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Predict Supply Chain Performance: incremental and stable Neural Networks training algorithm

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***Abstract*—A supply chain performance predicting system is the starting point for developing good strategies to deal with performance variability in today's increasingly complex and competitive markets. Several studies in the literature propose a system for predicting, each with its own advantages and limitations compared to other approaches. This motivates the development of artificial neural networks $(ANN)_s$ to make intelligent decisions while taking advantage of current processing power. Indeed, the choice of appropriate training and topological design of artificial neural networks are important issues for large applications. This paper discusses a contribution that will highlight ways to improve the quality of predictions through the application of the feedforward neural networks $(FNN)_s$ training algorithm. Compared to the incremental strategy and to the Lyapunov's stability, the combination of both approaches provides a high level of generalization as well as a stable training process.**

***Keywords*—supply chain management, Supply chain performance predicting system, Neural models, Incremental algorithm, adaptive learning rate.**

I. Introduction

In the supply chain literature, numerous authors present miscellaneous definitions. On the one hand, [6] define the supply chain as “a complex structure including a constant flow of information, products and funds between different phases”; on the other hand, [8] state that “a supply chain is the set of entities involved in the design of new products and services, the supply of raw materials, the processing into semi-finished and finished products, and their delivery to the end customer”. Thereby, the supply chain is typically is characterized by a method that encompasses three important phases: supply, production and distribution, which involves manufacturers, suppliers, transporters, warehouses, retailers and customers themselves that performs the function of procurement of materials, transformation of these materials into intermediate and intermediate and finished products, and the distribution of finished products to customers [5].

In addition, a supply chain management (SCM), It may be defined as “the management of flow of goods and services”. It includes the movement and storage of raw materials, of work in process inventory, and of finished goods from point of origin to point of consumption [7]. In a few words, it is a mechanism that includes order generation, order taking, information feedback and the efficient and timely delivery of goods and services. In this context, managing the performance of an organization and its critical first and second tier suppliers can improve considerably the quality of services and goods provided by supply chain [15].

Several studies have proposed conceptual or quantitative models to deal with supply chain performance assessment. In general, the conceptual models propose a set of performance metrics which involve financial and mostly nonfinancial measures associated with the business processes of strategic, tactical and operational levels [12]. In contrast, quantitative models for supply chain performance appreciation suggest the use of multicriteria decision-making techniques, simulation, mathematical programming methods, statistical, and artificial intelligence techniques to quantify the performance of supply chains [10].

The notion of ANN, an extraordinary computing information, was produced from the imitation of the human brain neurophysiology [19]. Thus, ANN very helpful method at detecting complex nonlinear relationships in high dimensional data [11]. The majority of business applications were reported to use multilayered feedforward neural networks with the backpropagation learning algorithm which is a gradient decrease method to minimize the squared output error. Therefore, the prediction using ANN backpropagation yields high level accuracy [2].

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In this study, modeling of supply chain performance system is assumed through a neural model whose architecture is chosen based on an approach derived from the combination of two strategies for neural network synthesis. This method leads to a reliable incremental learning algorithm Refer to Lyapunov theory. The rest of this work is distributed as follows. Section 2 the modelling of supply chain performance system is described. Also, several approaches based on neural networks are presented. Section 3 illustrates the results of the simulations obtained. Finally, the concluding observations are presented.

II. THEORETICAL FOUNDATION

This research based on fused underlying theories, supply chain performance, neural networks and data analytics. The combination between theories is shown on Fig. 1, supply chain performance predicts using the best network topology for each ANN model.

A. Conceptual Framework

Performance predicting systems are used to assess the results of delayed measurements (production variables) against the performance levels of the main measures (input variables), which are specified either by estimation or by actual performance data. Most performance prediction systems are based on artificial intelligence techniques that map mathematical functions concerning cause-and-effect relationships between metrics, which is done using learning algorithms [11].

There are some predicting systems in the literature that support decision making in the supply chain world. [16] designed a seminal performance prediction system that was implemented in a textile company and an industrial printer manufacturer. A Mamdani fuzzy inference system was installed to predict the supplier's performance on delivery times with the objective of identifying potential problems. The choice of input variables, the setting of internal parameters and the validation of results were based on the opinion of the company's employees. Another performance prediction system that use artificial intelligence techniques was proposed [4] and [11]. Utilizes a set of ANNs to predict the values of flexibility, responsiveness, costs and returns assets.

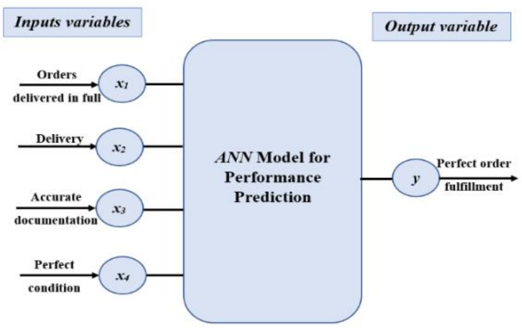

Fig. 1. Neural model for decision making

B. Neural Modeling and Synthesis

Artificial neural networks have enjoyed increasing success in recent decades in several fields, including: pattern recognition, failure detection and anomaly diagnosis, dynamic systems modeling, time series prediction [17].

The use of neural networks during a process identification problem is increased by the fact that they ensure the correct approximation of non-linear functions. This is guaranteed to the ability to reproduce fairly complex behaviours and dynamic learning performance offered by neural networks. In fact, neural modeling is robust to the parametric variations and disturbances that may accompany the operation of the highlighted system.

The design of a neural model requires, among other things, the selection phase of its structure, which is a crucial step. Indeed, this phase should lead to the determination of significant inputs and the choice of the simplest architecture providing a satisfactory approximation of the dynamics of the process under study.

The learning of multilayer networks was treated using the gradient method. Thus, the literature on non-linear optimization approaches applied to this type of problem is very rich. However, we focus the study on the error backpropagation algorithm, which is still the most popular and most widely used [13] and [18]. It is an optimization algorithm that seeks to minimize a cost function that focuses on the difference between the desired response and that delivered by the network.

In this work, develop an improved constructive training algorithm for feedforward neural network using Lyapunov stability theory is developed. It uses an incremental training approach where training patterns are learned one after the other. The Lyapunov stability theory has been put in place to adapt to the evolution of the learning rate, a ensuring the stability of training process.

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C. Lyapunov stability theory optimizes training algorithm

Training based on (BP) algorithm can lead to inadequate results. In the same way, this algorithm has inevitable disadvantages such as its slow convergence and its inability to establish global convergence. To solve this problem, Lyapunov's stability theory was used to obtain an adaptive learning rate that would increase the speed of convergence.

A simple (FNN)s with a single output is represented in Fig. 2.

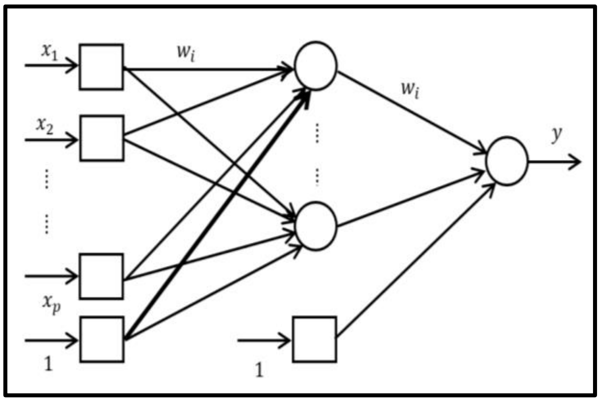

Fig. 2.: Feedforward Neural Network (FNN)

This neural network is modelled according to its weights, where:

$$w = [w_1, w_2, \dots, w_m]^T \in \Re^m \qquad (1)$$

The training data can be summarized in N models $\{x^p,\ y^p\}$, *p= 1,2,…, N.*

In the aim of deriving a law for updating weights, a Lyapunov function has been defined as:

$$V_1 = \frac{1}{2}(r^T r) \qquad (2)$$

Where r signifies the difference between the real output and the desired output, as:

$$r = \left[y_d^1 - y^1, \dots, y_d^p - y^p, y_d^N - y^N\right]^T \qquad (3)$$

The stability conditions ($\dot{V} \leq 0$) give the weights update law with an adaptive learning rate which can be written:

$$w(k+1) = w(k) + \varepsilon \frac{r_p^2}{\gamma + \|J_p^T r_p\|^2} J_p^T r_p \qquad (4)$$

Where:

r_p denotes the error for sample *p*, as:

$$r_p = \left(y_d^p - y^p\right) \in \Re \qquad (5)$$

p is the instantaneous value of the Jacobian, as:

$$J_p = \frac{\partial y^p}{\partial w} \ \Re^{l \times m} \qquad (6)$$

ε, γ are a constant and a very small constant to avoid numerical instability when error signal goes to zero respectively, which are selected heuristically.

More information about this algorithm noted LF1 can be obtained from [3].

In the next section, we introduce some improvements made to the above algorithm to handle an incremental structure of $(\text{FNN})_s$.

D. Improved incremental algorithm based on Lyapunov stability theory

[9] elaborated a new constructive training algorithm for Feedforward Neural Network. In his approach, the training starts with a single training pattern and a single hidden-layer neuron. The aim is to find a neural network topology such that the overall error of training is less than a specified error tolerance. In this instance, while the constructive learning strategy can provide a neural network with a small structure, the neural model may lead to over-trained beings. To remedy this problem, a modified version of this algorithm that eliminates poor generalization performance based on the regularization technique (early termination) has been developed in [1]. Early-stopping is the process of stopping the learning when a medium value of drive error is reached. In fact, at first, the criteria for learning and generalization are beginning to decline [20]. In a later phase, the learning criteria continue to decrease, but the generalization is starting to rise. At this time, the training must be stopped [7] and completed [8] .

It is to be noted that we are interested in a multi input -single output model and the weights update is based on the "equation (4)", furthermore, the suggested incremental learning algorithm can be presented as follows:

First step: select one pattern from the training base *(L=1).* Train the neural network with one hidden node using the selected pattern and compute the *EQMA (1)*, where*: EQMA* denotes the average quadratic error of training, which is defined as:

$$EQMA = \sqrt{\frac{1}{N_A}\sum_{p=1}^{N_A} r_p^2} \qquad (7)$$

N_A: indicates the number of samples in the training set.

r_i: the difference between the real output of sample i and output estimated by the neural model, respectively.

Second step: if ($L < N_A$), choose the next pattern *(L=L+1)* and go to step 3 for training; else *(L=N_A)*, end of the algorithm.

Third step 3: train the neural network with N_c hidden nodes using L patterns from the training set and calculate the values of *EQMA(L)* and *EQMV (N_c),* where *EQMV* designates the average quadratic error of validation,

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$$EQMV = \sqrt{\frac{1}{N_v}\sum_{i=1}^{N_v} r_p^2} \quad (8)$$

Here: N_v indicates the number of samples in the validation set.

If *(EQMA(L)* < *EQMA$_{tol}$)*, return to second step; otherwise, move on to fourth step for growing where *EQMA$_{tol}$* signifies a tolerated value average quadratic error of training.

Fourth step: if $(N_c = 1), then, (N_c = N_c + 1)$ and return to third step; else $(N_c > 1)$, two tests must be carried out to decide on the evolution of the network structure.

In the case of the growth of the generalization criterion *(EQMV)* with a value greater than a tolerated threshold *(EQMV$_{tol}$)*, the algorithm should go to fifth step. The similar step will be executed when the generalization criterion decreases. These cases are summarized as follows:

if $\left\{ \begin{array}{l} \left(\begin{array}{l} (EQMV(N_c) > EQMV(N_c{-}1)) \\ and \;\; (EQMV(N_c) > EQMVtol) \end{array} \right) \\ or \; (EQMV(N_c) < EQMV(N_c{-}1)) \end{array} \right\}$, then go to fifth step.

These tests are particularly satisfied in the beginning of the learning step when the generalization criterion can have an oscillatory behavior.

In the third case and when the generalization criterion grows with a value lower than $EQMV_{tol}$, then increase slightly the *EQMA$_{tol}$* and re-execute the third step. This case is summarized by:

if $\left\{ \begin{array}{c} EQMV(N_c) > EQMV(N_c{-}1) \\ and \\ (EQMV(N_c) > EQMV_{tol}) \end{array} \right\}$, *then* $(EQMA_{tol} = \alpha\, EQMA_{tol})$ where α is a constant slightly higher than 1, and go back to step 3.

In this matter, the network structure has appropriate hidden nodes and the neural network achieves a high learning performance with a generalization error that tends to increase. In this instance, the $(EQMA_{tol})$ is increased in order to slow down the recruitment of hidden nodes.

Fifth step: maintain the weights of the last-successfully trained neural network, augment the number of hidden neurons by one and attribute its initial weights. Move on to the third step.

E. Experiments and discussions

In this part, we expose the simulation results. The sufficiency of the suggested algorithm is analyzed. We utilize this algorithm for the neural identification of a supply chain performance.
The main goal of our simulation is to find the adequate structure of the input-output neural model which describes the dynamics of the supply chain performance by using the approach presented in previous section.

The supply chain performance parameters used in simulations are illustrated in "Table. I" [14]:

TABLE I. DESCRIPTION AND MEASUREMENT UNIT OF THE METRICS OF THE PROPOSED PREDICTION SYSTEM

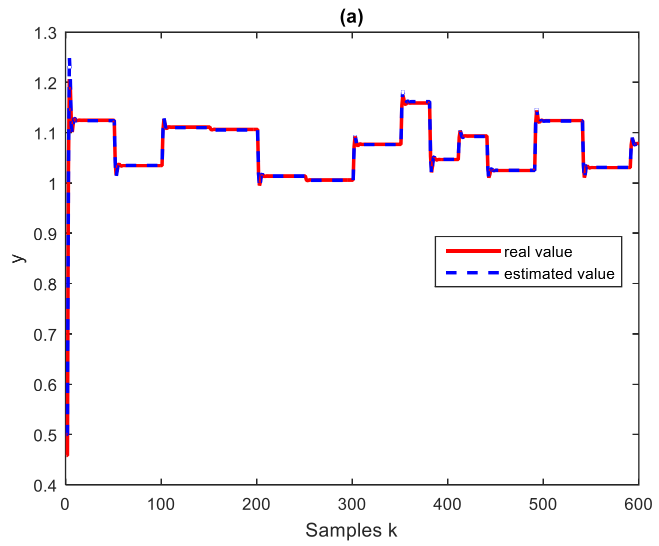
Model	Variable	Description	Measurement unit	Universe of discourse
ANN Model	x_1	Orders delivered in full:	Dimensionless	[0; 1]
	x_2	Delivery performance:	Dimensionless	[0; 1]
	x_3	Documentation accuracy	Dimensionless	[0; 1]
	x_4	Perfect condition:	Dimensionless	[0; 1]
	y	Perfect order fulfillment:	Dimensionless	[0; 4]

It can be shown that the suggested algorithm offers more efficient convergence characteristics in the training and validation phases than the LF1 and incremental algorithms.

"Table. II" illustrates the importance of the combination of the constructive approach and the LF1 algorithm. Indeed, we can see that the incremental algorithm provides a good performance but with a slow convergence time. In the same way, the LF1 algorithm has a minimum convergence time with degradation of the performance of the model acquired. The resulting algorithm guarantees both rapid convergence and higher learning and generalization capabilities.

The simulation result, which involves selecting the number of hidden neurons using Lyapunov's stability theory, an incremental learning algorithm, is illustrated in "Fig. 3" and "Fig. 4". Noted that the input is set of random values that varies in [0, 1] are presented over 600 examples.

The simulation results describing the performances of algorithms presented in this paper are illustrated in "Table. II".



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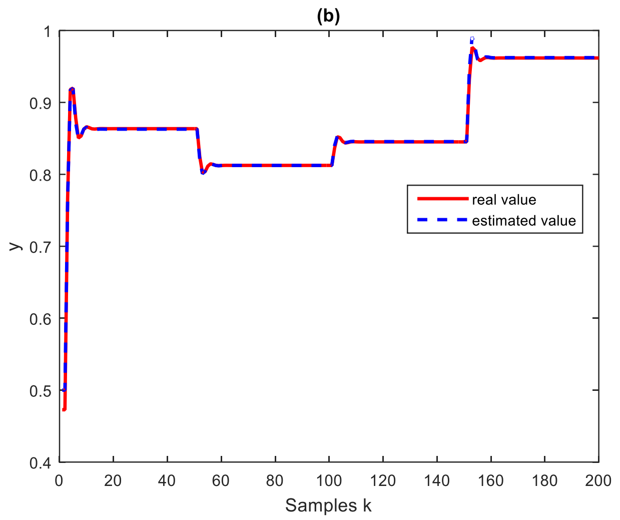

Fig. 3. Training and validation phases for the proposed algorithm ((a): training phase, (b): validation phase)

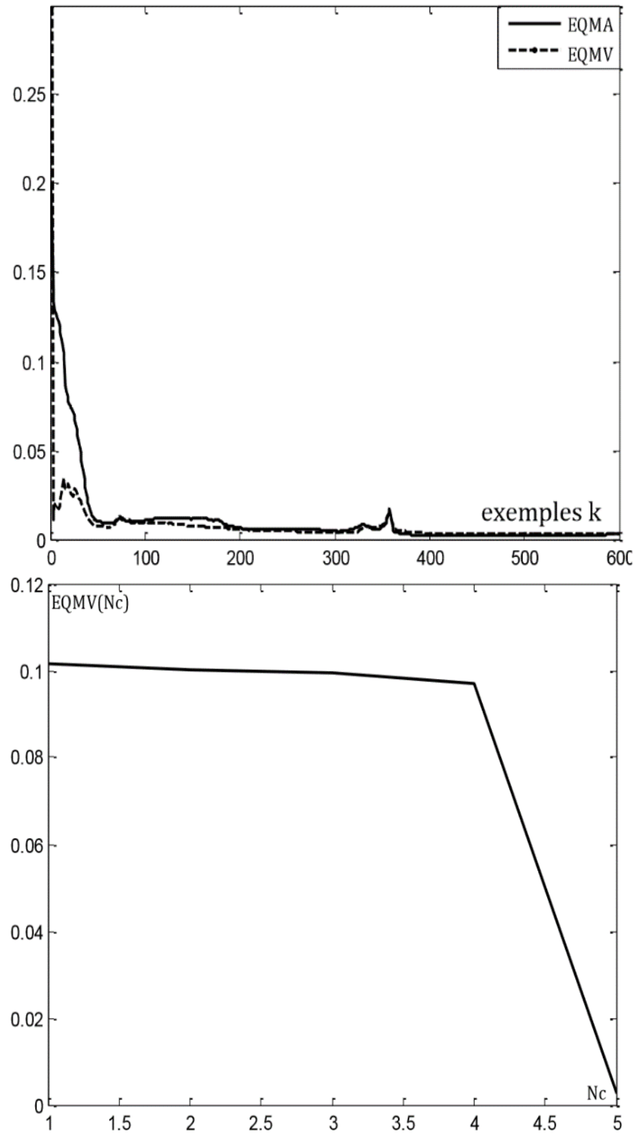

Fig. 4. Training and validation performances for the proposed algorithm *EQMA and EQMV, EQMV(N_c)*

TABLE II. PERFORMANCES OF DIFFERENT ALGORITHMS

Algorithm	Numerical simulation parameters	EQMA	EQMV	Nc	Run time
LF1 (fixed structure)	$\varepsilon = 0.56, \beta = 0.00012$	0.0054	0.005	5	8'55
Incremental algorithm	$\alpha = 1.03, EQMA_{tol} = 0.037,, EQMV_{tol} = 0.047$	0.0037	0.0034	5	16'70
Incremental algorithm with LF1	$\varepsilon = 0.56, \beta = 0.00012, \alpha = 1.03, EQMA_{tol} = 0.037, EQMV_{tol} = 0.047$	0.0041	0.0030	5	12'

III. CONCLUSION

This study proposed an advanced approach for neural models selection. The main contribution of this method is to demonstrate the upotential of the Lypunov stability theory for the synthesis of neural networks. To validate the reliability of the developed algorithm, neural modeling of the supply chain performance prediction system is used. The simulation results have showed that the advanced algorithm not only improve the training and generalization skills, but also reduces the runtime, which substantially improves the feasibility of this algorithm in both theoretical and real problems.

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