Accurate hybrid prediction model for poverty line, number, and percentage of impoverished individuals

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ABSTRACT

Poverty remains a major social issue in many developing countries, including Indonesia, as seen in the Central Java region. Over the last five years, the number of impoverished people in Central Java has shown fluctuations, with data from the Central Statistics Agency indicating figures of 3,897.20 thousand (2018), 3,743.23 thousand (2019), 3,980.90 thousand (2020), 4,109.7 thousand (2021), and 3,831.44 thousand (2022). Analyzing these trends is crucial for future poverty reduction efforts. This study aims to develop a web-based predictive system capable of forecasting the poverty line, as well as the number and percentage of poor residents in Central Java. The research utilizes a hybrid forecasting model that integrates the Holt-Winters triple exponential smoothing (HWTES) method with fuzzy time series (FTS), alongside algorithmic approaches such as rate of change (RoC) and frequency-based segmentation. The model's accuracy, evaluated using the average absolute percentage error (MAPE), shows low error rates: 0.9% for the number of impoverished people, 1.6% for the percentage, and 0.7% for the poverty threshold. Compared to the standard HWTES model, this hybrid model demonstrates greater precision. As a result, it can serve as an effective tool to support strategic planning and enhance poverty alleviation programs in Central Java.

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1. INTRODUCTION

Poverty remains a global issue, and nations within the European Union continue to contend with it in the contemporary era [1]. Approximately 30% of individuals in European nations consider themselves impoverished and one in seven households falls outside the poverty line, as reported in [2].

Nearly two billion individuals continue to reside in developing countries, rendering poverty a significant concern for the global populace today [3]. Poverty is a persistent socioeconomic issue that poses a substantial barrier to a nation's welfare and advancement [4]. Poverty impacts the overwhelming majority of developing countries globally. In 2015, the UN initiated the 2030 Sustainable Development Agenda, comprising 17 sustainable development goals (SDGs) designed to eliminate poverty, safeguard the environment, and guarantee prosperity and peace for all [5], [6].

As an emerging nation, Indonesia continues to seek solutions to the problem of poverty among its populace. Indonesia has achieved significant progress in poverty reduction, effectively eradicating extreme poverty. Nevertheless, over one-third of Indonesians continue to experience financial instability [7].

Poverty remains a significant concern in this nation and has traditionally pervaded all regions of Indonesia, including Central Java. Individuals seek coping mechanisms to mitigate poverty, a concern that often preoccupies them. The government emphasizes poverty alleviation in national development strategies to decrease the population of underprivileged individuals. Regional governments must adopt a more prominent role in designing and implementing poverty reduction initiatives, as they possess a more profound awareness of local situations than the federal government.

Forecasting is essential for assessing the policies of a regional government institution, both current and historical, and for determining their potential impact on the future. Employing forecasting as a basis for policy formation within a regional government entity improves the efficacy of a regional development strategy.

Numerous academics concentrate exclusively on the performance metrics and principles of the methodologies and algorithms employed in forecasting, overlooking the users' speed and complexity in the prediction and analysis process. Moreover, it is rare to examine the automation of web-based forecasting systems utilizing software technology.

The implementation of traditional forecasts and analysis will entail complex and demanding processes. Consequently, the creation of automated prediction systems is crucial to accelerate the formulation of strategic strategies that address existing difficulties.

Information systems are essential for improving an institution's reputation by enabling real-time productivity and demonstrating effectiveness and efficiency in all transactions. A prediction system is an essential automation tool in modern enterprises. The fundamental objective of this work is to develop a predictive system that enables efficient online management and monitoring.

Numerous concepts for tools that support software development have been presented to date. This study forecasts and examines data collected from an extensive community-based monitoring system in Central Java, encompassing both city and district levels. We utilized PHP technology, grounded in the CodeIgniter framework, alongside MySQL as the database, to develop a web-based poverty prediction system. To enhance the precision of our forecasts, we employed a methodology that integrates Holt-Winters triple exponential smoothing (HWTES) and fuzzy time series (FTS) techniques with the rate of change (RoC) and frequency-based partition (FbP) algorithms.

Tasks pertaining to FTS data, regarding FTS data, time series (TS) data elucidate the essential traits and inherent patterns of a particular system or activity [8]. Precise historical data, widely employed in nature, economics, and society, is essential for conventional TS analysis [9]. Research by Hudecová and Pešta [10] employs the term "resistance" to characterize a TS with a hybrid distribution, comprising a continuous component and a point mass at zero. The objective of TS forecasting is to utilize past TS observations to predict future variations [11]. This presents considerable challenges for various sectors, including finance [12]. In 2023, scholars undertook investigations in the domain of economics [13]. Likewise, scholars undertook inquiries into the subject of agriculture [14], [15]. The researchers [16]–[18] are undertaking investigations on the subject of energy. Simultaneously, [19] is involved in bioscience research. The researchers [20], [21] reference subsequent research that advances the field of engineering. The ambiguity and imprecision inherent in TS data intensify the difficulties related to forecasting and prediction errors. Numerous methodologies have been established for TS forecasting, one of which employs fuzzy set theory. This is mostly due to the inherent flexibility of fuzzy set theory in handling ambiguous data [22]. Fuzzy data are prevalent in everyday life. Significant volumes of unrefined data remain deficient and erroneous due to human error or absent metrics, leaving them unsuitable for societal applications [23]. Fuzzy theory has numerous applications [24], [25]. The bulk of research [26] initially references the FTS approach, which is based on fuzzy set theory [27]. The predominant focus of the literature is on time-invariant FTS approaches, which we categorize into two groups: time-invariant and time-variant [26], [28]. Conversely, the study [29] uses sophisticated optimization methods and FTS to forecast the influx of visitors to China. Rubio *et al.* [30] introduced an innovative method, the weighted fuzzy trend TS algorithm, to enhance the precision of stock index forecasting.

Identifying the optimal interval ratio length in FTS can enhance predictive accuracy [31]. Studies [32], [33] indicate that the length of the effective gap influences the formation of fuzzy sets and the establishment of fuzzy relations [34]–[37]. Another body of research [38]–[44] advocates for the utilization of annual percentage changes as the discourse universe in FTS. The study [45] proposed a fuzzy measurement technique utilizing frequency density partitioning to further enhance the predictive accuracy of the FTS model. The procedures delineated in [45] were likewise utilized in [46]–[49]. The recommended technique is a time-variant, kth order. The proposed solution demonstrates superior accuracy in forecasting enrollment compared to the current method.

FTS forecasting models are increasingly gaining traction as a specific technique within this methodology. The FTS forecasting model necessitates no assumptions. We must employ models associated with fuzzy set theory to analyze the uncertainties inherent in the majority of observed TS. Systems based on fuzzy set theory utilize membership values to denote uncertainty. We obtain membership values from model input through the application of membership functions.

Fuzzy set theory-based techniques utilize membership values derived from raw data to elucidate the uncertainty of the data, rather than employing the raw data itself. Fuzzy logic-based solutions utilize membership values to represent uncertainty, offering numerous advantages over alternative methods such as neural networks. This methodology enables fuzzy logic techniques to manage uncertainty more effectively than other soft computing methods, including neural networks.

Tasks pertaining to the implementation of the TES model, this method asserts that the constant exponential window function can refine the TS. Exponential smoothing (ES) is categorized into three types according to its frequency of application: single exponential smoothing (SES), double exponential smoothing (DES), and triple exponential smoothing (TES) [50]. Using the Holt DES model methodology, the study referenced as [51] developed an online web-based forecasting system to estimate the number of families receiving basic food social assistance benefits. The research [52] employed the TES algorithm to predict forthcoming trends in land subsidence in Lagos. This research [53] examines two forecasting methodologies, namely the DES and TES techniques, to anticipate the revenue of regional drinking water firms. Zhang *et al.* [54] suggested a hybrid model that integrates long short-term memory (LSTM) with TES as a proactive prediction technique for Docker container workloads. Conversely, Xie *et al.* [55] proposed the development of a hybrid triple exponential smoothing-autoregressive integrated moving average (TES-ARIMA) model capable of accurately forecasting the interactions between linear and nonlinear container loading sequences. The experiment Yudatama *et al.* [56] forecasted the rise in COVID-19 cases in Indonesia by integrating TES and FTS methodologies.

2. METHOD

2.1. Materials

The BPS evaluates poverty through the fundamental needs method, which relies on the capacity to satisfy essential requirements. Poverty is defined as the inability to afford essential commodities, including food and non-food essentials. The average monthly per capita income of those categorized as poor is below the federal government's poverty threshold.

The poverty line (GK) is the outcome of the amalgamation of the food poverty line (GKM), representing the food poverty line, and the non-food poverty line (GKNM), denoting the non-food poverty line. An individual is deemed impoverished if their average monthly per capita income is below the federal government's designated poverty threshold. The GKM, or daily caloric minimum for food expenditure, is 2,100 kilocalories per individual. The Basic Food Needs Commodity Bundle comprises 52 categories, including beans, fish, chicken, eggs, dairy products, vegetables, seeds, fruits, nuts, oils, and fats, among other goods. The GKNM delineates the essential requirements for habitation, apparel, healthcare, and education. The core non-food commodity bundle comprises 47 products for rural areas and 51 commodities for metropolitan areas. The head count index (HCI-P0) is utilized to ascertain the proportion of the population beneath the global poverty line (GK).

This study utilizes quantitative methods to gather data that can be analyzed by statistical, mathematical, and computational tools for a systematic evaluation of the experiences of those living in poverty. BPS offers genuine digital secondary data as the basis for data collecting and experimental materials. This study primarily aims to forecast the growth rates of GK, number of poor people (JPM), and percentage of poor population (PPM) in Central Java from 2002 to 2022.

2.2. Implementation framework

Figure 1 illustrates the proposed historical architecture for this paper. We utilize GK, JPM, and PPM poverty data to generate future estimates. The initial prediction process employs the HWTES method, the subsequent phase utilizes the FTS model with the RoC and FbP algorithm approach, and the final process implements a hybrid model that integrates both methodologies.

The proposed web-based system development model is founded on a hybrid forecasting methodology that integrates data from multiple sources to address the challenge of estimating the people living in poverty. Figure 1 illustrates the technologies underlying a web-based predictive system.

This approach uses the HWTES statistical technique in conjunction with the FTS, RoC, and FbP algorithms to predict poverty levels in Central Java. In this case, we forecast the forthcoming period with the HWTES. The FTS prediction process will integrate the outcomes of the HWTES.

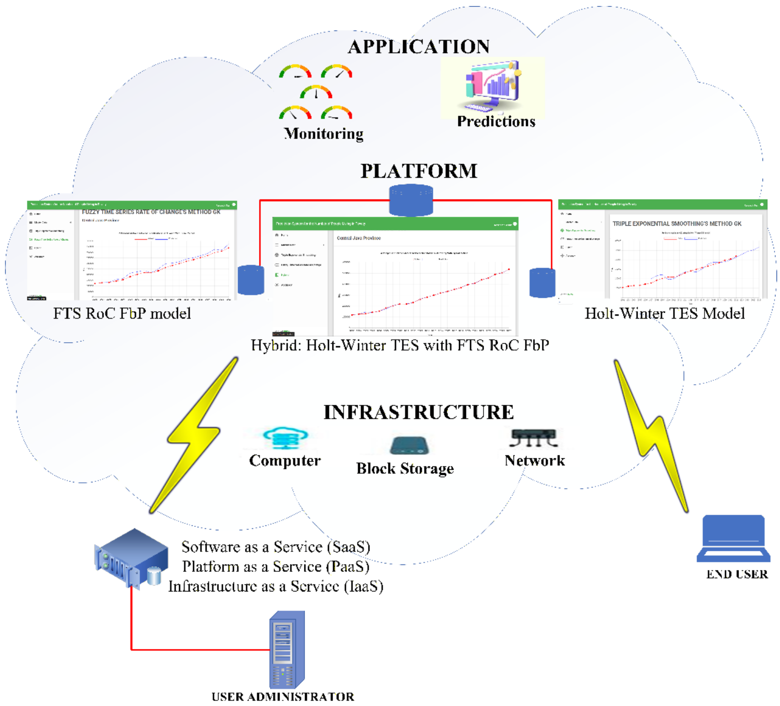

Figure 1. The technologies underlying a web-based predictive system

We employ and adapt the event discretization methodologies suggested by [38], [39], [43]–[56]. We employ these strategies to delineate the parameters of RoC discourse and to segment events in the TS related to RoC data. The intervals are subsequently weighted according to the current number of ROC frequencies, employing a distribution principle derived from the partition results of each frequency inside each interval. The subsequent step entails identifying the median value and applying fuzzification by the triangle membership function equation [57]. Ultimately, we provide forecast values (FRoC) predicated on the anticipated RoC.

2.2.1. Time series representation of poverty data

This observation, spanning from 2002 to 2022, employs quantitative time series data represented as $X=(x_1, x_2, x_3, \ldots, x_n)$ to delineate the progression of the number of impoverished individuals (JPM) in thousands, the percentage of impoverished individuals (PPM) in percent, and the poverty line data (GK) in IDR per capita per month.

Consequently, we affirm the precision and reliability of the secondary data collected for this study from official sources at BPS Central Java (2022). In this study, X={106438, 119403, 126651, ..., 438833} represents the TS data for GK. The JPM is denoted as X={7308, 6979.80, 6843.80, ..., 3831.44}. X={23.06, 21.78, 21.11, ..., 10.93} represents the TS data for PPM. Table 1 displays secondary data obtained from official sources [58].

Table 1. The real dataset GK, JPM, and PPM from 2002 to 2022

Year	GK	JPM	PPM
2002	106438	7308.00	23.06
2003	119403	6979.80	21.78
2004	126651	6843.80	21.11
2005	130013	6533.50	20.49
...	...	...	...
2019	369385	3743.23	10.80
2020	395407	3980.90	11.41
2021	409193	4109.75	11.79
2022	438833	3831.44	10.93

2.2.2. Holt-Winters triple exponential smoothing model procedure

The Holt–Winters triple exponential smoothing (TES) model is used to forecast time series data that exhibit level, trend, and seasonal components. The forecasting procedure of the TES model is described in the following steps:

Step 1: determine the optimal alpha (α), beta (β), and gamma (γ) parameters.

Generally, we establish user-defined constants (α, β, and γ) based on prior data. We employ the root mean square error (RMSE) method to assess the optimal values of these three parameters.
Step 2: formulating prognostications.

In (1) through (11) delineate the statistical methodology referred to as TES [59], [60], employed in the estimate procedure.

$$L_t = \alpha(Y_t/S_{t-m}) + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{1}$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)\, T_{t-1} \tag{2}$$

$$S_t = \gamma(Y_t/L_t) + (1-\gamma)\, S_{t-m} \tag{3}$$

$$F_{t+k} = (L_t + k * T_t) * S_{t-m+k} \tag{4}$$

The parameter L denotes the estimated level influenced by the α quantity, T signifies the trend estimate affected by the β quantity, S indicates the seasonal estimate impacted by the γ quantity, F represents the forecasted value for the future period, and k reflects the number of future times utilized in the prediction. When M is equal to four (per quarter):

$$\mathrm{S_1} = \frac{\mathrm{Y_1}}{\mathrm{average(Y_1,Y_2,Y_3,Y_4)}}; \tag{5}$$

$$\mathrm{S_2} = \frac{\mathrm{Y_2}}{\mathrm{average(Y_1,Y_2,Y_3,Y_4)}}; \tag{6}$$

$$\mathrm{S_3} = \frac{\mathrm{Y_3}}{\mathrm{average(Y_1,Y_2,Y_3,Y_4)}}; \tag{7}$$

$$\mathrm{S_4} = \frac{\mathrm{Y_4}}{\mathrm{average(Y_1,Y_2,Y_3,Y_4)}} \tag{8}$$

$$\mathrm{L_5} = \mathrm{Y_5/S_1} \tag{9}$$

$$\mathrm{T_5} = \frac{\mathrm{Y_5}}{\mathrm{S_1}}; -\frac{\mathrm{Y_4}}{\mathrm{S_4}} \tag{10}$$

Utilize (11) to ascertain seasonal values.

$$S_5 = \gamma(Y_5/L_5) + (1-\gamma)S_{5-4} \tag{11}$$

S_1, S_2, S_3, S_4, and S_5 denote the seasonal values for the initial five time points. From the initial to the fifth time point, the symbols Y_1, Y_2, Y_3, Y_4, and Y_5 represent measurement or observation values.
Step 3: examine the anticipated results.

The mean absolute percentage error (MAPE) is a commonly utilized metric for assessing prediction accuracy, noted for its scale independence and interpretability [61]. The MAPE model evaluates the efficacy of seasonal forecasting models in this experiment. In (12) and (13), respectively [62], demonstrate the feasibility of identifying a superior forecasting model characterized by reduced MAPE values.

$$PE_i = \left|\frac{X_i - F_i}{X_i}\right| \times 100\% \tag{12}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} |PE_i| \tag{13}$$

Predictions utilizing the MAPE methodology are crucial to circumvent several complications associated with interpreting accuracy metrics in relation to the scale of the predicted value [56], [63], as illustrated in Table 2.

Table 2. Significance of MAPE

MAPE	Significance
Less than	The predictive outcomes are exceptional.
Between 10% and 20%	The predictive outcomes are favorable.
Between 20% and 50%	The forecast outcomes are satisfactory.
More than 50%	Inaccurate predictive outcomes.

2.2.3. Hybrid model procedure

The forecasting procedure employs this hybrid model as a composite model for the prediction interval t+k [43], [44], [56]. According to (4), the HWTES statistical technique generates estimation data, which is subsequently utilized as actual data in the FTS method employing the RoC and FbP algorithm approaches during the prediction period t+k.

The FTS model integrates methodologies for RoC and FbP algorithms:

Step 1: specify the set U.

To illustrate this procedure, we will utilize the RoC set from time t to time t+1. Following the implementation of discretization techniques, (14) calculates the RoC of TS data [38]-[44], [56].

$$RoC_{(t+1)} = \frac{(X_{(t+1)}-X_{(t)})}{X_{(t)}} \times 100 \tag{14}$$

X (t+1) represents the value at index time t, whereas X (t) denotes the actual value at index time t. The rate of change is referred to as RoC. Identify the lower limit (LL) and upper limit (UL) according to the RoC. In (15) can be employed for the calculation of U [43], [44], [56].

$$U = [LL - D_1,\ UL + D_2] \tag{15}$$

Two integers, D_1 and D_2, facilitate the elucidation of the universal set, denoted by the sign U.

The RoC data for GK reveals an LL value of 0.05, an UL of 18.02, a D_1 of -0.05, and a D_2 of 0.98. For JPM, we derive LL=-12.44 and UL=8.68, with D_1=-0.56 and D_2=0.32. Concerning PPM, the numbers are LL=-12.99, UL=10.00, D_1=-1.01, and D_2=1.00. The calculated RoC defines U for GK as {0.00, 19.00}, for JPM as {-13.00, 9.00}, and for PPM as {-14.00, 11.00}. Calculate the quantity of interval classes utilizing (16) [64].

$$M = 1 + 3{,}3 * log(n) \tag{16}$$

A total of M intervals intersect with n RoC data points. Each example contains 24 RoC data points (GK, JPM, and PPM) due to identical causes.

$$M = 1 + 3{,}3 * \log(24)$$
$$M = 5.55 \approx 6$$

Subsequently, we employ (17) to determine the length of the equal distance between two points [63].

$$L = \frac{UL-LL}{M} \tag{17}$$

In the GK case, the interval length is L=(19.00-0.00)/6=3.17. The interval length in the JPM instance is L=(9.00-(-13.00))/6=3.67. In the PPM situation, the interval length is L=(11.00-(-14.00))/6=4.17. Consequently, the results of the technique produce an identical interval length.

Step 2: segment the interval inside the given U into several intervals according to the frequency.

The interval is either continuous, or it cannot be subdivided into smaller intervals based on frequency values if the frequency value lies between zero and one. These are the two potential outcomes. We explicitly incorporate and adapt the guidelines from [38], [39], [43]-[49]. The division for the forthcoming time follows the same protocols.

Step 3: fuzzification involves precisely defining the fuzzy set.

RoC fuzzification constructs each fuzzy set x_i from the sub-intervals that constitute the interval-defined fuzzy set. Consider the fuzzy set x_i, which denotes the temporal alterations in the linguistic value of RoC. Utilizing the triangle membership function [45], [57], [63], as delineated in (18), ascertain the midpoint of the established interval to evaluate the expected value of RoC.

$$FRoC = \begin{cases} \dfrac{1+0.5}{\frac{1}{a_1}+\frac{0.5}{a_2}} & , if\ j = 1, \\ \dfrac{0.5+1+0.5}{\frac{0.5}{a_{j-1}}+\frac{1}{a_j}+\frac{0.5}{a_{j+1}}} & , if\ 2 \leq j \leq n-2, \\ \dfrac{0.5+1}{\frac{0.5}{a_{n-1}}+\frac{1}{a_n}} & , if\ j = n. \end{cases} \tag{18}$$

Step 4: assess the values and defuzzify the information.

To forecast information, we calculate F(t) utilizing the findings from the RoC (FRoC) forecasts [38], [39], [43], [44], [56]. In (19) provides the value of F(t).

$$F_{(t)} = \left(\frac{FRoC}{100} * x_{t-1}\right) + x_{t-1} \quad (19)$$

In this context, the variable X(t-1) denotes the actual data up to time t-1.
Step 5: utilize the values derived from (12) and (13) to ascertain the mean error linked to the forecasts.

2.2.4. Evaluating the outcomes of predictions

This section conducts comparisons grounded in a study of the forecast outcomes of each model. The predictive performance is evaluated using standard accuracy metrics, including MAPE. These criteria enable a consistent and objective comparison of forecasting accuracy across different models.

2.2.5. Pseudocode

To guarantee consistency, we provide concise pseudocode outlining the algorithmic phases to elucidate the procedure. The stages of the algorithm are delineated in Table 3.

Table 3. Pseudocode: hybrid HWTES–FTS forecasting

Structure	Algorithm
Global	INPUT: D = time series data (2002 − 2022) for variables {GK, JPM, PPM} H = prediction horizon (e.g., 2023 − 2026) s = seasonal period (1, 2, or 4) Grid α, β, γ = [0.01 … 1.0] K = number of CV folds OUTPUT: Forecasts for each variable using HWTES, FTS, and HYBRID Evaluation metrics (MAPE)
Functions	MAPE(y_true, y_pred) HWTES_Forecast(series, s, α, β, γ, horizon, mode): Apply additive or multiplicative Holt − Winters equations Return forecast for horizon steps TuneHWTES(series, s, grid α, β, γ, K, mode): Perform grid search with rolling − origin CV Return best (α, β, γ) Compute_RoC(series): Return percentage rate of change series BuildUniverse(RoC): Partition universe of discourse into fuzzy intervals Return refined intervals Build_TriMFs(intervals): Construct triangular membership functions Return MF set Fuzzify(value, MF) Defuzzify(membership, MF) FTS_Forecast(series, horizon): Compute RoC Build universe and MF Estimate future RoC using last observed value Transform back to forecasted series Return forecast Combine_Hybrid(hwtes_pred, fts_pred): Learn weights from CV (or assign manually) Return weighted hybrid forecast
Main Pipeline	Forecast_Variable(series, s, grid α, β, γ, K, horizon, mode): (α ∗, β ∗, γ ∗) = TuneHWTES(series, …) hwtes_pred = HWTES_Forecast(series, α ∗, β ∗, γ ∗, horizon, mode) fts_pred = FTS_Forecast(series + hwtes_pred, horizon) hybrid_pred = Combine_Hybrid(hwtes_pred, fts_pred) Return all forecasts and best parameters Evaluate_All(true_values, hwtes, fts, hybrid): Compute RMSE for each model **Return metrics**
Main	For each variable in {GK, JPM, PPM}: Extract time series Forecast using Forecast_Variable Store results (parameters, forecasts) Return results

3. RESULTS AND DISCUSSION

The research utilizes historical data on poverty in Central Java spanning from 2002 to 2022. Our conclusions are derived from historical annual statistics on poverty in Central Java, specifically concerning GK, JPM, and PPM, with an emphasis on observations for the forthcoming projected period. To forecast the next period, we utilize the HWTES model, which is integrated into the FTS forecasting model employing RoC and FbP algorithm methodologies.

3.1. Results of the Holt-Winters triple exponential smoothing model

This study identified the best parameters α, β, and γ [59], [60]. Three parameters, α, β, and γ, regulate the relative smoothing of newly generated observations [59], [60]. The γ parameter regulates the smoothness of the processing of fresh observations to ascertain trend development, whereas the α parameter detects the existence of seasonal characteristics.

As per references [59], [60], we randomly choose the values of the α, β, and γ variables, which range from 0 to 1, or by minimizing the predicted error value. The HWTES methodology employs three smoothing variables. The α parameter is the primary variable that regulates the relative smoothing of observations. The β parameter is the second variable, responsible for regulating the relative smoothing of the most recent observations to ascertain the progression of a trend or its components.

The γ parameter regulates the relative smoothing of the latest observations and dictates the existence of seasonal components. In the research under consideration, we employ trial and error to determine the α, β, and γ values to reduce forecasting errors on test data. Table 4 illustrates the fluctuations in the α, β, and γ parameters utilized in this study.

Central Java exhibits three categories of poverty: GK, JPM, and PPM. According to the RMSE, which indicates the average squared errors, Table 4 presents the HWTES model with optimal α, β, and γ values. In (12) and (13) are employed to compute MAPE, while (20) [65] is utilized for RMSE calculation.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Predicted_i - Actual_i)^2}{N}} \quad (20)$$

Table 4. RMSE and ideal parameter values

Poverty	(α)	(β)	(γ)	RMSE
GK	0.26	1.00	0.88	23533.09
JPM	0.44	0.28	1.00	336.82
PPM	0.35	0.37	1.00	1.03

Figures 2 to 4 presents the results of three poverty forecasting models (GK, JPM, and PPM) in Central Java. The anticipated results, as ascertained by the HWTES methodology, illustrate the degree to which the projected outcomes for all three scenarios (GK, JPM, and PPM) align with the actual facts.

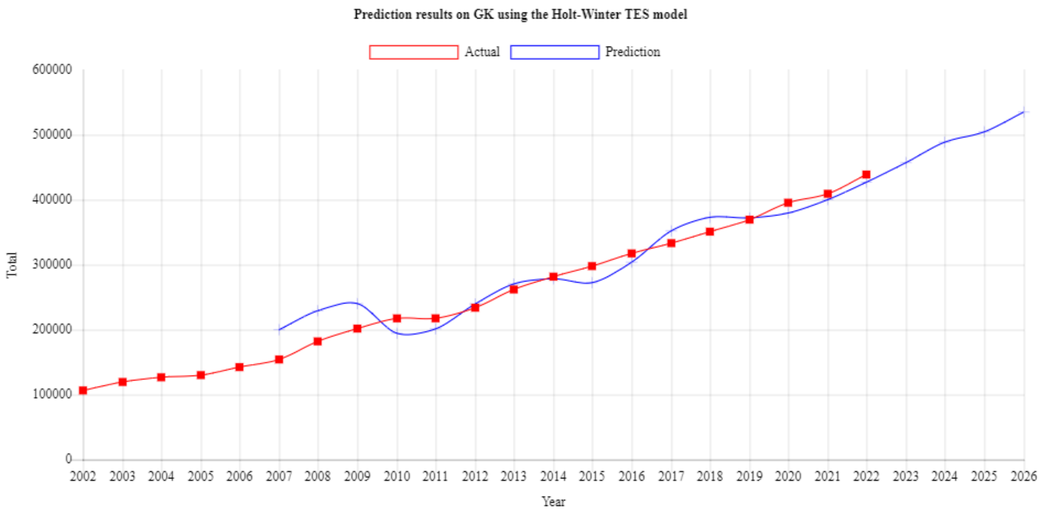

Figure 2. A graph depicting prediction outcomes with the hybrid model for GK

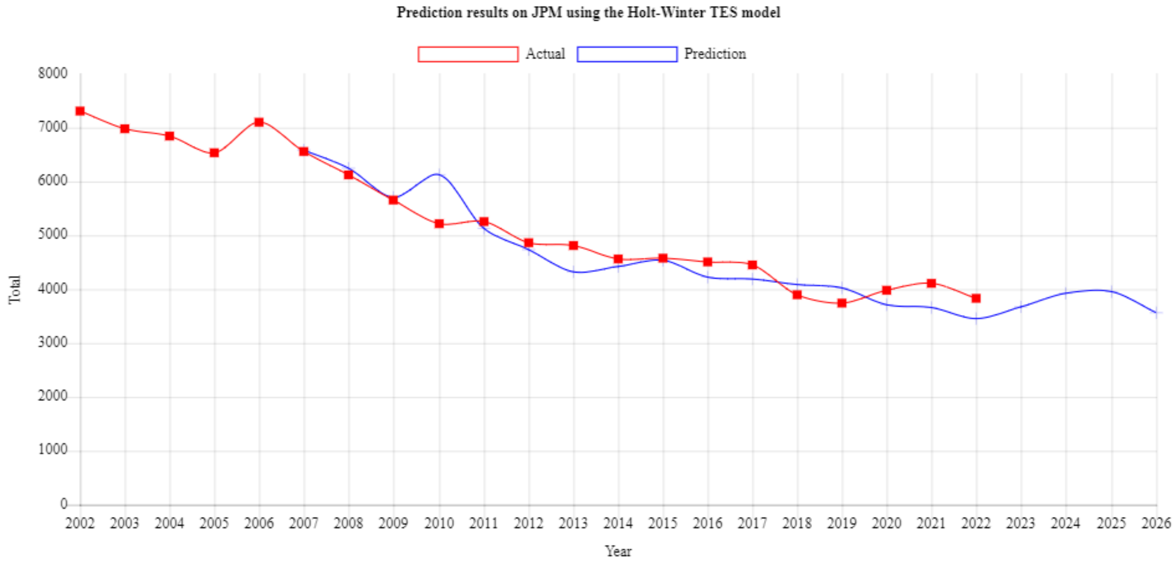

Figure 3. A graph depicting prediction outcomes with the hybrid model for JPM

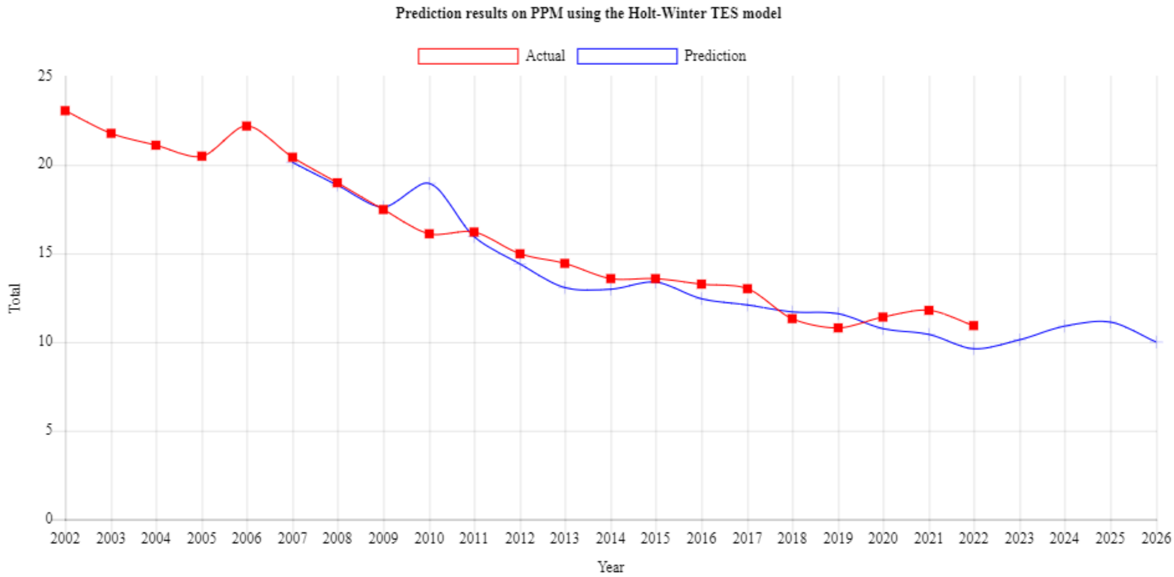

Figure 4. A graph depicting prediction outcomes with the hybrid model for PPM

This study uses the traditional HWTES prediction method to estimate the time t+4. Table 5 presents the results of the projections for individuals in Central Java with GK, JPM, and PPM for the years 2023, 2024, 2025, and 2026. The FTS approach, in conjunction with the RoC and FbP algorithms, synthesizes the predictive outcomes presented in Table 5, which serve as real-time series data for forecasting purposes.

Table 5. Projecting the results of the HWTES model over the subsequent four periods

Year	GK	JPM	PPM
2023	457250.68	3672.93	10.13
2024	488555.76	3924.88	10.89
2025	504545.76	3954.69	11.12
2026	535118.25	3564.04	10.00

3.2. Outcomes of the fuzzy time series model utilizing the rate of change algorithm

Initially, we obtain the RoC statistics depicted in Figures 5 to 7 from (14). The objective of the RoC data is to categorize TS occurrences and define the RoC-based discourse framework. The discretization process of FTS theory reduces the complexity of the discourse world. By correlating historical data, this procedure constitutes the initial phase in priming the discursive realm for quantitative assessment.

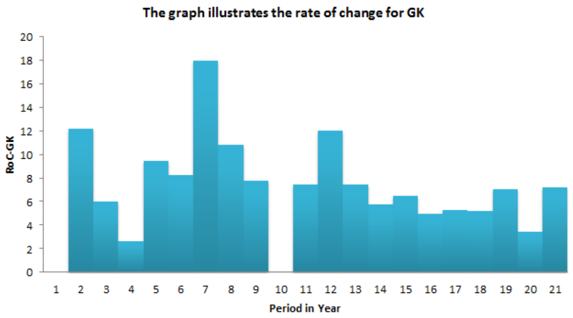

Figure 5. The graph illustrates the RoC for GK

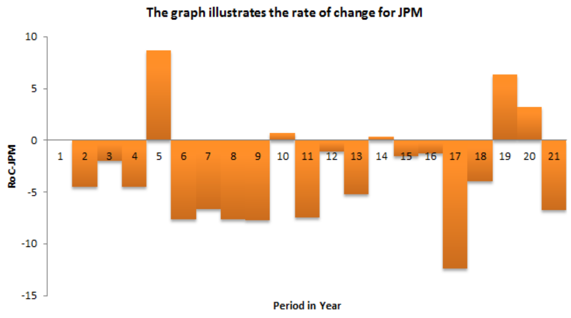

Figure 6. The graph illustrates the RoC for JPM

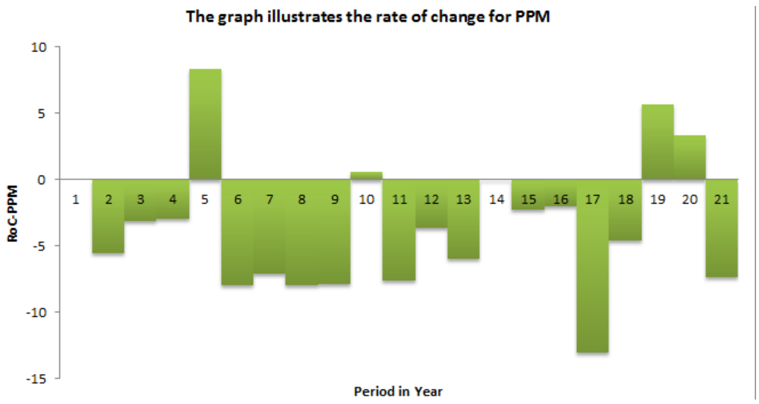

Figure 7. The graph illustrates the RoC for PPM

The initial steps in creating the discourse universe U, grounded in the RoC results, necessitate the application of (15) to (17). These procedures involve calculating the LL and UL, rounding the results, and ascertaining the quantity and length of each interval. Table 6 illustrates the results of identifying the universe of discourse U and its frequency.

Table 6. Establishing the universe of discourse (U) and its frequency

U	GK		JPM		PPM	
	Interval	Frequency	Interval	Frequency	Interval	Frequency
U1	$\{0.00, 3.17\}$	2	$\{-13.00, -9.33\}$	2	$\{-14.00, -9.83\}$	1
U2	$\{3.17, 6.33\}$	9	$\{-9.33, -5.67\}$	6	$\{-9.83, -5.67\}$	9
U3	$\{6.33, 9.50\}$	9	$\{-5.67, -2.00\}$	5	$\{-5.67, -1.50\}$	7
U4	$\{9.50, 12.67\}$	3	$\{-2.00, 1.67\}$	7	$\{-1.50, 2.67\}$	3
U5	$\{12.67, 15.83\}$	0	$\{1.67, 5.33\}$	1	$\{2.67, 6.83\}$	2
U6	$\{15.83, 19.00\}$	1	$\{5.33, 9.00\}$	3	$\{6.83, 11.00\}$	2

After delineating U into equal intervals, such as u1, u2, u3,..., un, partition the interval based on the frequency quantity into several smaller intervals: below are the necessary actions to follow: upon determining the quantity of RoC frequencies within each interval, subdivide it into smaller intervals according to that quantity. If the interval encompasses one or zero RoC frequencies, it remains constant and does not necessitate division. Table 6 presents an illustration of the GK scenario. The interval frequency is {0.00, 3.17}, indicating a total of two. During this interval, there exist two subintervals. The intervals {3.17, 6.33} and {6.33, 9.50} can be divided into nine smaller intervals. The interval {9.50, 12.67} has three subintervals. Given the presence of only two frequencies 0 and 1 the intervals {12.67, 15.83} and {15.83, 19.00} do not necessitate subdivision into several sub-intervals. In the context of partitioning an interval into numerous sub-intervals, both the JPM and PPM scenarios do this operation identically. To calculate the Forecasting RoC (FRoC) for GK, JPM, and PPM in FTS, we identify the median value of each subinterval and subsequently apply the triangle membership function outlined in (18). Figures 8 to 10 illustrate a contrast between the estimated findings and real poverty data (GK, JPM, and PPM) in Central Java, derived from (19).

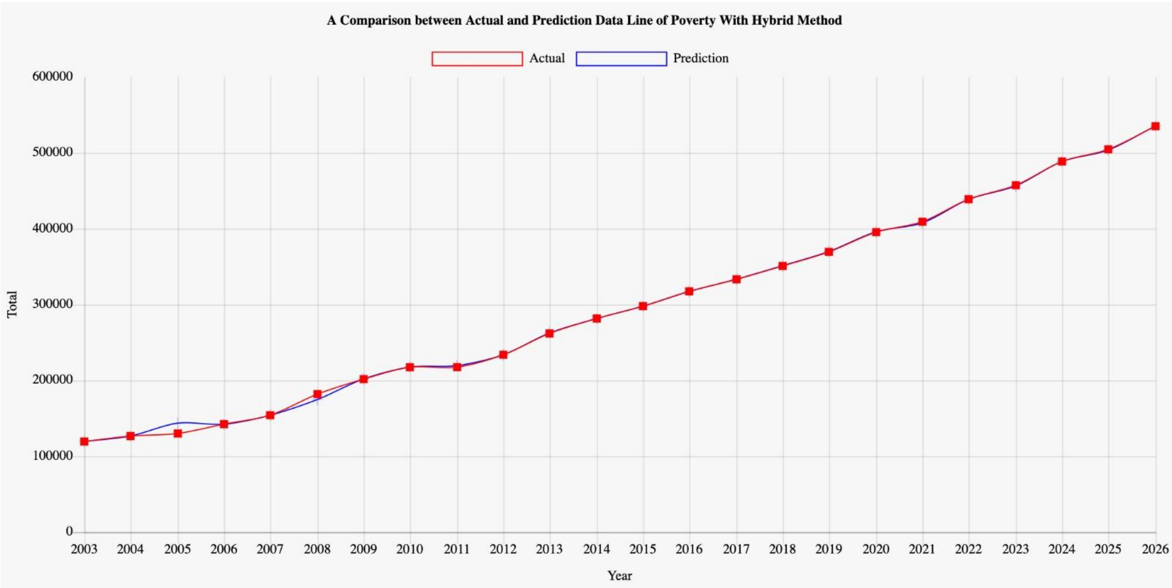

Figure 8. Graph depicting the predictive outcomes of the hybrid model in comparison to actual GK data

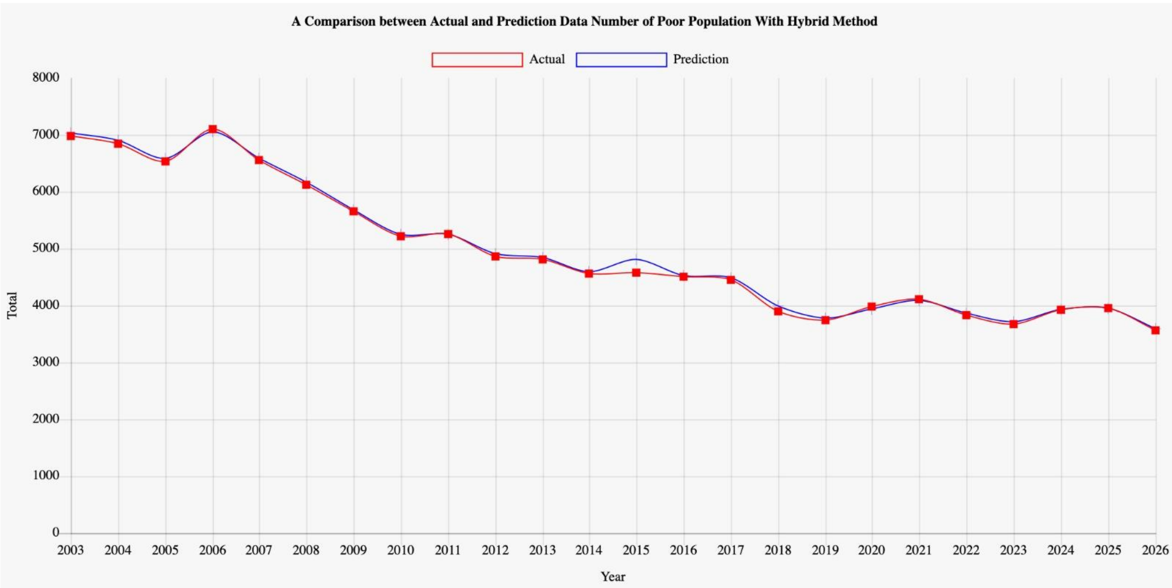

Figure 9. Graph depicting the predictive outcomes of the hybrid model in comparison to actual JPM data

In (19) underpins the forecasting computations for the years 2023, 2024, 2025, and 2026, employing the proposed hybrid model. Table 7 displays the expected results for the next four years. Table 8 displays forecast outcomes for the forthcoming four years by employing various other models.

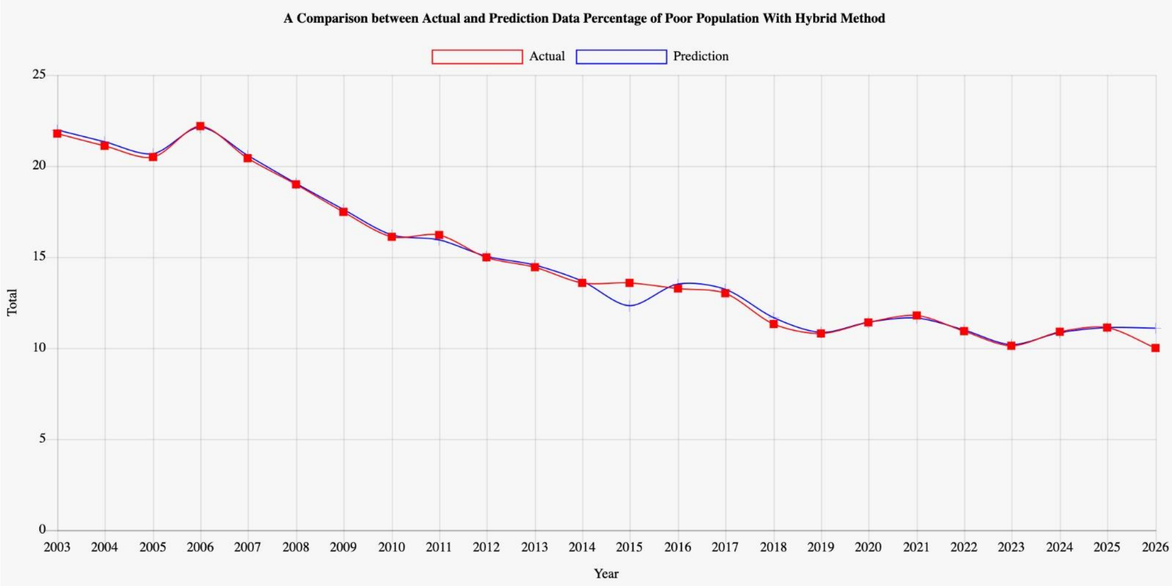

Figure 10. Graph depicting the predictive outcomes of the hybrid model in comparison to actual PPM data

Table 7. Forecast results of the hybrid model for the subsequent four periods

Year	GK	JPM	PPM
2023	456522.10	3716.08	10.19
2024	488581.86	3932.28	10.84
2025	503703.98	3952.03	11.12
2026	535561.90	3593.46	11.09

Table 8. Forecast outcomes for the subsequent four years utilizing other models

Model	Year	GK	JPM	PPM
DES	2023	382654	4142	10.91
	2024	400211	4098	10.63
	2025	417768	4055	10.36
	2026	435325	4011	10.08
SES	2023	362810	4205	11.23
	2024	362810	4205	11.23
	2025	362810	4205	11.23
	2026	362810	4205	11.23
FTS Chen	2023	395000	4100	10.50
	2024	415000	3900	10.00
	2025	435000	3700	9.50
	2026	455000	3500	9.00
FTS Lee	2023	390120	4050	10.80
	2024	412550	3920	10.40
	2025	435080	3790	10.00
	2026	457600	3660	9.60
FTS Cheng	2023	392500	4020	10.70
	2024	416200	3880	10.30
	2025	440000	3740	9.90
	2026	463800	3600	9.50
ARIMA	2023	348257	4401	12.42
	2024	363289	4357	11.82
	2025	378321	4319	11.23
	2026	393353	4285	10.63
SARIMA	2023	455420	3926	11.05
	2024	473815	3968	10.98
	2025	492090	4001	10.91
	2026	510505	4036	10.84
LSTM	2023	427638	3984	11.53
	2024	435912	3985	11.54
	2025	442307	3985	11.55
	2026	442606	3986	11.54

3.3. Comparative results

Table 9 shows that the proposed hybrid model consistently outperforms all benchmark methods, including Holt–Winters triple exponential smoothing (HWTES), double and single exponential smoothing (DES, SES), Chen's, Lee's, and Cheng's fuzzy time series (FTS), autoregressive integrated moving average (ARIMA), seasonal autoregressive integrated moving average (SARIMA), and long short-term memory (LSTM), as evidenced by the comparative analysis of forecasting results.

Table 9. Evaluating the model's performance outcomes using MAPE

Poverty	MAPE (%)									
	HWTES	DES	SES	FTS Chen	FTS Lee	FTS Cheng	ARIMA	SARIMA	LSTM	HYBRID
GK	6.4	2.5	3.3	2.4	1.9	1.8	3.5	2.9	6.2	0.7
JPM	4.4	6.8	7.9	6.0	4.9	4.7	10.6	8.5	4.1	0.9
PPM	4.5	4.9	5.9	4.9	3.9	3.9	7.7	6.1	3.8	1.6

We conducted a comparison of outcomes from eleven forecasting models for GK, JPM, and PPM. MAPE is a performance metric that signifies the accuracy of a forecasting model. Extremely low MAPE values across all categories signify the most precise models in this dataset, with the hybrid and Lee's FTS models demonstrating this trait. In comparison to other models, the HWTES, SARIMA, and LSTM models demonstrate elevated MAPE values, particularly in specific categories. The effectiveness of various FTS variants varies; Chen's FTS and Cheng's FTS demonstrate comparable performance; however, Lee's FTS yields commendable outcomes. The effectiveness of the exponential smoothing models (SES, DES, and HWTES) varies on their smoothing capacities. DES routinely surpasses SES and HWTES in all categories.

4. CONCLUSION

The preceding part outlined the observational findings, which illustrate the multiple advantages of the hybrid model forecasting introduced in this study. For example, it produces results deemed precise, with a MAPE of under ten percent in each poverty scenario (GK, JPM, and PPM).

This study illustrates that the proposed hybrid model is adept at managing TS data predictions. A poverty case study in Central Java revealed that the computation of GK, JPM, and PPM situations is highly precise. The precision is evidenced by the error test employing the MAPE method for each case, which produces negligible results. The error rate for GK stands at 0.7%. The outcomes are 0.9% for the JPM scenario and 1.6% for the PPM instance. This hybrid model demonstrates more accuracy compared to the findings produced by the HWTES and other models.

As a result, we may use this hybrid model as a decision-making tool to create strategic plans for the near future, including the planning and enhancement of poverty alleviation initiatives in Central Java. In the future, we expect that additional scholars will develop this hybrid forecasting model, broadening its use beyond poverty-related issues to more intricate scenarios.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Achmad Solechan				✓		✓	✓	✓	✓	✓		✓	✓	
Solikhin	✓	✓		✓	✓				✓	✓	✓		✓	
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The researchers conducting this investigation declare that no personal or financial conflicts of interest influenced the findings.

INFORMED CONSENT

We have secured agreement from all participants involved in the implementation of this domestic collaborative research (PKDN) program.

ETHICAL APPROVAL

The research related to human use has been complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY

The data supporting this study is publicly accessible at [Badan Pusat Statistik Provinsi Jawa Tengah] via https://jateng.bps.go.id/indicator/23/34/1/kemiskinan.html [58].

REFERENCES

[1] R. M. Dantas, S. Ali, M. Rafiq, J. M. Martins, A. Abreu, and M. N. Mata, "Exploring the Asymmetric Effect of Internal and External Economic Factors on Poverty: A Fresh Insight from Nonlinear Autoregressive Distributive Lag Model," *Emerging Science Journal*, vol. 7, no. 3, pp. 755–767, May 2023, doi: 10.28991/ESJ-2023-07-03-07.

[2] T. Hofmarcher, "The effect of education on poverty: A European perspective," *Economics of Education Review*, vol. 83, p. 102124, Aug. 2021, doi: 10.1016/j.econedurev.2021.102124.

[3] J. Korosteleva and P. Stępień-Baig, "Climbing the poverty ladder: the role of entrepreneurship and gender in alleviating poverty in transition economies," in *Entrepreneurship and Regional Development*, vol. 32, no. 1–2, 2020, pp. 197–220, doi: 10.1080/08985626.2019.1640482.

[4] F. Sofo and A. Wicks, "An occupational perspective of poverty and poverty reduction," *Journal of Occupational Science*, vol. 24, no. 2, pp. 244–249, Apr. 2017, doi: 10.1080/14427591.2017.1314223.

[5] H. Panchal *et al.*, "Performance evaluation of using evacuated tubes solar collector, perforated fins, and pebbles in a solar still – experimental study and CO2 mitigation analysis," *Environmental Science and Pollution Research*, vol. 30, no. 5, pp. 11769–11784, Sep. 2023, doi: 10.1007/s11356-022-22809-z.

[6] H. Panchal *et al.*, "Experimental investigation on the yield of solar still using manganese oxide nanoparticles coated absorber," *Case Studies in Thermal Engineering*, vol. 25, p. 100905, Jun. 2021, doi: 10.1016/j.csite.2021.100905.

[7] T. W. Bank, "Indonesia Poverty Assessment: Pathways Towards Economic Security," 2023. https://www.worldbank.org/en/country/indonesia/publication/indonesia-poverty-assessment. (Accessed: Aug. 12, 2024).

[8] B. Wang, X. Liu, M. Chi, and Y. Li, "Bayesian network based probabilistic weighted high-order fuzzy time series forecasting," *Expert Systems with Applications*, vol. 237, p. 121430, Mar. 2024, doi: 10.1016/j.eswa.2023.121430.

[9] V. Vamitha, "A different approach on fuzzy time series forecasting model," *Materials Today: Proceedings*, vol. 37, no. Part 2, pp. 125–128, 2020, doi: 10.1016/j.matpr.2020.04.579.

[10] Š. Hudecová and M. Pešta, "Quasi-Likelihood Estimation in Volatility Models for Semi-Continuous Time Series," *Journal of Time Series Analysis*, vol. 45, no. 6, pp. 859–883, Nov. 2024, doi: 10.1111/jtsa.12741.

[11] C. Zhu, X. Ma, C. Zhang, W. Ding, and J. Zhan, "Information granules-based long-term forecasting of time series via BPNN under three-way decision framework," *Information Sciences*, vol. 634, pp. 696–715, Jul. 2023, doi: 10.1016/j.ins.2023.03.133.

[12] K. Gajamannage, Y. Park, and D. I. Jayathilake, "Real-time forecasting of time series in financial markets using sequentially trained dual-LSTMs," *Expert Systems with Applications*, vol. 223, p. 119879, Aug. 2023, doi: 10.1016/j.eswa.2023.119879.

[13] J. Jiang, L. Wu, H. Zhao, H. Zhu, and W. Zhang, "Forecasting movements of stock time series based on hidden state guided deep

learning approach," *Information Processing and Management*, vol. 60, no. 3, p. 103328, May 2023, doi: 10.1016/j.ipm.2023.103328.

[14] R. Jaiswal, G. K. Jha, R. R. Kumar, and K. Choudhary, "Deep long short-term memory based model for agricultural price forecasting," *Neural Computing and Applications*, vol. 34, no. 6, pp. 4661–4676, Mar. 2022, doi: 10.1007/s00521-021-06621-3.

[15] J. A. Jiang, C. H. Syue, C. H. Wang, M. S. Liao, J. S. Shieh, and J. C. Wang, "Precisely forecasting population dynamics of agricultural pests based on an interval type-2 fuzzy logic system: case study for oriental fruit flies and the tobacco cutworms," *Precision Agriculture*, vol. 23, no. 4, pp. 1302–1332, Aug. 2022, doi: 10.1007/s11119-022-09886-3.

[16] M. A. Costa, R. Ruiz-Cárdenas, L. B. Mineti, and M. O. Prates, "Dynamic time scan forecasting for multi-step wind speed prediction," *Renewable Energy*, vol. 177, pp. 584–595, Nov. 2021, doi: 10.1016/j.renene.2021.05.160.

[17] A. K. Kushwah and R. Wadhvani, "Trend triplet based data clustering for eliminating nonlinear trend components of wind time series to improve the performance of statistical forecasting models," *Multimedia Tools and Applications*, vol. 81, no. 23, pp. 33927–33953, Sep. 2022, doi: 10.1007/s11042-022-12992-z.

[18] S. Tatinati, Y. Wang, and A. W. H. Khong, "Hybrid Method Based on Random Convolution Nodes for Short-Term Wind Speed Forecasting," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 10, pp. 7019–7029, Oct. 2022, doi: 10.1109/TII.2020.3043451.

[19] V. K. Sudarshan, M. Brabrand, T. M. Range, and U. K. Wiil, "Performance evaluation of Emergency Department patient arrivals forecasting models by including meteorological and calendar information: A comparative study," *Computers in Biology and Medicine*, vol. 135, p. 104541, Aug. 2021, doi: 10.1016/j.compbiomed.2021.104541.

[20] D. Mircetic, B. Rostami-Tabar, S. Nikolicic, and M. Maslaric, "Forecasting hierarchical time series in supply chains: an empirical investigation," *International Journal of Production Research*, vol. 60, no. 8, pp. 2514–2533, Apr. 2022, doi: 10.1080/00207543.2021.1896817.

[21] E. Zhao, P. Du, and S. Sun, "Historical pattern recognition with trajectory similarity for daily tourist arrivals forecasting," *Expert Systems with Applications*, vol. 203, p. 117427, Oct. 2022, doi: 10.1016/j.eswa.2022.117427.

[22] T. Carvalho, M. Vellasco, and J. F. Amaral, "Automatic generation of fuzzy inference systems for multivariate time series forecasting," *Fuzzy Sets and Systems*, vol. 470, p. 108657, Oct. 2023, doi: 10.1016/j.fss.2023.108657.

[23] J. E. Moreno *et al.*, "Design of an interval Type-2 fuzzy model with justifiable uncertainty," *Information Sciences*, vol. 513, pp. 206–221, Mar. 2020, doi: 10.1016/j.ins.2019.10.042.

[24] Z. Anari, A. Hatamlou, and B. Anari, "Automatic Finding Trapezoidal Membership Functions in Mining Fuzzy Association Rules Based on Learning Automata," *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 7, no. 4, pp. 27–43, Jun. 2022, doi: 10.9781/ijimai.2022.01.001.

[25] A. Ikidid, A. El Fazziki, and M. Sadgal, "Multi-Agent and Fuzzy Inference-Based Framework for Traffic Light Optimization," *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 8, no. 2, pp. 88–97, Jun. 2023, doi: 10.9781/ijimai.2021.12.002.

[26] Q. Song and B. S. Chissom, "Forecasting enrollments with fuzzy time series - Part I," *Fuzzy Sets and Systems*, vol. 54, no. 1, pp. 1–9, Feb. 1993, doi: 10.1016/0165-0114(93)90355-L.

[27] L. A. Zadeh, "Fuzzy Sets," in *Fuzzy Sets, Fuzzy Logic, and Fuzzy Systems: Selected Papers*, Eds. Singapore: World Scientific, 1996.

[28] Q. Song and B. S. Chissom, "Forecasting enrollments with fuzzy time series - part II," *Fuzzy Sets and Systems*, vol. 62, no. 1, pp. 1–8, Feb. 1994, doi: 10.1016/0165-0114(94)90067-1.

[29] P. Jiang, H. Yang, R. Li, and C. Li, "Inbound tourism demand forecasting framework based on fuzzy time series and advanced optimization algorithm," *Applied Soft Computing Journal*, vol. 92, p. 106320, Jul. 2020, doi: 10.1016/j.asoc.2020.106320.

[30] A. Rubio, J. D. Bermúdez, and E. Vercher, "Improving stock index forecasts by using a new weighted fuzzy-trend time series method," *Expert Systems with Applications*, vol. 76, pp. 12–20, Jun. 2017, doi: 10.1016/j.eswa.2017.01.049.

[31] K. Huarng and T. H. K. Yu, "Ratio-based lengths of intervals to improve fuzzy time series forecasting," *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, vol. 36, no. 2, pp. 328–340, Apr. 2006, doi: 10.1109/TSMCB.2005.857093.

[32] P. Singh, "An Efficient Method for Forecasting Using Fuzzy Time Series," in *Emerging Research on Applied Fuzzy Sets and Intuitionistic Fuzzy Matrices*, 2017, doi: 10.4018/978-1-5225-0914-1.ch013.

[33] S. M. Chen and B. D. H. Phuong, "Fuzzy time series forecasting based on optimal partitions of intervals and optimal weighting vectors," *Knowledge-Based Systems*, vol. 118, pp. 204–216, Feb. 2017, doi: 10.1016/j.knosys.2016.11.019.

[34] S. M. Chen and S. W. Chen, "Fuzzy forecasting based on two-factors second-order fuzzy-trend logical relationship groups and the probabilities of trends of fuzzy logical relationships," *IEEE Transactions on Cybernetics*, vol. 45, no. 3, pp. 391–403, Mar. 2015, doi: 10.1109/TCYB.2014.2326888.

[35] S. H. Cheng, S. M. Chen, and W. S. Jian, "A Novel Fuzzy Time Series Forecasting Method Based on Fuzzy Logical Relationships and Similarity Measures," in *Proceedings - 2015 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2015*, Oct. 2016, pp. 2250–2254, doi: 10.1109/SMC.2015.393.

[36] S. H. Cheng, S. M. Chen, and W. S. Jian, "Fuzzy time series forecasting based on fuzzy logical relationships and similarity measures," *Information Sciences*, vol. 327, pp. 272–287, Jan. 2016, doi: 10.1016/j.ins.2015.08.024.

[37] R. G. Del Campo, L. Garmendia, J. Recasens, and J. Montero, "Hesitant fuzzy sets and relations using lists," in *IEEE International Conference on Fuzzy Systems*, Jul. 2017, pp. 1–6, doi: 10.1109/FUZZ-IEEE.2017.8015516.

[38] M. Stevenson and J. E. Porter, "Fuzzy time series forecasting using percentage change as the universe of discourse," *World Academy of Science, Engineering, and Technology*, 2009.

[39] B. Garg, M. M. S. Beg, and A. Q. Ansari, "A new computational fuzzy time series model to forecast number of outpatient visits," in *2012 Annual Meeting of the North American Fuzzy Information Processing Society, NAFIPS 2012*, Aug. 2012, pp. 1–6, doi: 10.1109/NAFIPS.2012.6290977.

[40] F. H. Darzi, N. Khoshnazar, and M. Eslami, "Fuzzy time series forecasting Comparing Markov-Chain and percentage change models," in *4th Iranian Joint Congress on Fuzzy and Intelligent Systems, CFIS 2015*, Sep. 2016, pp. 1–4, doi: 10.1109/CFIS.2015.7391636.

[41] A. R. Lubis, S. Prayudani, and Al-Khowarizmi, "Optimization of MSE Accuracy Value Measurement Applying False Alarm Rate in Forecasting on Fuzzy Time Series based on Percentage Change," in *2020 8th International Conference on Cyber and IT Service Management, CITSM 2020*, Oct. 2020, pp. 1–5, doi: 10.1109/CITSM50537.2020.9268906.

[42] A. A. Husain, B. Surarso, Farikhin, and B. Irawanto, "Forecasting model of COVID-19 cases using fuzzy time series using persentage change," *Journal of Physics: Conference Series*, vol. 1943, no. 1, p. 012127, Jul. 2021, doi: 10.1088/1742-6596/1943/1/012127.

[43] Solikhin, S. Lutfi, Purnomo, and Hardiwinoto, "Prediction of passenger train using fuzzy time series and percentage change

methods," *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 6, pp. 3007–3018, Dec. 2021, doi: 10.11591/eei.v10i6.2822.
[44] Solikhin, S. Lutfi, Purnomo, and Hardiwinoto, "A machine learning approach in Python is used to forecast the number of train passengers using a fuzzy time series model," *Bulletin of Electrical Engineering and Informatics*, vol. 11, no. 5, pp. 2746–2755, Oct. 2022, doi: 10.11591/eei.v11i5.3518.
[45] T. A. Jilani and S. M. A. Burney, "A refined fuzzy time series model for stock market forecasting," *Physica A: Statistical Mechanics and its Applications*, vol. 387, no. 12, pp. 2857–2862, May 2008, doi: 10.1016/j.physa.2008.01.099.
[46] U. S. Mukminin, B. Irawanto, B. Surarso, and Farikhin, "Fuzzy time series based on frequency density-based partitioning and k-means clustering for forecasting exchange rate," *Journal of Physics: Conference Series*, vol. 1943, no. 1, p. 012119, Jul. 2021, doi: 10.1088/1742-6596/1943/1/012119.
[47] B. Irawanto, R. W. Ningrum, B. Surarso, and Farikhin, "An improved forecasting method of frequency density partitioning (FDP) based on fuzzy time series (FTS)," *Journal of Physics: Conference Series*, vol. 1321, no. 2, p. 022082, Oct. 2019, doi: 10.1088/1742-6596/1321/2/022082.
[48] R. Wulandari, Farikhin, B. Surarso, and B. Irawanto, "First-Order Fuzzy Time Series based on Frequency Density Partitioning for Forecasting Production of Petroleum," *IOP Conference Series: Materials Science and Engineering*, vol. 846, no. 1, p. 012063, May 2020, doi: 10.1088/1757-899X/846/1/012063.
[49] S. Hariyanto, Y. D. Sumanto, S. Khabibah, and Zaenurrohman, "Average-Based Fuzzy Time Series Markov Chain Based on Frequency Density Partitioning," *Journal of Applied Mathematics*, vol. 2023, pp. 1–9, May 2023, doi: 10.1155/2023/9319883.
[50] A. Boukerche, Y. Tao, and P. Sun, "Artificial intelligence-based vehicular traffic flow prediction methods for supporting intelligent transportation systems," *Computer Networks*, vol. 182, p. 107484, Dec. 2020, doi: 10.1016/j.comnet.2020.107484.
[51] M. M. Masrur, S. Solikhin, M. W. S. Churum, M. Z. Abdillah, and T. W. A. Putra, "Web-Based Forecasting Approach to Estimating the Number of Low-Income Households Eligible for Social Food Aid Using Holt's Double Exponential Smoothing," *Register: Jurnal Ilmiah Teknologi Sistem Informasi*, vol. 11, no. 2, pp. 91–105, Nov. 2025, doi: 10.26594/register.v11i2.4922.
[52] F. E. Ikuemonisan, V. C. Ozebo, and O. B. Olatinsu, "Investigation of Sentinel-1-derived land subsidence using wavelet tools and triple exponential smoothing algorithm in Lagos, Nigeria," *Environmental Earth Sciences*, vol. 80, no. 21, p. 722, Nov. 2021, doi: 10.1007/s12665-021-10020-1.
[53] D. M. Khairina, Y. Daniel, and P. P. Widagdo, "Comparison of double exponential smoothing and triple exponential smoothing methods in predicting income of local water company," *Journal of Physics: Conference Series*, vol. 1943, no. 1, p. 012102, Jul. 2021, doi: 10.1088/1742-6596/1943/1/012102.
[54] L. Zhang *et al.*, "A Novel Hybrid Model for Docker Container Workload Prediction," *IEEE Transactions on Network and Service Management*, vol. 20, no. 3, pp. 2726–2743, Sep. 2023, doi: 10.1109/TNSM.2023.3248803.
[55] Y. Xie *et al.*, "Real-Time Prediction of Docker Container Resource Load Based on a Hybrid Model of ARIMA and Triple Exponential Smoothing," *IEEE Transactions on Cloud Computing*, vol. 10, no. 2, pp. 1386–1401, Apr. 2022, doi: 10.1109/TCC.2020.2989631.
[56] U. Yudatama, Solikhin, D. E. Harmadji, and A. Purwanto, "COVID-19 Case Growth Prediction Using a Hybrid Fuzzy Time Series Forecasting Model and a Machine Learning Approach," *International Journal of Computing*, vol. 23, no. 1, pp. 43–53, Apr. 2024, doi: 10.47839/ijc.23.1.3434.
[57] W. Pedrycz, "Why triangular membership functions?," *Fuzzy Sets and Systems*, vol. 64, no. 1, pp. 21–30, May 1994, doi: 10.1016/0165-0114(94)90003-5.
[58] Badan Pusat Statistik Provinsi Jawa Tengah, "Poverty by District/City in Central Java Province (in Indonesia: *Kemiskinan Menurut Kabupaten/Kota di Provinsi Jawa Tengah*)," 2022, https://jateng.bps.go.id/indicator/23/34/1/kemiskinan.html. (Accessed: Jun. 22, 2023).
[59] C. C. Holt, "Forecasting seasonals and trends by exponentially weighted moving averages," *International Journal of Forecasting*, vol. 20, no. 1, pp. 5–10, Jan. 2004, doi: 10.1016/j.ijforecast.2003.09.015.
[60] P. R. Winters, "Forecasting Sales by Exponentially Weighted Moving Averages," *Management Science*, vol. 6, no. 3, pp. 324–342, Apr. 1960, doi: 10.1287/mnsc.6.3.324.
[61] S. Kim and H. Kim, "A new metric of absolute percentage error for intermittent demand forecasts," *International Journal of Forecasting*, vol. 32, no. 3, pp. 669–679, Jul. 2016, doi: 10.1016/j.ijforecast.2015.12.003.
[62] S. Makridakis *et al.*, "The accuracy of extrapolation (time series) methods: Results of a forecasting competition," *Journal of Forecasting*, vol. 1, no. 2, pp. 111–153, Apr. 1982, doi: 10.1002/for.3980010202.
[63] P. C. Chang, Y. W. Wang, and C. H. Liu, "The development of a weighted evolving fuzzy neural network for PCB sales forecasting," *Expert Systems with Applications*, vol. 32, no. 1, pp. 86–96, Jan. 2007, doi: 10.1016/j.eswa.2005.11.021.
[64] H. A. Sturges, "The Choice of a Class Interval," *Journal of the American Statistical Association*, vol. 21, no. 153, pp. 65–66, Mar. 1926, doi: 10.1080/01621459.1926.10502161.
[65] D. K. Sharma, M. Chatterjee, G. Kaur, and S. Vavilala, "Deep learning applications for disease diagnosis," in *Deep Learning for Medical Applications with Unique Data*, Elsevier, 2022, pp. 31–51, doi: 10.1016/B978-0-12-824145-5.00005-8.

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