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Innovative Applications of O.R.

Developing an early warning system to predict currency crises

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ABSTRACT

The purpose of this paper is to develop an early warning system to predict currency crises. In this study, a data set covering the period of January 1992–December 2011 of Turkish economy is used, and an early warning system is developed with artificial neural networks (ANN), decision trees, and logistic regression models. Financial Pressure Index (FPI) is an aggregated value, composed of the percentage changes in dollar exchange rate, gross foreign exchange reserves of the Central Bank, and overnight interest rate. In this study, FPI is the dependent variable, and thirty-two macroeconomic indicators are the independent variables. Three models, which are tested in Turkish crisis cases, have given clear signals that predicted the 1994 and 2001 crises 12 months earlier. Considering all three prediction model results, Turkey's economy is not expected to have a currency crisis (ceteris paribus) until the end of 2012. This study presents uniqueness in that decision support model developed in this study uses basic macroeconomic indicators to predict crises up to a year before they actually happened with an accuracy rate of approximately 95%. It also ranks the leading factors of currency crisis with regard to their importance in predicting the crisis.

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1. Introduction

A financial crisis is a state which causes economic, social, and political disasters that lead to a shift from equilibrium. This equilibrium creates uncertainty and chaos while causing redistribution of capital. Individuals who can foresee the crisis can use it to their advantage by reallocating capital and can transform the drawbacks of the impending crisis into opportunities. On the other hand, the ones who cannot foresee the crisis would suffer from unemployment and poverty. Therefore, the foresight to predict a crisis has attracted the attention of many researchers in the field of economics. However, due to the complexity of the context and number of factors that cause a crisis, predicting a crisis has been a very challenging problem. More interestingly, these factors have constantly changed over time. Considering all these, it would be a wise approach to take precautions against the potential crisis and prepare accordingly by foreseeing its effects via the past crisis and past economic indicators.

There are various methods in literature that have been used to predict the crisis, most of which are statistical and econometric models. Recently, machine learning models have also been effectively utilized in crisis prediction. Therefore, this study is aimed at developing an early warning system with machine learning and statistical models exemplified by the Turkish economy.

Market-threatening and effective crises have attracted the attention of many researchers. Studies pertaining to the prediction of financial crises have become more frequent since the 1990s. Some of these studies have focused on predicting crises by using a country's economic indicators, while some others have focused on determining common significant factors that help explain crises by inclusively considering economic indicators of various countries. The definition of "*crisis*", models utilized, and explanatory variables have varied from one study to another.

The aforementioned research can be categorized into three groups. The first category refers to the regression models (e.g. Logit–Probit models) in which financial crises are estimated ahead of time via leading indicators. The second category uses potential early warning indicators, and is associated with the Kaminsky, Lizondo, and Reinhart (KLR) Model (1998), which is also known as the signaling approach. The third category focuses on machine learning applications, which are relatively new in forecasting financial crises.

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Among the earliest studies of regression models, Eichengreen, Rose, and Wyplosz (1995) presented an empirical analysis of speculative attacks on pegged exchange rates in 22 countries between 1967 and 1992. Frankel and Rose (1996) utilized a panel of annual data for over 100 developing countries between 1971 and 1992 to qualify currency crashes. The authors described a "currency crash" as a large change of the nominal exchange rate that substantially increases the rate of change of nominal depreciation. Glick and Rose (1998) demonstrated the effect of currency crises on a cluster of countries, which are tied together by the international trade. In a study by Davis and Karim (2008), it was noted that a country's policy maker's objectives can affect their ability in recognizing crises and false alarms. Their study recommended logit estimation as the most suitable technique to predict global banking crisis, and that signal extraction is the best for predicting country-specific crisis as an early warning system. Likewise, Canbas, Cabuk, and Kilic (2005) proposed an integrated early warning system (IEWS) framework that can be used as a decision support tool in the prediction of commercial bank failure via multivariate statistical analysis of financial structures, specifically principal component analysis combined with discriminant, logit, and probit models. The application of the RS Theory was also presented by Sanchis, Segovia, Gil, Heras, and Vilar (2007) to predict the insolvency of insurance companies and financial instability in a country. Furthermore, Premachandra, Bhabra, and Sueyoshi (2009) compared the data envelopment analysis (DEA) approach with the logistic regression (LR) technique and revealed that DEA is an appealing method for bankruptcy assessment.

On the other hand, the second category (i.e. the KLR model) computes the deviation of the variables' values before and at the time of the crises. These variables are selected in a way that they are the best signaling indicators of the crisis. Kaminsky, Lizondo, and Reinhart (1998) was among the earliest studies of this method and used the signaling approach to predict currency crises for a sample of five industrial and 15 developing countries between the years 1970–1995. In their study, an indicator exceeding a specified threshold was interpreted as a warning signal that a currency crisis may take place within the next 24 months. They constructed such an early warning system that was proven to be able to accurately forecast the Asian crises. In this regard, their study also confirmed that economies in distress are at the origin of financial crises, such as the Asian crises, far from being of a "new breed". Kaminsky and Reinhard (1999) analyzed the links between banking and currency crises. They revealed that financial liberalization often precedes banking crises by showing that problems in the banking sector that typically precede a currency crisis. The currency crisis then deepens the banking crisis and causes a vicious spiral. Edison (2003) evaluated how the signal system can be applied to an individual country.

Within the last two decades, artificial neural networks (ANN) have been recognized by many researchers as a popular technique in financial prediction studies due to its high prediction accuracy rate (Akkoc, 2012). Results from the study by García-Alonso, Torres-Jiménez, and Hervás-Martínez (2010) indicated that ANN models, specifically product-unit neural networks, have shown the most accurate gross margin predictions in the agrarian sector. Based on the data sample of 220 manufacturing firms, Zhang, Hu, Patuwo, and Indro (1999) indicated that ANNs are also significantly better than traditional regression methods when solving real problems such as bankruptcy prediction. Lacher, Coats, Shanker, and Fant (1995) also revealed that ANN is able to achieve better results in estimating future financial health of a firm. Fethi and Pasiouras (2010) discussed the applications of various artificial intelligence (AI) techniques, such as ANN, decision tree, and support vector machines, in bank failure prediction, assessment of bank creditworthiness, and underperformance. Kumar and Ravi (2007) also examined the application of the same techniques in their study of the bankruptcy prediction issues faced by banks and firms during the 1968–2005 period.

In a similar vein, the use of machine learning methods such as artificial neural networks (ANN), decision trees, and support vector machines has recently proven to be a set of commonly used reliable methods in predictive analytics (Delen, Oztekin, & Kong, 2010; Delen, Oztekin, & Tomak, 2012; Oztekin, 2011; Oztekin, Delen, & Kong, 2009; Oztekin, Kong, & Delen, 2011). Oh, Kim, Lee, and Lee (2005) used ANNs and nonlinear programming to examine the construction process of a daily financial condition indicator, which can be used as an early warning signal. Fioramanti (2008) showed that further progress could be achieved by applying ANN to the data on the sovereign debt crises that occurred in developing countries from 1980 to 2004. Lin, Khan, Chang, and Wang (2008) presented a mixed model to predict the occurrence of currency crises by using the neuro-fuzzy modeling approach. The model integrated the learning ability of ANNs with the inference mechanism of fuzzy logic. Nan, Zhou, Kou, and Li (2012) compared neural networks on generating early warning signals of bankruptcy in a given company and reported that ARTMAP outperforms the other models. Yu, Wang, Lai, and Wen (2010) proposed a multi-scale neural network learning paradigm to predict financial crisis events via early warning signals. They applied the proposed paradigm to the exchange rate data of two Asian countries to forecast financial crisis.

A detailed analysis of currency crises of the last 30 years can be found in Kaminsky's study (2006). Additionally, a more recent review of financial crisis and banking default literature, according to financial and economic circumstances, is provided by Demyanyk and Hasan (2010).

2. Materials and methods

2.1. Definition of the crisis

Inspired from the study of Eichengreen et al. (1995), "crisis" is defined as the percentage change of the standardized average of the gross foreign exchange reserves of the Central Bank and the repo rate (in terms of the US Dollar $ exchange rate). This is also referred to as the Financial Pressure Index (FPI) in literature. An increase in the US Dollar exchange rate and the repo rates, as well as a decrease in the gross foreign exchange of the Central Bank, leads to an increase in the FPI. In this study, it is assumed that a financial crisis arises when a threshold of FPI is exceeded. The variables stated in the calculation of the crisis are normalized to compute the FPI as in Eq. (1).

$$\mathrm{FPI}_t = \frac{\left(\frac{e_t-\mu_e}{\sigma_e}\right) - \left(\frac{r_t-\mu_r}{\sigma_r}\right) + \left(\frac{i_t-\mu_i}{\sigma_i}\right)}{3} \tag{1}$$

where μ and σ represents mean and standard deviation, respectively.

$$e_t = \left(\frac{E_t - E_{t-1}}{E_{t-1}}\right) \tag{2}$$

$$r_t = \left(\frac{R_t - R_{t-1}}{R_{t-1}}\right) \tag{3}$$

$$i_t = \left(\frac{I_t - I_{t-1}}{I_{t-1}}\right) \tag{4}$$

where e_t, r_t, and i_t are the monthly percentage changes in the dollar exchange rate, monthly gross foreign exchange reserves of the Central Bank, and monthly change of overnight interest rates at month t, respectively. E_t, R_t, and I_t are the dollar exchange rate,

Table 1
Different coefficient a values from the literature.

$a = 1.5$	$a = 2$	$a = 2.5$	$a = 3$
Tambunan (2002)	Eichengreen et al. (1995)	Yap (2002)	Kaminsky et al. (1998)
Adiningsih, Setiawati, and Sholihah (2002)	Park (2002)	Edison (2003)	Berg and Pattillo (1999)
Tinakorn (2002)	Kamin and Babson (1999)		Peng and Bajona (2008)
Kibritcioglu et al. (2001)	Bussiere and Fratzscher (2006)		

the gross foreign exchange reserves of the Central Bank, and the average overnight interest rate at month t, respectively. The threshold value which signals a crisis is calculated as in Eq. (5).

$$\mathrm{TV} = \mu + a\sigma \tag{5}$$

The threshold value (TV) is defined as a slack over the mean μ with a factor, a, of the standard deviation. Subsequently, the presence of a crisis has been defined as in Eq. (6), in which dummy variable K equals 1 if there is a crisis; and 0 if otherwise.

$$K = \begin{cases} 1 & \text{if FPI} > \mathrm{TV} \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

The coefficient a takes values between 1.5 and 3 in the financial crisis literature. It is a heuristic value that seeks to improve the signal performance. Means, standard deviations, and weights are country-specific. Table 1 summarizes the applications for various values of the coefficient a.

2.2. Definition of the perfect signal

The perfect signal is an ideal series of signals that gives a warning of a crisis during the 12-month period before the time at which FPI assumes a crisis is at the door. This signal is defined as in Eq. (7) and based on Bussiere and Fratzscher (2006). The perfect signal takes a value of 1 if a crisis is expected to occur within the upcoming 12 months and a value of 0 if otherwise.

$$\mathrm{PS}_i = \begin{cases} 1 & \text{if } \exists k = 1, 2, \ldots, 12 \text{ subject to } \mathrm{FPI}_{i+k} > (\mu + a\sigma) \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

For instance, if a crisis is assumed in February of 1994, the perfect signal series always takes a value of 1 before the 12-month period of February 1994 as shown in Table 2.

It would be naïve to say that the target of the perfect signal is to warn before a crisis occurs. Therefore, it has been considered a false alarm to detect the deterioration in the metrics at the time of the crisis, and consequently a value of 0 has been assigned to the perfect signals during this time. This translates into the fact that the perfect signal would be assigned a value of 1 if there is no crisis within the currently studied month, but it is predicted to be observed within the upcoming 12 months.

Table 2
Perfect signal example.

Period	Crises	Perfect signal
February-93	0	1
March-93	0	1
April-93	0	1
May-93	0	1
June-93	0	1
July-93	0	1
August-93	0	1
September-93	0	1
October-93	0	1
November-93	0	1
December-93	0	1
January-94	0	1
February-94	1	0
March-94	1	0
April-94	1	0

2.3. Proposed methodology

This study is fundamentally based on the "leading indicator" approach. The leading indicator approach assumes that macroeconomic factors would have an abnormal pattern before the time of a crisis and aims to calculate that deviation from the expected pattern (Kaminsky, 2006; Kaminsky et al., 1998; Kibritcioglu, Kose, & Ugur, 2001). A signal for crisis is fired if abnormal changes are observed with respect to predetermined threshold values by inspecting the pattern of factors.

This study proposes the following methodology in constructing an early warning system for predicting currency crises:

Step 1. Use Eq. (1) to calculate the FPI.
Step 2. Determine months with crises using Eq. (6).
Step 3. Calculate the perfect signal.
Step 4. Determine the leading indicators.
Step 5. Build the model using the perfect signal as the desired variable and leading indicators as the input variables.
Step 6. Calculate the early warning signal and predict the currency crises.
Step 7: Conduct information fusion-based sensitivity analyses to determine the rank order of the most important variables in predicting currency crises.

A brief diagram of the proposed methodology can be seen in Fig. 1.

2.3.1. Early warning models via machine learning

Preliminary studies were conducted to determine which models perform better than the others in terms of classification error. Three classification models, two from machine learning field and one from statistics, were shown to outperform the others and the following models were adopted for this study's proposed approach: artificial neural networks, decision trees, and logistic regression. Brief descriptions of machine learning models used in this study are provided next.

Artificial neural networks (ANN) have been popular artificial intelligence-based data mining tools due to their superior prediction performance (Chang, 2011). Therefore, ANNs are widely used in forecasting the following: ATM cash demand, wind speed, foreign exchange rates, intraday electricity demand, and financial failure (Cao, Ewing, & Thompson, 2012; Jardin & Séverin, 2012; Kim, 2013; Sermpinis, Theofilatos, Karathanasopoulos, Georgopoulos, & Dunise, 2013; Venkatesh, Ravi, Prinzie, & Poel, 2014). In this study, Multi-Layer Perceptron (MLP) with back propagation learning algorithm is used due to its superiority over other ANN algorithms such as radial basis function (RBF) and recurrent neural network (RNN). Our pre-experiments also showed that MLP algorithm performs better than other ANN algorithms for this type of classification problem. In fact, Hornik, Stinchcombe, and White (1990) empirically showed that given the right size and structure, MLP is capable of learning arbitrarily complex nonlinear functions at arbitrary accuracy levels. Thus, in this study the optimal values of MLP size and structure with backpropagation learning are searched by genetic algorithms.

Quinlan's ID3, C4.5, C5 (Quinlan, 1986, 1993) and Breiman et al.'s CART (Classification and Regression Trees) (Breiman, Friedman, Olshen, & Stone, 1984) algorithms are well-known decision

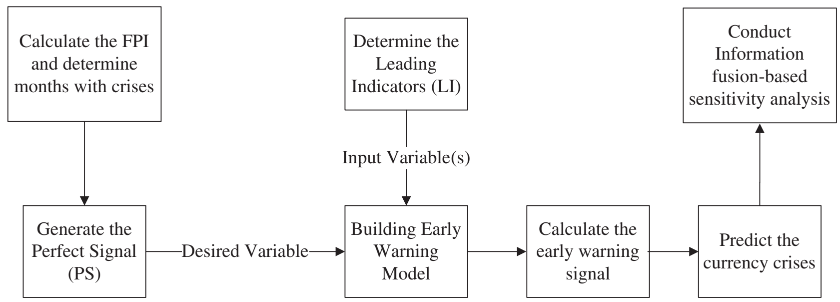

Fig. 1. The flowchart for the proposed early warning system.

tree algorithms. Compared to other machine learning methods, decision trees have the advantage of being explained as a series of "if-then rules" instead of being black boxes. This advantage makes them very valuable in forecasting crises. Based on favorable trials in this study, C5 algorithm, which is an improved version of C4.5 and ID3 algorithms, was chosen as the decision tree model. C5 algorithm differs from its predecessors namely C4.5 and ID3 in that it is faster, more efficient (use of less memory), more concise with smaller trees constructed, and allows for boosting, which improves the accuracy (Quinlan, 1993). During the construction of the decision tree, C5 algorithm selects the best variable which splits its set of data points into subsets having more cases/observations in one class. Information gain is adopted as the splitting criterion. The variables are then selected to form the tree and hence to make the decision with respect to their information gain. The same algorithm is recursively employed on the smaller sublists.

Logistic regression is a generalization of linear regression which is used to predict a categorical outcome (Hastie, Tibshirani, & Friedman, 2001). It is primarily used in predicting binary or multi-class dependent variables. It cannot be modeled directly by linear regression due to discrete nature of the response variable. Therefore, rather than predicting the point estimate of the event itself, it builds the model to predict the odds of its occurrence. In a two-class problem, odds greater than 50% would mean that the case is assigned to the class designated as "1" and "0" otherwise. While logistic regression is a very powerful modeling tool, the modeler must choose the right inputs and specify their functional relationship to the response variable based on his or her experience with the data and data analysis. In this study, a crisis occurring in the next 12 months or not is a two-class problem with odds greater than 50% assigned to the class designated as "1", indicating a currency crises within the next 12 months and "0" if otherwise, indicating a currency crisis will not occur within the next 12 months. Logistic regression is a powerful statistical modeling tool in financial crises literature, but it requires carefully chosen input variables. In this study, due to favorable results received, multinomial forward stepwise method is used to select the inputs during calculation steps with regard to their association with the response variable.

2.3.2. Performance criteria for model evaluation

In this study, the whole data set is divided into two mutually exclusive subsets; a model preparation (training) set and a testing set. Data in the testing set was never used while preparing the early warning models, instead it was used to evaluate the model performance on unseen data.

Researchers generally use *k*-fold cross-validation for machine learning models in order to minimize the bias associated with the random sampling of the training and hold-out data samples (Desai, Crook, & Overstreet, 1996; West, 2000). The whole data set (D) is divided into two mutual subsets as described above. The training subset (D^{Tr}) is used only for training whereas the testing subset (D^{Ts}) is never used for training. After completing the learning process, the overall generalization ability of the models can be measured by the unseen new data, which is separated at the very beginning as the testing data subset (D^{Ts}). In order to fairly measure the prediction accuracy of each early warning model, the same training and testing data subsets are used for each method.

In *k*-fold cross-validation, the complete training data is randomly split into k mutually exclusive sets (the folds: $D_1^{Tr}, D_2^{Tr}, \ldots, D_k^{Tr}$) of approximately equal size. In each epoch, an early warning model is trained on all but one fold (D^{Tr}) with tested on the remaining single fold (D^{Tr}). The cross-validation estimate of the overall accuracy is calculated as the simple average of the k individual accuracy measures as follows:

$$\mathrm{CV} = \frac{1}{k}\sum_{i=1}^{k} A_i \tag{8}$$

where CV represents the cross-validation accuracy, k is the number of folds used, and A is the accuracy measure of each fold.

In this study, 10-fold cross-validation is used to stop the training process and CV prevents overtraining or memorizing that inhibits the generalization ability of the model.

In order to compare early warning models, three performance criteria are adopted as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{10}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{11}$$

where TP, TN, FP, FN are True Positive, True Negative, False Positive, False Negative, respectively. Eq. (9) measures the proportion of correctly classified examples to give an overall probability that the model can correctly classify. Sensitivity and specificity, shown by Eqs. (10) and (11), measure the model's ability to recognize specific currency crisis groups. For example, sensitivity is the probability that a crisis signal indicates an actual crisis and specificity is the probability that a non-crisis signal indicates a crisis, in fact, will not occur in the next twelve months.

A matrix representation of the classification results based on actual classification vs. model classification, as shown in Fig. 2, is called the confusion matrix. In a two-class classification problem, as in our case, the upper left cell denotes the number of samples classified as positive, while they were positive in the actual classification (also called true positives). The lower right cell denotes the number of samples classified as negative, while they were actually negative (also called true negatives). The upper right cell represents the number of samples classified as negative, while they were actually positive (also called false negatives). The lower left

		Model Classification	
		Positive	Negative
Actual Classification	Positive	TP	FN
	Negative	FP	TN

Fig. 2. A confusion matrix representation for a two-class classification problem.

cell represents the number of samples classified as positive, while they were actually negative (also called false positives).

2.3.3. Information fusion-based sensitivity analyses

In data mining, there is no single method that works best for each and every problem. In other words, the performance of a model is derived by the studied scenario and the dataset being utilized (Ruiz & Mieto, 2000). Likewise, it is impossible to state the best strategy to deploy various data mining methods. Therefore, researchers tend to use "composite forecasts" by integrating multiple models in order to receive more accurate and effective results out of a set of data mining models (Batchelor & Dua, 1995). The *information fusion* outlines the process of combining the information extracted from a set of data mining models. There is a consensus that such a fusion produces more useful information in knowledge discovery in databases (KDD) practices (Armstrong, 2002; Chase, 2000).

The information fusion algorithm can be as formulated as in Eq. (12) where the output (dependent) variable is shown by variable y and the input (independent) variables by $x_1, x_2, \ldots, x_n$ (Oztekin, Delen, Turkyilmaz, & Zaim, 2013).

$$\hat{y} = f(x_1, x_2, \ldots, x_n) \tag{12}$$

Prediction model f can take many forms. For instance, a linear regression model can be written as Eq. (13)

$$f(x_1, x_2, \ldots, x_n) = \beta + \sum_{i=1}^{n} a_i x_i \tag{13}$$

where β is the intercept and a_i's are the coefficients for x_i's. For a Neural Network model, for a single neuron, it may be written as Eq. (14)

$$f(x_1, x_2, \ldots, x_n) = \phi\left(w_0 + \sum_{j=1}^{n} w_j x_j\right) \tag{14}$$

where ϕ is the transfer function and w_i's are the weights for x_i's.

If m number of prediction models is employed, the fusion model can be written as in Eq. (15)

$$\hat{y}_{fused} = \psi(\hat{y}_{individual,i}) = \psi(f_1(x), f_2(x), \ldots, f_m(x)) \tag{15}$$

where the ψ is the operator to fuse/integrate the predictions of models $f_1(x), f_2(x), \ldots, f_m(x)$.

If fusing operator ψ is a linear function, as the case in this study, then we can rewrite Eq. (15) as in Eq. (16):

$$\hat{y}_{fused} = \sum_{i=1}^{m} \omega_i f_i(x) = \omega_1 f_1(x) + \omega_2 f_2(x) + \cdots + \omega_m f_m(x) \tag{16}$$

where $\omega_1, \omega_2, \ldots, \omega_m$ refer to the weighting coefficients of each individual model, namely, $f_1(x), f_2(x), \ldots, f_m(x)$. Also, it can be assumed that the weights are normalized so that $\sum_{i=1}^{m} \omega_i = 1$ holds true.

The weights (ω's) are assigned proportional to the performance measure of each data mining model. In other words, the higher the accuracy of the data mining model, the higher the weight of that particular data mining model's results (Oztekin et al., 2013).

In addition, determining the rank order of independent variables in terms of their importance in prediction is also critical. In artificial neural networks, *sensitivity analysis* is the technique to do so for a trained ANN model (Davis, 1989). Through the sensitivity analysis, the learning algorithm of the ANN model is disabled after the learning is accomplished so that the network weights remain unaffected. Hence, the sensitivity score of a given input/independent variable is the percentage ratio of the ANN model error without the specified independent variable to the error of the model with all independent variables (Principe, Euliano, & Lefebvre, 2001). The more the model deterioration is without the particular variable, the higher the importance level of that variable would be. The same philosophy is valid in SVMs as well when determining the variable rank order in terms of their importance, which is quantified as "sensitivity measure" as defined by Eq. (17) (Saltelli, 2002).

$$S_i = \frac{V_i}{V(F_t)} = \frac{V(E(F_t|X_i))}{V(F_t)} \tag{17}$$

where S_i is the sensitivity score of the ith variable in the model, $V(F_t)$ is the unconditional output variance. In the numerator, the expectation operator E calls for an integral over X_{-i}; that is, over all input variables but X_i, then the variance operator V implies a further integral over X_i. Variable importance is then computed as the normalized sensitivity (Saltelli, Tarantola, Campolongo, & Ratto, 2004).

Considering Eqs. (16) and (17) simultaneously, sensitivity measure of the variable n with information fused by m prediction models can then be given by Eq. (18)

$$S_{n(fused)} = \sum_{i=1}^{m} \omega_i S_{in} = \omega_1 S_{1n} + \omega_2 S_{2n} + \cdots + \omega_m S_{mn} \tag{18}$$

where ω's refer to the normalized performance measure (i.e. accuracy value) of each prediction model with m models in total; and S_{in} is the sensitivity measure of the nth variable in the ith model.

3. Results and discussion

3.1. Calculating the Financial Pressure Index (FPI)

The first step of the study was calculating the FPI in order to determine the months in which a financial crisis was observed within the Turkish economy during the period of 1992–2011. Monthly dollar exchange rate, the gross foreign exchange reserves of the Central Bank, and overnight interest rates were obtained from the electronic data delivery system of the Central Bank of the Republic of Turkey and the FPI was calculated for each month using Eq. (1).

The calculated FPI is illustrated in Fig. 3 as a monthly series. The months that exceed the threshold value (TV) as calculated via Eq. (5) were marked as months of the crisis. By varying the standard deviation values with the coefficient of a at 1.5, 2, 2.5, and 3; four different TVs were calculated and depicted in Fig. 3 as well.

3.2. Determining months with crises

The second step of the study was determining and tabulating the months that were over the TVs with four different standard deviation levels, as shown in Table 3 where the smaller the threshold value (TV), the more months are determined as "months of crisis". The number of months of crisis affects the signal performance of the leading factors. If the sensitivity of FPI is increased and hence additional months are included in the model, a few indicators are not helpful in predicting the crisis and cannot signal. On the other hand, if the sensitivity of the FPI is rather decreased, there will be a misperception that there is no crisis in a given month even if there

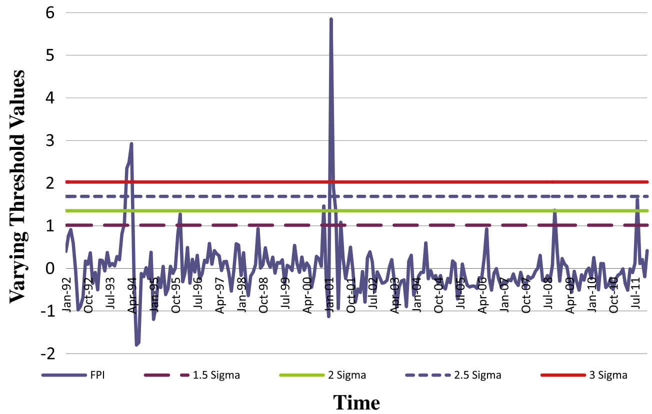

Fig. 3. Financial Pressure Index (FPI) for Turkey and various TVs.

Table 3
Months with crises with respect to varying sigma levels.

Months over 1.5σ	Months over 2σ	Months over 2.5σ	Months over 3σ
January-94			
February-94	February-94	February-94	February-94
March-94	March-94	March-94	March-94
April-94	April-94	April-94	April-94
December-95			
November-00	November-00		
February-01	February-01	February-01	February-01
March-01	March-01	March-01	
April-01			
June-01			
October-08	October-08		
August-11	August-11		

is in reality (false negative case). Therefore, experience-based intuitions and heuristics play a critical role in determining an appropriate threshold value for the specific country's economy.

Based on Sevim's (2012) research work on Turkey's financial crises, trial and error showed that the most meaningful results were obtained at the 3-sigma level. This current study also adopts the threshold value (TV) to be 3-sigma level. Sevim (2012) noted that adopting values smaller than the 3-sigma level causes more months to be considered as having financial crises and this decreases the correlation between the predictive variable and the perfect signal. In addition, it is worth noting that there is no research in literature which indicates financial crises in years 2008 and 2011 in Turkey, which is the case if lower sigma values are adopted, as seen in Table 3. Therefore, in this study, the coefficient of a in Eq. (5) is assigned to be 3 as well and then the months of crises are determined using Eq. (6).

3.3. Calculating the perfect signal

The third step of this study was calculating the perfect signal series using Eq. (7) that will be used as the desired variable (output) in each of the three prediction models, namely ANNs, decision trees, and logistic regression.

3.4. Determining leading indicators

The fourth step of the study was determining which macroeconomic indicators would be used as input (independent) variables in the three models. In this study, the monthly data for the period of 1992–2011 was used. The 32 most commonly used independent variables in literature were determined and retrieved from the database of the Central Bank of Turkey. The data related to these variables were transformed into either the monthly percent change or into the ratio. All of these 32 variables used in the analyses are tabulated in Table 4.

Table 4
Leading indicators used in the case of Turkish economy.

V1	Monthly change current account balance
V2	Monthly change in terms of trade
V3	Monthly change crude-oil prices
V4	Actual monthly change in treasury domestic debt
V5	Monthly change in ISE 100 index
V6	Export to import ratio
V7	Monthly change in export
V8	Monthly change in manufacturing production index
V9	Import to output ratio
V10	Monthly change in import
V11	Short-term capital inflows to output
V12	Budget balance to output
V13	Monthly change in capacity utilization rate
V14	Actual monthly change in M1
V15	M2 to CB's gross reserves
V16	Monthly change in M2 multiplier
V17	Actual monthly change in M2
V18	Monthly change in foreign exchange deposit to M2
V19	Actual monthly change in CB's domestic assets
V20	Deposit money banks foreign liabilities to foreign assets
V21	Actual monthly change in deposit money banks net past due loans
V22	Actual monthly change in total deposit
V23	Actual monthly change domestic credits to output
V24	Ratio of deposit money banks domestic credits to total assets
V25	Actual monthly change in deposit money banks domestic credits
V26	Actual monthly change in banking sector credits to private sector
V27	Actual monthly change in budget balance
V28	Trade balance/output ratio
V29	Monthly change in actual exchange rate index
V30	Monthly change in consumer price index
V31	Monthly change in short term gross external debt (Treasury) to CB's gross reserves
V32	Monthly change in USA-TR actual interest rate differential

3.5. Model building

In this study, the perfect signal was assigned as the desired (output/dependent) variable and leading indicators as input/independent variables. For each of the three models, the performance of the signal improved as the discrepancy between the perfect signal and the current signal decreased. In other words, by creating the perfect signal series it was targeted to calculate to what extent each of the macroeconomic criteria gets closer to the ideal state.

In this study Multi-Layer Perceptron (MLP) is used to represent the artificial neural network-based model, and the details of the MLP structure and reasons for selection can be found in Section 2. The MLP model used in this study has one input layer, one hidden layer, and one output layer. The input layer has 32 input neurons, each representing a variable (leading indicator). The hidden layer has 2 neurons with tangent hyperbolic transfer functions. The output layer has one neuron, equal to "1" for the case of having a crisis, and "0" for no crisis signal. MLP parameters, such as input variables, learning rate for each layer, and the number of neurons in the hidden layer are searched via the employment of genetic algorithms resulting in twelve neurons in the hidden layer for the best MLP structure. All of the searched MLP structures are trained with momentum gradient search-based supervised learning with a maximum of 1000 epochs. In order to prevent overfitting, which is the memorization with loss of generalization ability, the training process is stopped if the performance on cross-validated set does not change for 30 subsequent epochs. The final and the best MLP structure is pictorially represented as in Fig. 4.

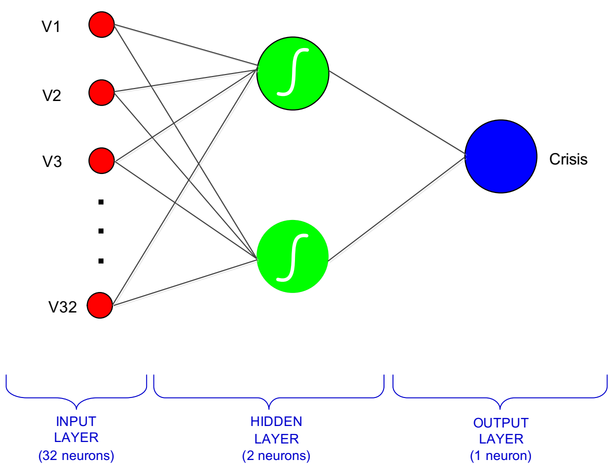

Fig. 4. ANN structure used in this study.

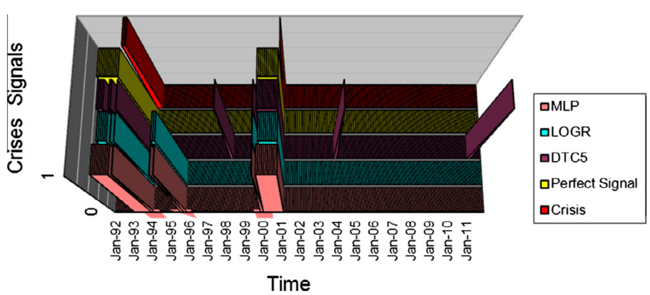

Fig. 5. Early warning signals.

Based on the favorable results received during the trials, a decision tree with a C5 algorithm is used in this study. The logistic regression model is based on multinomial forward stepwise selection, in which the predictive variables are chosen by the R^2 values.

3.6. Calculating the early warning signal

The early warning signals calculated based on the three prediction models are illustrated in Fig. 5. Eq. (1) quantifies the months of crisis using the FPI, and those months are represented by the red[1] bars at the very back. Following Eq. (7), the perfect signal series is also determined and is represented by yellow bars, which refer to the 12-month period before the crisis. In Fig. 5, as followed from Eq. (7), the perfect signal takes a value of 1 if a crisis is expected to occur within the upcoming 12-month period or a value of 0 otherwise, as explained in Section 2.2 earlier. Since it is more critical to determine the pattern of the perfect signal rather than the crisis itself, the signals estimated using the three models (i.e. ANN, DT, and LR) are expected to show a similar pattern to this desired variable, namely that of the yellow-marked perfect signal series. This is mainly because taking precautions ahead of time before the crisis occurs is a substantial effort instead of seeking remedies to overcome its drawbacks after it takes place. It is seen in Fig. 5 that the signals produced by the three prediction models very closely follow the pattern of this desired perfect signal series. Before a crisis occurs, all three models signal several times within the 12-month period. However, there are a few occasional false alarms in all of the three models. Of all three models, ANN produces the most accurate signals before the crisis, as seen in Fig. 5 by eyeballing. Specifically, in light of the calculated early warning signals, three models which are tested in the Turkish case give clear signals anticipating 1994 and 2001 crises 12 months earlier. Additionally, according to all of the three prediction models of a currency crisis, Turkey's economy is not expected to have a crisis (ceteris paribus) until the end of 2012.

Since the values for 2012 are now complete, the results received from this study with respect to crises have been realized and verified that there has not been a crisis in Turkey during the year 2012. This fact is pictorially represented in Fig. 6.

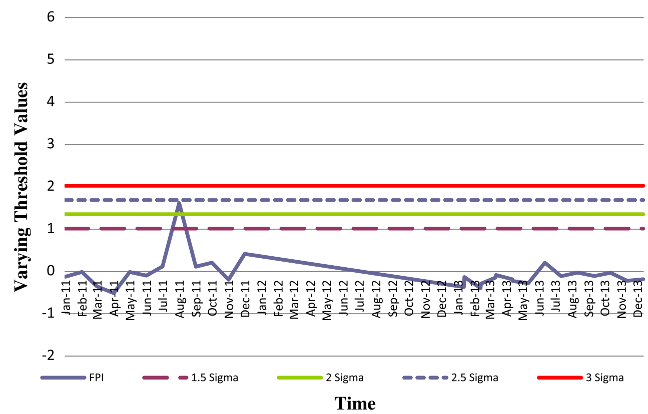

Fig. 6. The validation of the proposed early warning system with actual data.

3.7. Discussion

Decision tree results produced a four-branch depth tree with "V5: Monthly change in ISE 100 index", "V24: Ratio of deposit money banks domestic credits to total assets", "V6: Export to import ratio" and "V4: Actual monthly change in treasury domestic debt" as the most important variables in sequence. The remaining 28 variables were not used in the decision tree model by the C5 algorithm.

In the logistic regression model, six variables were entered to the model with Eq. (19):

$$y(1) = 65.56 + 52.36V_2 - 86.68V_6 - 5.87V_{10} + 5.34V_{20} - 63.89V_{24} + 68.79V_{30} \tag{19}$$

Interestingly, both decision tree and logistic regression models highlighted the variables "V24: Ratio of deposit money banks domestic credits to total assets" and "V6: Export to import ratio", as critical variables in predicting a crisis. On the contrary, the multi-layer perceptron used all 32 variables when it searched the input variables with genetic algorithms to produce the best results as summarized in Tables 5 and 6. Since there are three different types of prediction models, namely MLP-based artificial neural network, C5-based decision tree, and logistic regression employed in this study, each of which generating 10 sensitivity analysis results (one for each fold), the study ended up with 30 sensitivity analysis values for each variable. As explained earlier in Section 2.3.3, an information fusion-based sensitivity analysis was conducted for 10-fold cross validation of these three models. In order to achieve this, the following strategy was followed. First, sensitivity values within each model were normalized so that the relative importance values for independent variables would range between 0 and 100. Then using Eq. (18) for these three models with 10 folds, the normalized sensitivity results were combined by allowing each

[1] For interpretation of color in Fig. 5, the reader is referred to the web version of this article.

Table 5
Confusion matrix of each early warning method for test data and total data.

	Test		Overall	
	Crisis	No crisis	Crisis	No crisis
MLP				
Crisis signal	5	3	24	3
No crisis signal	0	40	0	213
DTC5				
Crisis signal	2	2	19	4
No crisis signal	3	41	5	212
LogR				
Crisis signal	4	3	19	4
No crisis signal	1	40	5	212

model to contribute to the combined sensitivity results, with respect to its prediction accuracy. In other words, more accurate models' sensitivity analysis results would be assigned higher weights in proportion to their accuracy. The final information fusion-based sensitivity analysis results are then tabulated and pictorially represented in Fig. 7. As seen in this figure, the topmost important leading factor (independent variable) in predicting a currency crises in Turkey was determined to be "V6: Export to import ratio", followed by "V24: Ratio of deposit money banks domestic credits to total assets", "V30: Monthly change in consumer price index", "V2: Monthly change in terms of trade", respectively. On the contrary, "V26 (Actual monthly change in banking sector credits to private sector)" and "V13 (Monthly change in capacity utilization rate)" were found to be the two least important leading factors of determining a currency crisis in Turkey.

A fall in the export to import ratio (V6) means that the growth rate of export falls behind the growth rate of import. Thus, the demand for foreign currency increases since the import rate increases at a faster scale. Increasing demand for foreign currency creates pressure on the exchange rate to rise. FPI is defined by an increase in the dollar exchange rate and overnight interest rate as well as a decrease of the gross foreign exchange reserves of the Central Bank. Accordingly, a rise in exchange rate and fall in exchange reserve has a doubled pressure on FPI. Corsetti, Pesenti, and Roubini (1999) presented similar evidence for sharp falls in export ratios by many Asian Countries during the Asian Crises between 1997 and 1998.

One of the major causes of a financial crisis is monetary expansion. An increase in inflation will arise with monetary expansion and interpreted as a crisis signal. Rising inflation causes an increase in interest rates and this rise of interest rates causes a direct rise in FPI. Such an effect of inflation on the FPI is confirmed in this study. On the contrary, the rise of interest rates creates a decrease in demand for domestic credits. In Turkey's case, the decrease of domestic credits (V24) creates a rise in FPI before the currency crisis. Thus, a powerful bond between banking crises and financial crises can be observed, and this bond was defined as "twin crises" by Kaminsky and Reinhard (1999).

Table 6
Performance of each early warning method for test data and total data.

Method	Test			Overall		
	Accuracy (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)
MLP	93.8	100.0	93.0	98.8	100.0	98.6
DTC5	89.6	40.0	95.3	96.3	79.2	98.1
LogR	91.7	80.0	93.0	96.3	79.2	98.1

The consumer price index (CPI) measures the change in the prices paid for consumer goods and services by urban consumers. The CPI also signals economic trends, such as inflation or deflation and affects government monetary policies. A low CPI indicates deflation or a struggling economy due to a decrease in consumer spending on goods and services. During a recession, businesses lower prices to attract consumers and raise sales levels. The government monetary policymakers respond to a recession by lowering interest rates to stimulate the economy. The study results determine that the monthly change in consumer price index (V30) ranks as the third most important leading indicator of a financial crisis. This can be attributed to the significance of the CPI measure on the behavior and actions of consumers, businesses, and government policymakers during a crisis.

The terms of foreign trade (V2) represents the ratio of exportable goods price index to importable goods price index. An increase of exportable goods price index and a decrease of importable goods price index indicate that the terms of foreign trade is in favor of the country. Normally, the terms of foreign trade is expected to fall before a crisis. However, interestingly, the opposite situation is observed in Turkey's case. The reason for this can be attributed to the price elasticity of foreign demand to the exportable goods and domestic demand to the importable goods. Aforementioned price elasticity leads to a decrease of export and an increase of import during before-crisis periods for Turkey's economy. Consequently, the changes in the export and import ratio directly affect FPI.

Due to high inflation and interest rate, public share in total credit volume is dominant in Turkey's case. The crowding-out effect of this dominance causes the actual monthly change in banking sector credits to private sector (V26) to be of lower importance in proposed models.

The capacity utilization rate (V13) is typically an indicator of the real sector. A direct and short-run effect is expected to be insignificant on FPI. Accordingly, this study has confirmed that this indicator has a significantly lower importance degree for predicting a currency crisis in Turkey's case.

The performance of each early warning method with respect to both the testing data and all data is given in Table 5, in which rows represent the generated signal from models and columns represent the desired signal. Using Table 5 results, Table 6 summarizes the accuracy, sensitivity, and specificity values for all three models. Overall, the results showed that early warning method with the MLP-based ANN model has better predicting capability.

Globalization offers invaluable opportunities to almost every entity in the markets: from individuals to corporations, and to even sovereign countries. However, the interdependencies in the same markets which are the direct results of globalization present tremendous challenges to the very same entities. Examples of such challenges can be found in the derivative markets in the form of hedging needs of corporations, crisis management, and prevention by Central Banks, or -plain and simple- portfolio insurance for investment professionals. One major factor common to all abovementioned examples is the volatility in the foreign exchange markets and its effects on the health of financial markets. Hence, it is essential for all of these entities to develop a better understanding of practical models that can predict future financial crises due to unfavorable movements in the foreign exchange markets. Given the mission of a typical Central Bank for market stability, macroeconomic and policy implications of such models have become increasingly important for policy makers, for both an effective monetary policy and a robust crisis prevention/management tool. In line with those, this study contributes to the existing literature by examining and identifying the strength of machine learning models and building upon the knowledge about the leading factors to financial crises, such as "export to import ratio" and "monthly

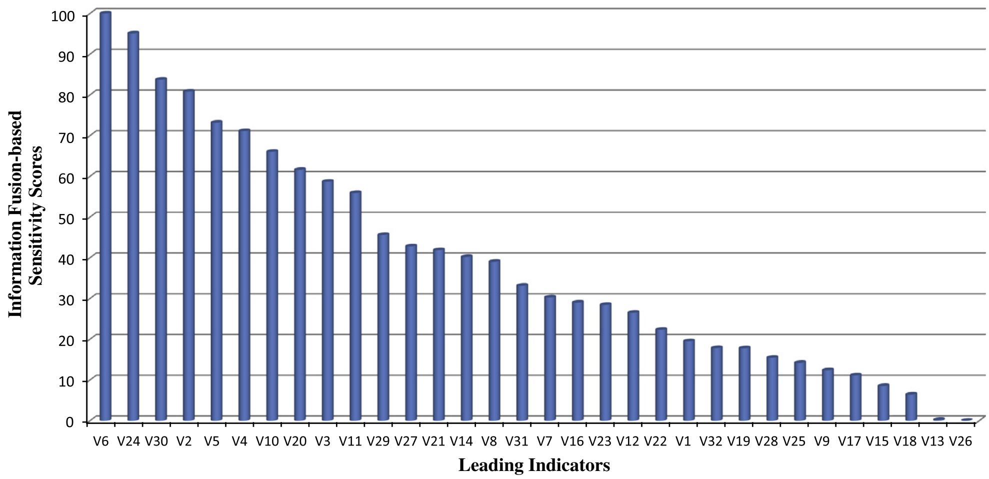

Fig. 7. Information fusion-based sensitivity analysis results for leading indicators.

change in consumer price index". More specifically, the study concludes with evidence from the Turkish economy case for the predictive power of artificial neural networks, decision trees, and logistic regression as well as the leading indicators of crises.

From the microeconomics perspective, the revenues and costs of multinational corporations (MNCs) are highly affected by future exchange rate movements. With options, swap, futures, and forward contracts on exchange rates, MNCs can reduce the risk of fluctuating cash flows. However, hedging is not costless. For options, there is the direct cost of premiums, while forward and future contracts may result in reduced revenues or increased costs when exchange rates move in a desirable direction for the unhedged MNC. This is the reason why most MNCs are continuously forecasting exchange rates. The ability to improve these forecasts reduces the need to fully hedge every position, and ultimately lead to increased profit. In this paper, an early warning system is developed to forecast exchange rate movements which can be directly used to increase the profitability at MNCs.

4. Conclusion

In this study, an early warning system was developed to predict currency crises using three prediction models i.e. artificial neural networks, decision trees, and logistic regression.

In the proposed methodology, FPI was first calculated, and in turn the months of crisis were determined. Using the months of the crisis, *the perfect signal series* was obtained. Then leading indicators in predicting the crisis were identified. Next, the perfect signal series was assigned as the desired variable while the leading indicators were assigned as input variables to the three prediction models. The data for the January 1992–December 2011 period in the Turkish economy revealed a significant similarity in the patterns of "the perfect signal series" and "the early warning signals" of the three models. Prediction models accurately gave early warning signals out several times before the crises occurred in reality. However, sometimes signals during one month are observed which do not last through following months. No crises have occurred after these false alarm signals. In other words, it would not be appropriate to conclude that a crisis will occur within the upcoming 12-month period based solely on a one-month crisis signal. Despite this, it would be hypothetically accurate to make an inference that the fragility and vulnerability of the economy would increase and in turn, a crisis will break out soon if consecutive warning signals are observed. The early warning systems developed in this study are able to accurately predict whether a crisis will occur or not within the upcoming 12-month period. Specifically, the dataset contains information regarding the end of December 2011. The results based on the logistic regression and MLP-based ANN models did not give any warning signals out. Therefore, it can be concluded that Turkey will not have a financial crisis until the end of 2011 with a 91.7% probability based on the logistic regression model and a 93.8% probability based on the MLP-based ANN model. However, the C5-based decision tree model signaled out in April 2011 once, and this signal was not continued in the following months. Therefore, there is no expectation for a financial crisis in 2012 when considering the decision tree model. While the results of this study are analyzed, it should be kept in mind that a crisis was defined as a drastic deviation in the foreign exchange rate and a drastic decrease in the foreign exchange reserves. To exemplify, new political regulations in the economic structure, political crises, or wars would hypothetically render these results invalid.

As a conclusion, this study revealed that machine learning models could be effectively utilized to predict financial crises, as in the case of conventional regression models. As a matter of fact, ANN has given superior results over the conventional regression model, namely logistic regression. This gives rise to the idea that ANNs could also be utilized to measure the loss caused by financial crises. In addition, it would be an interesting research study to implement additional nonlinear modeling techniques that provide causal insights regarding the relationship between leading indicators and the perfect signal, such as nonlinear PLS models, in order to reveal the cause-and-effect relationship.

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