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**Research Article / Araştırma Makalesi**

# REVENUE FORECASTING USING A FEED-FORWARD NEURAL NETWORK AND ARIMA MODEL

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**ABSTRACT**

Revenue forecasting using intraday updates, which provides managers to make a flexible decisions and plan short-term financing, is a very important problem. In this study, revenue forecasting hybrid model,which is a combination of ARIMA and feed-forward neural network models, is developed. At the end of this study, results with real data sets indicate that the combined model can be an effective way to improve forecasting accuracy achieved by either of the models used separately. This study has been tested in 130 stores of a fashion retail chain. Through this proposed prediction model, the best accuracy of prediction at the end of day could reach up to 80%-85%, and prediction for each hour could reach up to %90-%95.
**Keywords:** Feed-forward neural networks, ARIMA, revenue forecasting.

## 1. INTRODUCTION

Time series forecasting is an important area of forecasting in which past observations of the same variable are collected and analyzed to develop a model describing the underlying relationship. Managers should plan short-term financing, follow the revenue of stores etc. with monthly, weekly or daily revenue forecasting results. History of revenue, seasonality, special effects are used while forecasting the revenue.

In time series analysis, the Box–Jenkins method, named after the statisticians George Box and Gwilym Jenkins, applies autoregressive moving average ARMA or ARIMA (ARIMA-Autoregressive Integrated Moving Average) models to find the best fit of a time-series model to past values of a time series [1].

Neural network model is used to extrapolate the time series into the future. This modeling approach is particularly useful when little knowledge is available on the underlying data generating process or when there is no satisfactory explanatory model that relates the prediction variable to other explanatory variables. Much effort has been devoted over the past several decades to the development and improvement of time series forecasting models [2,3].

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Hu initiated the implementation of neural network (NN), an important Soft Computing methodology in weather forecasting [4]. Combined forecasts from a linear and a nonlinear model have been investigated for time series with possibly nonlinear characteristics. The forecasts have been combined by a constant coefficient regression method as well as a time varying method. The methods have been applied to Canadian lynx and sunspot series by Terui, van Dijk [5].

In this study, a hybrid model which combines ARIMA and feed-forward neural network models has been developed. This model has been used because of times series with different lengths. So, revenue of 130 stores of a fashion retail chain has been forecasted with a high accuracy by using a hybrid model which combines ARIMA and feed-forward neural network models. This model has been used because of times series with different lengths.

In this study, ARIMA methods of Box-Jenkins methodology and Autoregressive Feedforward Artificial Neural Networks are used. These methods are performed daily prediction, made at 9:00 a.m. with daily revenue forecast has been considered. In this section, we briefly discussed these methods, and the implementation of the problem of these models.

## 2. ARIMA

The Box-Jenkins forecasting method is the most comprehensive statistical method and commonly used in forecasting time series. (Arima Autoregressive Integrated Moving Average) The future value of a variable series of ARIMA is determined history values with a linear function of the random error assumption [2,3]. ARIMA model shown in (1).

$$\widehat{Y_t} = \delta + {}_1Y_{t-1} + \psi_1 e_{t-1} + \cdots + {}_pY_{t-p} + \psi_q e_{t-q} \tag{1}$$

Arima variables and parameters;

$Y_t$ : Dependent variable (Daily revenue),
$p$ : Autoregressive process-lag (ro) parameter,
$\delta$ : Constant variable,
$\psi_q$ : Moving average process parameter,
$e_{t-q}$ : Error.

## 3. AUTOREGRESSİVE FEED-FORWARD NEURAL NETWORKS

Neural networks (NN) concept, basic biological nerve systems (especially the human brain) has been developed and inspired by an array of neuron or identified as nodes. Artificial neural networks for complex predictive models, stationary and linearity assumption on predictions that produces good results without calling methods [2].

Autoregressive feed-forward neural networks is one of the model approach of feed-forward neural networks. Feedforward Autoregressive Artificial Neural Networks are model types obtained by adding sequential values of the series as independent variables to lagged structure ($Y_{t-k}$) [6].

$$\widehat{Y_t} = b_0 + w_j f_j(b_j + \textstyle\sum_{i=1}^{p} w_{i,j}\, x_i), \tag{2}$$

In this;

$p$ : Autoregressive lag constant (ro),
$b_j,\ w_{i,j},\ w_j$ : Constant variables,
$x_i$ : Independent variable,
$f(.)$ : Sigmoid function.

The coefficients in the model are calculated by the auto.arima function which found in R. In addition, because the series are not linear, Box-Cox transformations are used on dependent variables [7].

## 3. HYBRID MODEL

ARIMA and NN models have been tested for revenue forecasts of stores. Later, the results obtained from the model were subjected to cross validation tests. In these tests, it was determined that the NN model forecasted with a high accuarcy by length of time series which are more than 2 years. The approach is given in Equation 3.

$$f(x) = \begin{cases} \text{ARIMA} & 10 < n < 104 \\ \text{NNAR} & n > 104 \end{cases} \tag{3}$$

$n$: The lenghts of series

This approach was used to forecast the revenue forecast at the opening of the stores. Equation 4 was used until 01:00 p.m. in the rest of the day, and a different autoregressive model (Equation 5) was used after 01:00 p.m.

$$\hat{Y}_{t,s} = (\hat{Y}_{t,s} - (Y_{s-1} P_s)) + Y_{s-1} \tag{4}$$

$\hat{Y}_{t,s}$ : Daily revenue forecast
$Y_{s-1}$ : Realized sales
$P_s$ : Cumulative revenue rate of hour days

$$\hat{Y}_{t,s} = Y_{s-1} \div \frac{P_{s-1}+P_{t-1}+P_{t-2}+P_{t-3}+P_{t-52}}{5} \tag{5}$$

$P_{s-1}$ : Realized-cumulative revenue rate
$P_{t-1}$ : Revenue of the same day of the last week/ Revenue of the end-of-day

## 4. RESULTS

This study has been tested in 130 stores of a fashion retail chain. ARIMA and Autoregressive feed-forward Neural Networks have been applied to the data organized as weekly series. "forecast", "tseries", "ggplot2" and "reshape2" R packages were used to implement the methods [8].

In the series, known as the graphical method to test the stationary correlogram graphs. Autocorrelation and partial autocorrelation functions a priori information was acquired, both received notice from the first degree then “Augmented Dickey-Fuller” unit root test is applied [9]. After these tests, it was determined that the series were stationary.

**Table 1.** ADF test results of sample stores

| Store | ADF Unit Root Tests Results | |
|---|---|---|
| **Store 1** | Test Statistic | -6.90 |
| | P-value | 0.0002 |
| **Store 2** | Test Statistic | -5.76 |
| | P-value | 0.0010 |
| **Store 3** | Test Statistic | -6.34 |
| | P-value | 0.0001 |

The NNAR method is used more flexibly than the ARIMA method, the assumptions of the NNAR model are limited. Because of the positive revenue expectancy, the Box-Cox transformation parameter λ was chosen to be zero.

## 5. CONCLUSIONS

Statistical results are given by ARIMA and NNAR for the sample stores selected in Table 2.

**Table 2.** Statistical results of stores by ARIMA and NNAR.

| **Store** | **Model** | **SSE ($\sigma^2$)** | **MAPE** |
|---|---|---|---|
| **Store 1** | ARIMA (1,1,1) | 162100085 | 0.1300 |
| | NNAR (10,1,6) | 47164818 | 0.0700 |
| **Store 2** | ARIMA (0,0,1) | 136817100 | 0.1474 |
| | NNAR (11,1,6) | 50944724 | 0.0987 |
| **Store 3** | ARIMA (1,1,1) | 136817100 | 0.1503 |
| | NNAR (13,1,8) | 10265921 | 0.1169 |

When we examine the realized and predicted series, it can be seen that some special day effects (14 February – Valentine's Day, December 31st Christmas Holiday) can not be predicted. These unpredictable effects increased the deviations of the forecasts, resulting in a large value in the mean squared error. In the series where these effects were not observed, trend was accurate with ARIMA.

Nevertheless, it has been determined that the sudden releases of unexpected sales can be fitted by the NNAR method. It is determined error of the NNAR method is acceptable according to ARIMA when differences of error squares of ARIMA and NNAR method are considered (Figure 2).

Figures 1 and Figures 2 show fitted differences of the separately trained models in the long and short series of Store 2. Short term in the series, the ARIMA method, has given accurate results according to the method of NNAR. Long term in the series, has given better results by NNAR method. Artificial neural networks models are known to produce accurate results in long series [10].

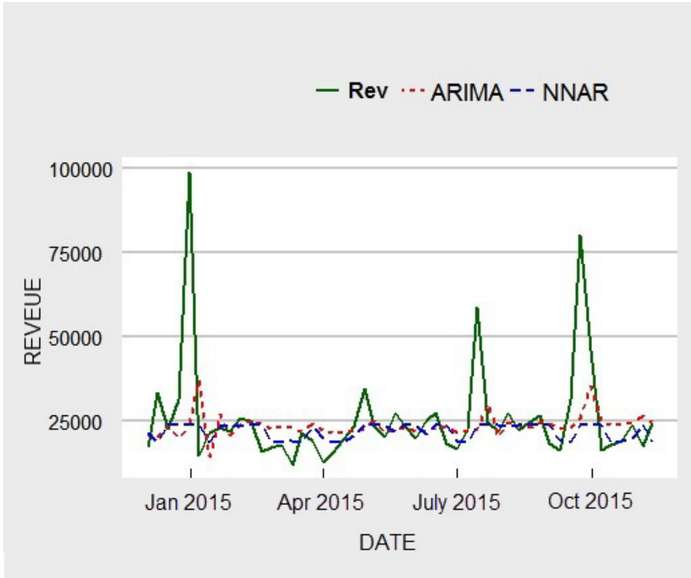


**Figure 1.** ARIMA-NNAR fitted comparison in Store 2's 2 year data.

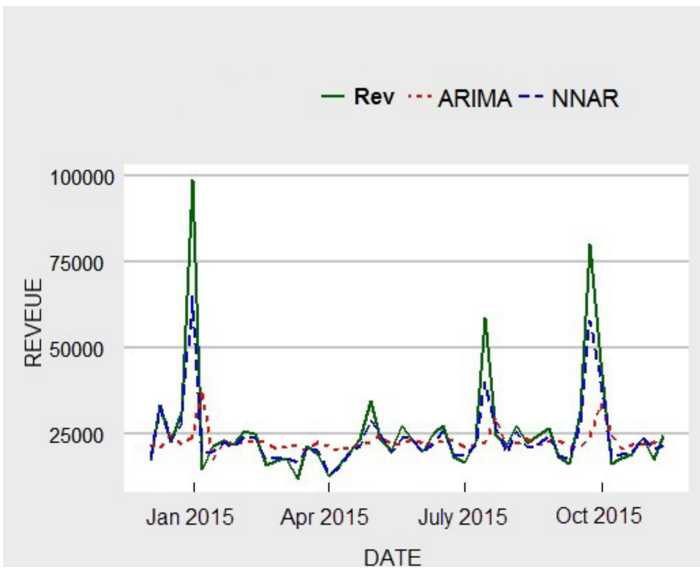


**Figure 2.** ARIMA-NNAR fitted comparison in Store 2's 4 year data.

Studies; 09:00 a.m.-1:00 p.m. hours between an average of a year longer because of the regularity of the sale; 2:00 p.m.-10:00 p.m. considering the established models gave accurate results, it was determined that the short term averages.

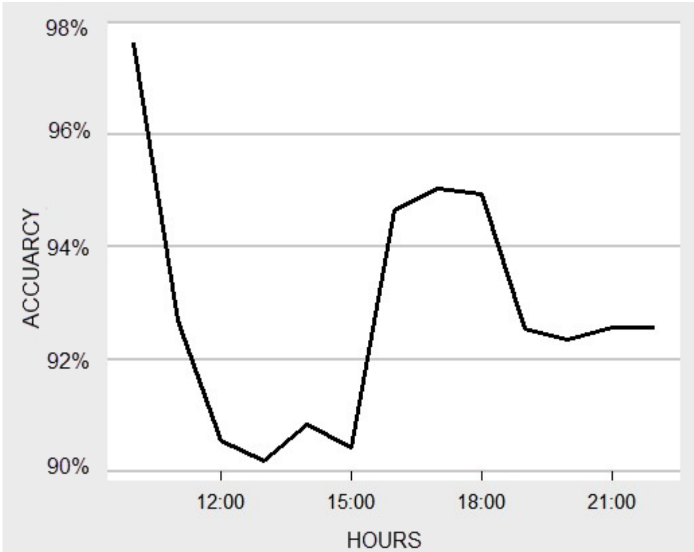


**Figure 3.** Hourly forecast-actual levels of Store 1.

The study's test phase; the different random day 85%-90% accuracy rate varies in the range. The ratio of hourly forecasts accuracy, has been determined 90%-95%.

In future studies, the subject and scope of hourly forecasts can be expanded. Sensor data can be collected with customer data, obtained with the revenue of the exchange in conjunction of the revenue forecasts to take place, instant forecast as a variable that contains the scope of work and will increase the accuracy.

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