besides, the event node represents the start event (when the
The empirical-based validation procedure for simulation workflow

The procedure of evaluating the credibility of simulation workflow proposed in this paper can be shown in Figure 2. It is established based on a historical evaluation database. Assume the influence relations between the internal features and the credibility for different simulation workflows are consistent, the database can thus be used to structure an empirical evaluation model and calculate the credibility value of a new simulation workflow further. When the database volume is insufficient (let us say the volume is less than 200 as an example), traditional qualitative and quantitative methods will be introduced to validate the specific model manually. Simultaneously, an incremental learning algorithm will be applied to establish the empirical evaluation model by training these historical data incrementally. When the database volume is sufficient, the empirical evaluation model will be invoked to validate the new workflow automatically.

Therefore, based on the internal features of simulation workflow, there are three main modules in this procedure, i.e.:

1) **Quantitative analysis:** This step refers to calculate the specific value of each evaluation index in accordance with the model internal features and some exact equations.

2) **Qualitative analysis:** According to the expert scoring on the importance between different evaluation indices, this module applied a qualitative method (such as a kind of analytic hierarchy process (AHP) algorithm) to calculate the weight of each validation index.

3) **Online establishment of empirical evaluation model:** In terms of the historical data initially obtained from the above traditional methods, this step adopts an online incremental learning algorithm to read the new historical data one by one and establish the empirical evaluation model. When the historical data reaches a large number, the evaluation model will be directly invoked to validate the specific simulation workflow in a short time.

We will provide the details of the three modules in the following sections respectively.

**4.1 Quantitative analysis**

Without the simulation results of under-layer models and the real data from practical objects, it is challenging to validate simulation workflow at design level. To analyze the simulation workflow from quantitative perspective, this paper modifies the credibility assessment scale (CAS) from NASA-STD-7009 [39] and provides 8 new validation factors as the main evaluation indices for simulation workflow validation, as shown in Figure 3.

These eight factors are modified from “verification, validation, input pedigree, uncertainty of results, robustness of results, use history, M&S management, and people” to completeness, accuracy, independence, uncertainty, robustness, historical use, reliability and reproducibility. The value of each index can be calculated either by the internal features of the simulation workflow, or by a number of simulation tests. In practice, the internal features are mapped to different evaluation indices according to their actual influence under certain situations.

Specifically, we considers mainly 14 internal features which can be quantitatively calculated from the specific simulation workflow. To obtain the value of each evaluation index, we provide 8 simple equations to represent the relation between the features and the indices as an example.
Figure 3 Hierarchical structure of credibility evaluation model on simulation workflow

Table 1 Notations of the internal features in simulation workflow

| Symbol   | Name                                      | Range          | Symbol   | Name                                      | Range          |
|----------|-------------------------------------------|----------------|----------|-------------------------------------------|----------------|
| $P_{match}$ | Interface matching degree between nodes | [0,1]          | $N_{history}$ | Number of historical data                  | [0,200]        |
| $P_{integrity}$ | Parameter configuration integrity        | [0,1]          | $P_{int_cons}$ | The consistency of the historical configuration | [0,1]          |
| $\hat{T}$      | Estimated execution time(s)              | [30,150]       | $N_{simulate}$ | Number of external stimulate events        | [0,10]         |
| $T$           | Average practical execution time(s)      | [30,150]       | $N_{incentive}$ | Number of incentive parameters             | [0,100]        |
| $V_t$         | Variance of execution time               | [0,3]          | $N_{ex \_incentive}$ | Number of external incentive parameters   | [0,20]         |
| $N_{\text{active}}$ | Average number of overtime activities    | [0,100]        | $P_f$     | Average failure rate of active node        | [0,1]          |
| $N_{\text{logic}}$ | Number of logical nodes                  | [0,100]        | $P_s$     | Success rate of historical usage           | [0,1]          |
| $N_{\text{model}}$ | Number of models linked to the workflow  |                |          |                                           | [0,100]        |

Table 2 Judgment matrix of 8 sub-factors

| Score |Completeness|Accuracy|Independence|Uncertainty|Robustness|Historical Use|Reliability|Reproducibility|
|-------|------------|--------|------------|------------|-----------|--------------|-----------|---------------|
| Value | 1          | 2      | 0.5        | 1          | 1         | 1            | 1         | 1             |

Assume the eight evaluation indices to be \( \{X_i \in [0,1] | i \in [1,8]\} \). Then the above-mentioned equations can be expressed as follows.

\[
X_1 = P_{\text{integrity}} \cdot P_{\text{match}}
\]

\[
X_2 = P_{\text{match}} \left( 1 - \frac{\left| \hat{T} - \frac{T}{V_t} \right|}{2} \right)
\]
\[
X_3 = 1 - \frac{N_{\text{logic}} + N_{\text{simulate}}}{N_{\text{logic}} + N_{\text{active}} + N_{\text{simulate}}}, \frac{N_{\text{exe..para}}}{N_{\text{exe..para}}}
\]
(3)

\[
X_4 = P_{\text{integrity}} \cdot P_j \cdot e^{-N_{\text{active}} + N_{\text{exe..para}}}
\]
(4)

\[
X_5 = e^{N_{\text{active}}}
\]
(5)

\[
X_6 = P_{\text{hist..cons..}} \cdot P_j \cdot e^{-N_{\text{active}} + N_{\text{exe..para}}}
\]
(6)

\[
X_7 = (1 - P_j) \cdot e^{-N_{\text{active}} + N_{\text{exe..para}}}
\]
(7)

\[
X_8 = P_{\text{hist..cons..}} P_{\text{integrity}} P_j (1 - P_j)
\]
(8)

It should be noticed that all of these equations can be replaced or modified into any other forms in accordance with the simulation objects and the working environment of simulation workflow.

4.2 Qualitative analysis

To further obtain the relationship between these evaluation indices and the final credibility value, the weighting scheme with expert scoring is adopted in this paper, as shown in Eq. (9).

\[
E = 100 \sum w_i X_i
\]
(9)

Where \( E \) represents the credibility value of a specific simulation workflow, \( w_i \) represents the weights of the \( i \)th index. For more intuitive understanding, the overall credibility value is scaled to the range \([0, 100]\).

According to the classical AHP algorithm, experts need to judge the importance of the 8 indices and finish the judgement matrix as shown in Table 2. The mathematic method is used for test the consistency of each matrix and obtain the eigenvector, so that the weight relationship of each factor can be obtained. Due to the limited space, the process of AHP will not be repeated here.

Clearly, it requires two steps to structure the two-layer relations between the workflow features, the evaluation indices and the credibility value. Both quantitative deduction of the evaluation indices in accordance with some empirical equations and qualitative calculation of their weights based on expert scoring should be carried out for each workflow. How to establish the direct influence of these features on the final model credibility is still challenging. To solve this problem, we apply two offline learning algorithms and two incremental learning algorithms for efficient validation of simulation workflow in the next section.

4.3 Online establishment of empirical evaluation model

In order to make full use of the historical data and implement more efficient validation, we adopt two offline algorithms (i.e., back propagation (BP) and Extreme learning machine (ELM)) and two online algorithms (i.e., Evolving Neo-Neuron (eNFN), Fast Incremental Gaussian Mixture Model (FIGMN)) to train the empirical evaluation model.

4.3.1 Offline learning

The objective of offline learning is to establish the relation function by using a group of datasets in advance. The relation will not be changed by further results or evaluation data. The advantage of this method is that the precision and convergence of training results are pretty good.

As shown in Fig. 4.1, the evaluation model will be directly invoked to validate the specific simulation workflow by using learning algorithms when the historical data reaches a certain number. In a fairly straightforward way, the offline learning algorithm will be set up based on the historical dataset and then obtain a regression model to represent the relation between the internal features of simulation workflow and its credibility value, as shown in Figure 4.

4.3.2 Incremental learning

However, in offline learning, new results cannot be effectively used in guiding the evaluation process since the expense for calculating the global gradient is too high. When the relations between the internal features and the evaluation indices vary with the structure of workflow and the weight of each evaluation index changes according to expert experience and simulation environment, offline learning scheme will fail to evaluate new workflows.

To make the predictor (i.e. the evaluation model) more adaptable in changing environment, incremental learning strategy should be introduced. It means to establish an approximate function incrementally by using the training data and extending the function step by step by updating its memory and knowledge over time. The procedure of using incremental learning algorithm in credibility evaluation of simulation workflow is shown in Figure 5. It can be seen that a real time data feedback is provided. The system might also incorporate real-time data feeds to analyze in conjunction with historical data.

4.4 CASE STUDY
In this section, a case study based on a group of landing simulation workflow for the aircraft is carried out to verify the performance of the proposed procedure and compare the four selected learning algorithms in generating the empirical evaluation model. There are a total of 2000 historical data for aircraft landing with different environment and different workflow structure. All of the data is come from a real simulation system which includes hundreds of simulation workflows for different aircrafts with changing flight missions. We firstly use traditional qualitative and quantitative analysis discussed in section 4.1 and 4.2 to calculate part of the historical data. Then, we adopt part of the data as training samples for the four learning algorithm and take the rest as testing samples.

5.1 Simulation workflow evaluation with the traditional quantitative and qualitative analysis

Table 3 provides an evaluation sample for a specific simulation workflow. According to Eq. (1) to (8), the 8 evaluation indices can be scored as shown in Table 4.

Table 3 an evaluation sample for a specific workflow

| Index          | Value         |
|----------------|---------------|
| $P_{\text{match}}$ | 1             |
| $P_{\text{energy}}$ | 0.9039        |
| $T_{\text{top}}$    | 142.85        |
| $T_{\text{af}}$     | 143.71        |
| $V_f$                | 3.5152        |
| $N_f$                | 3             |
| $N_{\text{active}}$ | 27            |
| $N_{\text{logic}}$ | 6             |
| $N_{\text{history}}$| 24            |
| $P_{\text{run_cons}}$ | 0.9632        |
| $N_{\text{stimulate}}$ | 5             |
| $N_{\text{per}}$    | 21            |
| $N_{\text{ex_per}}$ | 7             |
| $P_f$                | 0.0392        |
| $P_t$                | 1             |
| $N_{\text{model}}$  | 3             |

Table 4 Quantitative scores of the 8 evaluation indices

| Index       | Quantitative value | on 100 scale |
|-------------|--------------------|--------------|
| completeness| 0.9039             | 90           |
| accuracy    | 0.8847             | 88           |
| independence| 0.9035             | 90           |
| uncertainty | 0.8007             | 80           |
| robustness  | 0.8948             | 89           |
| historical use | 0.9239         | 92           |
| reliability | 0.9490             | 94           |
| reproducibility | 0.9254        | 93           |

In qualitative analysis, experts need to judge the importance of the 8 indices according to the basic AHP. Take the scoring case shown in Table 5 as instance. The eigenvectors of eight sub-factors are (0.1175, 0.1107, 0.1412, 0.0989, 0.1248, 0.0831, 0.1507, 0.1731), which are the final weights of them. By Eq. (9), the final credibility is 90.25. Then the data from Table 3 can be used as the input and the final credibility as the output of the training and testing samples.

5.2 Algorithms comparison between two offline learning algorithms

By accumulating a group of evaluation data according to the process of Section 5.1, offline learning algorithm can be setup for establishing an empirical evaluation model. In this paper, BP and ELM are introduced and compared in detail.

5.2.1 A brief introduction of BP and ELM

The back propagation (BP) neural network algorithm is one of the widely used off-line learning algorithms. It is a multilayer feedforward neural network, which is in accordance with the error back-propagation algorithm for learning and training. The structure of BP neural network are shown in Fig.6. The structure includes the input layer, hidden layer and output layer. Input layer consists of a series of input value, while the output layer consists of the output values. Input vector propagated forward through the network layer by layer until it reaches the output layer. The output of the network is then compared to the expected output. After that, an error value is calculated for each of the neurons in the output layer. The error values are propagated backwards to the hidden layer in order to change the weight $\Delta o$ of output layer and hidden layer (see Formula (1)).

Hidden layer to output layer:

$$\Delta o^{h+1} = \eta \delta^h y^h = \eta (d - o)(1 - o)y^h$$  \hspace{1cm} (1)

where $h$ refers to hidden layer nodes number, $y$ are hidden layer outputs, $\eta$ is learning rate, $o$ is expected output and $d$ is actual output.

In the hidden layer, the algorithm repeats a two phase cycle, weight update and propagation. Theoretically, BP neural network can approximate any continuous nonlinear function. Its pseudocode can be expressed in Algorithm 1.

![Fig.6 Structure of BP Network](image)

**Algorithm 1** Back Propagation neural network algorithm

**Step 1 Initialization**

**Step 2** Initialize network weights in hidden layer output layer

**Step 3** set variance $E=1$, learning rate $\eta = 0.1$

**Step 4 Execution:**

**Step 5** While $E > 0.1$ do

**Step 6** calculate the value of output layer based on network weights and the value of input layer

**Step 7** calculate the variance $E$ of expected output and actual output

**Step 8** If $E > 0.1$

**Step 9** For Each network weight

**Step 10** update $\Delta o$ for all weights from hidden layer to output layer

**Step 12** End For

**Step 13** End if

**Step 14** End While

**Step 15** End of training

ELM is a new representation of single hidden layer feedforward neural networks, of which the hidden node parameters are randomly generated and the output weights are analytically computed. Unlike BP, the parameters of hidden layers of ELM are randomly generated and needn’t to be tuned. The weights between hidden nodes and outputs are simplified
as a generalized inverse matrix, which essentially increase the training efficiency [40]. Its pseudocode can be expressed in Algorithm 2.

**Algorithm 2 Extreme machine learning**

**Step 1 Initialization**
1. Training set: $D=\{(x_i, t_i), i=1, ..., N\}$
   - where $x_i$ is input data; $t_i$ is expected output
2. Network weights: $w_i, i=1, ..., N$
3. Hidden layer bias: $b_i, i=1, ..., N$
4. Activation function: $G(x) = \frac{1}{1+e^{-x}}$

**Step 6 Execution**:
- Step 7: Calculate the hidden layer output matrix $H$.

**Step 8**
- Calculate the output weight $\beta$. $H \beta = T$.

**Step 9 End of training**

5.2.2 Comparison results

Firstly, a certain amount of data is randomly selected from the database as training data which used for network training, and the remaining data are used as test data to test the fitting performance of the network. The experimental results of BP and ELM are shown in Table 6.

| Score        | verification | accuracy | input uncertainty | robustness | historical data | people | management |
|--------------|-------------|----------|-------------------|------------|----------------|--------|------------|
| verification| 1           | 1.277    | 0.783             | 1.63       | 0.783          | 1.277  | 0.783      | 0.613      |
| accuracy     | 0.783       | 1        | 0.783             | 1.63       | 0.783          | 1.277  | 0.783      | 0.613      |
| input        | 1.277       | 1.277    | 1                 | 1.277      | 1.277          | 1.277  | 1          | 0.783      |
| uncertainty  | 0.613       | 0.613    | 0.783             | 1          | 0.783          | 1.277  | 0.783      | 0.613      |
| robustness   | 1.277       | 1.277    | 0.613             | 1.277      | 1              | 1.277  | 1          | 0.783      |
| historical data | 0.783     | 0.783    | 0.613             | 0.783      | 0.613          | 1.277  | 1          | 0.613      |
| people       | 1.277       | 1.277    | 1.63              | 1.277      | 1.277          | 1.277  | 1          | 1          |
| management   | 1.63        | 1.63     | 1.277             | 1.63       | 1.277          | 2.08   | 1.277      | 1          |

Table 5 Judgment matrix of the 8 evaluation indices

| Name    | Amount of training data | Amount of testing data | Average prediction error | Average error in percentage | Percentage of prediction-error $>2$ | Percentage of prediction-error $>5$ |
|---------|-------------------------|------------------------|-------------------------|----------------------------|------------------------------------|------------------------------------|
| BP      | 1900                    | 100                    | 0.6175                  | 0.7313%                    | 0.03                               | 0                                  |
| ELM     | 1900                    | 100                    | 0.4511                  | 0.5430%                    | 0.01                               | 0                                  |
| BP      | 1500                    | 500                    | 0.9434                  | 1.131%                     | 0.110                              | 0.002                              |
| ELM     | 1500                    | 500                    | 0.4434                  | 0.547%                     | 0.014                              | 0                                  |
| BP      | 50                      | 1950                   | 1.9404                  | 2.6678%                    | 0.3508                             | 0.04221                            |
| ELM     | 50                      | 1950                   | 2.7028                  | 3.694292%                  | 0.605                              | 0.1292                             |

When the training data is selected as the previous 1900 samples and the testing data is the rest 100 ones, the prediction-error can be shown in Figures 7 and 8. When the training data is reduced as the previous 1500 samples and the testing data is the rest 500 ones, the prediction-error can be shown in Figures 9 and 10. When the training data is further reduced to 100, the prediction-error can be shown in Figure 11 and 12.

It can be seen that BP and ELM has great ability of prediction when the amount of training data are large. It is clear that the prediction-error of ELM is smaller than that of BP as the training data source are in great amount, yet BP can show a better fitting effect as the data source are limited. The average percentage of prediction-error is maintained at about 1%, which is certainly in great ability of prediction. BP can stabilize the prediction-error value in 3% though the data source is limited. In summary, BP and ELM can be a good simplification way of calculating the credibility of simulation workflow instead of experts.
5.3 Algorithms comparison between two incremental learning algorithms

In order to establish such evaluation model in an efficient and incremental way with newly generated evaluation data, eNFN and FIGMM are introduced and compared in detail.

5.3.1 A brief introduction of FIGMM and eNFN

FIGMM is presented by Pinto in 2014 [41], which is an improved algorithm of incremental Gaussian Mixture Network (IGMN). IGMN is based on parametric probabilistic models (Gaussian mixtures), describing noisy environments in a very parsimonious way. It adopts a Gaussian mixture model of distribution components that can be expanded to accommodate new information from an input data point, or reduced if spurious components are identified along the learning process. IGMN adopts an error-driven mechanism to decide if it is necessary to add a neuron in each region for explaining a new data vector. It learns incrementally from data flows (each data can be immediately used and discarded) and asymptotically converges to the optimal regression surface as more training data arrive. On this basis, the fast Incremental Gaussian Mixture Network has powerful the formula using in IGMN (work directly with the inverse of covariance instead of calculating Mahalanobis distance, having better performance in high-dimension tasks.) and its pseudocode can be expressed in Algorithm 3.

Algorithm 3 Fast Incremental Gaussian Mixture Model

Step 1 Initialization
Step2: set $j^{th}$ component mean $\mu_j=x_j$
Step3: accumulator of component $j$: $s_{pj}^{'}=1$;
Step4: full covariance matrix $C_j=\sigma_j^{2}$
Step5: age of component $j$, $v_j=1$;
Step6: prior probability $p(j)=\frac{1}{\sum_{i=1}^{n}v_i}$
Step7: scaling factor $\delta=0.01$
Step8: meta-parameter $B=0.1$
Step9: Execution:
Step10: For Each component $j$
Step11: Compute $d_j=(x-\mu_j)^T A_j (x-\mu_j)$
Step12: If $d_j^2(x,j)<\sum_{i=1}^{k}d_i^2(x,j)$
Step13: Updated parameters of the algorithm
Step14: End If
Step15: End For
Step16: If the update condition is not met (prediction error $>5$)
Step17: then a new component $j$ is created (as initialization)
Step18: End If
Step19: If $v_j>v_{min}$ and $spj<>spmin$
Step20: then a component $j$ is removed
Step21: End If
Step22: End of training

Evolving neo-fuzzy neuron algorithm is proposed by Alissin[42] in 2012. It is special in that the structure and parameter of the neural network is constantly changing and developing as data are input. This algorithm mainly use the increamental learning plan in order to simultaneously update the input space and the neural network weights. Initially the space of each input variable is granulated using two complementary triangular membership functions. Then, computing the membership degrees of input $x_i$ find the most active membership functions, and update their modal values. Next, check whether the most active membership function represents well the neighborhood of $x_i$. Making a decision of whether a new membership function should be created and inserted to refine the neighborhood of $x_i$. Additionally, the oldest inactive membership function should be deleted if it has been inactive. Its pseudocode can be expressed in Algorithm 4.

Algorithm 4: Learning of eNFN

Step1: Initialization
Step2: the number of the membership functions of the i-th input variable $m_i=2$;
Step3: learning rate $\beta=0.1$
Step4: parameter $\eta=10$
Step5: maximum age of membership function $\sigma=150$
Step7: Execution:
Step8: For Each component $t$ of input $x_i$
Step9: If $x_i < x_{min}$, then $x_{min}=x_i$,
Step10: $b_{ij}=x_{min}$
Step11: End If
Step12: If $x_i > x_{max}$, then $x_{max}=x_i$,
Step13: $b_{ij}=x_{max}$
Step14: End If
Step15: Compute mean value $\tilde{\mu}_{m_i}$
Step16: \[
\tilde{\mu}_{m_i} = \tilde{\mu}_{m_i}-\beta(\tilde{\mu}_{m_i}-c_{ij}), e_{ij}^{y_{ij}^d} \]
Step17: $y_{ij}^d$: the corresponding output value
Step18: $e_{ij}^{y_{ij}^d}$: the desired output value
Step19: Compute variance $\tilde{\mu}_{m_i}^2$
Step20: \[
\tilde{\mu}_{m_i}^2 = (1+B)\tilde{\mu}_{m_i}^2 + \beta(\tilde{\mu}_{m_i}-e_{ij}^{y_{ij}^d})^2 \]
Step21: For $i = 1$ to $n$
Step22: If $b_{ij}^*<>m_i$
Step23: $d_{ij} = \frac{b_{ij}^* - b_{ij}^* - b_{ij}^*}{2}$
Step24: $new\ b_{ij} = b_{ij}^* + dist$
Step25: $new\ b_{ij} = b_{ij}^* - dist$
Step26: End If
Step27: End for
Step28: End for
Step29: End
Step30: End for
Step31: End for
Step32: End for
Step33: End for
Step34: End for
Step35: End for
Step36: End for
Step37: End for
Step38: End for
Step39: End for
Step40: if $y_{ij}^d (the index of the least active membership function enabled by $x_i$)
Step41: if $y_{ij}^d (the index of the least active membership function enabled by $x_i$)
Step42: if $y_{ij}^d (the index of the least active membership function enabled by $x_i$)
Step43: End for
Step44: End for
Step45: End of training

5.3.2 Comparison results
The experimental results of eNFN can be shown in Figures 13 to 17, while the results of FIGMM are shown in Figure 18.

As shown in Figure 13, the prediction-error decreases as the amount of input data increases at the beginning, the prediction-error will be stable in a certain area when it decreased to a certain extent. Due to the limited number of samples, the prediction-error are not as small as the offline learning algorithms after the stability. Figure 14 shows the prediction-error of 500 data sets based on this algorithm. Figure 15 shows the prediction-error of last 1500 data sets based on this algorithm. The absolute error of the average error is about 3.9125.
Figure 1
Output value based on Evolving Neo-Neuron algorithm (triangular membership function)

Figure 14
Prediction-error (absolute value) based on Evolving Neo-Neuron algorithm (triangular membership function)

The above experimental results are obtained by using the triangular membership function. We can also use the Gaussian curve membership function to replace the triangular membership function as a comparison task. Figure 16 shows the prediction-error of 500 data sets based on Gaussian curve membership function. Figure 17 shows the prediction-error of last 1500 data sets based on this algorithm. The mean prediction-error based on membership function of Gaussian curve is slightly reduced to 3.221 compared with the triangle membership function.

Compared with the above eNFN, the mean prediction-error of FIGMN is 3.5574 as shown in Figure 18, which is slightly smaller than the triangle membership function-based eNFN and larger than the Gaussian membership function-based one.

Compared these four learning algorithms, the results of offline learning algorithms are in a high precision, but it cannot improve their learning ability as the database increased or the evaluation environment changed. On the contrary, incremental learning algorithms allow new data to update the empirical model and make the prediction change with time. Although the prediction error is increased to some extent, it is much more efficient in such evaluation tasks and can be extended to more dynamic circumstances.
More dynamic situations and changing evaluation rules will be learned from existing offline and online methods. For instance, in constructing the empirical relation between the workflow Mixture Model (ENFN) and Fast Incremental Gaussian Mixture Model (FIGMM), those algorithms were used for constructing the empirical relation between the workflow credibility and its features. A case study on a specific simulation workflow was established to test the feasibility of the proposed method.

In future, a more comprehensive comparison on the existing offline and online learning algorithms on the empirical learning-based validation procedure should be carried out. More dynamic situations and changing evaluation rules will be combined and analyzed.

VI. CONCLUSIONS

This paper focused on the validation of upper-layer simulation workflow. An empirical learning-based validation procedure to implement a semi-automated evaluation was presented. In the first step, representative features as well as the validation indices of general simulation workflow were presented. Then, the evaluation process of workflow credibility based on Analytic Hierarchy Process (AHP) was introduced. Next, four learning algorithms are compared in offline environments (i.e., and back propagation (BP) and Extreme learning machine (ELM)) and online environments (i.e., Evolving Neo-Neuron (ENFN) and Fast Incremental Gaussian Mixture Model (FIGMM)). Those algorithms were used for constructing the empirical relation between the workflow credibility and its features. A case study on a specific simulation workflow was established to test the feasibility of the proposed method.

In future, a more comprehensive comparison on the existing offline and online learning algorithms on the empirical learning-based validation procedure should be carried out. More dynamic situations and changing evaluation rules will be combined and analyzed.

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