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Forecasting Enrolment Using 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 of the enrolment data.

Keywords— Forecasting, Holt's Double Exponential Smoothing Method, Particle Swarm Optimization

I. 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 a 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 [1].

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 [2]. 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.

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 [3].

Holt's linear method incorporates both level and trend components in a time series data. This can be used in forecasting exchange rates [4] and is 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) College of Information and Computing Sciences (CCIS). The Particle Swarm Optimization (PSO) is used to optimize the parameters of Holt's double exponential smoothing method.

II. LITERATURE REVIEW

A number of studies on forecasting enrolment have been explored with the application of exponential smoothing techniques. Recent studies have also integrated optimization algorithms to improve the performance of forecasting models.

The study on student enrolment forecasting and student performance analysis in higher education by James and Weese [5] investigated how neural networks can improve the accuracy of the forecasting models as compared to the traditional time series methods. Using 25 years of enrolment data, the findings showed that there is irregular and nonlinear enrollment patterns making classical models like exponential smoothing less optimal in forecasting. Similarly, Chen [6] conducted a comparative analysis of multiple forecasting models, including exponential smoothing, ARIMA, and neural networks. The results demonstrated that exponential smoothing offered superior stability and competitive accuracy in predicting enrolment proportions, particularly when the data exhibited consistent trends. This suggests that despite the availability of more advanced models, exponential smoothing remains a reliable technique for educational forecasting.

In another study, Silitonga et al. [7] focused on improving the accuracy of university admission prediction for new students using quantitative time series. The study used the Double Exponential Smoothing (DES) method as its time series method, as it fits data that has a trend. Results showed that DES was able to track enrollment trends effectively and with less forecasting error when appropriately tuned. The study finds that DES is a useful and effective tool for student admissions forecasting while encouraging the investigation of other possible forecasting methods.

Furthermore, Pringgondani and Bernando [8] examined both single and double exponential smoothing methods in forecasting new student admissions. The study revealed that while single exponential smoothing is useful for data without trend, double exponential smoothing provides better accuracy when trends are present. This comparison highlights the importance of selecting the appropriate smoothing technique based on the characteristics of the dataset.

In recent years, researchers have incorporated optimization algorithms to further enhance forecasting accuracy. Chouikhi et al. [9] applied Particle Swarm Optimization (PSO) to Echo State Networks (ESN) to pre-train fixed weights values within the network. Their findings revealed that PSO-enhanced models for time series prediction showed obvious enhancement of ESN learning results.

On the other hand, the study of Khan and Byun [10] proposed another methodology involving genetic algorithm (GA) feature selection combined with a hybrid ML model for energy consumption forecasting. The methodology included data preprocessing, exploratory analysis, feature engineering and training to incorporate the most suitable inputs for an accurate forecast. The findings showed that the hybrid model outperforms single models and other benchmark approaches at predicting energy consumption significantly better than both. The results illustrated that the combination of tuned feature engineering and ensemble learning showed a higher level of accurate and robust prediction.

Adaptive hybrid forecasting framework was proposed by Ritonga et al. [11], the study enhances the traditional ARIMA model by integrating Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) for continuous parameter optimization. Recognizing that financial time series are often non-stationary, volatile, and structurally unstable, the paper addressed the limitation of static ARIMA parameter estimation by introducing a dynamic mechanism guided by a Model Complexity Assessment (MCA). Empirical results using financial datasets (Gold, AAPL, and BNGA) show that the proposed hybrid model significantly improves forecasting accuracy compared to baseline ARIMA, achieving performance gains of over 80% in many cases, particularly for larger datasets and higher volatility conditions.

Moreover, the study of Nurdin [12] explored the use of data mining techniques to predict whether students will graduate on time, an important indicator of institutional performance in higher education. To further enhance model performance, the study integrated Particle Swarm Optimization (PSO) to optimize the neural network's parameters and feature weights. The results show a noticeable improvement, with accuracy increasing, indicating better classification performance.

Additionally, Kumar and Susan [13] proposed an advanced forecasting framework that enhances fuzzy time series (FTS) models by optimizing key hyper parameters using Particle Swarm Optimization (PSO). The results demonstrated that optimizing all FTS hyper parameters simultaneously significantly improved forecasting accuracy compared to traditional models such as ARIMA, FbProphet, and standard FTS. The study concluded that integrating PSO with FTS offers a robust and flexible approach for time series forecasting in complex, real-world scenarios, and suggests future improvements by incorporating external factors such as policy interventions and environmental variables to further enhance prediction accuracy.

Despite the effectiveness of exponential smoothing and optimization-based forecasting methods, several limitations remain evident in existing studies. Most prior research focuses either on traditional statistical models or hybrid optimization techniques, with limited integration between these approaches and system-level frameworks. While double exponential smoothing has been shown to effectively capture trends, there is limited exploration on enhancing its performance through optimization techniques such as metaheuristic algorithms. Additionally, many studies emphasize accuracy comparison but provide limited discussion on improving model adaptability to rapidly changing enrolment patterns. Furthermore, existing works often rely on conventional datasets and do not fully address the integration of advanced frameworks for simultaneous data updates or dynamic system environments.

Although previous studies have demonstrated that optimization algorithms such as PSO and GA significantly improve forecasting accuracy, most of these works focus on hybridizing optimization techniques with statistical or machine learning models. Existing studies primarily emphasize prediction accuracy without adequately addressing computational efficiency, scalability, and real-world implementation constraints. Many models are tested on conventional datasets and do not fully account for dynamic and rapidly changing enrolment patterns. Thus, there is a need to develop a more robust and optimized forecasting approach that integrates parameter optimization with efficient data representation and update mechanisms.

III. MATERIALS AND METHODS

A. Enrolment Data

The data set of this study is composed of NwSSU College of Information and Computing Sciences enrolment data from School Years 2016-2017 to 2025-2026. The training set covers the first six years, i.e., the enrolment data from SY 2016-2017 to SY 2021-2022. On the other hand, the remaining enrolment data constitute the test set, i.e., SY 2022-2023 to SY 2025-2026. See Table 1 for the distribution of the dataset.

Table 1. Dataset for the NwSSU College of Information and Computing Sciences Enrolment Forecasting Using Holt's Double Exponential Smoothing Method with Particle Swarm Optimization

Dataset	Period of Time	Number of Years
Training Set	SY 2016-2017 – SY 2021-2022	6 years
Test Set	SY 2022-2023 – SY 2025-2026	4 years

The student enrolment is the primary data utilized in this study; table 2 shows the enrolment data of NwSSU College of Information and Computing Sciences for the School Year 2016-2017 to 2025-2026. The table also presents the figures both for the 1st and 2nd semesters of the school year. The data simply projects that NwSSU College of Information and Computing Sciences student population is gradually increasing.

Table 2. Enrolment Data of NwSSU College of Information and Computing Sciences from SY 2016-2017 to SY 2025-2026

School Year	1st Semester Enrolment Data	2nd Semester Enrolment Data	Annual Enrolment Data
2016-2017	597	571	1168
2017-2018	401	392	793
2018-2019	522	460	982
2019-2020	454	406	860

2020-2021	645	569	1214
2021-2022	717	655	1372
2022-2023	802	785	1587
2023-2024	1139	1113	2252
2024-2025	1400	1367	2767
2025-2026	1734	1719	3453

B. 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. This method works effectively to time series data with consistent upward or downward trend. The formula below is used to compute for the forecast:

$$F_{t+m} = L_t + mT_t$$

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

$$L_t = \alpha Y_t + (1 - \alpha)(L_{t-1} + T_{t-1})$$
$$T_t = \beta(L_t - L_{t-1}) + (1 - \beta)T_{t-1}$$

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

- α (alpha): smoothing parameter for the level ($0 < \alpha < 1$)
- β (beta): smoothing parameter for the trend ($0 < \beta < 1$)
- L_t: level at time t
- T_t: trend at time t
- Y_t: actual value at time t
- F_{t+m}: forecast for m periods ahead

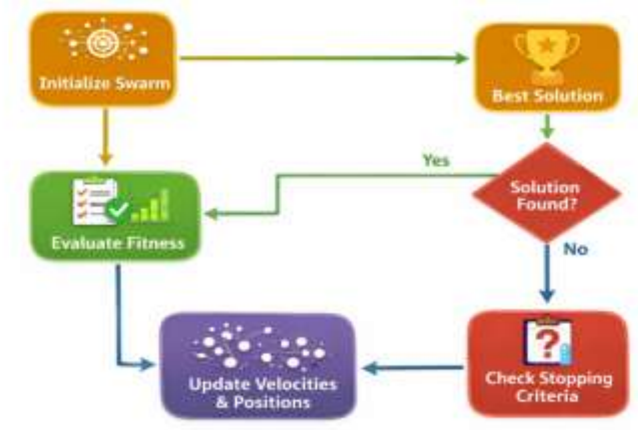
C. Particle Swarm Optimization

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 [14, 15].

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 (see the Figure 1 below for the PSO algorithm).

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.

Fig. 1. Diagram showing the Particle Swarm Optimization algorithm



D. Performance of the Model

To describe the performance of the model, the Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE) were computed to show forecasting errors. The MAD measures the magnitude of forecast errors showing how forecasts deviate from the actual values on average. On the other hand, MAPE expresses forecast errors as percentages showing how large errors are relative to actual values. See succeeding equations for the formula:

$\mathrm{MAD} = (1/n)\ \Sigma\ |A_t - F_t|$
$\mathrm{MAPE} = (1/n)\ \Sigma\ |(A_t - F_t)\ /\ A_t| \times 100$

For a more intuitive measure of model performance, the accuracy rate using MAPE is computed. The accuracy rate summarizes the overall performance of the model. The higher the accuracy rate, the more reliable is the forecasting model. Accuracy rate is computed as follows

Accuracy Rate = 100% − MAPE

IV. RESULT 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 2, 3 and 4. The computed R and R-Square Adjusted values showed that the time series enrolment data satisfies the linear trend assumption of using the model.

As shown in the figures, despite fluctuations in the earlier years, the enrolment data provides an increasing trend indicating steady growth from SY 2016- SY 2025. The graphs show a strong positive correlation between the enrolment data and the academic years involved in the study.

Fig. 2. Trend Analysis on the Enrolment Data of CCIS

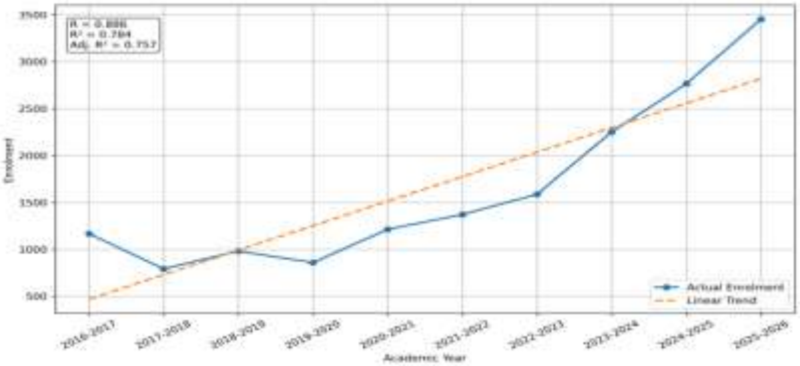


Fig. 3. Trend Analysis on the 1st Semester Enrolment Data of CCIS

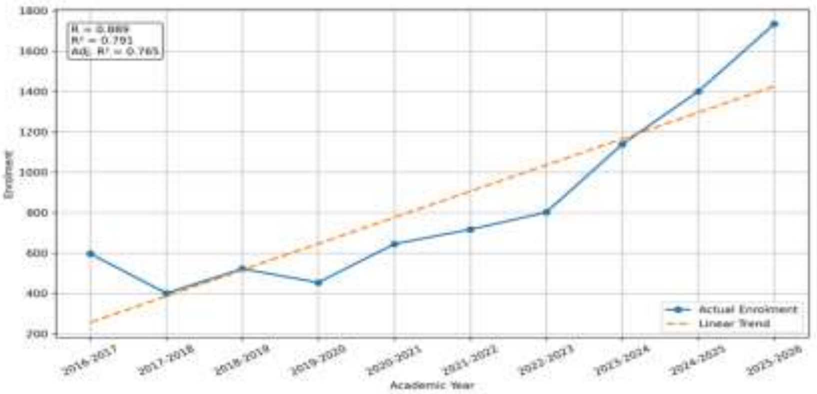
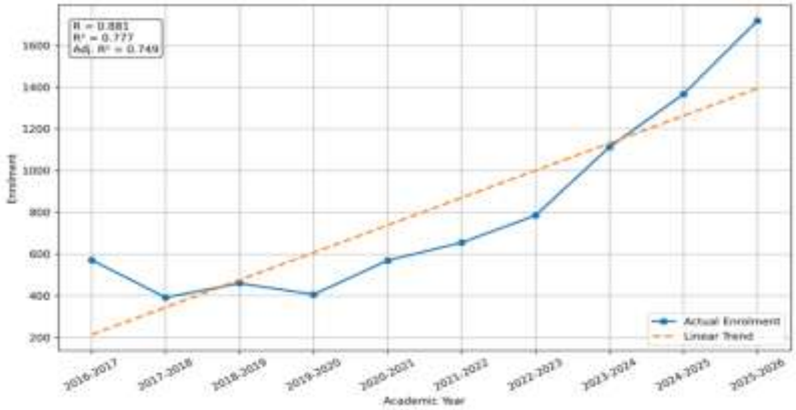


Fig. 4. Trend Analysis on the 2nd Semester Enrolment Data of CCIS



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)
School Year	0. 74513	0. 94408
1ST SEMESTER	0. 74860	0. 87522
2ND SEMESTER	0. 78489	0. 92013

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. 5, 6 and 7) show the actual data and the forecast values of the enrolment using Holt's Double Exponential Smoothing Method with Particle Swarm Optimization.

As observed in the graphs, there is a consistent upward trend in enrollment. Both the actual and forecasted values show steady increase in each academic year. While the model was able to correctly predict the rise of enrolment, the forecast values are lower than the actual values. This implies that the model slightly underestimates actual enrolment. However, the graphs show that the model was able to improve its forecasts accuracy over time. The gap between the actual values and forecast values decrease in later academic years.

Fig. 5. Enrolment Forecasts of CCIS using the Model

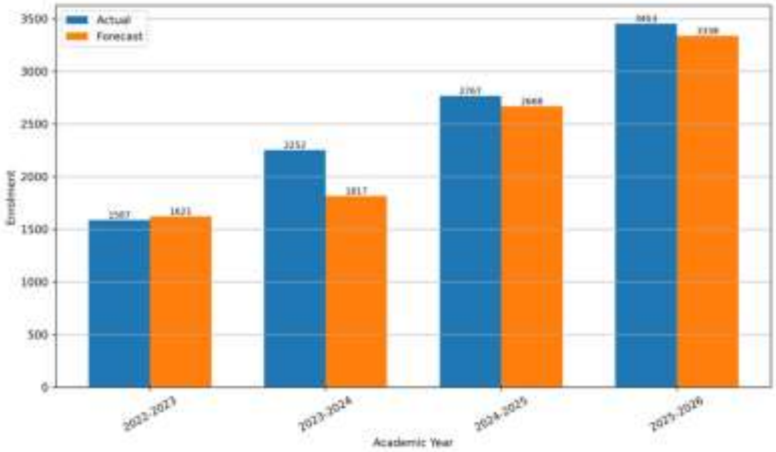


Fig. 6. 1st Semester Enrolment Forecasts of CCIS using the Model

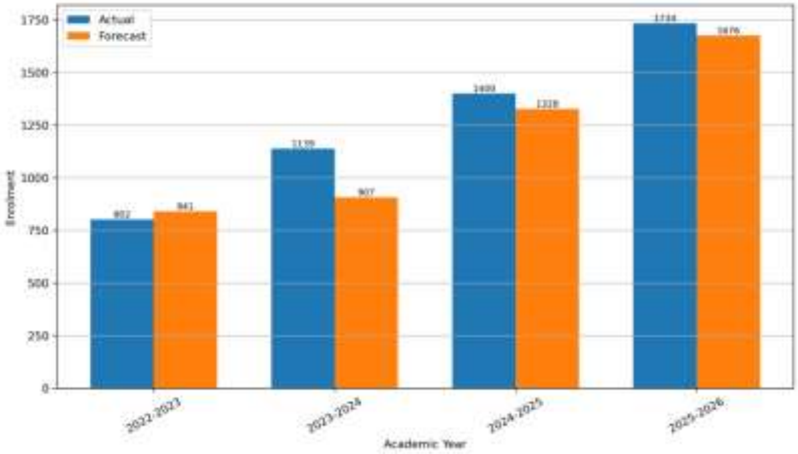


Fig. 7. 2nd Semester Enrolment Forecasts of CCIS using the Model

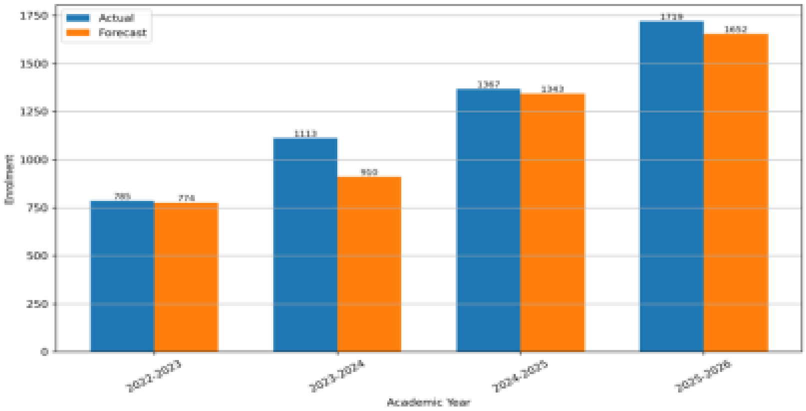


Table 4 presents the absolute error measures of the model. With the computed values of the MAD and MAPE across the annual, 1st semester and 2nd semester datasets, the table indicates how far the forecast values deviate from the actual values. As depicted in the table, the annual data has the highest errors; the 1st semester data shows moderate error levels while the 2nd semester data has the lowest errors.

Table 5 on the other hand, shows the accuracy rates of the model. As reflected in the table, the accuracy rate for the annual enrolment is comparatively the weakest performance. The 1st semester shows strong predictive performance but it is the 2nd semester that indicates the most reliable forecasts because of its highest accuracy. Overall, the model demonstrate good predictive capability across the datasets. However, the performance improves as the data becomes more granular.

Table 4. Absolute Error Measures

Data	MAD	MAPE
Year	176.74	12.67
1ST SEMESTER	100.99	8.43
2ND SEMESTER	79.71	6.28

Table 5. Accuracy Rates of the Model

Data	MAPE	ACCURACY RATE
Year	12.67	87.33%
1ST SEMESTER	8.43	91.57%
2ND SEMESTER	6.28	93.72%

V. 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 acceptable accuracy rates. The model was able to forecast both direction and enrolment data as shown in the tables and graphs. The forecasting model is highly reliable for semester-level forecasts but less precise when dealing with aggregated 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.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest, financial or non-financial, related to this research work.

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