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Forecasting Chaotic Series in Manufacturing Systems by Vector Support Machine Regression and Neural Networks

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Abstract:
Currently, it is recognized that manufacturing systems are complex in their structure and dynamics. Management, control and forecasting of such systems are very difficult tasks due to complexity. Numerous variables and signals vary in time with different patterns so that decision makers must be able to predict the behavior of the system. This is a necessary capability in order to keep the system under a safe operation. This also helps to prevent emergencies and the occurrence of critical events that may put in danger human beings and capital resources, such as expensive equipment and valuable production. When dealing with chaotic systems, the management, control, and forecasting are very difficult tasks. In this article an application of neural networks and vector support machines for the forecasting of the time varying average number of parts in a waiting line of a manufacturing system having a chaotic behavior, is presented. The best results were obtained with least square support vector machines and for the neural networks case, the best forecasts, are those with models employing the invariants characterizing the system's dynamics.
Keywords: chaos; forecast; neural networks; vector support machines; manufacturing systems

1 Introduction

Manufacturing systems are conceived as complex ones; although the complex term does not have a unique definition [1] it is possible to distinguish two kinds of complexities in production systems: a) structural complexity or static complexity dealing with the number of system's components and their relationships, and b) dynamic complexity dealing with the uncertainty in the systems behavior [2]. It may seem paradoxical that an artificial system engineered for making a set of given tasks had its own laws as if it was a natural system. This is due to the fact that production systems are becoming everyday more complex by the technological progress and the transformation of the supply chain. Flexible manufacturing machinery, global markets, and supply network relationships are typical examples of such changes. Managing these systems to bring them under control is today a difficult task. The dynamic complexity of production systems has been demonstrated by the kinds of behavior that they can exhibit, among these a chaotic behavior [3], [4], [5]. Several metrics have been proposed for measuring the complexity of manufacturing systems [2], [6], [7], [8]. These studies relate metrics of performance with metrics of complexity. In this article, a way of control by forecasting the system's behavior is shown. For this purpose, a time series of the average number of parts in the waiting line of a chaotic manufacturing system is utilized [3]. As forecasting methods, Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs) have been selected because these methods can distinguish chaotic patterns and therefore they can predict the evolution of an observed control variable. In [9] SVMs have been used for support vector regression (SVR) analysis of several exchange rates with respect to the US dollar. In the present work, a least square support vector regression

(LS-SVR) with less computational effort than the one reported in [10] is proposed. In [11] an ANN model for forecasting the observed error of monitoring units of the sea level in Singapore is presented. In [12] an ANN is constructed for forecasting the behavior of a diode having a chaotic pattern; in this case the local dimension and the time delay are proposed for determining the network architecture.

The originality of this work consists of the study of the performance of two forecasting techniques: LS-SVM and ANN as applied to chaotic series. Similar studies have been made but for series that are not chaotic [13], [14]. Also, it is a novel application in the manufacturing area.

The paper is organized as follows: section 2 shows in a summarized way the manufacturing system from which the time series was obtained; section 3 presents the methods utilized for the forecasting; section 4 shows the results of the analysis of the time series by using non-linear dynamic systems (NLDS) theory. Forecasting results are detailed in Section 5. Finally, conclusions and research directions are given.

2 System under study

2.1 Variable to be analyzed

The system under study is described in [3]. The variable to be analyzed is the average in time of the number of parts in the waiting line of a flexible manufacturing system. By utilizing a time series of this variable the system's dynamics is characterized by means of the theory of non-linear dynamic systems. The machining shop is formed by three different machines producing three types of parts. Each part has a set of operations which can be executed in different machines according to the operations sequence. Figure 1 shows the layout of the system under study.

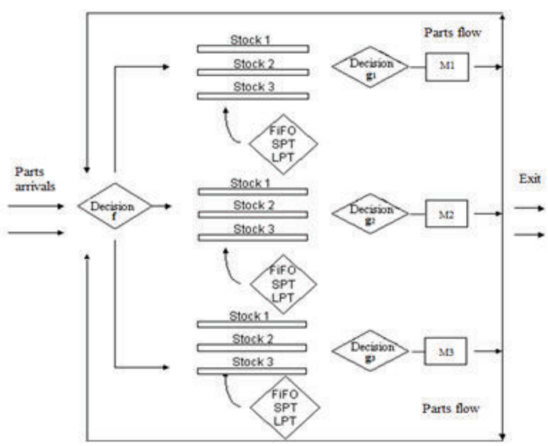

Figure 1: Machining shop layout.

2.2 Operation of the system

- The arrivals rate and service rate are such that the system is under equilibrium; that is, the number of parts neither tends to zero nor infinity.
- Upon arrival of a part, a function f assigns the part to a machine able to perform the operation and that has the least number of parts in queue.
- The priority of the queue of each part type at any machine is first-in first-out (FIFO).

- The machine works cyclically with a kind of part, during a time interval equivalent to the time needed to complete the stock of that kind of part at the k-th machine. The function gk manages the execution cycle according to the part type. The values of plant parameters are shown in Table 1, where β_j is the arrival rate of the j-th part type (number of parts/time unit) and Oij is the i-th operation of the j-th part. The values in the table represent the operation time at each machine.

TABLE I. MACHINING SHOP PARAMETERS

Operations	Machines		
Part type 1, $\beta_1 = 7.28$	M1	M2	M3
O_{11}	1/58	1/32	1/36
O_{21}	1/21	1/47	
O_{31}	1/60		4/105
Part type 2, $\beta_2 = 7.94$	M1	M2	M3
O_{12}	1/16		1/38
O_{22}		1/31	
O_{32}		1/58	
O_{42}	1/34		1/36
Part type 3, $\beta_3 = 15.81$	M1	M2	M3
O_{13}	1/32	1/22	1/57
O_{23}			1/49
O_{33}	1/42	1/38	1/40

3 Forecasting Methods Utilized

Research on forecasting models has received considerable attention over the last 50 years. Currently, there exist numerous forecasting methods [15]. For the case of chaotic systems, the very theory on NLDS provides forecasting methods [16]. In this article, NLDS theory is used as a base for constructing ANN and VSM models. These techniques are proposed due to their capacity for recognizing chaotic patterns.

3.1 Artificial Neural Networks

An artificial neural network (ANN) is a computational model of the brain. It consists of a limited number of connected elements (neurons) and it is distributed in an input layer, one or more hidden layers, and an output layer.An ANN is a mathematical structure that allows pattern recognition; in this work we use a Back-Propagation type of network, as shown in figure 2.

As it is known that the system is chaotic, it is proposed as the number of neurons in the input layer the dimension of the phase space. This value is obtained by the method of false neighbors. The temporal distance between the input variables corresponds to the time delay in the construction of the systemďż˝s attractor. This value is obtained from the average of the mutual information [16]. The transfer function is of the sigmoidal type and the network is defined by the equation (1).

$$x_t = \beta_0 + \sum_{i=1}^{n} \beta_i f(s\omega_{i0} + \sum_{j=1}^{d} \omega_{ij} x_{t-j}) \qquad (1)$$

Where n is the number of neurons in the hidden layer, d is the number of neurons in the

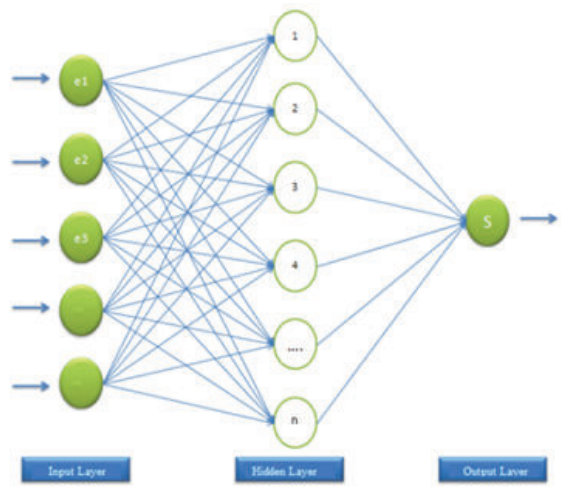

Figure 2: Neural Network for Forecasting

input layer, s is the standard deviation of the weights matrix and β_i, ω_{ij} are the weights. The number of neurons in the hidden layer is due to the following empirical relationship 2:

$$\frac{N_{obs}}{10} \geq (N_e + 1)N_c + (N_c + 1)N_s \tag{2}$$

Where $Nobs$ is the number of observations, Ne, Nc and Ns are the number of neurons in the input layer, hidden layer, and output layer, respectively.

3.2 Support vector machines for least squares regression

Support vector machines (SVM) algorithms emerged from the artificial intelligence field and they have been successfully used in a variety of applications for problems of classification and regression. The least-squares vector support machine is a modified version of a standard VSM for regression; the model is trained by solving a linear system instead of a quadratic programming optimization model [10]. The LS-SVM are closely related with regularization networks and Gaussian processes, buy they emphasize and exploit its interpretation from the viewpoint of the optimization theory. The general formulation for a LS-SVR is shown in (3):

$$y = w^T f(x) + b \tag{3}$$

Where x is the input vector of the data series, Y is the output vector. Parameters w and b are obtained from the optimization problem given by equations (4), (5).

$$Min\ \tau(w, b, e) = \frac{1}{2}\|w\|^2 + \gamma\frac{1}{2}\sum_{i=1}^{N} e_i^2 \tag{4}$$

$$s.t.\ (y_i - (\langle w, x_i \rangle) + b) = e_i\ \forall i = 1, ...N \tag{5}$$

In (4), γ is an arbitrarily chosen parameter. For learning, the kernel utilized is the radial base function (RBF) (6).

$$k(x_i, x_j) = exp(-\frac{\|y_i - x_i\|^2}{\sigma^2}) \tag{6}$$

The architecture of the LS-SVR [17] is shown in figure 3.

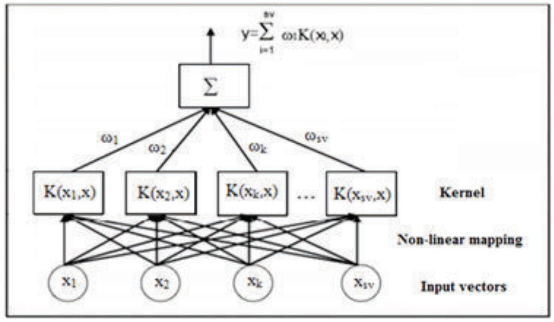

Figure 3: Architecture generated by regression SVM

4 Characterization of the system's dynamics

It has been stated that the system has a chaotic behavior; in figures 4, 5, 6, 7, 8, 9 the analysis confirming this assumption is shown. In figure 4 the time series plot is seen, figure 5 shows the Fourier spectrum where the erratic nature of the series is verified; figure 6 presents the time delay corresponding to the first minimum of the mutual information average. Figure 7 shows the phase space dimension d = 5, which has been obtained by the percentage of false neighbors [16]. However, figure 8 shows that the local dimension is 3 (correlation dimension 2.784). Finally, in figure 9 is observed that the highest Lyapunov's exponents value is 0.41, which corroborates the signal's chaotic character.

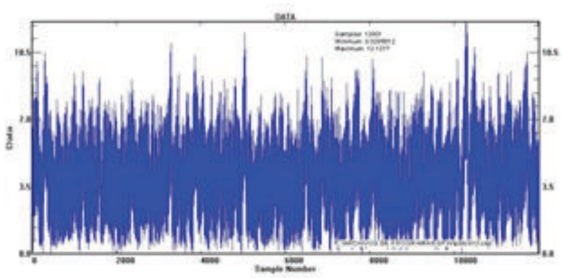

Figure 4: Average of the number of parts in time

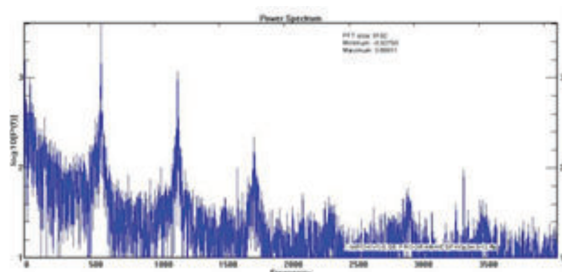

Figure 5: Fourier power spectrum

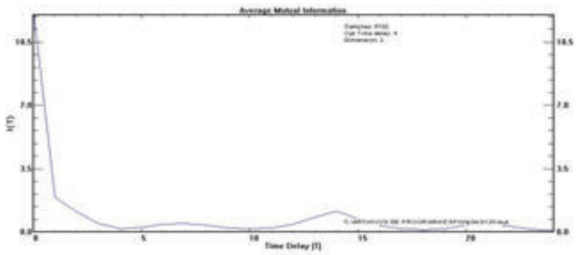

Figure 6: Mutual information average

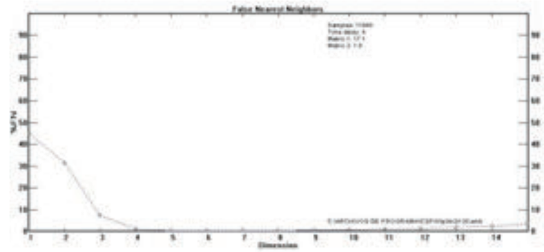

Figure 7: Dimension of phase space

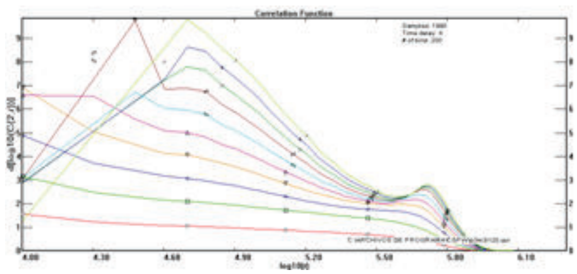

Figure 8: Correlation Dimension

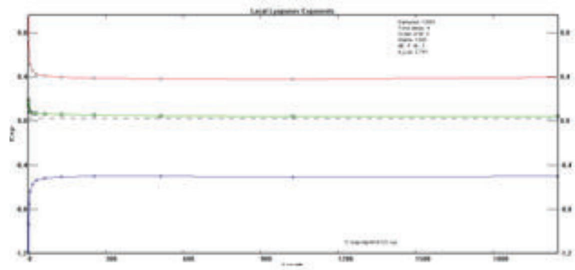

Figure 9: Lyapunov's exponents

5 Forecasting models results

In order to measure the performance of the models, the Apropiability Index (IA) and the Normalized root of quadratic error (RMS) are used, as defined by (7) and (8) respectively:

$$IA = 1 - \frac{\sum_{i=1}^{n}(y_i - y_i^{,})^2}{\sum_{i=1}^{n}(|y_i| + |y_i^{,}|)^2} \tag{7}$$

$$RMS = \sqrt{\frac{\sum_{i=1}^{n}(y_i - y_i^{,})^2}{\sum_{i=1}^{n}(y_i)^2}} \tag{8}$$

Where, y_i is the value of the average number of parts at period i, $y_i^{,}$ is the value predicted by the model, and n is the number of forecasted periods. The IA indicates the proportion of the variance that is explained by the model; values greater than 0.9 are expected. Whereas, the RMS compares the error between the desired output and the one generated by the model; values close or below to 0.1 are expected.

The series has 12001 data or periods, which correspond to the time persistent average number of parts in a time interval of 0.15 time units. A 70% is used for training and the remaining 30% for validation.

5.1 Experimental Results for ANN

For the forecasting model, a neural network is designed based on the time delay τ and the dimension d which were obtained from the chaotic system's characterization. Five forecasting models are constructed with 1, 3, 5, 7 and 10 neurons in the input layer, with a time delay $\tau = 4$ in each model. The number of neurons in the hidden layer is obtained by the relationship (2) for each model; thus it is obtained: 279, 167, 119, 93, 69 neurons, respectively. All of the models were implemented by using the $MATLAB^{TM} ANN$ toolbox. Figures 10, 11, and 12 show the results for the cases of 3, 5 and 10 neurons in the input layer.

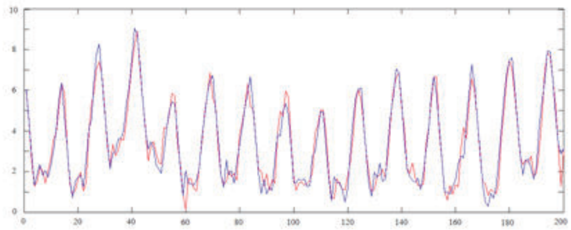

Figure 10: Forecast with three neurons in the input layer

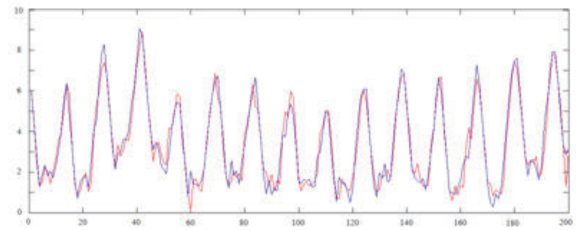

Figure 11: Forecast with five neurons in the input layer

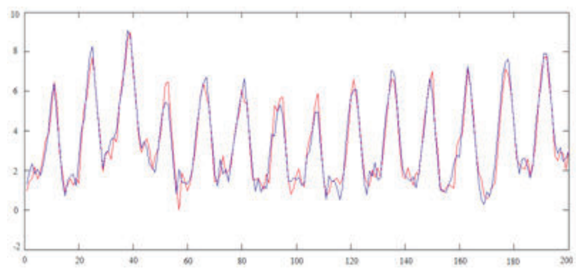

Figure 12: Forecast with ten neurons in the input layer

Table 2 show the values of IA and RMS indicators for the different models.

TABLE 2: PERFORMANCES INDICATORS

	Number of neurons in input layer			
	3	5	7	10
IA	0.9956	0.9958	0.9931	0.9961
RMS	0.1333	0.1293	0.1369	0.1342

It is observed that the model of 10 neurons is superior in 0.03% to the model with five neurons in the input layer. However, if the RMS of the same models are compared, the model with 10 neurons is greater in 3.65%. In a similar analysis between the models with three and ten neurons, it can be seen that the difference of the IAs is 0.05% and the RMS's 0.67%. Then, it is possible to state that the best models can be found between the ones with three and five neurons in the input layer. These values are exactly those corresponding to the local dimension and the global dimension in the phase space.

5.2 Experimental Results for LS-SVR

The values of the RBF kernel parameters associated with the optimization problem described by equations (4), (5) and (6) are $\gamma = 256$ and $\sigma = 8$. As time delay in the input variables $\tau = 4$ has been used. Likewise the ANN case, five models have been constructed with 1, 3, 5, 7 and 10 input vectors. The models were implemented by using $MATLAB^{TM}$ LSSVMlab1.7. Figures 13, 14 and 15 show results for 3, 5 and 10 input vectors.

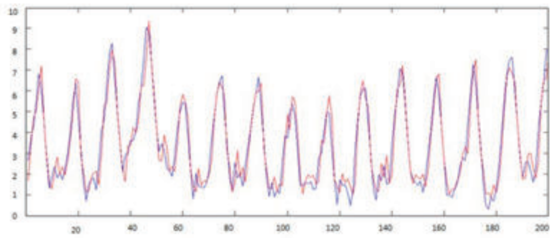

Figure 13: Forecast with three input vectors

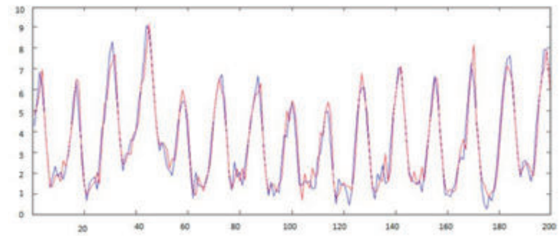

Figure 14: Forecast with five input vectors

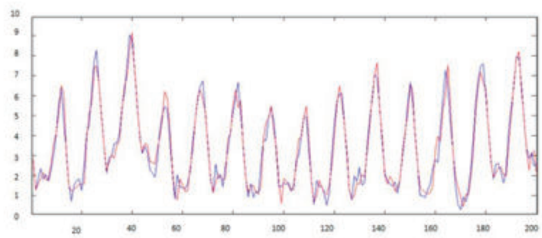

Figure 15: Forecast with ten input vectors

Table 3 shows the values of the indicators IA and RMS for the different models.

TABLE 3: PERFORMANCE INDICATORS WITH TIME DELAY 4

	Number of neurons in input layer			
	3	5	7	10
IA	0.9924	0.9871	0.9969	0.9966
RMS	0.1730	0.2246	0.1103	0.1158

The results in Table 3 are not the expected ones; the best results correspond to seven and ten input vectors but not between dimensions three and five as with ANNs. The same experiment was executed without time delay, that is $\tau = 1$ was assumed. The results are shown in Table 4.

TABLE 4: PERFORMANCE INDICATORS WITHOUT TIME DELAY

	Number of neurons in input layer			
	3	5	7	10
IA	0.9935	0.9951	0.9964	0.9965
RMS	0.1601	0.1386	0.1200	0.1170

Again, it is observed that best results are for seven and ten input vectors. Thus, for this specific case, it is verified that does not exists a behavior pattern based on NLDS characterization.

5.3 Comparison between experimental results for ANN and LS-SVR

Even though the difference between the IA of the best ANN and LS-SVR models is 0.11% in these models (five neuron for ANN and seven input vector for LS-SVR) the LS- SVR's RMS value is practically a half the ANN's. Hence, it is possible to conclude that the best model is the one constructed with LS-SVR. Nevertheless, it is observed that in general terms both approaches perform adequately.

6 Conclusions

As seen, the best results were obtained with least square support vector machines. Similar results have been reported for SVR and ANN for non-chaotic series [13], [14]. Notwithstanding, it can be stated that both models are efficient for the forecasting of a chaotic series obtained from a flexible manufacturing system. According to the results, it can be concluded that the system's behavior can be predicted in one time step, that is 0.15 time units. As research directions, it is suggested to develop models able to predict a longer time interval. For this purpose, ongoing work by the authors is addressing the use of the inverse of the Lyapunov's exponent in order to determine the number of neurons in the output layer for the ANN case, and of the number of output vectors for the LS-SVR.

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