ANFIS with fractional regularization for supply chains cost and return evaluation

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Abstract
In this paper, we discuss a variant of the Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict two performance attributes, i.e. total cost to serve and return on working capital, following the Supply Chain Operations Reference (SCOR) model on the basis of the state of the art, This variant is based on fractional Tikhonov regularization, a kind of penalized least squares that allows tackling ill-posed problems. Additionally, it does not use backpropagation, grid partitioning or clustering. The numerical experiments revealed the good performance of the approach, encouraging further developments.

Keywords
neuro-fuzzy systems, Tikhonov regularization, penalized least squares

1. Introduction

An efficient supply chain (SC) management is critical to many companies' operations. Connecting suppliers, producers and customers over vast geographical areas, SCs are demanded to meet some requirements impacting on the costs and the environment. Many techniques have been proposed for SC management (e.g. see [1, 2]). Anyhow, there is a need for suitable performance indicators for assessing the economic, environmental and social sustainability of SCs. In this process, the SCOR model provides a significant contribution, being a diagnostic tool for supply chain management in general and for assessing the involved processes. It was initially developed by PRTM, a management consulting firm, and later endorsed by the Supply Chain Council (SCC), an independent nonprofit organisation. Over the last years, the SCOR model has become very popular [3]. There are several papers discussing its use in different applications, especially in the agri-food field. For instance, in [4], the SCOR model was adopted for performance measurement in a coffee supply chain. In [5], SCOR is used to analyse the food supply chain activities across different levels and to support the collaboration among farmers. In [6], in order to evaluate sugarcane supply chain performance and to identify the risks for farmers and sugar mills, SCOR and fuzzy AHP were applied. Similarly, in [7], the SCOR model and AHP were jointly used for cocoa supply chain performance evaluation. The SCOR model has also been adopted for evaluating the performance of the supply chain of fruits and vegetables in order to reduce losses [8].

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The SCOR model itself is not able to adapt proactively to any changes in the system. It can be empowered by adopting artificial intelligence (AI) techniques that have the ability to learn the cause and effect relationships from historical performance data. In [9, 10, 11], the performance metrics proposed by the SCOR model are combined with AI techniques in order to have predictive evaluation systems.

In [9], a fuzzy inference system (FIS) was used to represent the cause-and-effect relationships among the SCOR metrics. In [10], a neural network (NN) based model was proposed with the same purpose. Anyway, both systems present a drawback. The fuzzy inference systems require collecting the opinion of experts to tune hundreds of inference rules, while the NN does not seem to be appropriate to support decision making processes under uncertainty. In order to address such issues, in [11], a new supply chain performance evaluation system based on ANFIS was adopted to predict the performance figures of SCOR level-1 metrics based on the values of level-2 metrics. Compared against the above-mentioned methods, ANFIS, which takes into account uncertainty thanks to fuzzy sets, allowed to achieve a greater accuracy of prediction, by using historical data. As discussed in [11], there are in literature some quantitative models for supply chain performance evaluation based on the SCOR metrics and multicriteria decision-making approaches, such as TOPSIS and AHP. Anyway, as their output is a value based on a weighted linear combination of inputs, they are not suitable to takle the relationships between the SCOR level-1 and level-2 metrics; this seems to be an ability of models based on AI techniques [9, 10, 11].

In this paper, we propose a variant of ANFIS to achieve a better accuracy with lower computational cost when evaluating performance attributes of supply chains, according to the SCOR model. This variant is based on a least square approach with fractional Tikhonov regularization, with no backpropagation, no grid partitioning or clustering. This kind of regularization was introduced in [12] to takle discrete ill-posed problems. It is well known that both grid partitioning and scatter partitioning by clustering may have a significant computational cost [13]. The aim of the proposed approach is the simplification of the rule base, since the number of rules equals the number of terms, which is fixed as small as possible. The numerical results are promising, encouraging further developments.

2. Supply chain performance evaluation

The supply chain performance can be regarded as the outcome of supply chain management, taking into account the logistical drivers (facilities, inventory, transportation) and cross functional drivers (information, sourcing and pricing).

The SCOR model has been used for supply chain performance evaluation. It was proposed by the Supply Chain Council to link business processes, best practices, performance metrics, people, and technology into a unified structure [14]. It has been widely applied in industry, representing a common reference model. In spite of this, its use in the academic literature is rather limited. SCOR introduces five attributes [17] for performance evaluation which are:

- Reliability, that is the capacity to do tasks according to plan; this also implies the predictability of a process's output;

- Responsiveness, the rate at which certain tasks are completed; practically, the time it takes to deliver items to a client;
- Agility, the capacity to react to external factors and market changes in order to obtain or retain competitiveness;
- Assets, the capacity to make efficient use of resources;
- Costs, the costs of running supply chain operations, including the costs of labor, materials, management, and transportation.

In order to measure the success of the implementation of these strategies, the SCOR model uses some level/strategic metrics for each attribute, which are arranged in three hierarchical levels for diagnostic purposes. Level-2 metrics serve as diagnostics for level-1 metrics, implying that the performances of the level-2 metrics are informative for implementing improvements for level-1 metrics. Similarly, level-3 metrics are meant as diagnostics for level-2 metrics.[14]. Some performance attributes and their level-1 and level-2 metrics are

- Responsiveness
  - Level-1 metrics: order completion time;
  - Level-2 metrics: time for sourcing, making, delivery and delivery retail;
- Assets
  - Level-1 metrics: return on working capital and fixed assets, cash to cash cycle time; the level-2 metrics on the return are listed in Table 2;
- Costs
  - Level-1 metrics: total cost to serve; the items in Table 1 are level-2 metrics.

In [11], seven ANFIS schemes were used to model the causal relationships defined by SCOR, to estimate the values of level-1 metrics on the basis of level-2 metrics. This model aims to support a predictive diagnosis to identify which level-1 metric(s) underperform and, consequently to take action. Hence, the inputs are level-2 metrics, whereas the output variables represent level-1 metrics. The authors used synthetic data by following [10].

In this work, we focus only on the total cost to serve and return on working capital, by means of two ANFIS models instead of the three ones adopted in [11]. Our ANFIS models adopt fractional Tikhonov regularization, as detailed in the next section. As mentioned before, we have two models: model 1, whose output is the total cost to serve, with eight input variables, and model 2, whose output is the return on working capital, with five input variables (see section 4.1). It is worth noticing that one of the input variables of model 2 is the output of model 1. In [11], an intermediate model was adopted with three inputs and its output used with the total cost to serve as an input to the model to predict the return on working capital. Since our variant more computationally efficient than the standard ANFIS, we could avoid an intermediate model, by keeping a good accuracy. In fact, it is important an accurate prediction of the total cost to serve in order not to affect significantly the prediction of the return.

3. ANFIS with fractional regularization

ANFIS was introduced by Jang [15] to represent the first-order Sugeno (or TSK) fuzzy inference system through a network architecture.

In general, ANFIS implements rules of the form

$$\text{If } x_1 \text{ is } A_{1r} \text{ and ... and } x_n \text{ is } A_{nr}$$

$$\text{then} \quad y_r = \xi_{0r} + \xi_{1r} x_1 + ... + \xi_{nr} x_n \tag{1}$$

where $A_{ir}, i = 1, 2, ..., n$, are fuzzy sets representing linguistic attributes of the input x_i in the r-th rule ($r = 1, 2, ..., R$), and ξ_{1r} are the unknown consequent parameters.

The ANFIS network structure consists of five layers. The first layer represents the fuzzification stage, returning the membership degrees of each input value x_i into the fuzzy sets A_{ir}. In the second layer those membership degrees are aggregated by means of a product-type t-norm, giving some weights, representing the firing strength of a rule. In the third layer, such weights are normalized, by dividing each one by the sum of all the weights. In the fourth layer, the normalized weights are applied to the consequents y_r, by giving partial outputs. The final output y^0 is obtained by summing all the partial outputs from the fourth layer.

The membership function (MF) for A_ir can be any suitable parameterized membership function, e.g. the generalized bell-shaped function or the Gaussian function. In our model, we adopted the latter because it has a parameter less than the ones in the generalized bell-shaped MF. The Gaussian MF is

$$\mu_{A_{ir}}(x) = \exp\left(-\left(\frac{x_i - b_{ir}}{a_{ir}}\right)^2\right), \tag{2}$$

where a_{ir} and b_{ir} are the premise parameters.

ANFIS uses a hybrid learning algorithm based both on backpropagation and least-squares (LS) method to determine the unknown parameters. Hence, by using the training data, one obtains a matrix equation such as $\mathbf{H}\theta = \mathbf{o}$, where θ collects the unknown parameters and $\mathbf{o}$ the target values. The least-squares (LS) method is formulated as

$$\min_{\theta} \|\mathbf{M}\theta - \mathbf{o}\|^2 \tag{3}$$

with the solution

$$\theta* = \overline{\mathbf{M}}\mathbf{o}, \tag{4}$$

where $\overline{\mathbf{M}} = (\mathbf{M}^T\mathbf{M})^{-1}\mathbf{M}^T$ is the pseudoinverse of $\mathbf{M}$. Backpropagation is then used to tune the premise parameters.

In the variant herein proposed, the learning algorithm is based only on least squares with fractional Tikhonov regularization.

The fractional Tikhonov method formalizes the following minimization problem

$$\min_{\theta} \|\mathbf{M}\theta - \mathbf{o}\|_P^2 + \lambda\|\theta\|^2, \tag{5}$$

where $\|\theta\|_P = (\theta^T\mathbf{P}\theta)^{0.5}$ and $\mathbf{P}$ is a symmetric positive semi-definite matrix defined as [12]

$$\mathbf{P} = (\mathbf{M}^T\mathbf{M})^{\frac{\alpha-1}{2}}. \tag{6}$$

When $\alpha = 1$, the method reduces to the standard l_2-norm based Tikhonov regularization [12], that is a kind of penalized LS approach.

The solution is [12]:

$$\theta* = \sum_{i=1}^{q} \frac{\sigma_i^\alpha}{\sigma_i^{\alpha+1} + \lambda}(\mathbf{u}_i^T\mathbf{o})\mathbf{v}_i, \tag{7}$$

where $\mathbf{u}_i$ and $\mathbf{v}_i$ are the vectors (columns of the matrices $\mathbf{U}$ and $\mathbf{V}$) coming from the singular value decomposition (SVD) of the matrix $\mathbf{M}$, that is $\mathbf{M} = \mathbf{U}\mathbf{S}\mathbf{V}^T$, being $\mathbf{S}$ the diagonal matrix of singular values σ_i in decreasing arrangement. The formulas above have been deduced in [12] in the general context of penalized LS approaches, but this kind of regularization was never applied before to ANFIS (to the best authors' knowledge).

The aim of using such learning algorithm is to avoid backpropagation and grid partitioning. The latter implies that the rules are generated by means of all possible combinations of membership functions of all inputs. This is cumbersome, since the number of fuzzy rules increases exponentially with the number of input variables.

4. Numerical experiments

In this section, we describe the data sets, the experiments and the results. We used synthetic data, whose ranges are fixed as suggested in [11], according to previous studies. By following [11], data was normalized and the performance values of the level-2 metrics were randomly generated considering the above-mentioned ranges, as detailed in the next subsection. As in [11], the data sets were split into two parts, with 70% of the samples used for the training and 30% for validation. Since, data was generated randomly in [11], we cannot compare our results against the published ones, but we replicated the experiments by using our randomly generated data sets. Hence, we compared the results by ANFIS with fractional regularization (ANFIS-F) against the ones by the standard ANFIS (as used in [11]). The standard ANFIS and the one with fractional regularization use Gaussian MFs. For the sake of completeness, we considered also the more efficient and popular ANFIS with Fuzzy C-Means clustering [16]. ANFIS-F was implemented in Scilab. All the experiments were run on a PC with Intel i7 9th generation processor and 16GB RAM. The adopted error measure is the Root Mean Squared Error (RMSE).

4.1. Data sets

As mentioned before, we considered as performance attributes to be predicted the total cost to serve and the return on working capital. The total cost to serve is given by the sum of the direct and indirect costs to deliver products and services to customers, i.e. the sum of planning cost, sourcing cost, material landed cost, production cost, order management cost, fulfilment cost, and returns cost. Its value may vary in the range [2,000,000, 3,530,000] USD. The return on working capital represents the magnitude of investment relative to a company's working capital position versus the revenue generated from a supply chain. Its value is assumed to vary

Table 1
Input variables to model 1 (total cost)

Variable	UoD	MU
Sourcing cost	[140,000; 300,000]	USD
Planning cost	[25,000; 50,000]	USD
Material landed cost	[70,000; 150,000]	USD
Production cost	[150,000; 380,000]	USD
Order management cost	[220,000; 480,000]	USD
Fulfillment cost	[45,000; 70,000]	USD
Returns cost	[50,000; 200,000]	USD
Cost of goods sold	[1,300,000; 1,900,000]	USD

Table 2
Input variables to model 2 (return)

Variable	UoD	MU
Inventory	[100,000; 2,000,000]	USD
Accounts payable	[500,000; 2,000,000]	USD
Accounts receivable	[500,000; 2,000,000]	USD
Supply chain revenue	[3,500,000; 10,000,000]	USD
Total cost to serve	[2,000,000; 3,530,000]	USD

in the range [-15, 100] %. The input values for the model 1, whose output is the total cost to serve, are listed in Table 1, with the universe of discourse (UoD) and measurement unit (MU). The input values for the model 2, whose output is the return on working capital, along with UoD and MU, are listed in Table 2. As mentioned in section 2, the total cost to serve is an input to predict the return.

4.1.1. Data Generation and Normalization

The input and output variable ranges (UoD) for model 1 and model 2 are given in Table 1 and Table 2, respectively. The values were uniformly random generated. The minimum and maximum range was set for each input and output variable. There were 1000 random data points generated for each variable in the model 1, and 500 points for each variable in model 2. The values of each variable were validated to make sure they fall in the given range each time the data points were generated.

The data was normalized using the min-max normalization (in the range [0, 1]). The general formula for min-max normalization is given as:

$$x' = \frac{x - min(x)}{max(x) - min(x)}$$

where x' is the normalized value and x is the original value.

Table 3
Test RMSE for model 1 (total cost)

Approach	Rules	RMSE	Time (s)
ANFIS	2^8	0.4822	4370.96
ANFIS-FCM	2	0.2979	5.10
ANFIS-FCM	3	0.2999	8.7210
ANFIS-F ($\lambda = 0.001$, $\alpha = 0.9$)	2	0.3003	0.083
ANFIS-F ($\lambda = 0.01$, $\alpha = 0.9$)	3	0.2979	0.108

Table 4
Test RMSE for model 2 (return)

Approach	Rules	RMSE	Time (s)
ANFIS	2^5	0.35078	233.794642
ANFIS-FCM	2	0.28813	3.0361
ANFIS-FCM	3	0.288385	5.073
ANFIS-F ($\lambda = 0.001$, $\alpha = 0.9$)	2	0.2789	0.053
ANFIS-F ($\lambda = 0.1$, $\alpha = 0.1$)	3	0.2717	0.067

4.2. Numerical results

Table 3 and Table 4 show the RMSE by the different techniques and the training time. The RMSE by ANFIS-F represents the best result obtained by varying λ and α in the sets $\{10^{-3}, 10^{-2}, \dots, 10^3\}$ and $\{0.1, 0.2, \dots, 0.9, 1\}$ respectively. As one can see, the RMSE by standard ANFIS is 1.6 greater than the one by ANFIS-F for model 1 and 1.3 for model 2. The RMSE by ANFIS-FCM is close to the one by the proposed variant, but the training time for our variant is almost 1/100 of the ANFIS-FCM'.

Figure 1 and Figure 2 show the RMSE behaviour for the proposed ANFIS-F, by varying λ and α in model 1 and 2 respectively, adopting 2 and 3 terms. In all the considered cases, the RMSE worsens by increasing λ for any value of α, while it seems that for any λ the results worsen for smaller values of α.

5. Conclusions

Inspired by a recent work adopting ANFIS to predict the performance attributes for SC management, following the SCOR model, we introduced a more computationally efficient variant of ANFIS for the same problem. This variant is based on an LS approach with Tikhonov fractional regularization. This allowed to get a good accuracy avoiding an intermediate model, adopted in the reference work, and the lowest computational effort even when compared to the popular ANFIS equipped with FCM. In a separate work, we have tested numerically and statistically the good performance of the approach over a number of publicly available datasets. As future work, we plan to develop a multi-input multi-output neuro-fuzzy inference system to include all the SCOR attributes and to apply it to a real-world case study.

(a) (b)

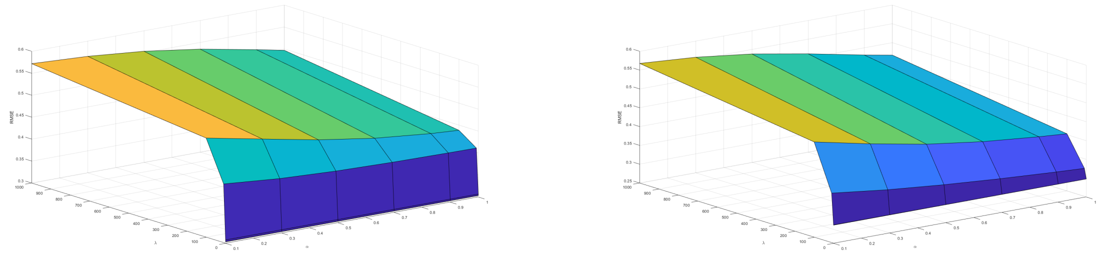

Figure 1: Model 1 - RMSE vs (λ, α): (a) 2 terms, (b) 3 terms.

(a) (b)

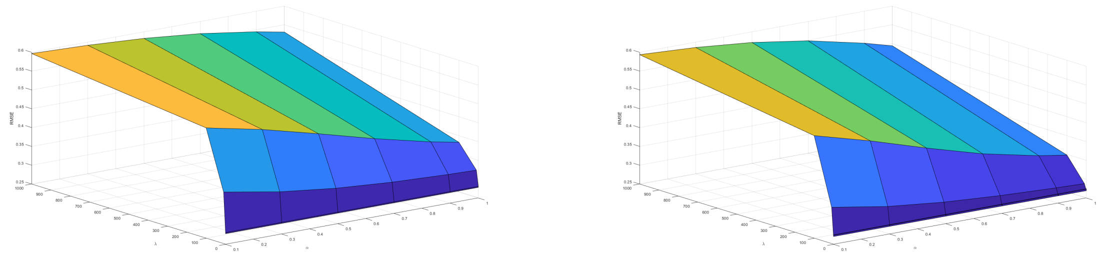

Figure 2: Model 2 - RMSE vs (λ, α): (a) 2 terms, (b) 3 terms.

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