

**APPLICATION OF HIGH ORDER CHEN FUZZY TIME SERIES
METHOD USING PARTICLE SWARM OPTIMIZATION
FOR FORECASTING THE STOCK INDEX
OF INDONESIAN ISLAMIC BANKS**

(Thesis)

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ABSTRACT

APPLICATION OF HIGH ORDER CHEN FUZZY TIME SERIES METHOD USING PARTICLE SWARM OPTIMIZATION FOR FORECASTING THE STOCK INDEX OF INDONESIAN ISLAMIC BANKS

By

Ilmiatul Karomah

This study aims to forecast the stock index of Bank Syariah Indonesia (BSI) using the High Order Chen Fuzzy Time Series (HOCFTS) method integrated with Particle Swarm Optimization (PSO). Forecasting financial data such as stock indices requires models capable of handling data uncertainty and non-linearity. The Chen Fuzzy Time Series method offers a flexible approach by utilizing fuzzy logic, and its higher-order variant improves accuracy by incorporating multiple past observations. However, determining optimal interval partitioning remains a challenge. To address this, PSO is employed to optimize interval lengths and enhance forecasting performance. Monthly stock index data of BSI from June 2018 to September 2024 were analyzed. Forecasting was conducted using the HOCFTS model from order 1 to 8, and the accuracy of each model was evaluated using Mean Absolute Percentage Error (MAPE). The results show that the fourth-order model with PSO optimization yields the lowest MAPE, indicating superior forecasting accuracy compared to other orders. This research contributes to the development of hybrid forecasting models in Islamic financial markets, providing more accurate tools for investors and financial analysts to make informed decisions.

Keywords: Fuzzy Time Series, Chen Model, High Order, Particle Swarm Optimization, Stock Index Forecasting, Bank Syariah Indonesia.

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ILMIATUL KAROMAH

Thesis

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Bachelor of MATHEMATICS

on

Departement of Mathematics

Faculty of Mathematics and Natural Sciences



**FACULTY OF MATHEMATICS AND NATURAL SCIENCES
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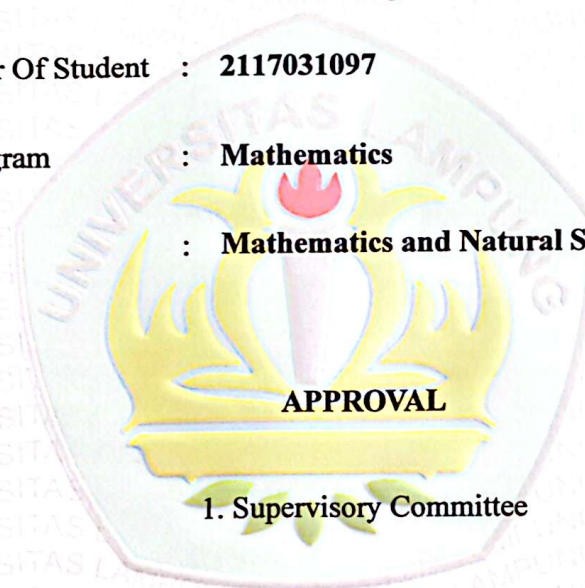
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WORDS OF INSPIRATION

"The most difficult form of patience is the ability to endure situations you don't want to be in."

-Gus Baha'

"Look at life like an artist looks at a canvas, create something beautiful.."

-Marcus Aurelius

"Every day is a new opportunity to improve yourself."

-Anonim

"Success does not belong to smart people, success belongs to those who constantly strive for it."

-B.J Habibie

"And Allah is sufficient as a witness."

(Q.S Al Fath: 28)

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By saying Alhamdulillah and thanks to Allah SWT for His blessings and guidance so that this research proposal can be completed properly and on time. With gratitude and happiness, I offer my gratitude to:

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CHAPTER I

INTRODUCTION

1.1 Background of the Problem

Time series analysis is a statistical technique used to analyze data that is collected or measured sequentially in time. This method allows researchers and analysts to identify patterns, trends, and fluctuations that occur in the data, as well as forecast future behavior based on historical data. Time series analysis is an important method in econometrics to handle time series data and avoid spurious regressions (Juanda and Junaidi, 2012). In various fields, including economics, finance, health, and social sciences, time series analysis is essential for informative decision making.

In a financial context, time series analysis can be used to forecast stock prices, interest rates, and other economic indicators. Although many traditional methods, such as ARIMA (AutoRegressive Integrated Moving Average) and Exponential Smoothing, have proven to be effective, they often rely on assumptions of normality and linearity that may not always fit the complex and fluctuating nature of real data. As a solution, Fuzzy Time Series (FTS) is emerging as a promising method for forecasting volatile financial data, particularly stock indices and commodity prices. This method uses fuzzy logic to capture the uncertainty and ambiguity in the data, allowing the model to operate on data that is uncertain and has high variability.

Chen's higher-order FTS model overcomes the limitations of the first-order model, thus providing easier calculations and better forecasting results (Own and Yu, 2005). Recent developments include modification of the universe of discourse partition using median ratio intervals (Vianita et al., 2022) and application of higher-order FTS to various domains such as cooperative sales forecasting (Arfiana et al., 2022). The effectiveness of FTS models is usually evaluated using accuracy metrics such as Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE). Ongoing research aims to improve the

FTS model by improving the interval partitioning method and addressing ambiguity in forecasting while reducing memory requirements for data storage (Own and Yu, 2005).

However, FTS has limitations in determining the optimal interval. To overcome this, researchers have integrated Particle Swarm Optimization (PSO) with FTS, resulting in more accurate forecasts for stock indices such as LQ45 (Ihsanuddin et al., 2023). FTS has been successfully applied to various financial time series, including the Jakarta Composite Index (JCI) (Hansun, 2013) and gold prices (Sugumonrong et al., 2019). These studies show that FTS, especially when combined with optimization techniques such as PSO, can provide reliable forecasts for financial data without requiring assumptions of normality or stationarity, thus making it a valuable tool for investors and analysts in predicting market trends.

Stock indices are important indicators that reflect market performance and provide an overview of a country's economic conditions. Rapid global economic development has led to dynamics in the stock market, including in Indonesia. In Indonesia, Bank Syariah Indonesia (BSI) as a leading Islamic financial institution is one of the growing banks that contribute to the Islamic financial sector. Forecasting the BSI stock index is very important for investors and stakeholders in making investment decisions.

Although there has been a lot of research in this area, there are still shortcomings in the application of Chen's higher-order fuzzy time series method combined with PSO for forecasting the BSI stock index. Therefore, this study aims to explore and analyze the effectiveness of the combination of these methods in forecasting the BSI stock index, which is expected to make a significant contribution to the development of investment strategies in the Indonesian Islamic capital market.

1.2 Research Objectives

1. Analyzing the accuracy level of Chen's high-order fuzzy time series model with PSO in predicting stock index movements.
2. Identifying the advantages of Chen's fuzzy time series combination method and PSO compared to conventional forecasting methods in the context of Islamic stock index forecasting.

3. Examining the effect of parameters in the PSO algorithm on improving the performance of Chen's higher-order fuzzy time series model in stock index forecasting.

1.3 Research Benefits

This research is expected to provide the following benefits:

1. Provide a more accurate and reliable forecasting method to predict the Islamic stock index, which is beneficial for investors, Islamic financial institutions, and regulators in decision making.
2. Develop hybrid techniques in Chen's fuzzy time series with PSO that can be applied to other forecasting fields.

CHAPTER II

LITERATURE REVIEW

2.1 Time Series Data Analysis

Time series data analysis is a statistical method used to model and predict patterns from a series of data observed at specific time intervals. Time series data is dynamic in nature as it is continuously observed over time, thus requiring a specialized approach in its analysis (Chatfield, 2003). Time series analysis can also be used to forecast and predict trends in various fields, such as economics and natural disasters. It involves analyzing periodic data to produce future projections (Henderi et al., 2019).

In time series data analysis, identifying data patterns is an important element that needs to be done to understand the behavior of the time series. The identification of these patterns allows researchers to select appropriate models for analysis, prediction, and forecasting. According to (Brockwell and Davis, 2016) time series data often consists of several main pattern components, namely trends, seasonality, cycles, and random fluctuations.

1. Trend Data Pattern

Trend data patterns describe the general direction of time series data in a given period, which can be an upward trend, downward trend, or stationary trend. These trends can arise due to various long-term factors, such as changes in the economy, technology, or government policies (Shumway and Stoffer, 2017).

2. Seasonal Data Pattern

Seasonal patterns indicate fluctuations that occur regularly within a fixed time interval, such as weekly, monthly, or annually. This phenomenon often appears in data related to human activity or nature, such as in the analysis of retail sales that spike during the holiday season, or temperature changes that occur every year (Hyndman and Athanasopoulos, 2018).

3. Cycle Pattern

Cyclical patterns are similar to seasonal patterns, but the difference lies in the duration and unpredictability of the period. Cycles reflect fluctuations that occur over a longer period and are not always fixed, such as economic cycles that can last for several years. According to (Ruhiat & Suwanda, 2019) cyclical analysis is very important in economics because it can reflect long-term fluctuations that affect the economy, both globally and domestically.

4. Random Fluctuation (Horizontal)

In addition to identifiable patterns, time series data also contain random components that are irregular and difficult to predict. These fluctuations do not follow a specific pattern and are often caused by external factors that cannot be explained by existing models. In the analysis process, these random components are often removed or minimized using smoothing or smoothing methods.

2.2 Fuzzy Logic

Fuzzy logic is a mathematical method used to handle uncertainty and imprecise data. It was introduced by Lotfi Zadeh in 1965 as a way to address the complexities that arise when interpreting data in the real world. Unlike classical logic which only recognizes two truth values (true or false), fuzzy logic introduces degrees of membership that allow truth values to range between 0 and 1, thus handling the concepts of "vagueness" and "imprecision" more flexibly (Zadeh, 2015).

In its applications, fuzzy logic is used in various fields, including system control, decision making, and forecasting and data analysis. According to (Wu et al., 2015) fuzzy logic is proven to be effective in handling data that has a high degree of uncertainty, especially in financial and economic analysis where predictions are often difficult to make with conventional approaches. They emphasized that fuzzy logic can provide more adaptive solutions compared to purely statistical-based methods, especially in dealing with volatile market variations.

In addition, research by (Wang and Tsaur, 2011) underscores the use of fuzzy logic in the development of more accurate forecasting models. Tsaur explains that by applying fuzzy concepts to historical data, prediction results can be improved, especially when the data contains elements of uncertainty or shifting trends that are difficult to capture by conventional methods.

2.3 Fuzzy Set

Fuzzy sets are a basic concept in fuzzy logic theory introduced by Lotfi A. Zadeh in 1965. These sets are designed to handle uncertain and ambiguous data, which often cannot be handled with conventional binary logic approaches. Unlike classical sets, where elements have only two possible states, namely member (1) or non-member (0), fuzzy sets allow degrees of membership that are continuous between 0 and 1, thus reflecting a more flexible reality (Zadeh, 2015). Fuzzy sets are very effective in representing uncertainty in various real situations.

Fuzzy sets have several main elements that distinguish them from classical sets:

1. Membership Degree

In fuzzy sets, each element has a degree of membership that varies from 0 to 1. This degree describes how strongly the element belongs to a particular set (Klir, 1995).

2. Membership Function

The membership function is a mathematical function that determines the degree of membership of an element in a fuzzy set. The form of membership functions can be linear, triangular, trapezoidal, Gaussian, and others. This function describes the way the degree of membership changes along the range of the variable (Zimmermann, 2001).

3. Operations on Fuzzy Sets

Like classical sets, fuzzy sets also support operations such as union, intersection, and complement. However, these operations in the fuzzy context do not have a clear binary result, but rather produce membership degrees calculated based on certain rules, such as min-max or product-sum (Mendel, 2017).

In the field of artificial intelligence and machine learning, fuzzy sets are also used to create models that are more adaptive and flexible in handling data uncertainty. According to (Jang et al., 1997), neuro-fuzzy models combine the advantages of fuzzy sets and artificial neural networks to improve performance in data-driven decision making.

2.4 Fuzzy Membership Function

The fuzzy membership function is a key component in fuzzy set theory, which is used to determine the degree of membership of an element in a fuzzy set.

This function describes how each element in the domain is defined by a membership value that ranges between 0 and 1, where 0 means the element is not a member of the set at all, and 1 means the element is fully a member. Membership degrees lower than 1 but higher than 0 reflect partial membership, which allows handling uncertainty in decision-making.

According to (Klir, 1995) a membership function is a curve that maps each element in a set to a value that indicates its degree of truth or membership. This function can take the form of various types of curves, depending on the characteristics of the data or the problem to be solved. Choosing the shape of the membership function is an important step in fuzzy analysis because it can affect the final result of information processing.

Some common forms of membership functions are:

1. Triangle Function

The triangular function is one of the simplest membership functions, which consists of three points, namely the starting point, the vertex, and the ending point. It forms a triangular curve that is suitable for many practical applications due to its simplicity and ease of implementation.

2. Trapezoid Function

The trapezoidal function is similar to the triangular function, but has a flat top. This function is often used when certain values are fully included in the fuzzy set, meaning there is a range of values where the elements have a degree of membership of 1 (Zimmermann, 2001).

3. Gaussian Function

The Gaussian function forms a smooth bell-shaped curve, with peak values at the center and decreasing symmetrically towards the edges. This function is used when the change in membership degree should be gradual and not abrupt (Mendel, 2017). Gaussian functions are often used in pattern recognition and fuzzy control applications because they are more realistic in representing natural phenomena.

4. Sigmoid Function

Sigmoid membership functions have a more complex form and are often used in artificial intelligence applications, such as fuzzy neural networks. This function can model non-linear relationships in data, with smooth transitions between full membership and none (Jang et al., 1997).

The selection of an appropriate membership function is very important in the development of fuzzy models because it will affect accuracy. Membership functions should be selected based on the nature of the variable being modeled as well as the needs of the specific application. Simple functions such as triangle or trapezoid are often used in applications that require quick and easy interpretation, while more complex functions such as Gaussian are used when higher precision is required, especially in control systems and pattern recognition.

According to (Driankov et al., 1996), a well-chosen membership function can result in a control system that is more efficient and more responsive to changes in environmental conditions. In the field of pattern recognition, membership functions are used to classify objects based on their degree of membership in a particular class.

2.5 Fuzzy Time Series

2.5.1 Definition of Fuzzy Time Series

According to recent research, fuzzy time series (FTS) is an effective method for modeling time series with uncertain and non-linear data, especially when conventional statistical models such as ARIMA are inadequate. As stated by (Panigrahi and Behera, 2020) FTS offers a more flexible approach as it allows data to have membership degrees in various fuzzy sets, which is not possible by traditional models that work with exact data.

The use of FTS allows historical data to be converted into fuzzy form through a fuzzification process, where each data value has a certain degree of membership in a fuzzy set. After that, fuzzy logic-based rules are used to perform forecasting, followed by a defuzzification process to convert the results back to numerical form (Christyawati et al., 2018).

Several recent studies have shown improvements in FTS methods, including the incorporation of optimization methods and machine learning techniques to improve prediction accuracy. For example, research by (Siami Namini et al., 2018) combined FTS with genetic algorithms to optimize fuzzy intervals, which resulted in more accurate predictions in ham price forecasting applications. According to Gani and colleagues, this approach successfully overcomes the weakness of classical FTS, which is often less accurate due to the suboptimal division of fuzzy intervals.

Another study by (Wen & Li, 2023) showed that using a hybrid FTS model combined with deep learning methods such as LSTM (Long Short-Term Memory) can provide better prediction results compared to traditional FTS models. The combination of FTS and deep learning allows the model to capture more complex and repetitive time series data patterns.

FTS differs from traditional time series forecasting models, such as ARIMA, which assume stationary data and rely on linear equations. According to (Wu et al., 2015) FTS offers advantages in handling the high uncertainty and variability that often arise in real-world data. This makes FTS particularly useful in fields such as economics, meteorology, and energy management, where uncertainty is often unavoidable.

Furthermore, in a study conducted by (Wang and Chaovalitwongse, 2011) it was stated that fuzzy time series have advantages due to their flexibility in handling non-linear and non-stationary data, which is a major drawback of traditional models. This makes FTS a popular choice in forecasting that involves a lot of uncertainty or volatile data, such as commodity prices, energy demand, and stock market indices.

Fuzzy time series are used in various fields such as economics, finance, and resource management. Research by (Wu et al., 2015) used fuzzy time series to predict electricity demand with more accurate results compared to conventional methods. In addition, fuzzy time series are also applied in stock management, decision support systems, and weather prediction, all of which involve uncertainty and dynamics that cannot be predicted easily.

2.5.2 Chen's Fuzzy Time Series Model

Fuzzy Time Series (FTS) is one of the approaches used to model time series data that have uncertain or fuzzy properties. One popular variant of this method is the model introduced by (Chen, 1996). This model offers a simple and efficient approach to prediction of time series data by converting numerical data into fuzzy intervals. According to Chen, this FTS model uses the approach of partitioning data into fuzzy intervals to capture time patterns. This approach is proven to be able to produce more accurate predictions on non-linear and complex data. In the prediction process, "Chen's model generates fuzzy logic relationships based on historical data, enabling better handling of uncertainty and ambiguity in time series forecasting" (Chen, 1996).

Chen's model became the basis for many subsequent studies that focused on developing and improving the prediction accuracy of fuzzy time series. For example, a recent study introduced a genetic-based optimization method to improve the prediction accuracy of the FTS model. They stated that "the integration of genetic algorithms into Chen's fuzzy time series model significantly improves forecasting performance, especially in handling large and volatile data sets" (Changxing et al., 2017). In addition, research by (Alyousifi et al., 2021) showed that the hybrid method between Fuzzy C-Means (FCM) and Chen's model can provide better results compared to other methods standard model. "Combining Fuzzy C-Means clustering with the Chen model increases the adaptability of the system to various data distributions, leading to more accurate forecasting".

The Chen fuzzy time series model is a widely use approach for time series forecasting, particularly effective for handling vague and uncertain data. Here are the step involved in applying Chen's fuzzy time series model:

1. Define the Universe of Discourse (UoD).

Identify the range of the data and Expand the range slightly to ensure coverage
Universe Formula

$$U = [D_{\min} - D_1, D_{\max} + D_2] \quad (2.5.1)$$

where

$D_{\min}$ = Data minimum

$D_{\max}$ = Data Maximum

D_1 dan D_2 are arbitrary positive numbers determined by the researcher.

2. Partition the Universe of Discourse:

Divide the UoD into equal or unequal intervals.

Each interval represents a linguistic term One method to determine the number of classes is to evaluate the effective interval length using an average-based approach. The steps according to (Xihao and Yimin, 2008) are as follows:

- a. Calculate all the absolute values of the difference between X_{t+1} and X_t ($t = 1, \dots, n - 1$) so as to obtain the average absolute difference value as follows (Xihao and Yimin, 2008):

$$Mean = \frac{\sum_{i=1}^n |X_{t+1} - X_t|}{n} \quad (2.5.2)$$

Where:

Mean : average

n : number of observations

Xt : data at time t

- b. Determine half of the average obtained from the first step to be used as the interval length with the following equation :

$$\ell = \frac{\text{mean}}{n} \quad (2.5.3)$$

Where ℓ is the interval length

3. Define the Fuzzy set A_i and fuzzify the observed historis data.

The membership degree value of $\mu A_i(u_i)$ is determined based on the rule as below (Chen, 1996):

Rule 1: If the historical data X_t belongs to u_i , then the membership degree value for u_i is 1, and u_{i+1} is 0,5 and if not u_i and u_{i+1} , then it is zero.

Rule 2: If the historical data X_t belongs to u_i , $1 \leq i \leq p$ then the membership degree value for u_i is 1, for u_{i-1} and u_{i+1} is 0,5 and if not u_i , u_{i-1} and u_{i+1} then it is zero.

Rule 3: If the historical data X_t belongs to u_p , then the membership degree value for u_p , is 1, for u_{p-1} , is 0,5 and if not u_p and u_{p-1} , then it is zero.

For example $A_1, A_2, \dots, A_k$ are Fuzzy sets that have linguistic values of a linguistic variable, defining Fuzzy sets $A_1, A_2, \dots, A_k$ in the universe of speech U is as follows:

$$\begin{aligned} A_1 &= \frac{1}{u_1} + \frac{0.5}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \dots + \frac{0}{u_p} \\ A_2 &= \frac{0.5}{u_1} + \frac{1}{u_2} + \frac{0.5}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \dots + \frac{0}{u_p} \\ A_3 &= \frac{0}{u_1} + \frac{0.5}{u_2} + \frac{1}{u_3} + \frac{0.5}{u_4} + \frac{0}{u_5} + \dots + \frac{0}{u_p} \\ &\vdots \\ A_p &= \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \dots + \frac{0.5}{u_{p-1}} + \frac{1}{u_p} \end{aligned}$$

Where: $u_i (i = 1, 2, \dots, p)$ is an element of the set universe and the number symbolized “/” expresses the degree of membership $\mu_{A_i}(u_i)$ to $A_i (i = 1, 2, \dots, p)$ where the value is 0, 0.5 or 1.

4. Perform and create a *Fuzzy Logical Relationship* (FLR) table based on historical data. FLR $A_j \rightarrow A_k$ means if the enrollment value in year I is A_j then in year $i+1$ is A_k . A_j as the left side of the relationship is called the current state and A_k as the right side of the relationship is called the next state. And if there is a recurrence of the relationship then it is still counted once.
5. Classify the FLRs that have been obtained from the 3rd stage into groups so that a Fuzzy Logical Relationship Group (FLRG) is formed and combine the same relationships.
6. Defuzzification is the process of calculating the results of the forecasting output to then be calculated so as to get the results of crisp numbers, then added to the actual data at the previous time so that the forecasting results are obtained. The forecasting value in the Chen Fuzzy time series model method has several forecasting rules that must be considered, including:

Rule 1: If the fuzzification result in year t is A_j and there is a Fuzzy set that does not have Fuzzy logic relations, for example if $A_i \rightarrow \emptyset$, where the maximum value of the membership function of A_i is in the interval u_i and the middle value of u_i is m_i , then the forecasting result F_{t+1} is m_i .

Rule 2: If the fuzzification result of year t is u_i and there is only one FLR in FLRG, for example if $A_i \rightarrow A_j$ where A_i and A_j are Fuzzy sets and the maximum value of the membership function of A_j is in the interval u_j and the middle value of u_i is m_j , then the forecasting result F_{t+1} is m_i .

Rule 3: If the fuzzification result in year t is A_j and A_j has how many FLRs in FLRG, for example $A_{j1} \rightarrow A_{j1}, A_{j2}, \dots, A_{jk}$ where $A_i, A_{j1}, A_{j2}, \dots, A_{jk}$ are Fuzzy sets and the maximum value of the membership function of $A_{j1}, A_{j2}, \dots, A_{jp}$ is in the interval $u_{j1}, u_{j2}, \dots, u_{jk}$ and $m_{j1}, m_{j2}, \dots, m_{jk}$, then the forecasting result of F_{t+1} is as follows (Chen, 1996):

$$F_{t+1} = (m_{j1} + m_{j2} + \dots + m_{jk})/k \quad (2.5.4)$$

Where k is the number of middle values and to find the middle value (m_i) in the

Fuzzy Set interval, the following equation can be used (Chen, 1996):

$$m_i = \frac{(\text{upper limit} + \text{lower limit})}{2} \quad (2.5.5)$$

2.5.3 High Order Chen Fuzzy Time Series

The higher-order Chen model is an improvement over the basic model that takes into account more than one previous time period in the prediction process. If in the basic model the prediction is based on only one previous fuzzy set, in the higher-order model the prediction takes into account several past fuzzy sets. This approach allows the model to better understand long-term patterns long and more complex fluctuations in the data. According to research, higher-order model Chen is able to improve forecasting accuracy because more information from the past is considered in the forecasting process.

The higher-order Chen FTS model has been applied to various forecasting problems, showing better accuracy than the first-order model. Research has applied this method to forecast cooperative sales (Arfiana et al., 2022) and monthly income (Yuliyanto et al., 2022), with higher-order models generally producing better results. The fourth-order FTS consistently shows the lowest error rate in this application. (Own and Yu, 2005) proposed an improved heuristic higher-order FTS model to overcome limitations in Chen's original method, in particular its dependence on the highest-order series and extensive memory requirements. Further modifications to Chen's method have been explored, such as using median ratio intervals to partition the universe of discourse, which resulted in better forecasting accuracy when tested on Indonesian rubber production data (Vianita et al., 2022). These studies collectively highlight the flexibility and continuous development of high-level FTS models for time series forecasting.

The advantage of the higher-order Chen model lies in its ability to capture broader patterns in the data, especially when there are significant fluctuations over a long period of time. In addition, the model is relatively easy to implement due to its simple mathematical structure. Research shows that the higher-order Chen model has been successfully applied in various fields, including prediction of student enrollment in universities, stock prices, and energy demand. For example, the model has proven effective in predicting university enrollments with more accurate results than traditional methods.

2.6 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a heuristic global optimization method inspired by the social behavior of birds and fish (Zhan et al., 2009). Introduced by Kennedy and Eberhart in 1995, PSO has been widely used due to its efficiency, robustness, and simplicity (Benuwa et al., 2016). The algorithm initializes a swarm of particles with random positions and velocities, which then move through the search space to find the optimal solution (Juneja and Nagar, 2016). PSO performance can be improved through various modifications, including quantum-behaved PSO, chaotic PSO, and fuzzy PSO (Zhan et al., 2009). Algorithm parameters, such as inertial weights, refinement factors, and cognitive and social weights, play an important role in its effectiveness (Sengupta et al., 2018). PSO has been successfully applied in various fields, including electrical engineering, automation control, and medicine (Liu et al., 2020). Recent developments have focused on hybridization with other optimization techniques and adaptation to specific problem types (Sengupta et al., 2018).

2.6.1 Basic PSO Mechanism

PSO uses a collaborative approach, where particles work together to reach the optimal solution. Each particle updates its position based on two main components:

1. Inertia

Inertia is the tendency of a particle to keep moving in its previous direction.

2. Cognitive and Social Components

The cognitive component represents learning from the particle's own experience, while the social component represents the influence of the best particle in the herd.

The velocity and position update formula in PSO is as follows:

$$v_i^{t+1} = wv_i^t + c_1r_1(p_i^{best} - x_i^t) + c_2r_2(g^{best} - x_i^t) \quad (2.6.6)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (2.6.7)$$

Where:

- a. v_i^t is the velocity of particle i at iteration t,

- b. x_i^t is the position of particle i at iteration t ,
- c. p_i^{best} is the best position ever reached by particle i ,
- d. g^{best} is the best position of all particles,
- e. w is the inertia factor,
- f. c_1 and c_2 is the weighting constant of the cognitive and social components, and
- g. r_1 and r_2 is a random number between 0 and 1.

According to (Aladag et al., 2012, “PSO offers advantages in its simplicity of implementation and flexibility in handling different types of optimization problems”.

2.6.2 PSO Advantages

PSO has several advantages over other optimization algorithms, such as Genetic Algorithm (GA). Some of these are:

1. Simplicity of algorithm
2. PSO is easy to implement because it only uses a few parameters that must be set.
3. PSO can achieve the optimal solution in fewer iterations than other algorithms.
4. This algorithm can avoid getting stuck in local solutions because all particles consider the global best solution in the swarm.

As explained by (Kuo et al., 2010) “PSO often provides optimal solutions faster than other methods in the context of non-linear and multi-dimensional optimization”.

2.6.3 PSO Application

PSO has been widely applied in various fields, such as design optimization, artificial neural network tuning, classification, and function optimization. For example, in a study by (Insani and Sari, 2020), PSO was used for optimization in an industrial scheduling problem, and they found that “PSO is able to find more efficient solutions with shorter computation time than traditional methods”.

In addition, PSO is also used in image processing, financial modeling, and multi-objective problem solving. In the context of image processing, (Ait-Aoudia et al., 2014) explained that "PSO is effectively used to optimize medical image segmentation with high accuracy results".

2.6.4 PSO Modification

Along with the development, various PSO modifications have been proposed to overcome limitations that may be encountered in certain applications, such as overexploitation or getting stuck on local solutions. One of the modified approaches is Adaptive PSO (APSO), where PSO parameters such as inertia and social/cognitive weighting are dynamically changed during the iteration process. (Chen, 1996) stated that "PSO modification with inertia parameter adaptation shows significant performance improvement on multi-objective optimization problems".

2.7 Forecasting Accuracy Measure

In the context of forecasting, a measure of forecasting accuracy is very important to measure how accurate the forecasting results are compared to the actual values that occur. Some measures of accuracy commonly used in the literature are Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE).

2.7.1 Mean Absolute Error

Mean Absolute Error (MAE) measures the average of the absolute errors between the predicted and true values. MAE is used because it provides an easy interpretation of how much the average prediction deviates from the original data in the same units as the data. According to (Shumway and Stoffer, 2017) "MAE provides a stable measure of error and is less affected by extreme values in the data, making it suitable for many practical use cases".

MAE measures the absolute average of the difference between the actual value and the forecasted value. The smaller the MAE value, the more accurate the forecasting results. The MAE formula is:

$$MAE = \frac{1}{n} \sum_{t=1}^n |A_t - F_t| \quad (2.7.8)$$

Where:

A_t is the actual value in period t

F_t is the value of the forecasting result in period t

n is the amount of data.

According to recent research, MAE is often used due to its simplicity and does not provide additional penalties for larger errors. For example, (Cerqueira et al., 2020) states that “MAE provides a clear and direct measure of the magnitude of the forecasting error without taking into account the square of the error”.

2.7.2 Mean Square Error (MSE)

MSE is the average square of the difference between the actual value and the forecasted value. MSE is more sensitive to outliers because it uses the square of the error. The MSE formula is:

$$MSE = \frac{1}{n} \sum_{t=1}^n (A_t - F_t)^2 \quad (2.7.9)$$

According to (Aminuddin et al., 2013) MSE is used when we want to give a larger penalty to significant forecasting errors. It is suitable for models that want to minimize large errors, as explained in their research, “MSE is very effective in conditions where large errors should be avoided”.

2.7.3 Mean Absolute Percentage Error

Mean Absolute Percentage Error (MAPE) measures the forecasting error as a percentage, which is often easier for decision makers to understand. However, MAPE has a drawback when there are observation values close to zero. “MAPE is useful in many business and economic applications, but its use can be biased if the data is close to zero” (Wang and Chaovaitwongse, 2011).

MAPE measures the error in percentage terms, which makes it easier to compare between different forecasting models. The MAPE formula is:

$$MAPE = \frac{100\%}{n} \sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right| \quad (2.7.10)$$

MAPE is popular because the results are expressed in percentages, which makes interpretation easy. MAPE is very useful when we want to measure the

degree of error on a relative scale, especially in the context of business and economics (Nabillah and Ranggadara, 2020).

2.7.4 Root Mean Squared Error (RMSE)

RMSE is the square root of MSE, which returns the error scale to the same units as the original data. The formula is:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{t=1}^n (A_t - F_t)^2} \quad (2.7.11)$$

RMSE is often used when we want to understand the error distribution in the same units as the data. (Achmadin et al., n.d.) states that “RMSE provides a measure of error that is easy to understand because it is on the same scale as the predicted value”.

Therefore, the selection of forecasting accuracy measures must consider the characteristics of the data and the objectives of the analysis to be achieved. Each measure has advantages and disadvantages that must be taken into account in different applications.

2.8 Bank Syariah Indonesia

2.8.1 Introduction to Bank Syariah Indonesia

Bank Syariah Indonesia (BSI) is the result of the merger of the three largest Islamic banks in Indonesia, namely Bank Syariah Mandiri, BNI Syariah, and BRI Syariah. This merger was carried out on February 1, 2021 as a strategic step to strengthen Islamic banking in Indonesia and increase competitiveness in the domestic and global markets. According to (Widianto Putri and Ningtyas, 2022) This merger provides benefits in terms of economies of scale, operational synergies, and increased efficiency that can boost the financial performance of Bank Syariah Indonesia in the future.

According to (Sari et al., 2024) BSI shares experienced a significant increase in trading volume after the merger, along with increased investor confidence in the financial performance and growth potential of Islamic banks in Indonesia.

In addition, the performance of BSI shares is also influenced by the growth of Islamic assets in Indonesia. The increase in BSI's assets and number of customers after the merger increased investor interest in investing in BSI shares, as it is considered a stock with long-term growth potential (Widianto Putri and Ningtyas, 2022). Fluctuations in BSI's share price are influenced by market sentiment towards monetary policy and domestic economic growth, especially regarding the effect of interest rates on Islamic banking (Wafi et al., 2024).

Despite the volatility, BSI stock shows steady growth in the medium term. In the 2022-2023 period, BSI recorded solid financial performance, including significant profit growth, which had a positive impact on its share price. The improvement in BSI's financial performance, especially in terms of asset growth and net profit, provides positive sentiment that has an impact on the stability of BSI's share price in the capital market (Lestari, 2024).

2.8.2 Factors Affecting BSI Stock Movement

Some of the factors that influence the movement of BSI shares include macroeconomic conditions, the development of the Islamic banking industry, and government policies related to regulations and incentives for Islamic banking. Government policies that support the development of Islamic banking, such as tax relaxation and increased investment in the Islamic sector, also have a positive impact on BSI stock performance (Christyanti et al., 2023).

In addition, the growth of BSI shares is also influenced by the level of investor confidence in the prospects of the Islamic economy. The high interest in sharia-based investments in Indonesia, especially from millennials and the younger generation, provides a significant boost to the increased liquidity of BSI shares (Wahyudi et al., 2024).

2.8.3 BSI's Financial Performance and Its Effect on Shares

BSI's financial performance, which continues to show growth in terms of net profit, assets, and third-party funds, has a direct influence on investor interest. BSI's success in increasing profitability is a key factor in maintaining a competitive share price in the capital market (Yunistiyani and Harto, 2022).

2.8.4 Challenges and Future Prospects

The outlook for BSI shares is positive given the huge potential of Indonesia's growing Islamic finance market. With the largest Muslim population in the world, the market for Islamic financial products in Indonesia is vast, including in Islamic banking services. The growth prospects of BSI's shares will largely depend on the bank's ability to expand its range of innovative sharia products and services, as well as capitalize on the untapped market potential (Wahyudi et al., 2024)

Although BSI's stock is performing well, there are several challenges it faces in maintaining this performance. The biggest challenge for BSI is to maintain performance stability amidst the increasingly fierce competition in the banking industry, as well as overcoming regulatory changes that may affect the operations of Islamic banks.

CHAPTER III

RESEARCH METHODS

3.1 Time and Place of Research

This research was conducted in the odd semester of the 2023/2024 academic year at the Department of Mathematics, Faculty of Mathematics and Natural Sciences, Lampung University, located at Jalan Prof. Dr. Ir. Soemantri Brojonegoro, Gedong Meneng, Rajabasa District, Bandar Lampung City, Lampung.

3.2 Research Data

The data used in this study are monthly data on the BSI Bank Stock Index and are secondary data taken from Yahoo.Finance from June 2018 to September 2024.

3.3 Research Method

The steps taken in this research are as follows:

1. Defining the Universe Discourse.
2. Partition the Universe of Discourse:
3. Define the Fuzzy set A_i and fuzzify the observed historis data.
4. Performing historical data fuzzification, which is representing actual data in the form of fuzzy sets according to predetermined intervals.
5. Higher Order Fuzzy Rule Formation.
6. Define the PSO Objective Function to minimize the forecast error.
7. Determine PSO Parameters (Swarm size (number of particles), Maximum number of iterations, Lower limit and upper limit).

8. Fuzzy Parameter Optimization with PSO.
9. Defuzzification to Generate Predictions.
10. Evaluate the Prediction results and draw conclusions.

CHAPTER V

CONCLUSIONS AND SUGGESTIONS

Based on the results of the research that has been carried out, the following conclusions are obtained:

1. The application of Chen's high-order Fuzzy Time Series (FTS) method combined with the Particle Swarm Optimization (PSO) algorithm is proven to be able to improve forecasting accuracy on Bank Syariah Indonesia (BSI) stock index data which is volatile and non-linear.
2. The higher-order Chen model has the advantage of utilizing historical information of more than one period, resulting in more complex fuzzy logic relationships and being able to reflect stock movement patterns more accurately.
3. The forecasting results show that the fourth-order model provides the best results with a Mean Absolute Percentage Error (MAPE) value of 12.02%, which indicates a low and accurate prediction error rate.
4. The integration of PSO in the process of forming fuzzy intervals succeeded in optimizing the model structure, resulting in a MAPE value of 16.76% at 7 intervals and 15.25% at 8 intervals.
5. The results of this study can be a reference for investors, financial analysts, and other related parties in supporting more appropriate and strategic investment decision making.

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