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# Enrolment Forecasting using Holt's Double Exponential Smoothing Method with Particle Swarm Optimization

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## Abstract

Higher education institutions usually do enrolment forecasting to predict the number of students in the future academic year. It is an essential process that plays a crucial role in the effective planning, resource allocation and decision-making activities within the university. In this study, the enrolment was forecasted using Holt's double exponential smoothing method with the application of particle swarm optimization. The enrolment data was collected from the historical data of the university registrar. The dataset involved ten years of enrolment data, where six years were allotted for the training set and the remaining four years were used for the test set. Pre-testing of the data showed the linear trend and applicability of the model. The training set was used to compute for the smoothing constants of the Holt's Double Exponential Smoothing Method where the process was optimized using particle swarm optimization (PSO). The test set was then used to measure the performance of the model. Generally, the model performed well on making forecasts and was able to correctly detect rise and fall of the enrolment data.

**Keywords:** Forecasting, Holt's double exponential smoothing method, Particle swarm optimization

## 1. Introduction

Enrolment forecasting basically is a multidimensional process that involves analyzing time series historical data, demographic trends and other relevant factors to predict the number of students of the future academic year. Both internal and external factors like population demographics, economic conditions and societal changes influence the enrolment forecasts. Having near accurate projections of the enrolment data can significantly help the university in coming up with effective and sound educational plans, efficient management of resources and strategic decision-making programs of the organization (Liu et al., 2023).

Typically, enrolment forecasts begin with examining the past enrolment data. Moreover, higher educational institutions also consider other factors like government policies, advancement of technologies and educational preferences that may somehow impact enrolment trends. Investigations like checking for some trends and patterns prove to be beneficial.

To have a more accurate enrolment forecasts, institutions often utilize dominant tools and techniques like using statistical models, data analytics, machine learning and predictive algorithms (Qreshi et al., 2023). Additionally, institutions also conduct feasibility studies and surveys from the stakeholders to gather insights regarding student preferences that may affect student admissions. These methods and tools enable the organization to better analyze enrolment trends and patterns and make informed decisions about future trends.

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Exponential smoothing is a time series forecasting technique and a widely used tool for forecasting enrolment. It tries to apply weighted averages on the past enrolment data to predict the future forecasts. However, exponential smoothing can only be used if there is no trend in the time series data. Assuming trend exists, Holt's double exponential smoothing method can be employed (Rushton et al. 2023).

Holt's linear method incorporates both level and trend components in a time series data. This can be used in forecasting exchange rates (Ortiz, 2011) and commonly used in enrolment forecasting to capture trend levels in the overall enrolment data. In this study, the Holt's Double Exponential Smoothing Method with particle swarm optimization was utilized in forecasting enrolment of Northwest Samar State University (NwSSU). The Particle Swarm Optimization (PSO) is used to optimize the parameters of Holt's double exponential smoothing method.

## 2. Materials and Method

### *2.1 Enrolment Data*

The data set of this study is composed of NwSSU enrolment data from School Year 2003 to 2013. The training set covers the first six years, i.e., the enrolment data from SY 2003 – 2009. On the other hand, the remaining enrolment data constitute the test set, i.e., SY 2009 -2013. See Table 1 for the distribution of the dataset.

**Table 1** Dataset for the NwSSU Enrolment Forecasting Using Holt's Double Exponential Smoothing Method with Particle Swarm Optimization

| Dataset | Period of Time | Number of Years |
|---|---|---|
| Training Set | 2003-2009 | 6 years |
| Test Set | 2009-2013 | 4 years |

The student enrolment is the primary data utilized in this study; Table 2 shows the enrolment data of Northwest Samar State University for the school year 2003 up to 2013. The table also presents the figures both for the 1st and 2nd semesters of the school year. The data simply projects that NwSSU student population is gradually increasing.

**Table 2** Enrolment Data of NwSSU from School Year 2003-2013

| School Year | Yearly Enrolment Data | 1st Semester Enrolment Data | 2nd Semester Enrolment Data |
|---|---|---|---|
| 2003-2004 | 8,053 | 4,246 | 3,807 |
| 2004-2005 | 7,613 | 4,042 | 3,571 |
| 2005-2006 | 7,362 | 3,918 | 3,444 |
| 2006-2007 | 7,514 | 3,965 | 3,549 |
| 2007-2008 | 8,383 | 4,381 | 4,002 |
| 2008-2009 | 8,948 | 4,702 | 4,246 |
| 2009-2010 | 9,658 | 5,028 | 4,630 |
| 2010-2011 | 10,956 | 5,750 | 5,206 |
| 2011-2012 | 11,214 | 5,811 | 5,403 |
| 2012-2013 | 12,274 | 6,343 | 5,931 |

### *2.2 Holt's Double Exponential Smoothing Method*

The enrolment forecasting of the study will employ the Holt's Double Exponential Smoothing Method. It is a forecasting technique used to predict future values in time series data. It extends the basic exponential smoothing by introducing a trend smoothing factor. This method uses two smoothing equations: one for the level and another for the trend. The formula below is used to compute for the forecast:

$$F_{t+k} = E_t + k \cdot T_t \quad (1)$$

The intercept and the slope are then computed recursively using the following:

$$E_t = \alpha \cdot (Y_t) + (1-\alpha) \cdot (E_{t-1} + T_{t-1}) \quad (2)$$

$$T_t = \beta \cdot (E_t - E_{t-1}) + (1-\beta) \cdot T_{t-1} \quad (3)$$

Refer to the following as to the terms and symbols in the formula mentioned above:

$F_{t+k}$ := forecast value $k$ periods from $t$
$Y_{t-1}$ := actual/observed value for previous period $(t-1)$
$E_{t-1}$ := estimated value for previous period $(t-1)$
$T_{t-1}$ := trend value for previous period $(t-1)$
$\alpha$ := smoothing constant for estimates
$\beta$ := smoothing constant for trend
$k$ := number of periods

The smoothing parameters α and β control the responsiveness of the method to recent observations and changes in the level and trend. These smoothing factors determine the weight given to the most recent enrolment value and the weight given to the most recent trend. Typically, the values are between 0 and 1 for the level and trend components. Various optimization techniques like grid search, cross-validation and optimization algorithms can be used to search for the optimal values of the parameters.

### *2.3 Particle Swarm Optimization*

Particle Swarm Optimization is an evolutional and powerful optimization algorithm that offers alternative approach to traditional optimization techniques. The effectiveness of this method lies in the collective intelligence of the swarm particles to search and converge towards optimal solutions (Chang et al., 2009).

In finding the optimal solution, the particles as candidate solutions move through the search space. The particle's position and velocity are potential solution. At each iteration, particles adjust their positions and velocities. The position update of a particle is influenced by two factors: its personal best position and the global best position. The movement of particles is guided by mathematical equations that determine their velocity and position updates. PSO aims to efficiently navigate the search space and converge towards the optimal solution.

The PSO (Particle Swarm Optimization) code was written in JAVA programming language. The code basically returned the values for the global best particles alpha and beta. To ensure that the study built the right model, verifications and validations were made. Testing and source code review were also applied.

### *2.4 Performance of the Model*

To describe the performance of the model, the accuracy rate adapted from the study of Chen et al. (2008) was used. It is defined as:

$$\text{Accuracy\_Rate} = \frac{\text{Number\_of\_Correct\_Direction\_Forecasts}}{\text{Total\_Number\_of\_Direction\_Forecasts}} \quad (4)$$

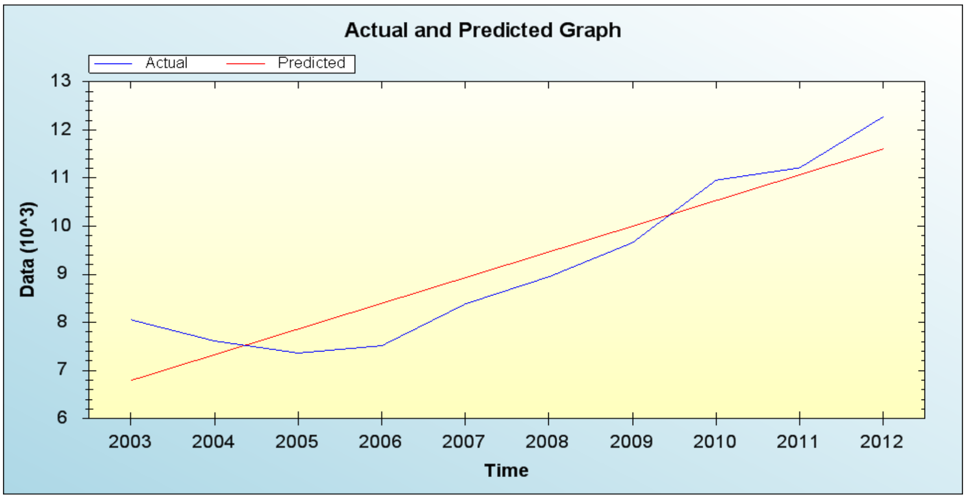
Moreover, Mean Absolute Deviation (MAD) and Residual Standard Error (RSE) were also computed to show forecasting errors. See succeeding equations for the formula:

$$\text{MAD} = \sum_{t=1}^{n} \frac{|Y_t - Y_t'|}{n} \quad (5)$$

$$\text{RSE} = \sqrt{\sum_{t=1}^{n} \frac{|Y_t - Y_t'|^2}{n-1}} \quad (6)$$

## 3. Results and Discussion

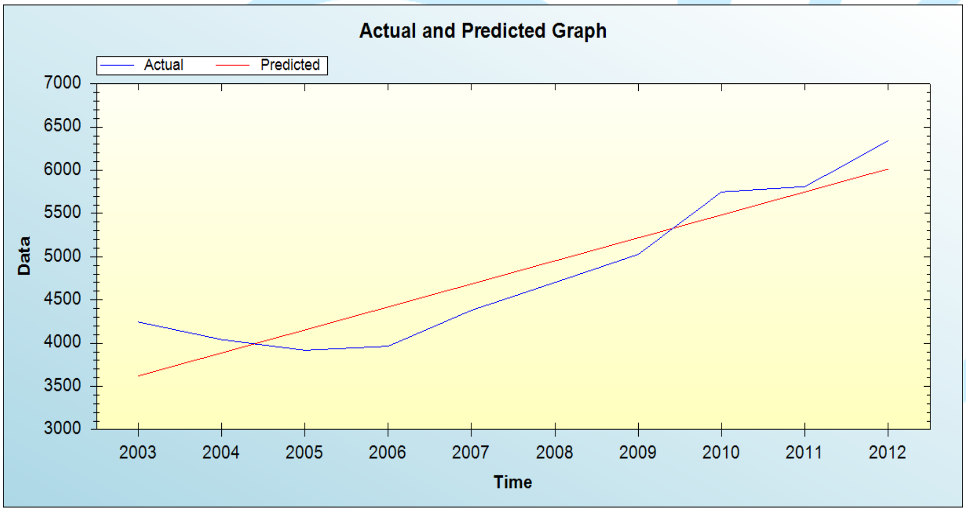
Pre-testing of the dataset was implemented to show that trend exists in the time series data. A free and open-source software application was used in its trend analysis. The line plots of the actual and forecasted data are shown in Figures 1, 2 and 3. The computed R and R-Square Adjusted values showed that the time series enrolment data satisfies the linear trend assumption of using the model.




R
= 0.924046

R-Square Adjusted
= 0.999927

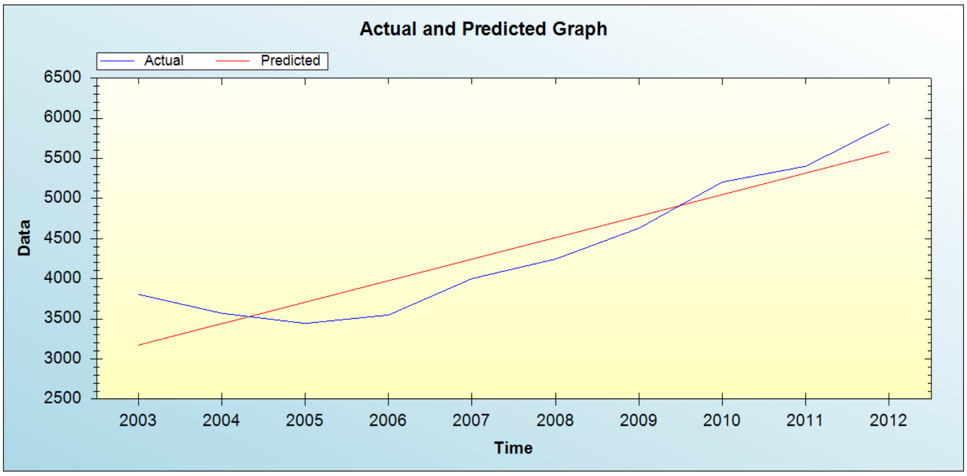
**Fig. 1** Trend Analysis on the Enrolment Data of NwSSU




R
= 0.920816

R-Square Adjusted
= 0.999851

**Fig. 2** Trend Analysis on the 1st Semester Enrolment Data of NwSSU




R
= 0.926569

R-Square Adjusted
= 0.999857

**Fig. 3** Trend Analysis on the 2$^{nd}$ Semester Enrolment Data of NwSSU

After implementing the simulations, the Particle Swarm Optimization (PSO) program returned the optimized values for the Alpha and Beta smoothing constants. See Table 3 for the corresponding values.

**Table 3** Alpha and Beta Smoothing Constants returned by the PSO

| Data | Alpha (α) | Beta (β) |
|---|---|---|
| 10 School Year | 0.94189624 | 0.7251067 |
| $1^{ST}$ SEMESTER | 0.95669049 | 0.82933391 |
| $2^{ND}$ SEMESTER | 0.93628780 | 0.62699298 |

Using the computed smoothing constants from the training set, the values were used in the parameters of the exponential smoothing method used in the study. The following figures (see Figs. 4, 5 and 6) show the actual data and the forecast values of the enrolment using Holt's Double Exponential Smoothing Method with Particle Swarm Optimization.

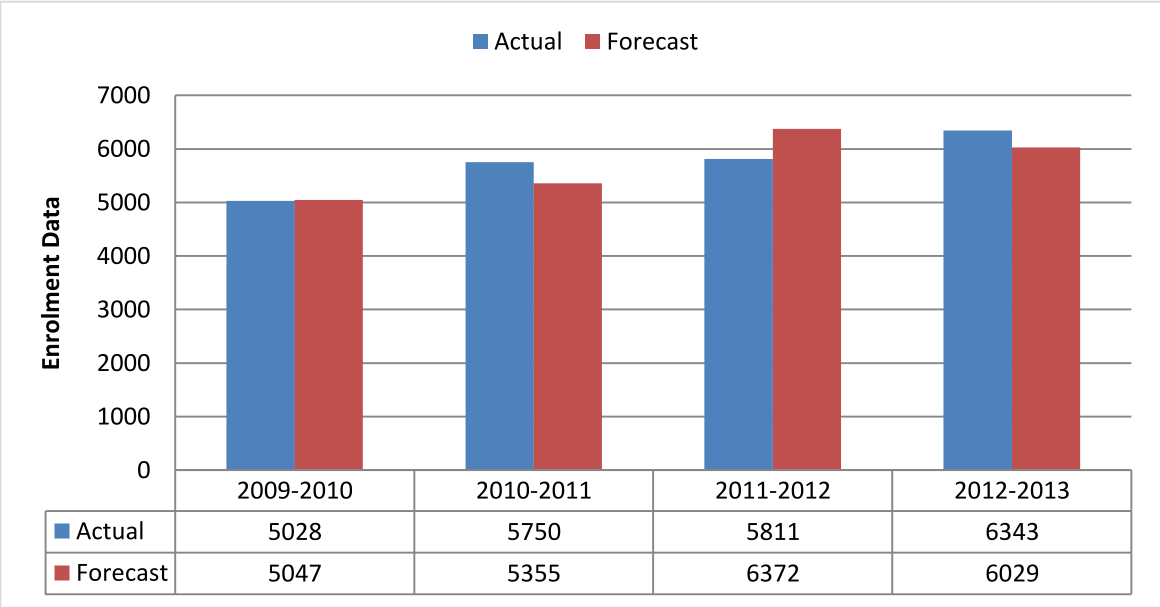



**Fig. 4** Enrolment Forecasts of NwSSU using the Model

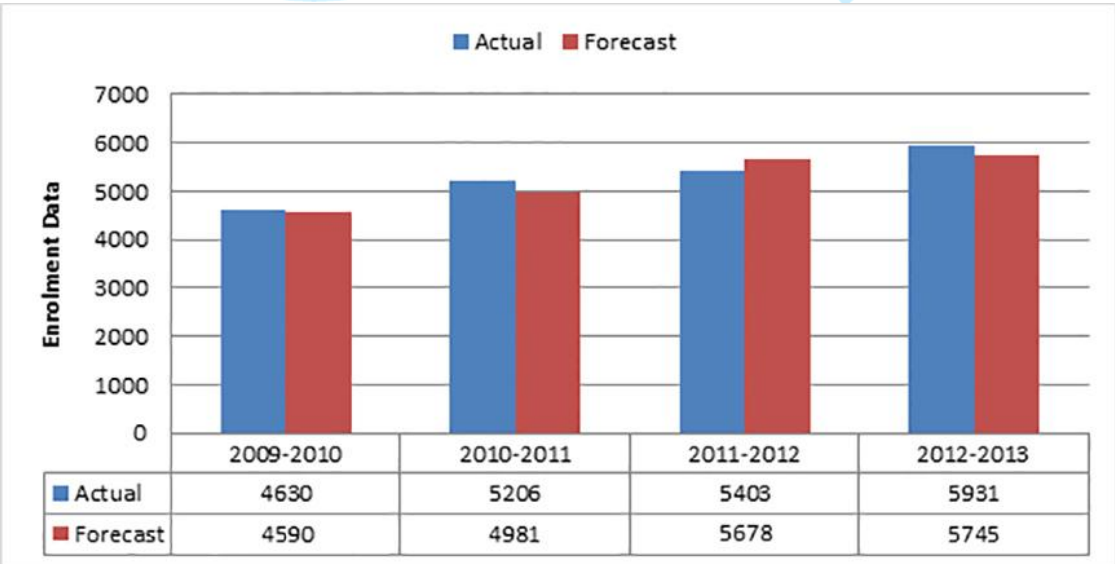



**Fig. 5** $1^{st}$ Semester Enrolment Forecasts of NwSSU using the Model

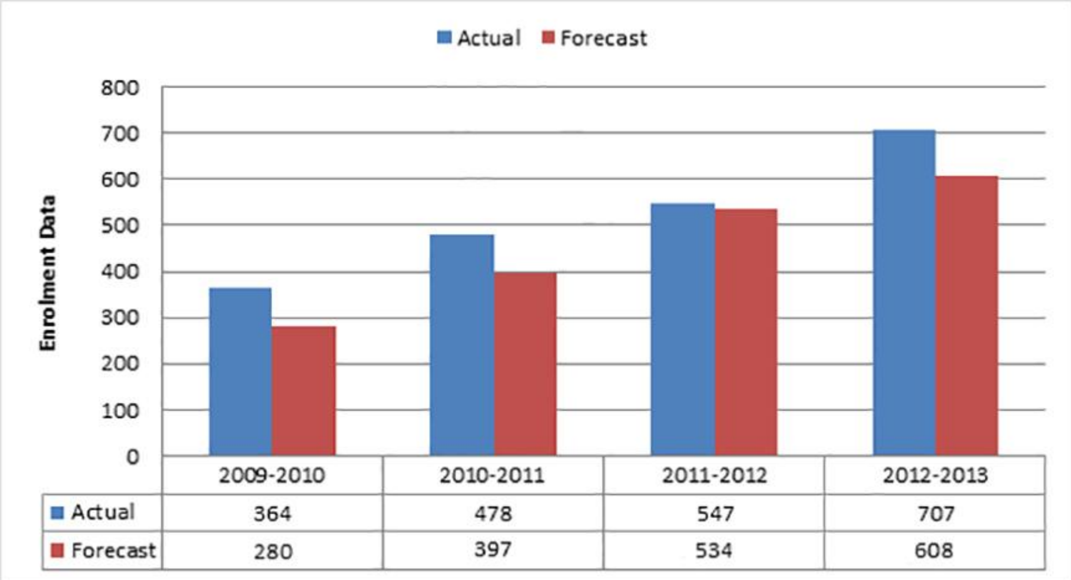



**Fig. 6** 2nd Semester Enrolment Forecasts of NwSSU using the Model

Table 4 presents the absolute error measures of the model. With smaller values of the MAD and RSE, the model's performance in terms of its accuracy and direction of forecasts is better. Table 5 on the other hand, shows the accuracy rates of the model using the test set. A number of factors can be considered in forecasting enrolment. With accuracy rate returned by the simulation, the Holt's Double Exponential Smoothing Method with Particle Swarm Optimization (PSO) performed well in determining the direction and making forecasts.

**Table 4** Absolute Error Measures

| Data | MAD | RSE |
|---|---|---|
| Year | 444.93 | 27.23 |
| 1ST SEMESTER | 276.83 | 21.48 |
| 2ND SEMESTER | 186.86 | 17.65 |

**Table 5** Accuracy Rates of the Model

| Data | Correct Forecasts | Total Forecasts | Accuracy Rate | Incorrect at Year |
|---|---|---|---|---|
| Year | 3 | 4 | 75% | 2012-2013 |
| 1ST SEMESTER | 3 | 4 | 75% | 2012-2013 |
| 2ND SEMESTER | 4 | 4 | 100% | None |

## 4. Conclusion

Forecasting enrolment is a complex and challenging task; no technique can guarantee 100% accuracy rate. However, with Holt's Double Exponential Smoothing Method with Particle Swarm Optimization to estimate the smoothing constants, the study was able to show that it can make forecasts with lower mean error rate. The model was able to accurately forecast both direction and enrolment data as shown in the tables and graphs. Moreover, the model was able to correctly detect the rise and fall of the enrolment data.

Conduct of pre-testing of the datasets helped in determining the applicability of Holt's Double Exponential Smoothing Method satisfying the trend component in the time series data. Given the uncertainties, regular monitoring and recalibration of the model based on new data can help improve the accuracy and robustness of enrolment projections. Alternatively, employing combination of data analysis, using multiple methods and other optimization algorithms can improve the effectiveness of enrolment forecasts.

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**Declaration of Conflict**
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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