

Time Series Analysis and Forecasting of University Enrolment Using Grid Search–Optimized Holt–Winters Algorithm: Evidence from Tawi-Tawi, Philippines

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Abstract—Student enrolment forecasting supports institutional planning and resource allocation. This study employed grid-based structural selection of Holt–Winters Exponential Smoothing models to analyse enrolment records from Mindanao State University–Tawi-Tawi College of Technology and Oceanography covering academic years 2011–2012 to 2025–2026. A total of 69,103 student records were aggregated by semester, academic program, and sex. Six model configurations were considered, with smoothing parameters estimated internally using the statsmodels optimizer. Forecasting performance was assessed through expanding-window rolling-origin evaluation across ten one-step-ahead forecast periods using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), the Coefficient of Determination (R^2), and Mean Absolute Percentage Error (MAPE). Five of the 34 enrolment series achieved MAPE values below 10%: female (4.42%), overall (4.57%), male (4.95%), BS in Fisheries (8.92%), and Bachelor of Elementary Education (9.19%). Higher forecasting errors in other programs were associated with potentially irregular enrolment patterns and the sensitivity of MAPE to small enrolment counts. The projected overall enrolment for the next three academic semesters was 3,519, 3,375, and 3,633 students, respectively. The findings suggest that Holt–Winters models may provide supplementary quantitative information for short-term institutional planning. However, program-level forecasts should be interpreted cautiously, considering differences in predictive accuracy, limited historical observations, forecasting uncertainty, and potential changes in institutional conditions.

Keywords—Enrolment forecasting; Holt-Winters exponential smoothing; grid search optimization; higher education trends; time series analysis

I. INTRODUCTION

Student enrolment is a significant concern in higher education because changes in student numbers directly affect institutional planning particularly in resource allocation, staffing, and infrastructure development [1, 2, 3, 4]. Mindanao State University - Tawi-Tawi College of Technology and Oceanography (MSU-TCTO), a chartered University located in the southernmost part of the Philippines, caters to an average of

3,000 undergraduate and graduate students each semester. In recent years, MSU-TCTO has significantly expanded its curriculum, with the number of academic programs prior to 2018 curriculum increasing by more than 100%. The curriculum expansion resulted in fluctuation in overall enrolment and enrolment in particular programs, which resulted in shortage in resources in one college and un-used resources in other colleges.

In higher education, enrolment time series study is important to examine historical patterns, identify trends and fluctuations, and generate forecasts that can support evidence-based planning, resource allocation, and decision-making [4, 5]. Time series and trend analysis are useful for understanding changes in data over time [6, 15]. However, enrolment datasets in academic institutions are often relatively small and limited in length such as yearly or semester-based records, which poses challenges for complex forecasting models that typically require large volumes of data for reliable training and generalization. In such cases, simpler and more robust statistical approaches become more suitable. Choices in time series analysis and forecasting techniques therefore depend on data characteristics and application context [7].

Considering the nature of student enrolment data, which may exhibit trend and seasonal variation despite its limited size, the use of Holt-Winters Exponential Smoothing is appropriate. Exponential smoothing methods are well-suited for small datasets because they rely on recursive updating and place greater weight on recent observations, enabling stable and interpretable forecasts even with limited data [8]. Prior studies have demonstrated the effectiveness of exponential smoothing techniques for forecasting temporal data and their value in enrolment forecasting [7, 9, 10].

The forecasting performance of exponential smoothing depends on the choice of model components and smoothing coefficients. In this study, an exhaustive search compares a finite set of six Holt–Winters structural configurations, while the statsmodels numerical optimizer estimates the applicable smoothing coefficients internally. The distinction is important: the structural search does not enumerate numerical grids for α ,

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β , or γ , and any accuracy benefit over a fixed or naïve model requires an independent baseline comparison [11, 14, 18].

Using enrolment data from AY 2011–2012 to 2025–2026, this study examines enrolment patterns and applies grid-based structural selection of Holt–Winters exponential smoothing models to produce three-semester forecasts for MSU-TCTO. Forecast performance is examined using several complementary metrics, and results are interpreted as preliminary planning evidence rather than definitive resource-allocation instructions.

II. THEORETICAL BACKGROUND

A. Holt-Winters Exponential Smoothing Algorithm

The Holt–Winters algorithm or Triple Exponential Smoothing algorithm, extends Holt’s linear trend model by incorporating a seasonal component, making it exceptionally effective for time series that exhibit both a consistent direction and periodic fluctuations. By modeling the three distinct aspects of a time series such as level, trend, and seasonality, the method can capture changing data behavior with high precision [17]. Mathematically, these components are updated recursively, ensuring that the model stays responsive to the most recent data points. According to Hyndman & Athanasopoulos [16], the additive framework is expressed through the following system of equations:

$$\ell_t = \alpha(y_t - s_{t-m}) + (1 - \alpha)(\ell_{t-1} + b_{t-1}) \quad (\text{Level}) \quad (1)$$

$$b_t = \beta^*(\ell_t - \ell_{t-1}) + (1 - \beta^*)b_{t-1} \quad (\text{Trend}) \quad (2)$$

$$s_t = \gamma(y_t - \ell_{t-1} - b_{t-1}) + (1 - \gamma)s_{t-m} \quad (\text{Seasonal}) \quad (3)$$

Here, ℓ_t represents the level at time t , b_t is the trend, and s_t is the seasonal component. The smoothing parameters α , β^* , and γ control how much weight is given to recent data for level, trend, and seasonality. The parameter m represents the length of the seasonal cycle, ensuring that the model accounts for repeating patterns over time [16].

The three equations of the Holt–Winters method work as an interconnected feedback system where level, trend, and seasonality are updated together by adjusting for each other’s effects. The level equation (Equation 1), estimates the baseline by removing the seasonal component from the observed value and combining it with the previous level and trend [16]. The trend equation (Equation 2), captures the direction of change by comparing the current and previous levels while smoothing it with the past trend [16]. The seasonal equation (Equation 3), isolates repeating patterns by removing level and trend effects and updating them using the previous seasonal cycle [16]. Finally, the forecast is generated by combining all three components by projecting the level forward, adding the trend over the forecast horizon, and incorporating the seasonal pattern, resulting in predictions that reflect both overall direction and recurring fluctuations, as expressed in the forecast equation:

$$\hat{y}_{t+h|t} = \ell_t + hb_t + s_{t+h-m(k+1)} \quad (4)$$

$$k = \lfloor (h - 1)/m \rfloor \quad (5)$$

Based on the structural characteristics of the Holt–Winters algorithm, it is most effective for time series data that show clear trend and seasonal patterns. It performs well also when datasets are small to moderate in size because it updates values recursively using recent observations, making it computationally efficient and stable even without large historical data. The method is also suitable for short to medium term forecasting since it gives more weight to recent changes, allowing it to quickly adapt to new patterns.

B. Grid-Search Algorithm

Grid Search is a systematic hyperparameter tuning method that evaluates all possible combinations of predefined parameter values to find the best model performance. It is a deterministic approach that does not involve randomness, as it exhaustively searches the entire parameter space. Based on brute-force optimization, it forms all combinations of hyperparameters $\theta = (\theta_1, \theta_2, \dots, \theta_k)$ using a Cartesian product, then trains and evaluates the model for each one. The combination that produces the lowest error such as MAPE, is selected as the optimal set of parameters [18, 14]. Mathematically, this can be expressed as:

$$\theta^* = \operatorname{argmin}_{\theta \in \Theta} L(\theta) \quad (6)$$

where Θ represents the full grid of parameter combinations and $L(\theta)$ is the loss function computed for each configuration.

Grid search ensures that the best solution within the defined parameter grid is found, but it can be computationally expensive when the number of parameters or their possible values increases. Despite this, it is still widely used because it is simple, easy to implement, and guarantees the best result within the given search space [18, 14].

III. RESEARCH METHODS

A. Data Gathering and Pre-processing

The dataset was obtained through an official request from the Office of the University Registrar of MSU-TCTO. It includes complete enrolment records for all undergraduate and graduate programs from Academic Years 2011–2012 to 2025–2026. In this study, summer sessions were excluded due to the negligible number of enrolled students throughout the study period. Furthermore, the study focused on the two regular academic semesters, as these are the primary periods considered by the university administration for institutional planning and resource allocation.

The programs included in the dataset are: AB History, AB Islamic Studies, AB Political Science, AB Language and Cultural Studies, BA English Language Studies, Bachelor of Early Childhood Education, Bachelor of Elementary Education, Bachelor of Public Administration, BS in Statistics, BS in Business Administration, BS in Computer Applications, Bachelor of Secondary Education, BS in Environmental Science, BS in Fisheries, BS in Food Technology, BS in Information Technology, BS in Mathematics, BS in Marine Biology, BS in Teaching Arabic, Diploma in Fish Technology, Diploma in Office Management, Professional Diploma in Physical Education, Master of Arts in Education, Master of Arts in English Language Teaching, Master of Arts in Islamic Education, Master of Arts in Public Administration, Master of

Science in Aquaculture, Master of Science in Education, Master of Science in Marine Biology, Master of Science in Mathematics, and PhD in Education Management. A total of 69,103 individual student records were collected and aggregated by semester, program, and sex.

After data collection, preprocessing included cleaning the dataset by handling missing values, duplicates, outliers, and inconsistencies, along with setting up necessary Python libraries and suppressing non-critical warnings. The data were then converted into a structured panda DataFrame, and the target variable was extracted as a numeric time series, ensuring it was properly formatted and sequentially organized for forecasting and analysis.

B. Time Series Stationary Test

Stationarity was tested using the Augmented Dickey Fuller ADF test at a 0.05 significance level. The null hypothesis assumes the presence of a unit root indicating non-stationarity while the alternative hypothesis assumes stationarity. A series is considered stationary when the p-value is < 0.05 [13]. The ADF test results show that Bachelor of Secondary Education, Bachelor of Public Administration, and Bachelor of Elementary Education series are non-stationary, while Bachelor of Early Childhood Education, BS in Marine Biology, MS in Aquaculture, MS in Marine Biology, MS in Mathematics, and Professional Diploma in Physical Education are stationary based on their respective ADF statistics and p-values. Since dataset are composed of stationary and non-stationary series, Holt Winters Exponential Smoothing method is one of the appropriate methods as it is capable of capturing level trend and seasonal components without requiring strict stationarity.

C. Grid-Based Structural Selection of Holt-Winters Exponential Smoothing Models

This study employed an exhaustive grid-based model selection procedure to identify suitable Holt-Winters Exponential Smoothing structures for university enrolment forecasting. Rather than directly searching numerical values of the smoothing coefficients, the procedure evaluated six valid combinations of trend, seasonal, and damped-trend components. This approach systematically identifies the most appropriate model structure for each enrolment series while reducing the need for manual configuration.

The candidate configurations included additive or absent trend components, additive or absent seasonal components, and damped or undamped trends where applicable. Specifically, the six configurations consisted of (1) no trend and no seasonality, (2) additive trend without seasonality, (3) damped additive trend without seasonality, (4) additive seasonality without trend, (5) additive trend and seasonality, and (6) damped additive trend with additive seasonality. For seasonal configurations, a seasonal period of two observations was specified to represent the two regular academic semesters, excluding the summer term due to its negligible enrolment and limited relevance to institutional resource allocation planning.

Each candidate model was fitted using the ExponentialSmoothing class from the Python statsmodels library (version 0.14.6). The implementation specified `initialization_method='estimated'`, allowing the initial model

states to be estimated during fitting. With `optimized=True`, the library's internal numerical optimizer estimated the smoothing coefficients, including the level (α), trend (β), and seasonal (γ) parameters where applicable. No nondefault optimization method or additional optimizer options were explicitly specified. Thus, the grid-based procedure performed structural model selection, while numerical parameter estimation was handled internally by statsmodels.

To determine the most appropriate configuration, an expanding-window rolling-origin validation procedure was applied to the development dataset. Each candidate model was repeatedly fitted using progressively increasing training observations, and its forecasting accuracy was assessed using Mean Absolute Error (MAE). The configuration yielding the lowest average validation MAE was selected for each enrolment series. The selected model was subsequently evaluated using an independent test set consisting of the four most recent semester observations, which were excluded from model selection. Finally, the selected configuration was refitted using the complete historical dataset to generate enrolment forecasts for the next three academic semesters. This procedure ensured a systematic separation between structural model selection, parameter estimation, and independent forecasting evaluation.

D. Model Evaluation and Forecasting

The forecasting performance of the Holt-Winters Exponential Smoothing models was evaluated using Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2). MAE measures the average magnitude of forecasting errors in terms of student counts, while MAPE expresses the average percentage difference between actual and predicted enrolment values. RMSE measures the magnitude of forecasting errors by assigning greater weight to larger deviations, making it useful for identifying models that produce substantial forecasting errors. Meanwhile, R^2 evaluates predictive performance relative to a model that consistently predicts the mean of the observed values, where higher values indicate better performance [12]. Lower MAE, MAPE, and RMSE values indicate better forecasting accuracy. Since MAPE is sensitive to small enrolment values and undefined when actual enrolment is zero, MAE and RMSE were included to provide additional measures of forecasting accuracy.

The mathematical expressions for the evaluation metrics are presented below:

$$MAPE = \frac{100}{n} \sum_{t=1}^n \left| \frac{y_t - \hat{y}_t}{y_t} \right| \quad (7)$$

$$MAE = \frac{1}{n} \sum_{t=1}^n |y_t - \hat{y}_t| \quad (8)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2} \quad (9)$$

$$R^2 = 1 - \frac{\sum_{t=1}^n (y_t - \hat{y}_t)^2}{\sum_{t=1}^n (y_t - \bar{y})^2} \quad (10)$$

where y_t represents the actual observed enrolment at time t , $\hat{y}_t$ denotes the corresponding forecasted value, $\bar{y}$ is the mean of the observed evaluation values, and n represents the total number of forecast observations. MAE and RMSE are expressed in student counts, whereas MAPE is expressed as a percentage. R^2 is dimensionless and may take negative values when the forecasting model performs worse than predicting the mean of the observed values. MAPE is considered undefined when actual enrolment values are zero, while R^2 is undefined when the observed evaluation values have zero variance.

To ensure an objective assessment of forecasting performance, a three-stage evaluation framework was employed, consisting of model development, structural model selection, and independent testing. This approach separates model configuration selection from final performance assessment, reducing the risk of selection bias associated with using the same observations for both model selection and evaluation.

In the first stage, model development, the historical enrolment data were chronologically organized to preserve the temporal characteristics of each time series. The observations were divided into a development set and an independent test set, with the four most recent semester observations reserved exclusively for final testing. The development set was used for model fitting and structural selection, while the independent test set was excluded from all model-selection procedures. This chronological partitioning ensured that future observations were not used to predict earlier enrolment periods.

In the second stage, structural model selection, an expanding-window rolling-origin validation procedure was applied exclusively to the development set. The procedure evaluated six valid Holt–Winters model configurations involving additive or absent trend components, additive or absent seasonal components, and damped or undamped trends where applicable. For each validation fold, the candidate model was fitted using the available historical observations and subsequently used to predict the next semester's enrolment using a one-semester forecasting horizon. The training window progressively expanded from an initial training size of 20 semesters as the forecasting origin moved forward, allowing each candidate configuration to be evaluated across multiple forecasting periods rather than relying on a single validation split.

The smoothing parameters, including level (α), trend (β), and seasonality (γ), were estimated internally using the optimization procedure provided by the Python statsmodels library, with `optimized=True` and `initialization_method='estimated'`. Forecasting errors across the rolling-origin validation folds were aggregated using Mean Absolute Error (MAE) as the selection criterion, and the configuration yielding the lowest average validation MAE was selected for each enrolment series.

In the third stage, independent model evaluation, the selected Holt–Winters configuration was fitted using the complete development set and evaluated against the four most recent semester observations reserved for independent testing. Since

these observations were not utilized during model selection, the resulting forecasting errors provided an independent assessment of predictive performance. MAE, MAPE (%), RMSE, and R^2 were used to evaluate the accuracy of the selected configurations. Models with higher forecasting errors were retained in the evaluation results to provide a comprehensive assessment of performance across programs with different enrolment characteristics.

Finally, for enrolment forecasting, the selected Holt–Winters configurations were refitted using all available historical observations from AY 2011–2012 to AY 2025–2026. The resulting models were used to forecast enrolment for the first and second semesters of AY 2026–2027 and the first semester of AY 2027–2028. Approximate lower and upper forecast bounds were also generated to illustrate forecasting uncertainty.

Approximate lower and upper forecast bounds were estimated using the sample standard deviation of the residuals obtained from the Holt–Winters model fitted to the complete historical enrolment series. For each forecast horizon, the uncertainty margin was calculated by multiplying the residual standard deviation by 1.96 and the square root of the forecast horizon. The margin was subtracted from and added to the point forecast to obtain the corresponding lower and upper bounds. Negative lower bounds were restricted to zero to reflect the nonnegative nature of student enrolment. Although the multiplier of 1.96 corresponds to a conventional normal approximation, the resulting bounds were treated as heuristic uncertainty estimates rather than statistically calibrated 95% prediction intervals.

IV. RESULTS AND DISCUSSION

A. Total Institutional Enrolment Data Trend

Fig. 1 illustrates an increasing number of students from AY. 2011-2012 to AY. 2025-2026, with short-term fluctuations. Enrolment dropped significantly in AY 2016-2017 to 2017-2018 as the K-12 curriculum reforms were fully implemented in the Philippines. The two-year transition left higher education institutions with no freshmen. Enrolment recovered after this period, but remained low in the second semester of AY. 2019-2020 due to the COVID-19 pandemic. The shift to modular classes during the pandemic posed significant challenges, especially for those students residing in the remote island provinces of Tawi-Tawi, which may have contributed to the low enrolment. Despite the challenges, the enrolment remained relatively stable, indicating MSU-TCTO's resilience.

An increase in the series began in AY 2021-2022, coinciding with the lifting of national mobility restrictions due to the pandemic. Enrolment has continued to increase since then, as student intake and retention improved, curricular programs expanded, and free higher education was implemented. The recurring intra-year fluctuations in the series indicate a seasonal pattern, consistent with the Office of the University Registrar's records showing that every second semester, there was an increase in official dropouts because of financial burden, especially the cost of transportation and requests for honorable dismissal due to academic difficulty and family problems. It indicates that these variations are influenced by student attrition

due to financial constraints, academic difficulties, personal circumstances, and inter-institutional transfers.

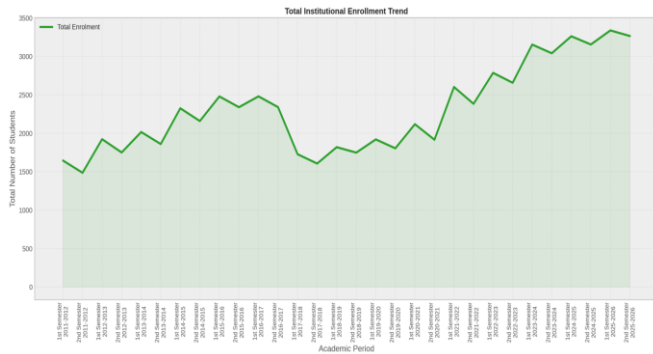


Fig. 1. Total institutional enrolment trend.

B. Institutional Enrolment Trend Data by Sex

Fig. 2 illustrates the University enrolment trend by sex. The series shows an upward trajectory with short fluctuations. The minimum number of male and female enrollees is 691 and 1,038, respectively. The maximum number of male and female enrollees is 1,317 and 2,021, respectively. Furthermore, a notable distance between male and female trajectories has been observed from the first semester of AY. 2015-2016 to the second semester of AY. 2016-2017, and again in the first semester of 2021-2022, with the gap widening until AY 2025-2026.

The time series grouped by sex shows the same overall pattern as total enrolment, but with differences between male and female trends. Female enrollees consistently outnumber male enrollees across the academic years. The gap between the two indicates a long-term widening difference in enrolment by sex.

This trend was backed by several factors in existing literature. According to UNESCO [19], the disparity may be linked to poverty and the need for males to enter the workforce earlier, leading to lower male enrolment. Yamauchi & Tiongo [20] also found that some Filipino families prioritize educating daughters, believing that education provides greater long-term benefits for females, given economic challenges. National trends in education, labor participation, poverty, and household decisions may contribute to the widening gap between male and female enrollees.

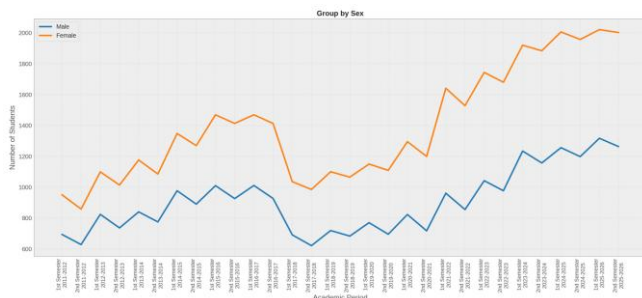


Fig. 2. Institutional enrolment trend by sex.

C. Cumulative Enrolment Metrics

Table I presents the maximum, and total enrolment across 21 undergraduate programs and reveals a markedly uneven

distribution of students among academic offerings. The Bachelor of Elementary Education recorded the highest maximum enrolment of 519, and the largest cumulative total enrolment of 11,297, indicating the program consistently attracted the greatest number of students across the periods covered in this study. Followed by the Bachelor of Secondary Education, with a maximum of 462, and a total of 8,065, while the Bachelor of Arts in History ranked third a maximum of 467, and a total of 5,608. The succeeding program showed a gradual decline in enrolment, suggesting that student participation is concentrated in only a few programs, while the remaining offerings account for a relatively small share of the undergraduate population. Thus, the pattern demonstrates that some programs have become more established and attractive to students.

TABLE I. BASIC STATISTICS SUMMARY FOR UNDERGRADUATE PROGRAMS

Undergraduate Program	Maximum Enrolment per Semester (Students)	Cumulative Semester Enrolment (Student-Semester Counts)
Bachelor of Elementary Education	519	11297
Bachelor of Secondary Education	462	8065
AB History	467	5608
Diploma in Fish Technology	404	5107
BS in Fisheries	269	4646
BS in Information Technology	224	3664
BA English Language Studies	180	3386
AB Political Science	146	2815
BS in Mathematics	170	2206
BS in Teaching Arabic	138	2152
Diploma in Office Management	210	2125
BS in Marine Biology	100	1373
BS in Environmental Science	70	1131
Bachelor of Public Administration	241	1041
AB Islamic Studies	86	946
BS in Statistics	60	945
Bachelor of Early Childhood Education	110	660
BS in Business Administration	165	617
AB Language and Cultural Studies	43	181
BS in Computer Applications	32	130
BS in Food Technology	29	120

A closer examination of Table I further shows that the first several programs maintained substantially higher enrolment levels than the rest, which indicates strong student preference, greater program visibility, and a longer period of institutional establishment. In contrast, the lower-ranked programs posted smaller mean and total enrolment values. For instance, the AB Language and Cultural Studies, BS in Computer Applications, and BS in Food Technology recorded the lowest means among

others. However, their low values should not be interpreted in the same manner as those of the older programs, since the last three programs in the tables are newly offered by the University (AY. 2023-2024). Their limited enrolment may therefore be attributed to their recent introduction, a short operating period, and still-developing student awareness, rather than weak demand or poor program viability. Which, in sense, their present enrolment levels may reflect a transitional stage of program development rather than a definitive indicator of long-term performance.

The results highlight the importance of aligning academic planning, faculty allocation, facility provision, and program promotion with actual enrolment patterns, while also recognizing that newer programs may require sufficient time and support before their growth potential can be assessed more accurately.

TABLE II. BASIC STATISTICS SUMMARY FOR GRADUATE PROGRAMS

Undergraduate Program	Maximum Enrolment per Semester (Students)	Cumulative Semester Enrolment (Student-Semester Counts)
Master of Arts in Education	110	1392
Master of Arts in Public Administration	110	1087
MA in English Language Teaching	39	556
MS Aquaculture	29	403
Master of Science in Mathematics	28	293
Prof. Diploma Physical Education	16	232
Master of Arts in Islamic Education	25	128
Master of Science in Education	35	112
PhD in Education Management	23	97
Master of Science in Marine Biology	13	18

Table II presents the maximum and total enrolment across the 10 graduate programs of MSU-TCTO and shows that enrolment is concentrated in only a few offerings. The Master of Arts in Education recorded the highest mean enrolment (46.40), tied for the highest maximum enrolment (110), and the largest cumulative total (1,392), indicating that it consistently attracted the greatest number of graduate students, and due to the demand since a lot of DepEd schools are catered to in the province of Tawi-Tawi. This was followed by the Master of Arts in Public Administration, which registered a mean of 36.23, a maximum of 110, and a total of 1,087. The succeeding graduate programs showed much lower values, with the Master of Arts in English Language Teaching recording a mean of 18.53 and a total of 556, while other programs posted mean enrolments below 14 and totals below 500. Overall, the table suggests a clear declining pattern from the first two graduate programs to the rest, implying that graduate enrolment is concentrated in a limited number of established programs, while the remaining

offerings serve a comparatively smaller portion of the graduate student population.

The lowest enrolment values were observed in the Master of Science in Marine Biology, which registered a mean of only 0.60, a maximum of 13, and a total of 18. This is because the program is a new graduate offering (AY. 2025-2026) offered by the MSU-TCTO. The low program enrolment may therefore be attributed to its recent implementation, shorter period of availability, and limited visibility among prospective students, rather than weak program viability or limited academic relevance. In the same way, the gap between the higher-enrolled and lower-enrolled graduate programs may reflect differences in program maturity and student awareness.

Thus, these findings highlight the need to align graduate program planning, faculty assignment, and resource allocation with actual enrolment trends, while also providing sufficient time and promotional support for new offerings to build their enrolment base and demonstrate long-term potential.

D. Enrolment Density by Program

Fig. 3 shows enrolment patterns across programs and academic years. From 2011 to 2018, education programs like BEED and BSED had the highest enrolment because the university only offered 13 undergraduate programs at that time, so most students chose teaching-related degrees. After this period, some established programs started to decline. BEED briefly increased after the COVID-19 period (2020–2021) but dropped again in 2023 due to stricter admission rules. BSED and AB History also decreased slightly, likely because students shifted to newer programs as more courses became available. Other programs show different trends. Diploma in Fish Technology shows a steady decline, possibly because students now prefer direct entry to degree programs instead of diploma courses. Across all programs, enrolment dropped during COVID-19 (2020–2021) and then slowly recovered, showing that the pandemic affected all programs. For example, BS in Information Technology dropped during COVID-19 but recovered afterward, while BS in Fisheries stayed relatively stable.

New programs show mixed growth. Bachelor of Public Administration increased strongly, BS in Business Administration and BS in Computer Applications increased slowly, while BS in Food Technology remains low because it is still newly offered. Older programs in humanities, math, and statistics show stable but moderate or low enrolment, meaning they still attract students but are not dominant. Diploma programs show mixed patterns, with some declining and others fluctuating due to changes in student preferences and competition from degree programs.

Graduate programs have lower enrolment overall because they have smaller class sizes. Established graduate programs show moderate growth, while newer ones like MS Education, MS Marine Biology, PhD in Education Management, and MA Islamic Education remain low since they are still developing and have limited student enrollees.

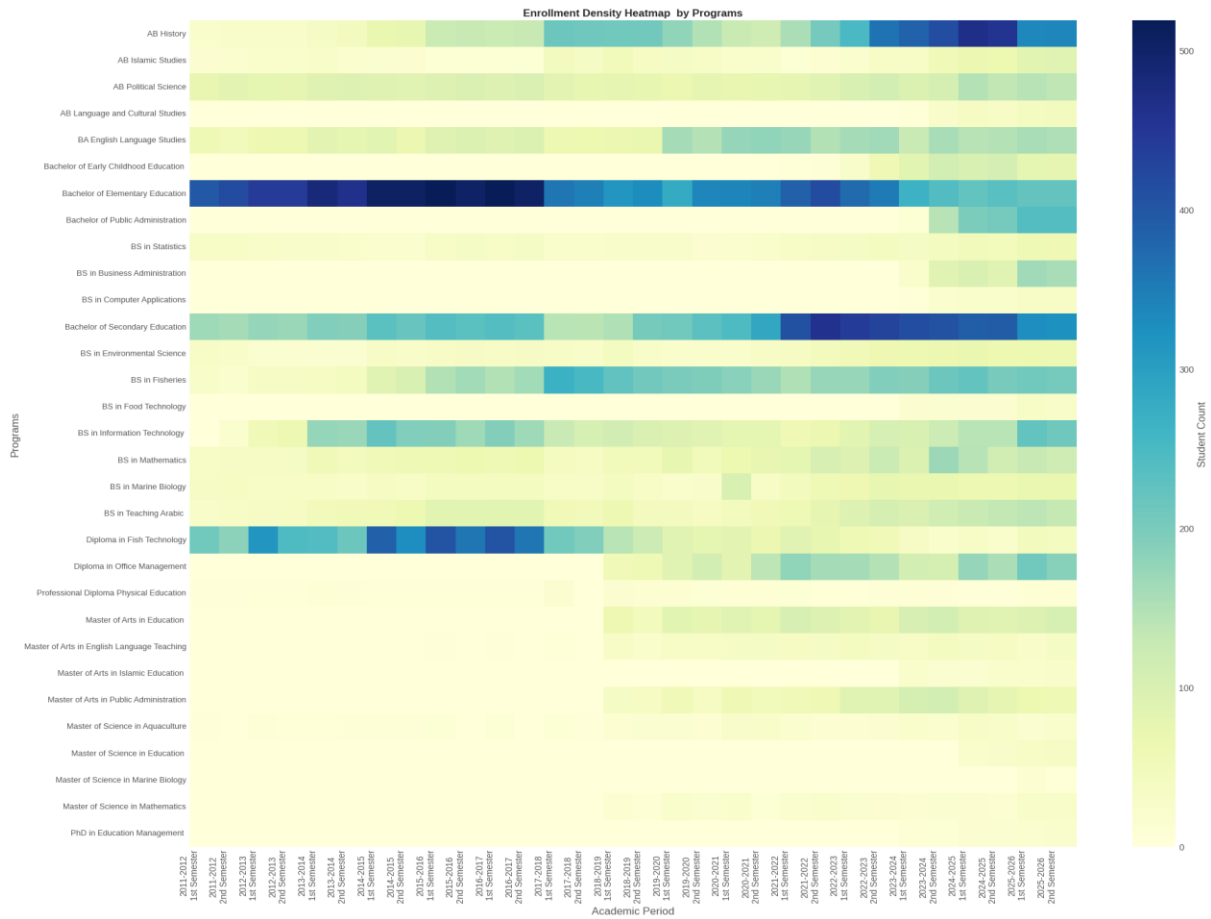


Fig. 3. Enrolment density by program.

E. Model Evaluation Results

The results, presented in Table III, reveal substantial differences in forecasting accuracy across enrollment categories and academic programs. Five of the 34 evaluated enrolment series achieved MAPE values below 10%. This threshold was used solely as a descriptive reference for comparing forecasting performance and was not applied as a criterion for selecting or excluding forecasting models. Female enrollment (Trend=None, Seasonality=None, Damped Trend=False) obtained the lowest MAPE of 4.42%, followed by overall enrollment (Trend=None, Seasonality=None, Damped Trend=False) with a MAPE of 4.57%, male enrollment (Trend=None, Seasonality=Add, Damped Trend=False) with a MAPE of 4.95%, BS in Fisheries (Trend=None, Seasonality=Add, Damped Trend=False) with a MAPE of 8.92%, and Bachelor of Elementary Education (Trend=None, Seasonality=None, Damped Trend=False) with a MAPE of 9.19%. These findings suggest that the selected Holt-Winters models were comparatively effective in forecasting enrollment for these categories. The relatively low MAPE values for overall, male, and female enrollment may be attributed to the aggregation of enrollment observations across multiple academic programs. Aggregated data can reduce the influence of program-specific fluctuations, potentially producing more stable enrollment patterns that are easier for time-series models to capture.

TABLE III. ROLLING-WINDOW FORECASTING PERFORMANCE ACROSS ENROLLMENT CATEGORIES AND ACADEMIC PROGRAMS

Target / Academic Program	RMSE	MAE	R ²	MAPE (%)
Female	123.83	78.16	0.453	4.42
Overall Sum	192.88	129.77	0.6251	4.57
Male	77.14	53.12	0.7294	4.95
BS in Fisheries	19.99	16.21	0.1049	8.92
Bachelor of Elementary Education	37.75	28.77	0.7462	9.19
AB Political Science	16.54	12.24	0.4846	10.49
BS in Teaching Arabic	12.21	10.44	0.7455	10.56
BS in Environmental Science	7.23	5.44	0.4672	10.65
Bachelor of Secondary Education	56.59	43.15	-0.7848	10.81
BA English Language Studies	22.49	16.24	-2.249	11.19
BS in Statistics	6.19	5.22	0.5679	12.4
Master of Arts in Education	15.6	13.13	-1.299	14.26
Master of Arts in English Language Teaching	6.31	4.78	-2.3724	14.71

BS in Marine Biology	4.28	1.67	-0.1314	87.19
AB History	64.68	51.01	0.5739	16.83
Master of Arts in Public Administration	17.2	14.34	0.1708	18.94
Diploma in Office Management	36.83	33.53	-0.4358	21.25
BS in Mathematics	36.12	27.9	-1.0738	23.85
BS in Information Technology	32.86	26.76	0.6151	24.5
Master of Science in Mathematics	6.95	5.52	-1.0247	28.31
Diploma in Fish Technology	14.75	12.16	0.458	29.13
AB Islamic Studies	13.04	10.29	0.7727	30.33
Master of Science in Aquaculture	7.32	6.06	-0.9929	33.56
Master of Arts in Islamic Education	8.94	4.64	0.302	36.78
PhD in Education Management	4.55	2.57	0.7263	37.01
Bachelor of Early Childhood Education	17.92	13.76	0.7763	38.47
BS in Food Technology	8.13	4.86	0.4288	43.21
Bachelor of Public Administration	54.18	31.79	0.7326	46.1
Master of Science in Education	9.81	4.58	0.5184	49.38
AB Language and Cultural Studies	10.97	6.79	0.6189	51.81
BS in Computer Applications	8.48	5.73	0.5318	53.92
BS in Business Administration	41.13	28.3	0.5707	57.22
Professional Diploma Physical Education	3.89	3.22	-1.1174	63.99
Master of Science in Marine Biology	4.28	1.67	-0.1314	87.19

Among individual academic programs, their performance may indicate relatively consistent enrollment patterns or trends that are adequately represented by the Holt-Winters model. Nevertheless, their R^2 values differed considerably. BS in Fisheries obtained an R^2 of 0.1049, whereas Bachelor of Elementary Education achieved an R^2 of 0.7462. This difference indicates that a low percentage forecasting error does not necessarily correspond to a high R^2 value.

In contrast, several academic programs exhibited substantially higher percentage forecasting errors. Master of Science in Marine Biology recorded the highest MAPE of 87.19%, followed by Professional Diploma Physical Education with a MAPE of 63.99%, BS in Business Administration with a MAPE of 57.22%, BS in Computer Applications with a MAPE of 53.92%, and AB Language and Cultural Studies with a MAPE of 51.81%. These findings indicate that the selected Holt-Winters models were less effective in minimizing percentage forecasting errors for these programs.

One possible explanation for the poor performance is the sensitivity of MAPE to small actual enrollment values. Hyndman and Koehler [11] identified an important limitation of percentage-based forecasting metrics, particularly when actual observations approach zero. Because MAPE divides the absolute forecasting error by the actual observation, even a small

difference between forecasted and observed values can result in a disproportionately large percentage error.

This limitation may explain the results for Master of Science in Marine Biology, which recorded a MAPE of 87.19% despite having an MAE of only 1.67 students and an RMSE of 4.28 students. Similarly, Professional Diploma Physical Education obtained a MAPE of 63.99% with an MAE of only 3.22 students. These findings suggest that the high percentage errors may be partly associated with small actual enrollment values rather than consistently large deviations in student counts.

Another possible factor is the presence of irregular enrollment patterns or abrupt changes that cannot be adequately represented by the level, trend, and seasonal components of Holt-Winters models. Exponential smoothing methods primarily rely on historical patterns to generate future estimates [4]. Therefore, sudden increases or decreases in enrollment, particularly those associated with changes in admission policies, program offerings, student preferences, or institutional circumstances, may reduce forecasting accuracy.

Additionally, several programs obtained negative R^2 values, including BA English Language Studies with an R^2 value of -2.2490, Master of Arts in English Language Teaching with an R^2 value of -2.3724, and BS in Marine Biology with an R^2 value of -1.6084. These values indicate that the models produced greater squared prediction errors than a constant prediction based on the mean of the evaluated observations. Such results suggest that the models did not adequately capture the observed enrollment variations during the test periods.

The findings also highlight the importance of using multiple metrics to assess forecasting accuracy. For instance, Bachelor of Public Administration with an R^2 of 0.7326 and a MAPE of 46.10% and Bachelor of Early Childhood Education with an R^2 of 0.7763 and a MAPE of 38.47% demonstrated relatively high R^2 values despite substantial percentage errors. Hyndman and Koehler [5] emphasized the limitations of individual accuracy measures and recommended complementary metrics such as MASE. Furthermore, differences in enrollment size may affect MAPE interpretation, as demonstrated by overall enrollment with a MAE of 129.77 and a MAPE of 4.57% and MS Marine Biology with a MAE of 1.67 and a MAPE of 87.19%. These results emphasize the need to consider both percentage errors and absolute forecasting errors when evaluating model performance.

F. Enrolment Forecast

The Holt-Winters forecasting results as shown in Table IV present the projected student enrollment across academic programs for the first and second semesters of AY 2026–2027 and the first semester of AY 2027–2028. The overall enrollment is projected at 3,519 students in the first semester of AY 2026–2027, followed by a decrease to 3,375 in the second semester and an increase to 3,633 in the first semester of AY 2027–2028. This pattern suggests a possible semester-based fluctuation in enrollment, with higher enrollment during the first semesters.

Female enrollment is projected to remain higher than male enrollment throughout the forecast periods. Female enrollment is expected to range from 2,071 to 2,211 students, while male enrollment is projected between 1,304 and 1,422 students. These

findings suggest the continued predominance of female students, which may be considered in institutional planning and the allocation of student support services.

TABLE IV. FUTURE ENROLMENT FORECASTS ACROSS ACADEMIC PROGRAMS AND DEMOGRAPHICS

Target / Academic Program	Future Semester	Lower Bound (Approx.)	Forecasted Students	Upper Bound (Approx.)
AB History	2026-2027 1st Sem	267	346	424
	2026-2027 2nd Sem	245	356	468
	2027-2028 1st Sem	229	365	501
AB Islamic Studies	2026-2027 1st Sem	75	94	113
	2026-2027 2nd Sem	70	96	123
	2027-2028 1st Sem	70	102	134
AB Political Science	2026-2027 1st Sem	120	140	161
	2026-2027 2nd Sem	114	143	172
	2027-2028 1st Sem	109	144	180
AB Language and Cultural Studies	2026-2027 1st Sem	37	47	57
	2026-2027 2nd Sem	36	50	64
	2027-2028 1st Sem	38	55	72
BA English Language Studies	2026-2027 1st Sem	117	161	204
	2026-2027 2nd Sem	97	158	219
	2027-2028 1st Sem	90	165	240
Bachelor of Early Childhood Education	2026-2027 1st Sem	42	59	76
	2026-2027 2nd Sem	37	61	85
	2027-2028 1st Sem	16	45	74
Bachelor of Elementary Education	2026-2027 1st Sem	135	210	285
	2026-2027 2nd Sem	108	214	320
	2027-2028 1st Sem	74	204	334
Bachelor of Public Administration	2026-2027 1st Sem	201	250	299
	2026-2027 2nd Sem	190	259	328
	2027-2028 1st Sem	179	264	349
BS in Statistics	2026-2027 1st Sem	50	61	72

	2026-2027 2nd Sem	46	62	77
	2027-2028 1st Sem	44	63	82
BS in Business Administration	2026-2027 1st Sem	162	195	229
	2026-2027 2nd Sem	170	218	265
	2027-2028 1st Sem	188	247	305
BS in Computer Applications	2026-2027 1st Sem	26	32	38
	2026-2027 2nd Sem	24	33	42
	2027-2028 1st Sem	23	34	45
Bachelor of Secondary Education	2026-2027 1st Sem	254	326	398
	2026-2027 2nd Sem	228	330	432
	2027-2028 1st Sem	208	332	457
BS in Environmental Science	2026-2027 1st Sem	53	65	76
	2026-2027 2nd Sem	49	65	82
	2027-2028 1st Sem	46	67	87
BS in Fisheries	2026-2027 1st Sem	162	212	262
	2026-2027 2nd Sem	138	209	280
	2027-2028 1st Sem	129	216	303
BS in Food Technology	2026-2027 1st Sem	26	33	40
	2026-2027 2nd Sem	25	35	45
	2027-2028 1st Sem	28	40	52
BS in Information Technology	2026-2027 1st Sem	189	242	295
	2026-2027 2nd Sem	168	243	318
	2027-2028 1st Sem	175	267	359
BS in Mathematics	2026-2027 1st Sem	94	129	164
	2026-2027 2nd Sem	85	134	183
	2027-2028 1st Sem	75	135	195
BS in Marine Biology	2026-2027 1st Sem	45	72	99
	2026-2027 2nd Sem	29	68	106
	2027-2028 1st Sem	28	75	122
BS in Teaching Arabic	2026-2027 1st Sem	112	134	155

	2026-2027 2nd Sem	106	137	167
	2027-2028 1st Sem	103	140	178
Diploma in Fish Technology	2026-2027 1st Sem	0	48	148
	2026-2027 2nd Sem	0	40	182
	2027-2028 1st Sem	0	48	222
Diploma in Office Management	2026-2027 1st Sem	155	203	251
	2026-2027 2nd Sem	134	202	270
	2027-2028 1st Sem	132	215	298
Master of Arts in Education	2026-2027 1st Sem	83	111	140
	2026-2027 2nd Sem	69	109	149
	2027-2028 1st Sem	68	118	167
Master of Arts in English Language Teaching	2026-2027 1st Sem	18	30	42
	2026-2027 2nd Sem	19	36	53
	2027-2028 1st Sem	11	32	53
Master of Arts in Islamic Education	2026-2027 1st Sem	19	28	36
	2026-2027 2nd Sem	17	29	41
	2027-2028 1st Sem	17	32	46
Master of Arts in Public Administration	2026-2027 1st Sem	42	64	86
	2026-2027 2nd Sem	30	61	92
	2027-2028 1st Sem	29	67	105
Master of Science in Aquaculture	2026-2027 1st Sem	17	26	36
	2026-2027 2nd Sem	11	24	37
	2027-2028 1st Sem	12	28	44
Master of Science in Education	2026-2027 1st Sem	33	41	48
	2026-2027 2nd Sem	34	45	55
	2027-2028 1st Sem	37	50	63
Master of Science in Marine Biology	2026-2027 1st Sem	1	6	10
	2026-2027 2nd Sem	0	5	12
	2027-2028 1st Sem	0	6	14
Master of Science in Mathematics	2026-2027 1st Sem	21	29	38

	2026-2027 2nd Sem	15	28	40
	2027-2028 1st Sem	16	31	46
PhD in Education Management	2026-2027 1st Sem	22	25	29
	2026-2027 2nd Sem	22	27	32
	2027-2028 1st Sem	23	29	35
Professional Diploma Physical Education	2026-2027 1st Sem	3	10	17
	2026-2027 2nd Sem	0	7	17
	2027-2028 1st Sem	0	10	22
Male	2026-2027 1st Sem	1224	1381	1538
	2026-2027 2nd Sem	1082	1304	1526
	2027-2028 1st Sem	1150	1422	1695
Female	2026-2027 1st Sem	1900	2139	2377
	2026-2027 2nd Sem	1734	2071	2408
	2027-2028 1st Sem	1798	2211	2624
Overall Sum	2026-2027 1st Sem	3129	3519	3910
	2026-2027 2nd Sem	2823	3375	3927
	2027-2028 1st Sem	2957	3633	4309

At the program level, AB History, Bachelor of Secondary Education, Bachelor of Public Administration, and BS in Information Technology are among the programs with relatively high projected enrollment. AB History is expected to increase from 346 to 365 students, while BS in Information Technology is projected to increase from 242 to 267 students between the first semesters of the two academic years. BS in Business Administration also shows a notable projected increase from 195 to 247 students. These trends may indicate potential areas of enrollment growth that warrant consideration in planning faculty assignments, classroom utilization, and instructional resources.

Conversely, several graduate and diploma programs show relatively low projected enrollment. Master of Science in Marine Biology is expected to maintain approximately five to six students, while Professional Diploma Physical Education is projected to have seven to ten students. Although the projected enrollment remains low, these programs may require further assessment to determine appropriate resource allocation and program sustainability.

The forecast intervals also indicate increasing uncertainty over longer forecasting horizons. For instance, the overall enrollment interval widens from approximately 3,129–3,910 students in the first semester of AY 2026–2027 to 2,957–4,309 students in the first semester of AY 2027–2028. This widening

suggests that longer-term projections should be interpreted cautiously, particularly when used for institutional decision-making.

Overall, the forecasting results provide preliminary estimates that may support enrollment planning and future resource allocation. However, considering the differences in model accuracy identified during rolling-window evaluation, particularly among programs with higher MAPE values, the forecasts should be interpreted alongside historical enrollment trends and other relevant institutional factors. Programs with relatively lower forecasting errors may provide more useful planning estimates, while those exhibiting greater uncertainty require cautious interpretation and further validation.

V. CONCLUSION AND RECOMMENDATIONS

This study applied grid-based structural model selection with Holt-Winters Exponential Smoothing to forecast student enrollment at Mindanao State University–Tawi-Tawi College of Technology and Oceanography (MSU-TCTO) using historical enrollment records from AY 2011–2012 to AY 2025–2026. The findings revealed an overall increasing enrollment trend with fluctuations associated with curriculum reforms, the COVID-19 pandemic, and changes in academic program offerings. Female enrollment consistently exceeded male enrollment, while enrollment patterns varied considerably across academic programs, highlighting the importance of program-specific forecasting for institutional planning.

The rolling-window evaluation demonstrated varying forecasting accuracy across 34 enrollment categories and academic programs. Five targets achieved MAPE values below 10%, with female enrollment recording the lowest error (4.42%), followed by overall enrollment (4.57%), male enrollment (4.95%), BS in Fisheries (8.92%), and Bachelor of Elementary Education (9.19%). However, several programs exhibited higher forecasting errors, potentially due to irregular enrollment patterns, limited historical observations, and the sensitivity of MAPE to small enrollment populations. These findings emphasize the importance of using multiple accuracy metrics when evaluating forecasting performance.

The forecasting results projected overall enrollment of 3,519, 3,375, and 3,633 students for the first semester of AY 2026–2027, second semester of AY 2026–2027, and first semester of AY 2027–2028, respectively. These projections suggest continued semester-based fluctuations and potential growth in selected academic programs. The generated forecasts may serve as supplementary references for institutional planning, particularly in faculty deployment, classroom utilization, scholarship planning, and resource allocation. However, programs exhibiting higher forecasting errors and wider forecast bounds require cautious interpretation and further assessment before the projections are used in institutional decision-making.

Based on these findings, it is recommended that MSU-TCTO periodically update and reevaluate its forecasting models as new enrollment data become available. Future studies may compare Holt-Winters Exponential Smoothing with alternative forecasting approaches, such as ARIMA and seasonal naïve models, and incorporate additional evaluation metrics, including

Mean Absolute Scaled Error (MASE). Furthermore, considering external factors such as admission policies, curriculum changes, program openings, student retention, and demographic trends may improve the interpretation of enrollment fluctuations. Future research should also evaluate prediction interval coverage to strengthen uncertainty assessment. These improvements may contribute to more reliable enrollment forecasting and support evidence-based institutional planning and sustainable resource management.

VI. DECLARATIONS

The authors hereby declare that ChatGPT and Google Gemini were used solely to assist with drafting and language refinement, including improving grammar, clarity, sentence structure, and readability. These tools were not used to generate research data, perform analysis, formulate conclusions, or replace the authors' original intellectual work. All authors reviewed, verified, and approved the final content and collectively assume full responsibility for its accuracy, originality, and integrity.

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