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Optimizing Holt-Winters Exponential Smoothing Parameters for Construction Cost Index Forecasting with PSO and Walk-Forward Cross-Validation

İnşaat Maliyet Endeksi Tahmininde Holt-Winters Üstel Düzeltme Parametrelerinin PSO ve İleri Walk-Forward Cross-Validation ile Optimizasyonu

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ÖZ

Bu çalışmada, İnşaat Maliyet Endeksi (CCI) tahmininde Holt-Winters Üstel Düzeltme Parametrelerinin Parçacık Sürü Optimizasyonu (PSO) ve Walk-Forward Cross-Validation (WFCV) ile optimizasyonu yoluyla, Ortalama Mutlak Yüzde Hatasını (MAPE) en aza indirmeye odaklanılarak, tahminin doğruluğunu artırmak amaçlanmaktadır. Bu amaca ulaşmak için, Holt-Winters model parametreleri PSO ve WFCV ile optimize edilmiştir. Bir metasezgisel optimizasyon algoritması olan PSO, sırasıyla geçmiş gözlemlerin, eğilimlerin ve mevsimselliğin ağırlığını belirleyen yumuşatma parametrelerinin (alfa, beta ve gama) optimal değerlerini aramak için uygulanmaktadır. WFCV, modelin performansını değerlendirir ve sağlamlığı sağlar. CCI tahminleri için 22'ye ve eğitim verileri için 2'ye düşürülen MAPE'ler, çalışmada optimize edilmiş Holt-Winters modelinin bulgularıdır. Elde edilen alfa, beta ve gama değerleri sırasıyla 0.99, 0.77 ve 0'dır ve mevsimselliğin ihmal edilmesinin önemini vurgulamaktadır. Yakınsama grafikleri, optimizasyon yaklaşımının geleneksel parametre değerleri veya rastgele seçimlere göre üstünlüğünü gösterir. Sonuçlar, Holt-Winters modeli, PSO ve WFCV kullanılarak hassas CCI tahmini için verimli bir şekilde hesaplanmıştır. Optimize edilmiş parametre değerleri, inşaat projesi maliyet tahmini ve bütçe yönetiminde bilinçli karar vermeye yardımcı olabilir niteliktedir. Bu çalışmanın, CCI tahmini için güvenilir ve sağlam bir optimizasyon metodolojisine katkıda bulunarak alandaki ilerlemeleri desteklediği düşünülmektedir.

Anahtar Kelimeler: İnşaat Maliyet Endeksi, Holt-Winters, Walk Forward Cross-Validation, Particle Swarm Optimization, Parametre Optimizasyonu

ABSTRACT

This research aims to enhance the accuracy of Construction Cost Index (CCI) forecasting using Holt-Winters exponential smoothing (ES) by optimizing its parameters, focusing on minimizing the Mean Absolute Percentage Error (MAPE) for precise CCI forecasts. To reach this aim, The Holt-Winters model parameters are optimized through Particle Swarm Optimization (PSO) and Walk-Forward Cross-Validation (WFCV). PSO, a metaheuristic optimization algorithm, is being applied to search for optimal values of the smoothing parameters (alpha, beta, and gamma) that determine the weightage of past observations, trends, and seasonality, respectively. WFCV assesses the model's performance and ensures robustness. Reduced MAPEs of 22 for CCI forecasts and 2 for training data are the findings of the optimized Holt-Winters model. The obtained alpha, beta, and gamma values are 0.99, 0.77, and 0, respectively, highlighting the importance of while neglecting seasonality. Convergence graphs demonstrate the superiority of the optimization approach over conventional parameter values or random selections. By employing PSO and WFCV, the study efficiently fine-tunes the Holt-Winters model for precise CCI forecasting. Optimized

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parameter values enable data driven decision-making in construction project cost estimation and budget management. This research contributes a reliable and robust optimization methodology for CCI forecasting, supporting advancements in the field.

Keywords: Construction Cost Index, Holt-Winters, Forward Cross-Validation, Particle Swarm Optimization, Parameter Optimization, Metaheuristics

INTRODUCTION:

The Construction Cost Index (CCI) plays an important role in the construction industry, helping in project cost estimation, inflation adjustments, and precise budgeting. It also guides resource allocation, project planning, and financial reporting while keeping track of cost changes influenced by economic factors to manage risks effectively (Liu et al., 2021). Within the construction sector, the CCI serves as a significant metric, assessing cost trends and facilitating estimation and budgeting endeavours (Velumani & Nampoothiri, 2021). Ensuring accurate forecasts of the CCI is useful for cost estimators and contractors, enabling them to create precise bids and steer clear of under or overestimations (Ashuri & Lu, 2010).

Nevertheless, the reliability and validity of the CCI pose notable implementation challenges in the industry. These challenges have the potential to impact the accuracy of cost predictions (Choi et al., 2021). The CCI might not fully reflect local variations in construction costs, necessitating adjustments to factor in specific regional circumstances (Zhan et al., 2021). Additionally, the CCI may not comprehensively consider the influence of macroeconomic elements on construction expenses, prompting the exploration of other economic indicators to enhance cost predictions (Fachrurrazi, 2016).

This study aims to improve the accuracy of CCI estimates. The research question focuses on how integrating PSO with the Holt-Winters ES model besides WFCV can enhance the precision of CCI forecasts by minimizing the MAPE. The research's importance is in its potential to offer stakeholders a more accurate tool for cost estimation and management. Improved CCI forecasts empower data driven decision, optimize resource allocation, and enhance risk management, thereby benefiting the planning and execution of construction projects.

The scheme of the study is as follows:

Literature Review: A thorough exploration of existing literature concerning CCI forecasting, with a focus on methodologies and techniques aimed to increase the accuracy of forecasts. Methodology: A comprehensive explanation of the research design, data sources, and the proposed optimization framework. Methodology section explains the combination of PSO and WFCV into the Holt-Winters model. Results and Discussion: The presentation and examination of findings resulting from the optimization process. This section illustrates the impact of the combined approach on the precision of CCI forecasts and discussing on the implications of these findings. Conclusion: A synthesis of the study's contributions to the domain of CCI forecasting and the management of construction projects.

By addressing the fundamental research question, this study contributes to the progression of cost estimation and project management within the construction industry as acting like a bridge between theoretical models and practical applications.

1. Literature Review

The CCI plays a multifaceted role within the construction sector, functioning as a versatile tool with various applications, including project cost estimation, inflation adjustment, and meticulous budgeting (Tey et al., 2015). Its utility extends to encompass resource allocation, project planning, and the realm of financial reporting. Furthermore, the CCI assumes a pivotal role in the monitoring of cost fluctuations to economic variables, thus enabling the facilitation of astute risk management strategies (Ashuri & Shahandashti, 2012). The CCI also serves as a metric that effectively captures the shifts in prices of construction items over time, thereby allows both project owners and contractors to view the fluctuations within the construction market's landscape (Liu et al., 2021). Furthermore, the CCI assumes an additional role as a business cycle indicator, contributing to crucial tasks such as budget formulation, cost modelling, and the complicated process of cost projection in various phases of construction projects (Tey et al., 2015).

CCI is useful for potential enhancements in the areas of construction cost estimation and cost performance (Tey et al., 2015). This index is pivotal in forecasting the future movements of the CCI, an important undertaking for activities like budget planning and contract bidding (Choi et al., 2021). Another valuable application is in exploring the interplay between macroeconomic elements and construction costs, thereby observing a more comprehensive comprehension of fluctuations in construction costs within the larger economy (Ashuri & Shahandashti, 2012). Notably, the CCI serves as a yardstick for assessing unit price offers in competitive bidding, paralleling the scrutiny of contractual unit prices (Fachrurrazi, 2016).

Various forecasting models and techniques have been used to predict the CCI, encompassing linear forecasting models, ES methodologies such as Holt ES and Holt-Winters ES, multivariate time series models, and smoothing techniques (Choi et al., 2021; 2010; Velumani & Nampoothiri, 2021). These models draw insights from historical data and the intrinsic attributes of the CCI to systematic forecasts (Velumani & Nampoothiri, 2021).

The predictability of these models is diverse, with certain models showcasing superior accuracy for in-sample or out-of-sample forecasting scenarios. For instance, the Seasonal Autoregressive Integrated Moving-Average (SARIMA) model emerges as exceptionally accurate for in-sample CCI forecasting, while the Holt-Winters ES model excels in out-of-sample scenarios (Ashuri and Lu, 2010).

A good example is provided by the article titled "Predicting ENR Construction Cost Index Using Machine-Learning Algorithms," authored by Wang and Ashuri, which explains the analysis of the Engineering News-Record (ENR) CCI using the Holt-Winters method. The study seeks to determine optimal parameter values for the Holt-Winters model, thereby elevating the precision of CCI forecasting. Observing data from January 1960 to December 2008, the authors systematically compare the performance of the Holt-Winters method with other time series models. The findings underscore the superior efficacy of the Holt-Winters method in terms of forecast accuracy, warranting its endorsement for CCI forecasting. The study emphasizes the importance of parameter optimization in reaching precise and dependable forecasts (Wang & Ashuri, 2017).

Similarly, the article titled "Time Series Analysis of Building Construction Cost Index in Türkiye," authored by Aydınlı, focuses on the analysis of the CCI in Turkey using the Holt-Winters method. The research objective mirrors that of Wang and Ashuri's study, aiming to pinpoint optimal parameter values for the Holt-Winters model to enhance CCI forecasting accuracy. Analysing data from January 2005 to December 2019, the author examines the performance of the Holt-Winters method vis-à-vis alternative time series models. The outcomes prove the supremacy of the Holt-Winters method in terms of forecast accuracy, thereby advocating for its adoption in CCI forecasting endeavours (Aydınlı, 2022).

Furthermore, the article titled "Predicting City-Level Construction Cost Index Using Linear Forecasting Models," written by Choi, Ryu, and Shahandashti (2021), examines linear forecasting models to predict the CCI at the city level. The study's noteworthy discovery is in the superior performance of their developed ES models when juxtaposed with forecasts made by experts. The potential implications of these models extend to the increasing cost estimation and project budgeting use within the construction industry, potentially leading to more precise bids and reduced construction costs (Choi et al., 2021).

Ashuri and Lu (2010) contribute to this discourse through their study centered on the ENR Construction Cost Index, employing time series analysis. The researchers develop forecasting models for the CCI, leveraging two ES methods: Holt ES and Holt-Winters ES. The study's findings underscore the superior predictability of the developed Holt ES model when compared to forecasts crafted by ENR experts. The practical implications of these findings are pivotal for the construction industry, enable contractors the ability to formulate more accurate estimates and empowering owners to more effectively budget for construction projects (Ashuri & Lu, 2010).

A parallel research by Joukar and Nahmens (2016) uses two ES methods, namely Holt ES and Holt-Winters ES, to examine the underlying attributes of CCI data and make craft systematic forecasts. The study highlights the enhanced predictability of the developed Holt ES model in contrast to forecasts made by ENR experts. This observation increases the value of this model in refining cost estimations for contractors and enhancing budget planning for owners (Joukar & Nahmens, 2016).

Another contribution by Velumani and Nampoothiri (2021) revolves around the development of two ES models aimed at forecasting the volatility of the Construction Industry Development Council CCI. In this endeavour, Holt ES and Holt-Winters ES methodologies are applied. Notably, the predictability of both models surpasses that of forecasts produced by ENR subject matter experts. This finding positions the developed Holt ES model as a tool to make more precise estimates for contractors and owners, ultimately contributing to the reduction of construction costs through well-timed project execution (Velumani & Nampoothiri, 2021).

In the article titled "Forecasting Engineering News-Record Construction Cost Index Using Multivariate Time Series Models," authored by Shahandashti and Ashuri (2013), time series analysis is enlisted to construct CCI forecasting models, with a focus on Holt ES and Holt-Winters ES methodologies. The enhanced ES models outperform the forecasts generated by ENR experts. The study underscores the significance of accurate CCI forecasting and highlights the potency of time series analysis, particularly the Holt ES method, in achieving this end (Shahandashti & Ashuri, 2013).

In the area of predictive models, the Holt model emerges as a robust tool for forecasting the CCI, boasting a mean R-Squared coefficient of 98% and a MAPE of 0.217% (Jiang, Awaitey, & Xie, 2022). As evidenced by a study conducted by Jiang et al. (2022), the Holt model demonstrates exceptional predictive capabilities with a mean R-Squared coefficient of 98% and a MAPE of 0.217%. This finding underscores the reliability of the Holt model in predicting the CCI and positions it as a reliable forecasting mechanism. Moreover, the independent variables exhibit an overall R-squared of 84.7%, underscoring the model's efficacy in terms of fit, with a corresponding MAPE of 5.5%, further accentuating its suitability for subsequent analysis (Jiang et al., 2022).

Parallel to this discourse, Particle Swarm Optimization (PSO) is a versatile optimization technique renowned for its adaptability, ease of implementation, and applicability across diverse domains. The tutorial by Marini and Walczak (2015) highlights PSO's vast potential and aims to encourage broader interest and adoption of this technique within the field (Marini & Walczak, 2015).

Cross-validation is a widely used data resampling method to assess the generalization ability of a predictive model and to prevent overfitting. The purpose of cross-validation is to estimate the true prediction error of a model by evaluating its performance on an independent data set. Overfitting occurs when a model is too complex and fits the training data too closely, resulting in poor performance on new data. Cross-validation prevents overfitting by evaluating the model's performance on multiple independent data sets, which helps to ensure that the model is not just fitting the noise in the training data. By estimating the true prediction error of a model, cross-validation can help to select the best model and tune its parameter (Berrar, 2019).

2. Methodology

This research adopts an empirical approach to enhance the accuracy of CCI forecasting using the Holt-Winters ES method. The study utilizes a combination of quantitative data analysis and optimization techniques to achieve the research objectives.

The data employed in this study originates from the Turkish Statistical Institute, specifically the dataset relating to the Construction Cost Index (CCI). This dataset serves to monitor alterations in construction costs, encompassing both labour and materials, thus giving valuable insights for the area of forecasting. The data is collected at regular intervals on a monthly basis, encompassing the geographic scope of Turkey.

The tasks involving data analysis and optimization are carried out through the employment of the Anaconda platform, offering a comprehensive array of tools tailored for data science purposes. To facilitate the development and execution of the research code, the Python programming language is employed in conjunction with JupyterLab.

For the purpose of forecasting the CCI, the Holt-Winters model, well-regarded for its proficiency in time series prediction, is used. This model incorporates additive trend and seasonal components. By configuring the gamma parameter to 0, the emphasis is redirected towards capturing the trend and level components, while minimizing consideration of seasonality. This strategic decision provides several advantages within the area of construction cost forecasting. Primarily, the disregard for seasonality increases the model's interpretability and its explanatory prowess and provides a deeper comprehension of construction cost dynamics. Moreover, this simplification contributes to increased model stability, particularly when grappling with noisy or sporadically recorded data. The resulting reduction in intricacies and uncertainties during the estimation process creates a more robust and dependable forecasting methodology. Additionally, the decreased reliance on seasonality streamlines both the implementation and maintenance of the model, rendering it more manageable and less susceptible to issues of overfitting or underfitting. Ultimately, the accentuation of trend and level components ensures precise encapsulation of long-term growth and comprehensive cost trends, aligning harmoniously with the pragmatic requisites of construction cost management.

The MAPE is a metric that measures the average percentage deviation between forecasted and actual values. It provides a straightforward interpretation as a percentage and emphasizes relative forecast errors, making it suitable for comparing accuracy across diverse datasets. Additionally, MAPE effectively handles both positive and negative errors without cancellation. MAPE values can be interpreted as follows: 0 signifies a perfect forecast, 10 reflects excellent accuracy, 20 indicates good accuracy, 30 implies fair accuracy, 40 denotes moderate accuracy, and 50 suggests poor accuracy.

To optimize the Holt-Winters model's smoothing parameters (alpha, beta, and gamma), we employ the PSO algorithm. The PSO algorithm explores the parameter space using swarms of particles to find the optimal parameter values. The optimization process aims to minimize the MAPE and fine-tune the model for better forecasting accuracy.

The PSO optimization process employs the following objective function:

z = sqrt(mape_predicted * mape_forecasted).

The main aim is to minimize this function to derive the optimal values of alpha, beta, and gamma. The choice of using the product of mape_predicted and mape_forecasted in the objective function is driven by the intent to jointly consider the effect of prediction accuracy and forecasted accuracy during optimization. The objective extends beyond merely minimizing the prediction error (mape_predicted) to encompass the forecast quality (mape_forecasted) as well.

By using the product of these metrics, the objective function accentuates scenarios where both prediction accuracy and forecast accuracy are simultaneously enhanced. Suboptimal values in either metric will be reflected in the product, encouraging the optimization algorithm to explore parameter values that gives balanced and optimal outcomes for both mape_predicted and mape_forecasted. The square root operation moderates the influence of the product's magnitude, making it more comprehensible and facilitating interpretation.

Ultimately, minimizing the product of mape_predicted and mape_forecasted empowers the PSO algorithm to identify an advantageous combination of parameters, effectively balancing prediction accuracy and forecast accuracy. This fosters the overall effectiveness of the optimization process, thereby enhancing the performance of the algorithm for the given task.

The performance of the optimized Holt-Winters model is evaluated using WFCV. This validation method simulates real-world forecasting scenarios, where the last 12 available periods of the training dataset are used as the test dataset. The evaluation process ensures the reliability and robustness of the model's forecasting capabilities.

Table 1: Steps of Walk-Forward Cross-Validation on Dataset

Forward Cross Validation Step	**Train Data First Element**	**Train Data Last Element**	**Test Data First Elemet**	**Test Data Last Element**	**MAPE Predict Cumulative**	**MAPE Forecast Cumulative**
1	1	65	66	90	1.387005738	25.00819325
2	2	66	67	91	2.740810357	48.75804146
3	3	67	68	92	4.120194317	72.72975125
4	4	68	69	93	5.438001055	94.6843463
5	5	69	70	94	6.690759543	118.9291964
6	6	70	71	95	7.911263302	139.4237037
7	7	71	72	96	9.111404012	157.3117648
8	8	72	73	97	10.32296264	176.6915456
9	9	73	74	98	11.58103653	195.4634163
10	10	74	75	99	12.94014219	223.9324221
11	11	75	76	100	14.30999421	251.9198364
12	12	76	77	101	15.69411189	278.0107289
				Mean:	1.307842657	23.16756074
				Objective Function Value:		30.2995242

Table1 presents the sequential execution of the Forward Cross Validation process on the dataset, showcasing the systematic division of data into training and testing sets. Each row represents a unique step, providing a clear representation of how the model undergoes iterative training and evaluation on distinct subsets to assess its forecasting performance. The provided table encompasses multiple columns that offer crucial insights into each stage of the validation process.

Forward Cross Validation Step: This column denotes the iteration number within the Forward Cross Validation process, outlining the sequence of steps taken during both training and testing phases.

Train Data First Element: This column specifies the index of the initial data point in the training dataset for the present step. This index serves as the starting point of the subset utilized for training the model.

Train Data Last Element: This column displays the index of the final data point within the training dataset for the given step. It signifies the conclusion of the subset employed for training purposes.

Test Data First Element: This column indicates the index of the first data point in the test dataset corresponding to the current step. This index marks the initiation of the subset used to evaluate the model's predictions.

Test Data Last Element: This column showcases the index of the last data point in the test dataset relevant to the present step. It signifies the conclusion of the subset used for testing.

MAPE Predict Cumulative: In this column, the Holt-Winters model provides the Mean Absolute Percentage Error (MAPE) for each test subset. MAPE gauges the precision of the model's forecasts, representing the average percentage deviation between predicted and actual values.

MAPE Forecast Cumulative: This column accumulates the MAPE forecasts throughout the validation process, presenting a cumulative perspective on the model's predictive accuracy as the validation advances.

Table 1 encapsulates step numbers, training and testing data indices, and cumulative MAPE forecasts. The MAPE metric serves as a gauge of forecast accuracy. In essence, Table 1 offers an overview of the model's performance during validation, aiding in the assessment of its suitability for predicting the Construction Cost Index (CCI).

For the PSO optimization process, the following parameters are established: swarmsize=15 and maxiter=30. The PSO optimization involves variables such as alpha, beta, and gamma, which correspond to the smoothing parameters of the Holt-Winters model. To define the bounds for PSO optimization, the parameter bounds are specified as:Lower Bound: [0.001, 0.001, 0] and Upper Bound: [1, 1, 0]. These bounds delineate the scope of the search space within the optimization process.

The PSO optimization algorithm, represented by the minimize function, plays a crucial role in finding the optimal smoothing parameters to achieve the desired forecasting accuracy. The study employs the Holt-Winters ES model with additive trend and seasonal components. Notably, the model disregards seasonality (gamma=0) to enhance interpretability and stability.

In the methodology section, a comprehensive approach to optimizing the Holt-Winters model is described, including PSO and WFCV. This approach is discussed in order of data preprocessing, model optimization and performance evaluation. The intended objective is to provide reliable estimates for the Construction Cost Index (CCI).

3. **Results and Discussion**

The subsequent sections offer a comprehensive exploration of our research findings and their implications.

3.1 Principal Findings and Outcomes:

The optimized model demonstrated significantly reduced MAPE values of 22 for CCI forecasts and an impressively low MAPE of 2 for training data. The parameter values of alpha=0.99, beta=0.77, and gamma=0 underscored the significance of past observations and trends while disregarding seasonality.

3.2. Visualization and Interpretation:

Below, visual graphics obtained with the CCI forecast model are shown:

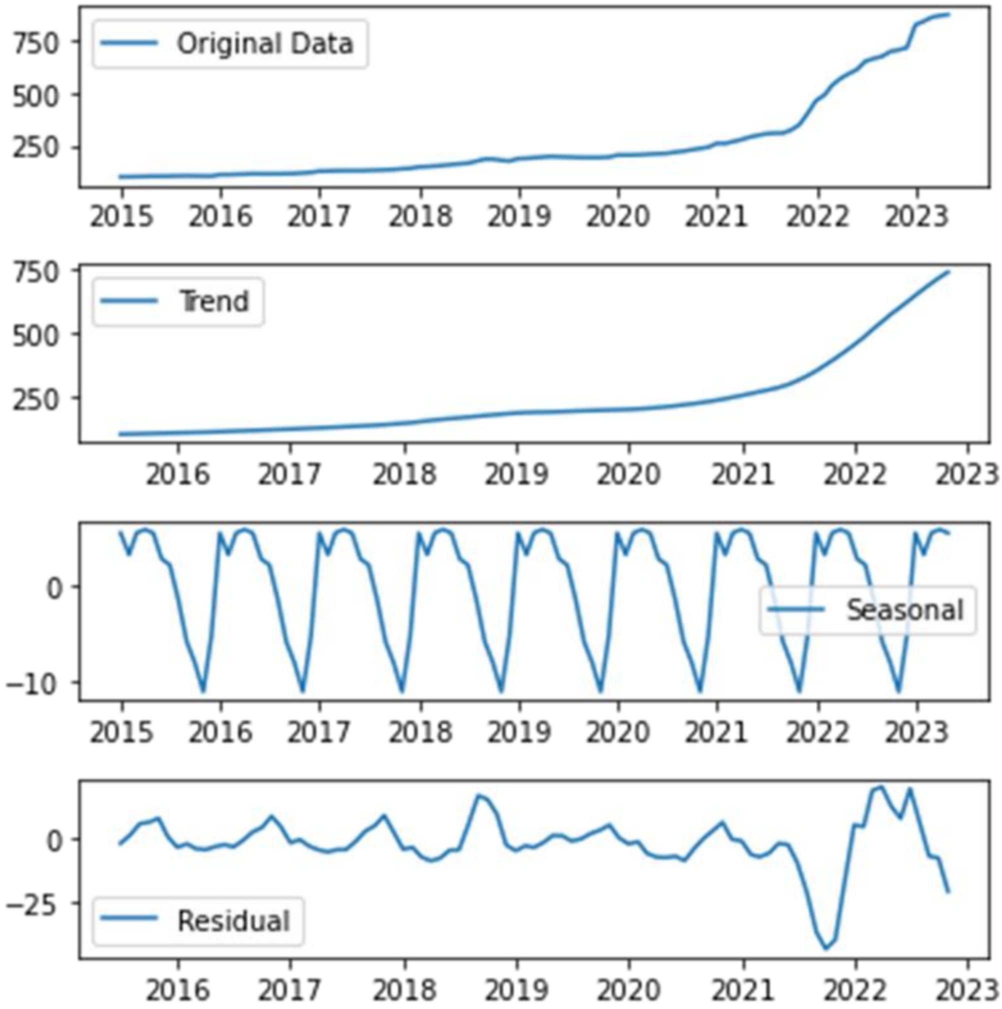

Figure 1: CCI Seasonal Trend Decomposition

This graph illustrates the Seasonal Trend Decomposition of the CCI. It dissects CCI into trend, seasonality, and residuals, enhancing the comprehension of underlying patterns and forecasting.

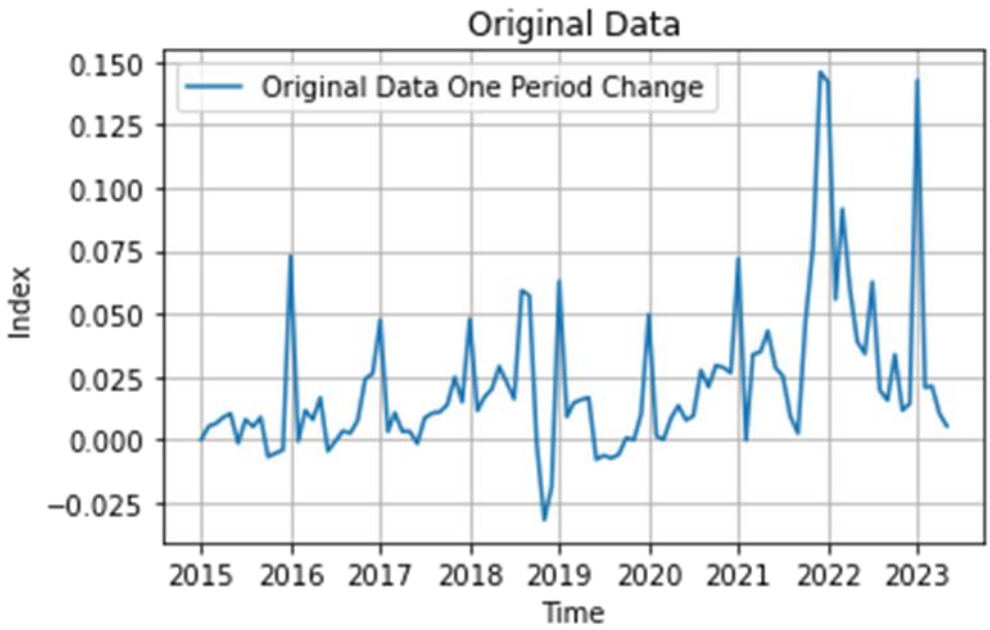

Figure 2: CCI One Period Change

Figure 2 displays the one-period change in CCI values over time, this graph visualizes the magnitude and direction of CCI fluctuations from one time period to the next, aiding the discernment of short-term trends and volatility.

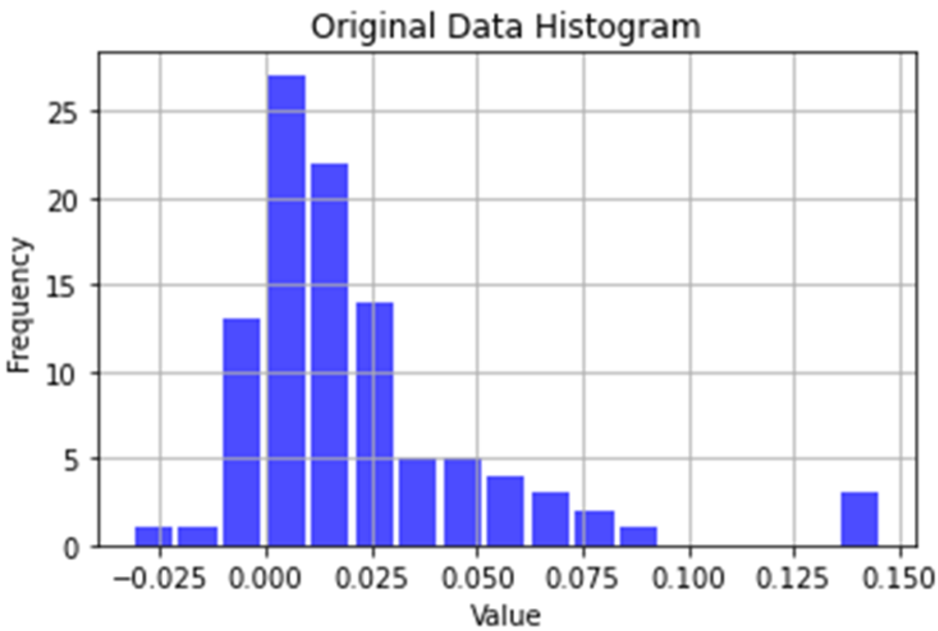

Figure 3: CCI Histogram

Figure 3 depicts the distribution of CCI values, this histogram offers a visual representation of the frequency of CCI occurrences, assisting in understanding central tendency and variability in construction costs.

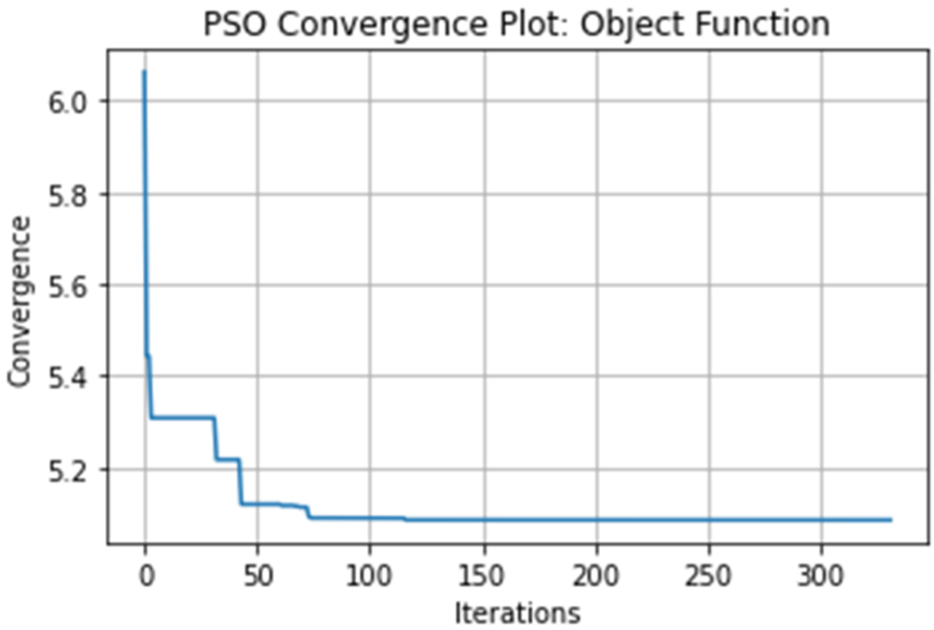

Figure 4: PSO Objective Function Convergence

Figure 4 showcases the convergence of the PSO objective function during the optimization process, PSO's progress in minimizing the product of prediction and forecast accuracy (mape_predicted * mape_forecasted). This leads to optimal values of alpha, beta, and gamma for the Holt-Winters model, aiding in assessing optimization efficiency and identifying convergence stability.

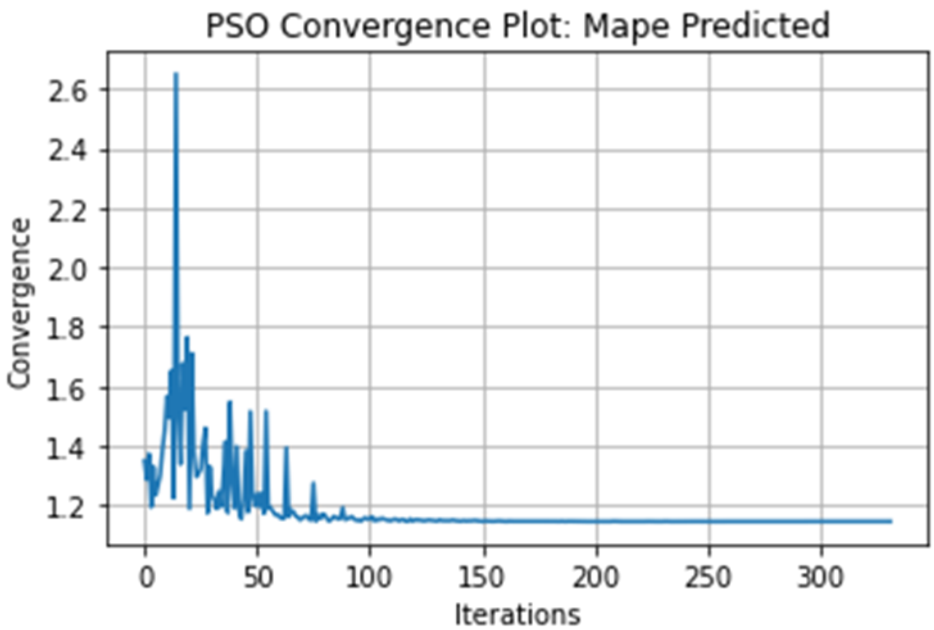

Figure 5: PSO Convergence for MAPE Predicted

Figure 5 presents the MAPE predicted by the PSO algorithm during parameter optimization for the Holt-Winters model. This graph demonstrates the continuous enhancement in prediction accuracy as optimization progresses. It sheds light on the effectiveness of PSO in minimizing prediction errors.

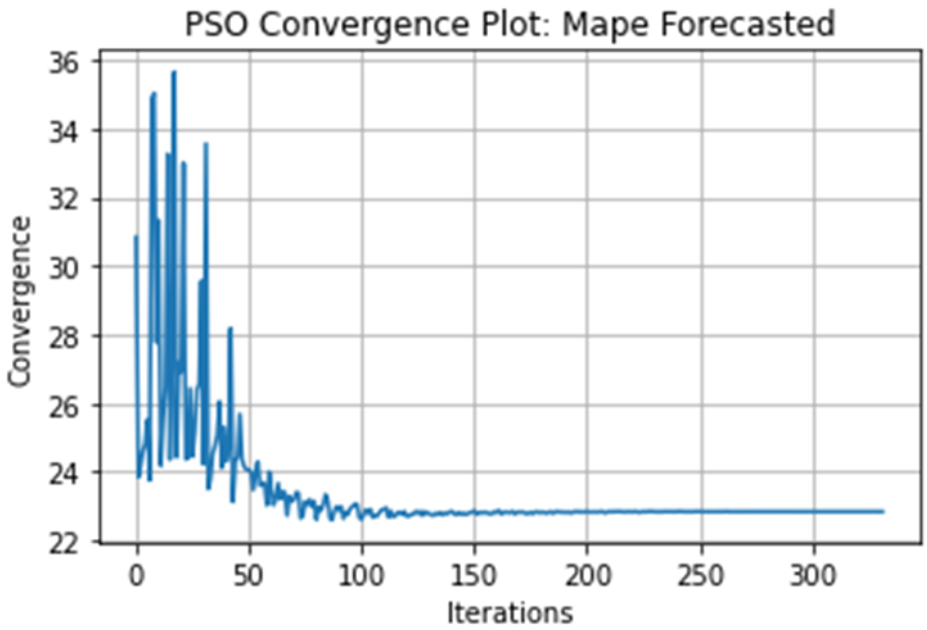

Figure 6: PSO Convergence for MAPE Forecasted

Figure 6 depicts the convergence of the MAPE forecasted by the PSO algorithm during parameter optimization for the Holt-Winters model. This graph highlights the reduction in forecast errors as the optimization process advances. It indicates ongoing improvement in forecast accuracy, assessing the effectiveness of PSO in refining the model's predictions.

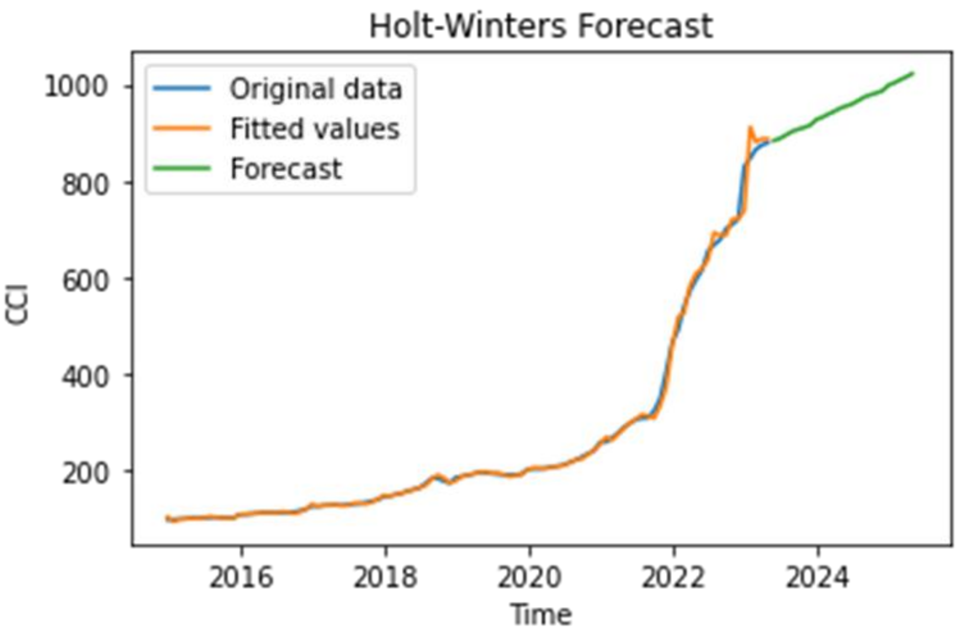

Figure 7: Holt-Winters CCI Forecast

Figure 7 presents the outcomes of the Holt-Winters model optimization for the CCI. This graph compares actual, fitted, and forecasted CCI values. It serves as a valuable tool for evaluating model performance and visualizing the accuracy of optimized forecasts.

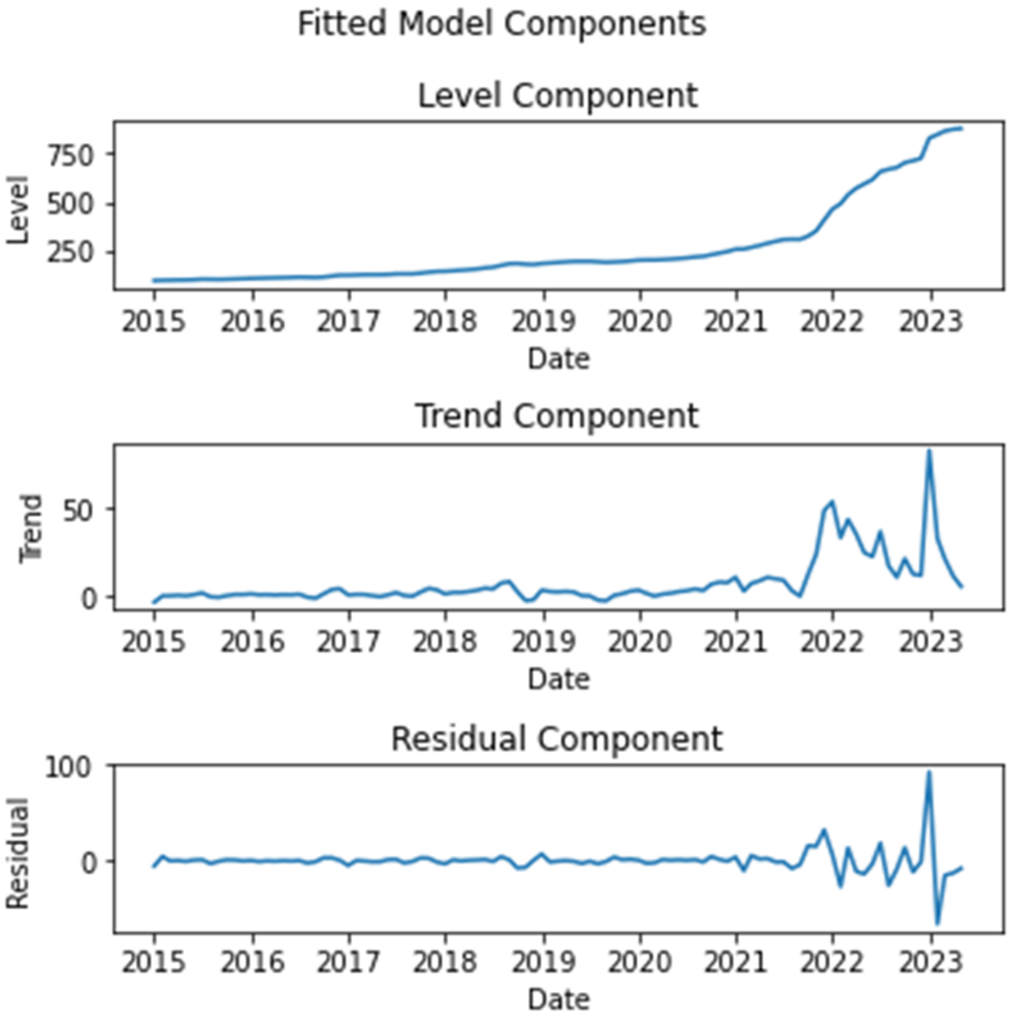

Figure 8: Holt-Winter Optimization-Fitted Model Components

Figure 8 showcases the decomposition of model outputs, encompassing Level, Trend, and Residual components resulting from Holt-Winters model optimization. It illustrates the model's adeptness in capturing and representing distinct factors, contributing to improved forecasting accuracy.

3.3. Comparison of Baseline Study and this Study:

In the upcoming section, a comparison will be made between the baseline study (Aydınlı, 2022) and this study. Table 2 assesses various aspects, including methodologies, data size, validation techniques, optimization methods, evaluation criteria, research findings, and visual representations. This systematic comparison aims to clarify the differences and contributions in both studies.

Access: Baseline study: Aydınlı, S., (2022). Time series analysis of building construction cost index in Türkiye. Journal of Construction Engineering, Management & Innovation (Online), vol.5, no.4, 218-227.

The Idea behind Training: While the baseline study emphasized the importance of best fit in the training set for test set forecasts, our study extended this concept by highlighting the significance of concurrent best fit in both training and validation sets. Additionally, we took into account the performance of the past 12 periods to enhance the accuracy of our forecasting approach.

The Idea behind Forecast: Similar to the baseline study, our study also focused on parameter optimization to minimize forecasting errors. However, we advanced this approach by implementing parameter optimization not only in the training set but also in the validation set. Moreover, we incorporated a 12-step Forward Cross Walk technique to further enhance the accuracy of our forecasts.

Table 2: Comparison of Baseline Study and Our Study

Subject	**Baseline study**	**Our study**
Acces	Aydınlı, S., (2022). Time series analysis of building construction cost index in Türkiye. Journal of Construction Engineering, Management & Innovation (Online) , vol.5, no.4, 218-227.	This Study
The idea behind training	Emphasis on best fit in Training set for test set forecasts	Importance of concurrent best fit in both Training set and Validation set for Test set forecasts, consideration of past 12 period performance for enhanced accuracy
The idea behind forecast	Focus on parameter optimization to minimize error in training set for forecasting	Implementation of parameter optimization to minimize error in both training set and validation set, utilization of 12-step WFCV for enhanced forecasting accuracy
Data Size	99 samples of CCI dataset	101 values of CCI dataset
Split data set for Validation	68 samples of Training Set and samples and 23 samples of Testing Set	Training set, Validation set, and Test Set
Optimization process	Singular step approach	Iterative 12 Step WFCV methodology
Object Function	Error minimization within training data	Dual objective: Error minimization within both training data and validation data
Metrics	AIC, BIC, RMSE, RMSPE	MAPE
Findings	Holt-Winters model showcases enhanced prediction accuracy, though limitations in volatile economic conditions observed	Acceptable forecast ability beyond threshold values, while acknowledging boundary of volatile economic conditions
Visual Output	Fig. 3. Models' Predictions on Page 7	Figure 9: Models' Predictions in Baseline Study at Fig 3 Page 7 Figure 10: Forecast Result of Our Model Applied to Baseline Study Data
Result	Models have extremely low performance in forecasting test data. Test data cover the 2020-9 – 2022-07 period which is highly volatile.	MAPE calculated from the forecasted values applied to the baseline study dataset met the quality threshold, registering at 16.88%.

Data Size: The baseline study used a dataset consisting of 99 samples of construction cost index (CCI), whereas our study expanded the dataset to include 101 CCI values, enabling a more comprehensive analysis.

Split Data Set for Validation: In the baseline study, the dataset was divided into a training set of 68 samples and a testing set of 23 samples. In this study, we employed a more comprehensive approach by utilizing a training set, a validation set, and a test set to ensure robust model evaluation.

Optimization Process: While the baseline study employed a singular step approach for optimization, this study introduced an iterative 12 Step Forward Cross Walk methodology, offering a more refined and progressive optimization process.

Object Function: The baseline study focused on minimizing errors within the training data, whereas this study adopted a dual objective approach, aiming to minimize errors not only within the training data but also within the validation data, ensuring a more comprehensive and accurate forecasting model.

Metrics: In the baseline study, metrics such as AIC, BIC, RMSE, and RMSPE were employed for evaluation. In contrast, this study utilized the MAPE as the primary metric to assess the accuracy of our forecasting model.

Findings: The baseline study identified the enhanced prediction accuracy of the Holt-Winters model, with the caveat of limitations in volatile economic conditions. In this study, we found the presented model exhibited acceptable forecast ability beyond threshold values, considering the constraints posed by volatile economic conditions.

Visual Output: While the baseline study presented visual output in the form of Fig. 3 illustrating model predictions, this study introduced multiple visual outputs. These included Figure 9, showcasing predictions from the baseline study; Figure 10, presenting the forecast result of our model applied to baseline study data.

Result: The baseline study highlighted the extremely low performance of models in forecasting highly volatile test data. In contrast, this study demonstrated the quality of our model by achieving a Mean Absolute Percentage Error (MAPE) of 16.88% when applied to the baseline study dataset, meeting the established quality threshold.

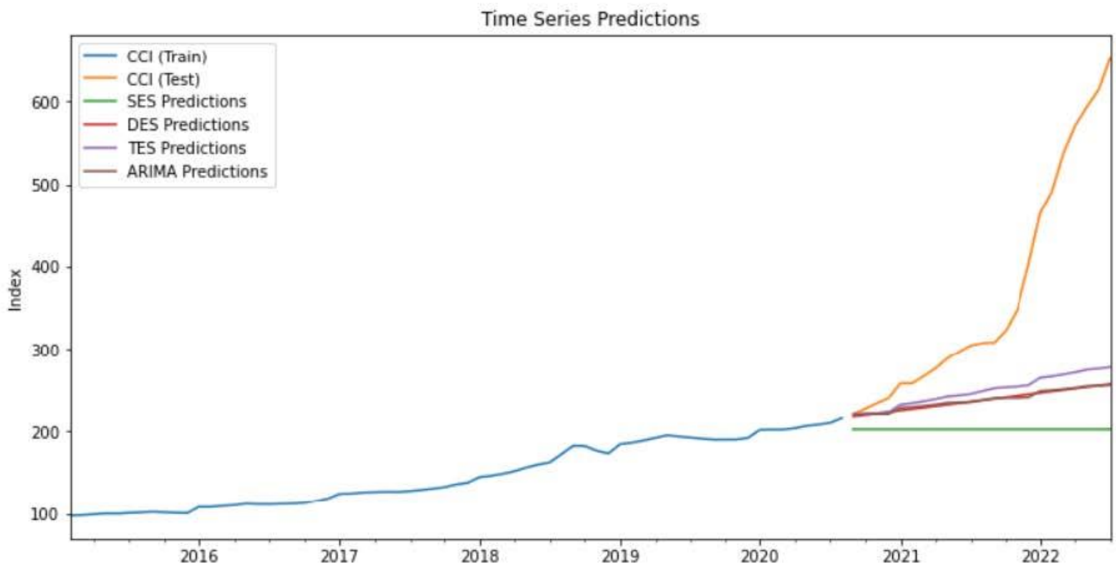

Figure 9: Models' Predictions in Baseline Study at Fig 3 Page 7

Figure 9 presents the outcomes of the baseline study. In this visualization, the yellow line represents the Construction Cost Index (CCI) values, while the other lines display the forecasted values generated by the models tested in the study. As the author points out, these models have followed their past trends but struggled to accurately predict a sudden emerging trend. Among these models, the Holt-Winters approach has demonstrated the most promising performance. In the baseline study, the dataset was divided into a training set containing 68 samples and a testing set comprising

23 samples. Due to the limited size of the testing set, the ongoing trend wasn't adequately captured within the training data, leading to the model's inability to identify the trend or its starting point.

Figure 10 illustrates the alignment of this study's forecast values with the dataset used by the baseline study. The blue line represents the Construction Cost Index (CCI) values from the test dataset, the yellow line showcases the fitted values obtained after the prediction process, and the green line depicts the values obtained following the forecasting process. The segmentation of the data into Training, Validation, and Test Sets, coupled with the implementation of parameter optimization to reduce errors within both the training and validation sets, along with the utilization of a 12-step WFCV, has enabled a more rapid response to trends. Due to the influence of a strong and abrupt trend, the forecast values were overestimated. In our study, which utilizes up-to-date data, the model managed to capture the slowdown in the trend, leading to forecast values that align with the new situation.

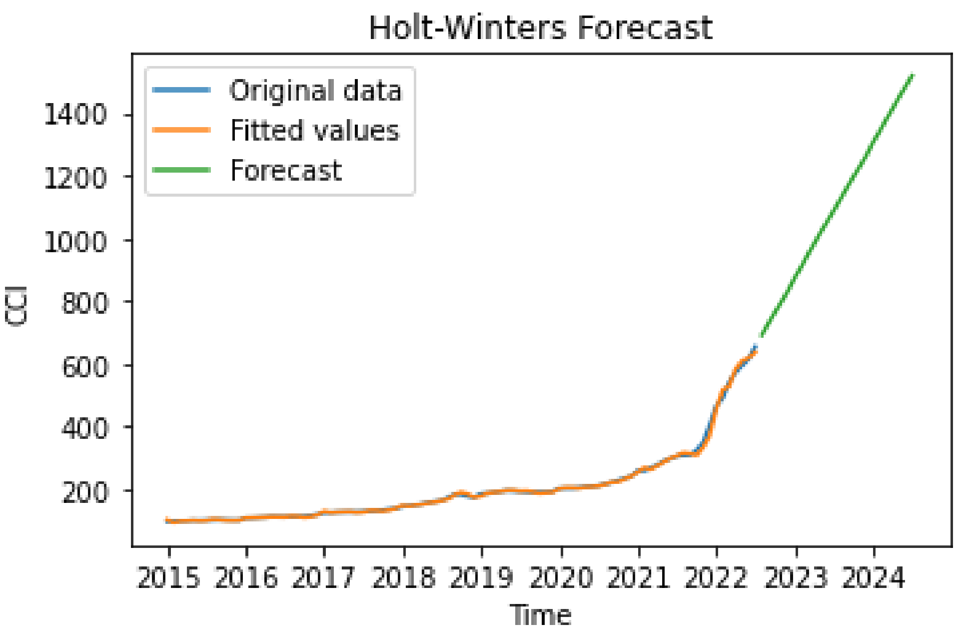

Figure 10: Figure 10: Forecast Result of Presented Model Applied to Baseline Study Data

The comparative analysis between the baseline study and this study provides valuable insights into the advancements and refinements achieved in the realm of construction cost forecasting. The approach extends beyond the baseline study by emphasizing concurrent best fit in both training and validation sets, harnessing parameter optimization in tandem with a 12-step WFCV methodology for enhanced accuracy. The integration of a more comprehensive data set, the utilization of a validation set, and the adoption of the MAPE as the primary metric further contribute to the robustness of the forecasting model. While both studies acknowledge the challenges posed by volatile economic conditions, this study showcases the potential to achieve acceptable forecast ability even within these boundaries. By offering practical recommendations for adapting to high-volatility environments and trends, the study underscores the importance of continuous improvement and informed decision-making in construction cost prediction.

CONCLUSION:

In this study, it is optimized that the Holt-Winters ES model parameters for CCI forecasting through the PSO and WFCV. The research focused on minimizing the MAPE, leading to substantial enhancements in forecast accuracy. Noteworthy findings include the achievement of significantly reduced MAPE values, particularly 22 for CCI forecasts and 2 for training data. Findings underscored the pivotal role of disregarding seasonality in refining the CCI forecasts. WFCV added rigor to the evaluation process, ensuring the model's reliability. This research aims to enhance the accuracy of CCI forecasting using Holt-Winters ES by optimizing its parameters, focusing on minimizing the MAPE for precise CCI forecasts. The methods employed in this study have demonstrated their effectiveness in achieving the research objectives. This study's contribution to existing knowledge is in its innovative optimization approach that enhances the accuracy of CCI forecasting.

The optimized Holt-Winters model can be used as an important tool for construction stakeholders in the construction industry by data driven decision making in cost estimation, budgeting and risk management processes. The success of the optimization methodology demonstrates the potential of metaheuristic techniques such as PSO to improve time series prediction accuracy.

While this study provides significant insights, it has certain limitations. The focus on a specific geographical region, namely Turkey, may limit the generalizability of the findings to other contexts. Future research should include the integration of exogenous factors.

In light of our study's findings, two practical recommendations emerge. In high-volatility environments, considering a shorter forecast horizon proves advantageous, particularly when contrasted with low-volatility scenarios. Furthermore, in the face of heightened volatility or an emerging upward trend, a proactive approach is encouraged. This approach supports regular updates to forecast results, prompt communication with stakeholders, and the implementation of robust risk management protocols.

Consequently, the role of forecasting is to delve into the future and exploit this information without clinging to its certainty. While certainty in predictions remains elusive, even a gauge with fluctuations holds more value than having no information at all. Scientific predictions provide a reliable measure for comparing probabilities, as opposed to the less reliable nature of intuition or rumor. Therefore, adopting data-driven forecasting enables decision makers to navigate the uncertain path of construction cost management, with a reliable compass to guide them through complex and unpredictable complexities. This underscores the importance of using accurate and informed approaches to address the uncertainties inherent in construction cost management.

Compliance with Ethical Standard

Conflict of Interests: *There is no conflict of interest between the authors or any third-party individuals or institutions.*

Ethics Committee Approval: *Ethics committee approval is not required for this study.*

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