

A Hybrid Model for Forecasting Sales in Turkish Paint Industry

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Abstract

Sales forecasting is important for facilitating effective and efficient allocation of scarce resources. However, how to best model and forecast sales has been a long-standing issue. There is no best forecasting method that is applicable in all circumstances. Therefore, confidence in the accuracy of sales forecasts is achieved by corroborating the results using two or more methods. This paper proposes a hybrid forecasting model that uses an artificial intelligence method (AI) with multiple linear regression (MLR) to predict product sales for the largest Turkish paint producer. In the hybrid model, three different AI methods, fuzzy rule-based system (FRBS), artificial neural network (ANN) and adaptive neuro fuzzy network (ANFIS), are used and compared to each other. The results indicate that FRBS yields better forecasting accuracy in terms of root mean squared error (RMSE) and mean absolute percentage error (MAPE).

Keywords: Sales forecast, Hybrid model, Fuzzy rule based system, Multiple linear regression and Paint industry.

1. Introduction

The Turkish paint industry is the sixth-largest in Europe, with a capacity of 800000 metric tons annually. Paint is manufactured in the five Turkish cities with the highest population. The surge of new immigrants into these cities has increased demand for new housing and will be key to sustaining future growth in the paint market with demand estimated at about 600000 metric tons annually. Since the industry is dependent upon imported raw materials, companies should ensure that they are properly positioned to meet future Turkish demand. Therefore, it is important for paint companies to have an efficient and accurate forecasting model to predict future monthly sales.

A major requirement of successful marketing is accurately forecasting sales. First, market opportunities are identified through marketing research. The size, growth and profitability of each market opportunity are then measured and/or forecasted. Sales forecasts are used by

- finance divisions to raise cash needed for investments and operations,
- manufacturing divisions to establish capacity and output levels,
- purchasing divisions to acquire the necessary supplies,
- human resources divisions to hire the necessary number of workers.

Thus, an accurate sales forecast facilitates effective planning. Over-estimates of demand can lead to several problems, such as occupancy of valuable shelf space and increased inventory carrying charges. On the other hand, under-estimates of demand can lead to stock depletion, lost sales, and expensive overtime production to compensate for customer demand. Given the potentially negative impact of inaccurate forecasts, marketers use a variety of techniques to accurately forecast sales.

This research focuses on monthly sales forecasting for the largest paint manufacturer in Turkey. A hybrid model that integrates AI and MLR methods is proposed

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for predicting this company's sales. The model is then applied to historical sales data for this specific Turkish paint producer. Fuzzy rule based system (FRBS), artificial neural network (ANN) and adaptive neuro fuzzy network (ANFIS) methods are used in the proposed hybrid model and their relative performances are compared to each other. The purpose of the study is to improve forecasting accuracy and thus to help managers improve their decision making.

The remainder of the paper is organized as follows. Section 2 summarizes the existing literature in related areas. Section 3 describes the methodology used in this study. In Section 4, the proposed hybrid forecasting model and the FRBS, ANN and ANFIS methods are presented. The hybrid models using different AI methods are applied to sales data for the largest Turkish paint company, and the results are compared. In the final section, conclusions are presented, and further research is proposed.

2. Background

Multiple linear regression (MLR) is commonly used for forecasting data with several relevant independent variables. The technique has been used to make forecasts in a wide range of areas, including tourism volume¹, industrial electricity consumption², and retail sales.³ MLR has often been utilized to forecast demand based on known marketing variables and macroeconomic measures.⁴

Although traditional sales forecasting methods have proven effective, they still have certain drawbacks.⁵ As stated by Kuo and Cohen⁶, newly developed artificial intelligence (AI) models have more flexibility and can be used to estimate non-linear relationships, without the limits of traditional models. As a result, an increased number of researchers are using AI forecasting models to deal with problems. Hruschka⁷ studied the use of artificial neural networks to predict market response using consumer brand data and market response functions. Agrawal and Schorling⁸ compared the forecasting accuracy of artificial neural networks with multinomial logit models in the context of frequently purchased grocery products for a retailer. West et al.⁹ demonstrated the appropriateness of artificial neural network modeling for predicting consumer choice based on product attributes and suggested its potential for use in numerous other marketing applications. Alon et al.¹⁰ addressed forecasting of U.S. aggregate retail sales, a

time-series with trend and seasonal patterns. In this study, ANN is compared to the more traditional time-series forecasting methods, including Winters' exponential smoothing, autoregressive integrated moving average (ARIMA) modeling, and multiple linear regression. The results indicate that on average ANN is favorable, compared to the more traditional statistical methods, followed by the Box-Jenkins model.

Since Zadeh¹¹ introduced the concept of fuzzy logic, fuzzy theory has been widely applied in forecasting.¹²⁻¹⁴ Fuzzy systems can handle the imprecision that is inherent in human reasoning, especially when dealing with complex problems. Based on the concepts of fuzzy sets and fuzzy logic, fuzzy systems encode linguistic samples in a designated numerical matrix, which links input to output through fuzzy membership functions and sets of fuzzy rules. Therefore, fuzzy rules are compact, efficient representations of human knowledge. Thus, fuzzy rules provide a human-like thinking ability which allows expert knowledge to be incorporated into systems.¹⁵ Traditionally, these fuzzy rule bases (FRBs) are provided and extracted from domain experts.

In recent years, many researchers have proposed methods for generating FRBs from a set of sample data.¹⁶⁻¹⁷ Adaptive neuro-fuzzy inference systems (ANFIS), which integrate fuzzy logic and neural networks, is one of the most recently developed techniques for forecasting. ANFIS has features of neural networks, such as learning abilities, optimization abilities, and features of fuzzy inference systems, such as human-like reasoning using IF-THEN rules and ease of incorporating human expert knowledge. IF-THEN rules can be created (learned) and refined from pre-existing data sets. Several attempts have been made to develop ANFIS-based systems to predict product demand. For example, Escoda et al.¹⁸ examined the development and representation of linguistic variables to qualify the product demand using ANN and ANFIS. By integrating ANN and ANFIS, Kuo and Xue¹⁹, Kuo et al.²⁰ developed intelligent sales forecasting systems that consider both quantitative and qualitative variables. Kuo²¹ proposed an ANFIS-based decision support system for the stock market. Thomassey et al.²² proposed a sales forecasting system for a French textile distributor based on both fuzzy logic and ANN. This model is composed of several sub-models and forecasts for various time horizons and sales aggregation levels. Efindigil et al.²³ proposed a new forecasting algorithm

that uses artificial intelligence techniques and compares ANN and ANFIS to manage the fuzzy demand with incomplete data. This algorithm was applied to data from a company that is active in a Turkish durable consumer goods industry. Balan et al.²⁴ tuned a fuzzy logic controller using an adaptive neuro-fuzzy inference system (ANFIS) to forecast demand with less distortion, thus improving supply chain effectiveness. Wang and Chen²⁵ (2008) proposed an ANFIS model to predict rush orders and regulate the capacity reservation mechanism in advance. Ying and Pan²⁶ applied ANFIS to forecast the regional electricity demand in Taiwan and demonstrated this method's effectiveness in forecasting performance.

In this study, a hybrid forecasting model is proposed, which uses an AI method with multiple linear regression (MLR). In the proposed model, annual product sales are estimated for a Turkish paint company using MLR in the first phase. And in the second phase, an AI method is used to estimate the monthly product sales as a percentage of the estimated annual sales. The overall motivation is to develop an intelligent forecasting method using artificial intelligence (AI) methods with MLR and to help paint companies accurately forecast monthly sales. The hybrid models using fuzzy rule base (FRBS), artificial neural network (ANN) and adaptive neuro fuzzy network (ANFIS) methods are compared to each other.

3. Methodology

This study is conducted using data from the largest Turkish paint company, with a 25% market share of the Turkish paint industry. Before determining the best forecasting model, the main product groups were classified. The independent variables influencing

product sales were then determined. The forecasting results of the proposed hybrid models using FRBS, ANN, and ANFIS methods were compared in terms of root mean squared error (RMSE) and mean absolute percentage error (MAPE). Actual value and forecast value are denoted as A and F respectively in Eqs. (1) and (2).

$$RMSE = \sqrt{\frac{\sum (A_i - F_i)^2}{n-1}} \tag{1}$$

$$MAPE = \frac{\sum \frac{|A_i - F_i|}{A_i} \times 100}{n} \tag{2}$$

The given company has three main product groups: interior paints, exterior paints and solvent-based paints. After several interviews and meetings with experts in the paint industry, five independent variables were selected for use in the forecasting models according to their correlation with sales data:

- probability of spending for housing repairs and renovations in the next 6 months,
- monthly construction expenses,
- consumer trust index,
- price discount rate and
- campaign type.

The first two variables are used in the MLR method to estimate the annual cumulative sales rate of change in the first phase of the hybrid model. And in the second phase, the last three variables are used in the AI methods to estimate the monthly sales. The model training and forecasts were performed using actual monthly data of a five-year period (January 2004 - December 2008) (Fig 1). In the first phase, the cumulative yearly sales data from 2004 to 2007 was

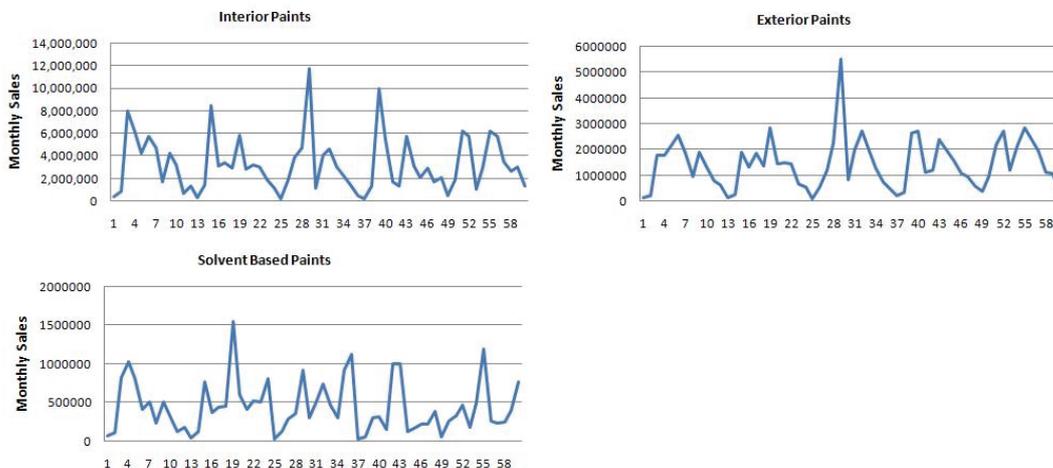


Fig. 1. Actual monthly product sales.

used to estimate the cumulative sales rate of change in 2008. In the second phase, the first 48-month data set was used to train the models of ANN and ANFIS. In FRBS method, the experts create the rule base analyzing the first 48 month data and using their experience. The performances of the three models were tested and compared through the last 12 months of data. Monthly data for the first two independent variables were obtained from the Turkish Statistical Institute, and data for the other independent variables were obtained from sales and marketing experts in the company.

4. Application

In this section, the proposed hybrid forecasting model and the FRBS, ANN, and ANFIS methods that are used in this hybrid model are presented. The models are then applied to the actual sales data. Finally, RMSE and MAPE values are calculated for the last 12 months of data, and the models are compared.

4.1. The proposed hybrid forecasting model

The proposed hybrid forecasting model has a top-down approach consisting of two phases. In the first phase, the annual cumulative sales rate of change is forecasted for each product group using MLR. In the second phase, the monthly sales of each product group are estimated as a percentage of the annual cumulative sales forecast on the basis of the price discount rate, the consumer trust index and campaign type using an AI method (Fig. 2).

Multiple linear regression (MLR) attempts to model the relationship between two or more explanatory variables and a response variable by fitting a linear relationship to observed data. MLR is a statistical method that models the relationship between a dependent variable Y , independent variables X_i , ($i = 1, \dots, p$) and a random term ε . In the proposed model, the monthly product sales are estimated as a percentage of the annual cumulative sales forecast. Before determining the monthly percentages the expected annual sales volume of the product is forecasted using a MLR. The probability of spending for housing repair/renovation in the next 6 months and the monthly construction expenses were used as the independent variables in the MLR. Thus, the MLR model can be written as in Eq. 3:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \tag{3}$$

In this study, the expected annual cumulative sales rate of change of each product group was forecasted for the year 2008 using the company sales data between 2003 and 2007. As shown in Table 1, the expected market growth of interior paints, exterior paints and solvent-based paints is 1.15%, 15.89% and 12.88%, respectively.

Table 1. Cumulative sales forecast for 2008.

	Interior paints	Exterior paints	Solvent- based paints
Forecast for cumulative sales rate of change	1.15%	15.89%	12.88%
Actual sales in 2007	37 508 247	16 753 564	3 950 678
Sales forecast for 2008	37 941 439	19 415 619	4 459 644

In the second phase of the hybrid model, three alternative AI methods, FRBS, ANN and ANFIS, are used and compared to each other.

4.1.1 Fuzzy Rule Based System (FRBS)

A fuzzy rule-based system (FRBS) is a systematic reasoning methodology that can capture the contextual judgment of experts by using fuzzy set theory. There are two main types of fuzzy modeling schemes: Takagi–Sugeno models and Mamdani models. The Takagi–Sugeno modeling is a data driven approach in which membership functions and rules are developed using a training data set. The parameters for the membership functions and rules are subsequently optimized to reduce training error.²⁷ The Mamdani modeling structure is constructed manually on the basis of expert knowledge, and the final model is neither trained nor optimized. Both model types are similar and consider fuzzy inputs; however, while Mamdani models return fuzzy outputs, Takagi–Sugeno models return crisp outputs (linear combination of the inputs).²⁸⁻²⁹ Since the Mamdani approach is not exclusively reliant on a data set, with sufficient expertise regarding the involved system, a generalized model can be obtained for effective forecasting.³⁰ Utilizing a completely linguistic form of rule set, Mamdani models have advantages in representing expert knowledge and linguistically interpreting dependencies.

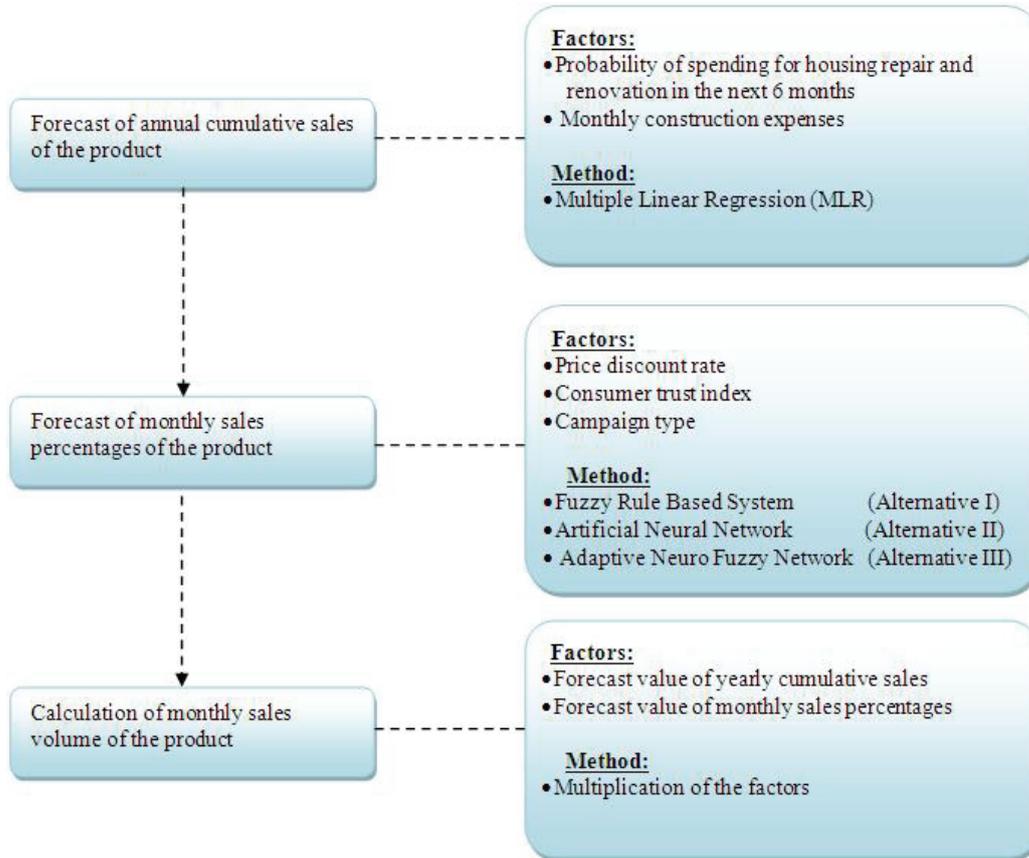


Fig. 2. The proposed hybrid forecasting method

The structure of the Mamdani-type fuzzy logic rule is expressed as follows:²⁸

IF x_1 is A_1 AND x_2 is A_2 AND . . . AND x_n is A_n , THEN y is B , where x_i ($i = 1, 2, \dots, n$) are input variables and y is the output variable. A_1, A_2, \dots, A_n and B are the linguistic terms (L-Low; M-Medium; H-High) used for the fuzzy subsets (membership function distributions) of the corresponding input and output variables, respectively. The output of a fuzzy rule-based model whose rule base is constructed using Mamdani-type fuzzy logic rules is obtained as follows (the centroid method is considered for defuzzification):

$$Y = \frac{\sum_{r=1}^{R^l} A^{ar} C_{A^{ar}}}{\sum_{r=1}^{R^l} A^{ar}} \tag{4}$$

where A^{ar} is the area of the fuzzy subset of output variables, covered by a membership value α that is

obtained by the r^{th} rule after the fuzzy inference method; $C_{A^{ar}}$ is the center distance of the area A^{ar} , and

$$\alpha = \text{Min}_{v=1}^n \mu_v(x_v) \tag{5}$$

where $1 \leq v \leq n$ is the number of input variables that appear in the rule premise, and n is the total number of inputs. $R^l (R^l \subseteq R)$ is the number of rules fired out of a total of R rules present in the rule base for a set of input values. $\mu_v(x_v)$ is the value of the membership function for the x_v input variable.

In this study, the paint company arranges a marketing campaign for its dealers two times a year. The campaigns last three months and begin in March and August. The company applies two types of campaigns:

- (a) descending discount rate,
- (b) constant discount rate.

In the first type, the company decreases the price discount rate for the next month of the campaign. Thus,

the dealer tends to place the order with the paint company in the beginning of the campaign. In the second type of campaign, the price discount rates do not change during the campaign, and the dealers have the same advantage for all months of the campaign.

In order to estimate the monthly percentages of sales, marketing and sales experts of the company created a rule base using the price discount rate and the consumer trust index (Table 2-3). According to their opinion, the consumer trust index is an indicator for economic uncertainty, and the price discount rate is an indicator for the campaign value.

Table 2. Fuzzy rule base for descending rate and constant rate campaigns

For Months: 3;4;5;8;9;10 Campaign Type: Descending / Constant Discount Rate					
IF	Price Discount Rate	AND	Consumer Trust Index	THEN	Sales (%)
	High		High		High
	High		Medium		High
	High		Low		Medium
	Medium		High		High
	Medium		Medium		Medium
	Medium		Low		Low
	Low		High		Medium
	Low		Medium		Low
	Low		Low		Low

As shown in Tables 2 and 3, twelve rules were determined for the hybrid forecasting model in this study. As there is no campaign in months 1, 2, 6, 7, 11 and 12, the consumer trust index is the determining variable for forecasting the sales percentages (s_i) in these months. In the rule base, triangular and trapezoidal fuzzy numbers are used to develop the membership functions of the price discount rate, the consumer trust index and the monthly sales percentages.

For Months: 1;2;6;7;11;12 Campaign Type: No campaign			
IF	Consumer Trust Index	THEN	Sales (%)
	High		High
	Medium		High
	Low		Medium

Table 3. Fuzzy rule base for “no campaign” status

The same price-discount-rate and consumer-trust-index membership functions are used for each month. Alternatively, different sales percentage membership functions are determined for each month depending on the product and campaign type. The max-min method is used for the aggregation mechanism, and the centroid method is used for defuzzification of the fuzzy outputs. Since the sum of the monthly sales percentages must be 100% for a year, the defuzzified forecasted values (s_i) are adjusted using Eq. (6) to remove small deviations.

$$s'_i = \frac{s_i}{\sum_{i=1}^{12} s_i} \times 100 \tag{6}$$

The membership functions for the price discount rate and the consumer trust index are shown in Figs. 3 and 4, respectively. The membership functions for the sales percentage change for each month depending on the product and campaign type. The membership function for the “interior paint” product is shown in Fig. 5 for the month of March and a decreasing discount rate campaign type.



Fig. 3 Membership function for price discount rate.

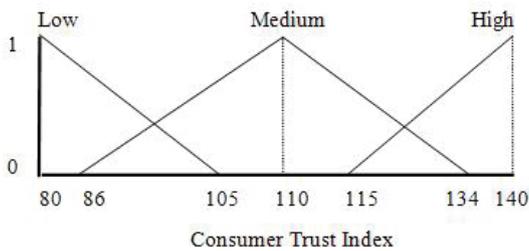


Fig. 4. Membership function for consumer trust index.

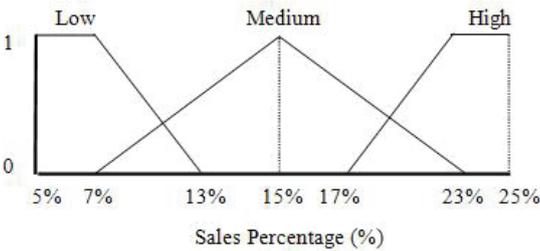


Fig. 5 Membership function for sales percentage in March for a decreasing discount rate campaign type and the interior paint product.

By implementing the input data for 2008 into the model, the FRBS sales percentage outputs were determined, shown in Table 4.

4.1.2 Artificial Neural Networks

There are many types and structures of neural networks. The type of ANN used in this study is a standard feed-forward multilayer network. A feed-forward multilayer network consists of different layers of units that are interconnected by a set of weighted connections. Signals can be propagated in two directions: function signals are propagated forwards, and error signals are propagated backwards. The back-propagation algorithm is used to adjust the weights of the connections and is the ANN algorithm that is most frequently compared to models derived from multivariable regression analyses.³¹ The output pattern produced by the network using the input is compared with the ideal target pattern, and the error is propagated back through the network. The training process is repeated with many examples until the error is below some tolerance.

In this study, the ANN model was designed using the Matlab Neural Network Tool. The proposed feed-forward, multilayer ANN model has three layers: input, hidden and output. The two model inputs are the consumer trust index and the price discount for decreasing/constant rate campaign type. And, the price discount is the single model input for ‘no campaign’ status. For the hidden layers, various layer structures with various numbers of neurons were tested in the ANN model. The best product group forecasts for decreasing/constant rate campaign type were obtained

Table 4. Adjusted FRBS outputs for 2008

Month	Price Discount Rate	Consumer Trust Index	Campaign Type	Interior paints	Exterior paints	Solvent-based paints
Jan-08	-	117	-	1.40%	2.00%	0.95%
Feb-08	-	130	-	5.30%	5.00%	5.14%
Mar-08	15%	132	Decreasing	20.00%	12.00%	8.80%
Apr-08	12%	130	Decreasing	18.30%	15.00%	10.27%
May-08	10%	130	Decreasing	4.00%	7.50%	4.40%
Jun-08	-	128	-	9.00%	11.50%	10.79%
Jul-08	-	125	-	12.00%	10.00%	19.49%
Aug-08	12%	125	Constant	8.00%	10.50%	7.33%
Sep-08	12%	120	Constant	8.00%	10.00%	4.40%
Oct-08	12%	105	Constant	7.00%	7.50%	6.60%
Nov-08	-	100	-	4.00%	5.50%	7.30%
Dec-08	-	100	-	3.00%	3.50%	14.53%
Total				100%	100%	100%

using four hidden layers consisting of 2, 5, 3 and 2 neurons, respectively. And for ‘no campaign status’, four hidden layers were used consisting of 1, 5, 3 and 2. A log-sigmoid transfer function was applied for the activation function that calculates the output neurons.

4.1.3 Adaptive Fuzzy Neural Networks

ANFIS are a class of adaptive networks that are functionally equivalent to fuzzy inference systems.³² It is assumed that the fuzzy inference system has two inputs x and y and one output z . A first-order Takagi and Sugeno fuzzy model has the following rules:²⁹

RULE 1: If x is A_1 and y is B_1 , then $f_1 = p_1x + q_1y + r_1$

RULE 2: If x is A_2 and y is B_2 , then $f_2 = p_2x + q_2y + r_2$

In ANFIS architecture, the node functions in the same layer belong to the function families described below:

Layer 1: Every node i in this layer is an adaptive node with a node function

$$Q_i^1 = \mu_{A_i}(x) \tag{7}$$

where the I is the input node and A_i is the linguistic label associated with this node function. Gaussian functions are commonly used membership functions in ANFIS, such as the following:

$$\mu_{A_i}(x) = \exp\left(\frac{-(x - c_i)^2}{2\sigma_i^2}\right) \tag{8}$$

where c_i and σ_i are the centers and widths of the functions, respectively, and are referred to as the antecedent parameters for the membership function.

Layer 2: Every node in this layer is a circle node labeled Π , which multiplies the incoming signal and outputs the product.

Layer 3: Layer 3 is the normalization layer where the rule strength is normalized as follows:

$$\bar{w}_i = \frac{w_i}{\sum w_i} \tag{9}$$

where w_i is the firing strength of the i th rule. The number of nodes in this layer is the same as in the last layer. This layer computes each rule’s firing strength to the sum of all the rules’ firing strengths.

Layer 4: Every node in this adaptive layer is a linear function, and the coefficients of the function are adapted

through a combination of least squares approximation and back propagation.

$$\bar{w}_i f_i = \bar{w}_i (c_0 + c_1x_1 + c_2x_2 + \dots + c_nx_n) \tag{10}$$

Layer 5: It is the output layer. The result of this layer is obtained as a summation of the outputs of the nodes in the previous layer as follows:

$$\sum_i \bar{w}_i f_i = \frac{\sum w_i f_i}{\sum w_i} \tag{11}$$

where $\bar{w}_i f_i$ is the output of node i from the previous layer.

In this study, the Matlab ANFIS tool was used to train the zero-order Sugeno model ($p=q=0$) with the two input variables for decreasing/constant rate campaign and single input for “no campaign” status as in the ANN model. The Gaussian membership functions are trained by the hybrid optimization method consisting of backpropagation for the parameters associated with the input membership functions, and least squares estimation for the parameters associated with the output membership functions. In this model, 9 rules were created for decreasing/constant rate campaign and 3 rules for “no campaign” status.

4.2. Comparison of the results

In our study, two phases of the proposed hybrid forecasting model are conducted. In the first phase, the annual cumulative sales rate of change is forecasted for each product group using MLR. As the variables of the probability of spending for housing repair/renovation in the next 6 months and the monthly construction expenses influence the total market growth of the paint industry according to the sales and marketing experts of the company, they are used as the independent variables in the MLR to estimate the annual cumulative sales. And then in the second phase, the monthly sales of each product group are estimated as a percentage of the estimated annual cumulative sales forecast on the basis of the price discount rate, the consumer trust index and campaign type using an AI method. Three different AI methods, FRBS, ANN and ANFIS, are used in the hybrid model and compared to each other in terms of RMSE and MAPE. As shown in Table 5, using fuzzy rule base methods, FRBS and ANFIS, in the hybrid model, give better sales forecasts for each product group

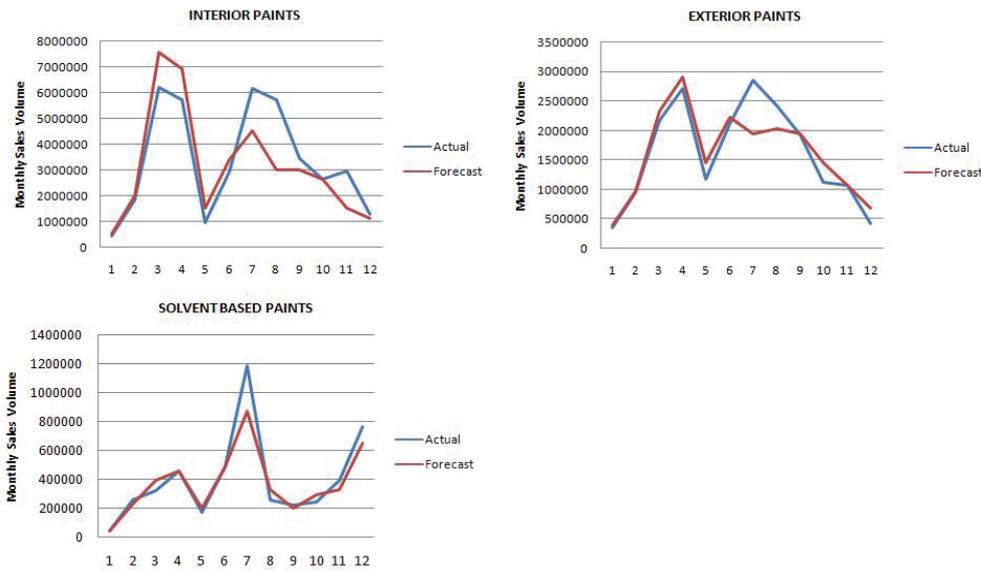


Fig. 7. Forecast generated by the proposed hybrid FRBS model

for the year 2008. Therefore, it can be stated that the rule base is more suitable to forecast the sales of the Turkish paint producer. Table 5 suggests that the FRBS is superior to the ANFIS and ANN with respect to MAPE and RMSE. Hence, it indicates that the rule base created by the sales and marketing experts of the company has a better outcome than the rule base created by ANFIS. The actual and forecasted data generated from the proposed hybrid model used with FRBS are shown in Fig. 7.

Table 5. Comparison of the different methods used in the hybrid model

Product	Forecast Error	Hybrid Model		
		FRBS	ANN	ANFIS
Interior Paints	RMSE	1216726	1978247	1637113
	MAPE	23.47	61.23	43.25
Exterior Paints	RMSE	345587	584864	390527
	MAPE	15.90	25.21	18.22
Solvent-Based Paints	RMSE	110651	185733	135536
	MAPE	14.40	40.46	36.32

5. Conclusion

To enhance commercial competitive advantage in a constantly fluctuating sales environment, an organization's management must make the appropriate decisions based on the available information. An efficient forecasting system can improve machine utilization, reduce inventories, achieve greater flexibility to changes and ultimately increase profits. In particular, sales forecasting is very important, as its outcome is used by many functions in the organization.⁴

In this paper, a hybrid forecasting model is presented to help paint companies forecast monthly sales. The purpose of the study was to develop an intelligent forecasting method that integrates traditional and well-known artificial intelligence (AI) forecasting methods. Using a combination of MLR and AI techniques, the proposed hybrid forecasting method is easy applicable. It has a top-down approach consisting of two phases. In the first phase, MLR method is used to forecast annual cumulative sales. And in the second phase, three different AI methods are used to estimate the monthly sales percentages and compared to each other. In this study, FRBS, ANN and ANFIS are used in the hybrid model and compared to each other. According to the results, in the hybrid model, the use of fuzzy rule base created by the experts provides high precision and strong forecasting ability of monthly

sales. However, competitors' sales data were not available. In future studies, the proposed model will be improved, and new variables associated with competitors' data will be included.

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