

Integration Of ARIMA And Grey Wolf Optimizer Models For Multi-Criteria Optimization Of Stunting-Oriented Nutritional Menus Based On Food Price Forecasting

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Abstract

Stunting among children under five is closely associated with the fulfillment of adequate nutritional requirements, while the affordability of nutritional menus is influenced by changes in food prices. This study aims to develop an adaptive nutritional menu optimization model for children under five that responds to food price changes by integrating price forecasting and the Grey Wolf Optimizer (GWO). The study uses data from eight food commodities, namely premium rice, broiler chicken, chicken eggs, mackerel, carrots, potatoes, green beans, and beef, with 821 daily observations for each commodity over the period from April 1, 2024, to June 30, 2026. The research stages include preprocessing, stationarity testing, ARIMA modeling, forecasting

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evaluation, 30-day price forecasting, price pattern and volatility analysis, formulation of the GWO fitness function, and menu composition optimization based on the nutritional requirements of children under five. The results show that the lowest testing MAPE of 0.26% was obtained for premium rice and beef, while the rolling forecast for premium rice achieved an average MAPE of 0.1131%. The 30-day forecasts indicate that green beans experienced the highest projected price increase of 13.1344%, whereas carrots showed a projected price decrease of 1.8907%. In the GWO optimization, the price and volatility weights were 0.676063 and 0.323937, respectively, while return received no weight. The optimization produced a total menu portion of approximately 445.34 grams, with an estimated cost of IDR 9,557.65, while satisfying all minimum targets for energy, protein, fat, and carbohydrates. These findings indicate that integrating food price forecasting with metaheuristic optimization can support the development of nutritional menus that account for future price conditions, thereby potentially improving cost efficiency and the adaptability of nutritional menu planning for children under five.

Keywords: Menu optimization; Grey Wolf Optimizer; forecasting; ARIMA; food prices.

INTRODUCTION

Stunting remains a major public health problem faced by many developing countries, including Indonesia. This condition reflects impaired linear growth in children resulting from chronic undernutrition and long-term health-related factors, characterized by length- or height-for-age below -2 standard deviations from the median of the World Health Organization (WHO) Child Growth Standards (Organization, 2022). Stunting not only indicates impaired physical growth but is also associated with impaired cognitive development, increased vulnerability to disease, reduced learning capacity, and consequences for productivity in adulthood (Loriza & Mahmudiono, 2024). The problem is particularly important because some of the consequences of stunting may persist over the long term if interventions are not implemented during critical periods of child growth, particularly throughout the first 1,000 days of life.

The prevalence of stunting in Indonesia indicates that the problem has not been fully resolved despite a decline in prevalence. According to the Indonesian Nutritional Status Survey (SSGI), the national prevalence of stunting decreased from 21.5% in 2023 to 19.8% in 2024 (Badan Kebijakan Pembangunan Kesehatan [BKPK], 2025). This figure indicates that nearly one in five children remains affected by stunting, highlighting the need for prevention strategies that are not



solely oriented toward addressing health conditions but also toward ensuring the sustainability of children's nutritional requirements. One important component of such efforts is the provision of complementary foods that meet children's requirements for energy, protein, fat, vitamins, and minerals in accordance with their growth needs. Therefore, the quality of menu planning represents an important aspect of supporting adequate child nutrition.

The importance of fulfilling children's nutritional requirements extends beyond the health dimension to include social and ethical dimensions. From an Islamic perspective, the responsibility to prepare a strong generation can be associated with the message of the Qur'an in Surah An-Nisa, verse 9, which emphasizes the prohibition against leaving behind a weak generation (*dzurriyyatan dhi'afan*) (Shihab, 2002). Meeting children's nutritional requirements through high-quality food constitutes a preventive effort to support the physical growth and intellectual development of future generations (Witari & Astuti, 2024). However, meeting nutritional requirements cannot be separated from household economic capacity. Nutrient-dense foods, particularly animal-based protein sources such as eggs and chicken, as well as other food commodities, are subject to price changes over time. Such changes may increase household expenditure and potentially influence the choice of food ingredients used in menu planning (Igwe, 2024; Sideropoulos, 2025).

This situation creates two requirements that must be addressed simultaneously. On the one hand, the menu must satisfy children's nutritional requirements; on the other hand, the cost of providing the menu must remain affordable and capable of accommodating changes in food prices. A menu optimized solely according to nutritional content may result in high costs, whereas a menu focused exclusively on cost minimization may fail to meet nutritional requirements. The problem becomes more complex when food prices fluctuate because a solution that is optimal in one period may no longer be optimal in the subsequent period. Therefore, menu planning to support stunting prevention can be regarded as a multi-constraint optimization problem that requires simultaneous consideration of nutritional requirements, cost, and food-price dynamics.

Several previous studies have demonstrated that computational approaches can be applied to nutritional menu optimization problems. Ridha (2025) and Sa'adah (2022) employed optimization approaches to determine food combinations that satisfy nutritional requirements while considering cost constraints. Metaheuristic approaches have subsequently been applied to address complex search spaces because combinations of food ingredients can produce a very large number of alternative solutions. Algorithms based on Swarm Intelligence possess



exploration and exploitation capabilities that can be utilized to obtain solutions to high-dimensional optimization problems (Albetar, 2023; Harifi, 2022). Approaches such as Genetic Algorithms (GA) and Goal Programming have also been applied to menu planning and food optimization while considering nutritional and cost requirements (Heryati, 2024; Pratama & Baita, 2025).

Research development has occurred not only in optimization but also in modeling food-price changes. Time-series forecasting methods are used to estimate prices based on historical patterns, allowing price information to serve purposes beyond retrospective analysis. Autoregressive Integrated Moving Average (ARIMA), for example, has been applied to model and predict time-series data based on temporal relationships within historical observations (Rahayu & Utomo, 2023; Gupta & Singh, 2024). In addition to price forecasting, price movements can be analyzed using Open-High-Low-Close (OHLC) data to describe price ranges and volatility characteristics of commodities (Tan & Lim, 2024; Hidayat, 2023). On the optimization side, the Grey Wolf Optimizer (GWO) has been developed as a metaheuristic algorithm for solving various complex optimization problems through a search mechanism that balances exploration and exploitation of the solution space (Makhadmeh, 2024; Chen, 2025).

Although these three groups of approaches have developed substantially, previous studies still exhibit limitations when they are applied in an integrated manner to nutritional menu planning. Existing menu optimization studies generally use food prices as static parameters, making the resulting solutions highly dependent on the price conditions prevailing at the time of optimization (Heryati, 2024; Pratama & Baita, 2025). This condition becomes less adaptive when prices change in subsequent periods. Conversely, time-series forecasting studies primarily focus on price prediction without linking the predicted results to decision-making processes concerning nutritional menu composition (Rahayu & Utomo, 2023; Gupta & Singh, 2024). Price volatility analysis is also generally used to describe price movement characteristics but has rarely been incorporated as a risk parameter in menu optimization. Consequently, a separation remains between price forecasting, price-risk analysis, and nutritional optimization processes.

This research gap indicates the need for a computational framework capable of connecting current price conditions, future price estimates, price-change characteristics, and nutritional requirements within a unified decision-making process. The fundamental issue is not merely how to obtain a minimum-cost menu, but how to develop a menu that continues to satisfy nutritional requirements when the underlying economic conditions change. Therefore, the



optimization approach needs to shift from a static-price optimization paradigm toward adaptive-price optimization, allowing price changes to be considered during the solution-generation process.

Based on this research gap, this study proposes an adaptive nutritional menu optimization model based on the Grey Wolf Optimizer (GWO) by integrating food-price forecasting using the Autoregressive Integrated Moving Average (ARIMA) method and price-pattern and volatility analysis based on Open-High-Low-Close (OHLC) data. ARIMA is used to generate estimated commodity prices for future periods, while OHLC characteristics are used to represent price-change patterns and volatility levels. These two types of information are subsequently integrated with nutritional and cost parameters into a dynamic GWO fitness function. Through this mechanism, the optimization process does not merely search for low-cost combinations of food ingredients but also considers projected price conditions and the risk of price changes.

The novelty of this study lies in the integration of price forecasting, price-risk characterization, and nutritional menu optimization into a single adaptive decision-making framework. Unlike previous approaches that use static food prices, the proposed model utilizes historical price information to generate future price estimates and incorporates price-change characteristics into the fitness function. Consequently, GWO serves not only as a search mechanism for optimal solutions based on nutritional and cost requirements but also as an optimization mechanism designed to generate solutions that are more adaptive to food-price uncertainty. This novelty is further strengthened through a backtesting mechanism used to evaluate whether menus generated from historical information and forecasts can maintain cost feasibility and nutritional adequacy when compared with actual price conditions in subsequent periods.

Based on the identified problem and research gap, this study formulates four main research questions. First, how can an ARIMA model be developed to predict the prices of food commodities used in nutritional menu planning? Second, how can OHLC data be utilized to identify price-change patterns and volatility as risk parameters? Third, how can predicted prices, volatility risk, nutritional requirements, and costs be integrated into a GWO fitness function to generate optimal and adaptive menus? Fourth, how well does the proposed model maintain nutritional feasibility and cost efficiency when evaluated against actual price conditions through backtesting?



In line with these research questions, this study aims to develop an adaptive computational model for nutritional menu planning in the context of stunting prevention. Specifically, the study aims to develop a food-price forecasting model using ARIMA, analyze price patterns and volatility using OHLC data, develop a dynamic GWO fitness function that integrates nutritional requirements, cost, price forecasts, and price risk, and evaluate the robustness of the resulting solutions through backtesting. The study is expected to produce a decision-support framework capable of providing nutritional menu recommendations that not only satisfy nutritional requirements but also consider cost efficiency and adaptability to food-price dynamics.

RESEARCH METHODOLOGY

Research Data

This study uses secondary data consisting of daily food price data and food nutritional composition data. The price data cover eight commodities used as candidate ingredients for menu construction, namely premium rice, broiler chicken, chicken eggs, mackerel, carrots, potatoes, green beans, and beef. Each commodity contains 821 daily price observations covering the period from April 1, 2024, to June 30, 2026. The price data are used as the basis for time-series forecasting, price-change calculations, volatility analysis, and estimation of menu costs for future periods.

Nutritional composition data are used to determine the contribution of each commodity to energy, protein, fat, and carbohydrate requirements. Nutritional values are expressed per 100 grams of food. Data on the Supplementary Feeding Program (PMT) are used as a reference for determining food candidates relevant to meeting the nutritional requirements of children under five. The integration of price and nutritional data is performed by aligning the identity of each commodity so that each food ingredient has corresponding price and nutritional attributes that can be consistently used during the optimization process.

Research Stages

The study is designed in seven main stages: data collection, preprocessing, food-price forecasting, price-pattern and volatility analysis, optimization-parameter formulation, optimization using the Grey Wolf Optimizer (GWO), and solution evaluation. These stages are



arranged sequentially to transform historical price data and nutritional information into the basis for generating menu recommendations that are adaptive to changes in food prices.

The overall research workflow is presented in Figure 1.



Figure 1. Research Stages

Figure 1 illustrates the overall research process, beginning with the collection of food price and nutritional composition data, followed by the preprocessing stage. The processed price data are subsequently used to develop Autoregressive Integrated Moving Average (ARIMA) models. The best-performing model for each commodity is used to generate 30-day price forecasts. The forecasting results are then used to calculate price changes (*returns*) and volatility as representations of food-price dynamics. Subsequently, the forecasted prices, returns, and volatility are used to formulate optimization parameters and the GWO fitness function. In the final stage, GWO determines the quantity of each food ingredient in grams while considering nutritional requirements and menu costs.

Data Preprocessing

The preprocessing stage is conducted to ensure that the price data have an appropriate structure for time-series modeling and can be integrated with nutritional composition data. The preprocessing procedures include checking for missing values, handling missing observations,

sorting observations chronologically, checking the consistency of commodity identities, and synchronizing price data with nutritional data.

Missing values in the price data are handled using time-based interpolation. This approach is applied to maintain the continuity of the time series without altering the temporal sequence of observations. Following interpolation, all observations are sorted according to their observation dates to ensure that the ARIMA modeling process uses the correct chronological order. Subsequently, commodity identities in the price data are aligned with those in the nutritional composition data so that each food ingredient has a consistent pair of price and nutritional information.

The preprocessing stage produces a final dataset consisting of daily price series for eight commodities and nutritional attributes used during the optimization process. The dataset is subsequently utilized separately according to the requirements of each research stage, namely time-series modeling for price data and nutritional contribution calculations during optimization.

Food-Price Forecasting Using ARIMA

Food-price forecasting is performed using the Autoregressive Integrated Moving Average (ARIMA) method. Modeling is conducted individually for each commodity because different commodities may exhibit distinct price patterns and temporal dynamics.

The initial modeling stage involves testing the stationarity of the price series using the Augmented Dickey-Fuller (ADF) test. This test is used to determine whether the price series satisfies the stationarity assumption. If the series is found to be non-stationary, differencing is applied until a stationary series is obtained. The resulting order of differencing is subsequently used as the integration parameter in the ARIMA model.

ARIMA models are constructed using combinations of autoregressive (p), differencing (d), and moving average (q) parameters. Candidate models are compared based on their predictive performance on the testing data. The best-performing model is selected as the representative model for each commodity. Model performance is evaluated using the Mean Absolute Percentage Error (MAPE).

In addition to evaluation using the testing data, rolling forecasting is conducted to assess the stability of the model's predictive performance across multiple observation periods. This approach reduces dependence on a single train-test split and provides an indication of the



model's consistency when repeatedly applied to temporal data. The best-performing model for each commodity is subsequently used to generate price forecasts for the following 30 days.

Price-Pattern and Volatility Analysis

The 30-day price forecasts are used to obtain information regarding the future price dynamics of each commodity. The analysis uses three main parameters: price, return, and volatility. Price represents the projected commodity value for the future period, while return represents the relative change in price between consecutive periods. Volatility represents the degree of price fluctuation during the observation period.

Return is calculated based on the relative change between the price in a given period and the price in the preceding period. A positive return indicates an increase in price, whereas a negative return indicates a decrease. Volatility is used to represent the instability of price changes and is calculated based on the variation in returns during the observation period.

Based on the combined information from price, return, and volatility, the movement characteristics of each commodity are analyzed to identify upward trends (*uptrend*), downward trends (*downtrend*), or sideways movements. These characteristics are subsequently used as parameters for determining commodity values during the optimization stage. Thus, the optimization process considers not only price levels but also the characteristics of price changes and price stability.

Optimization Parameter Formulation Using GWO

Menu composition optimization is performed using the Grey Wolf Optimizer (GWO). GWO is employed to search for combinations of food quantities that produce optimal solutions based on price, price dynamics, and nutritional requirements. Each candidate solution is represented as a vector containing the quantity of each food ingredient in grams.

The economic parameters used in the optimization consist of forecasted price, return, and volatility. Forecasted prices represent the estimated cost of food ingredients in the future period. Return represents the direction of price changes, whereas volatility serves as an indicator of price instability.

During the weighting stage, GWO is used to obtain the relative weights of the price, return, and volatility criteria. These weights are subsequently used to formulate the commodity evaluation values and fitness function. Based on the weighting optimization results, price



received a weight of 0.676063, volatility received a weight of 0.323937, whereas return received a weight of 0. The resulting weights indicate that, under the configuration employed in this study, price and volatility constitute the two primary components of the economic assessment of food ingredients.

The basic GWO mechanism is not modified. The adjustment is made to the fitness-function formulation so that the algorithm can be applied to the menu optimization problem while considering cost and nutritional constraints. Under this approach, GWO functions as a search mechanism within the solution space of food-ingredient combinations that satisfy all constraints defined in the study.

Fitness Function and Nutritional Constraints

The fitness function is used as the evaluation mechanism for determining the quality of each candidate solution. The decision variables represent the quantity of each food ingredient in grams. Conceptually, the fitness function is designed to minimize menu cost and penalties resulting from violations of nutritional constraints while incorporating economic parameters derived from price analysis.

The total nutritional content of a candidate menu is calculated based on the quantity of each food ingredient and its nutritional composition per 100 grams. The minimum nutritional targets used in this study are presented in Table 1.

Table 1. Minimum Nutritional Targets for the Children's Menu

Nutritional Component	Minimum Target
Energy	1,350 kcal
Protein	20 g
Fat	45 g
Carbohydrates	215 g

A candidate solution is considered feasible if it satisfies all minimum requirements for energy, protein, fat, and carbohydrates. Candidates that fail to satisfy one or more minimum requirements are assigned a penalty in the fitness function. The penalty is intended to reduce the likelihood that nutritionally infeasible candidates are selected as the final solution.

Under this formulation, the optimization process is directed toward obtaining a combination of food ingredients with relatively low cost while satisfying all minimum nutritional



targets. The prices used in the cost calculation are obtained from the forecasting results; therefore, the resulting cost represents an estimated expenditure based on projected food-price conditions for the future period.

Model and Menu Solution Evaluation

The evaluation process consists of two main components: forecasting-model evaluation and nutritional-menu optimization evaluation. Forecasting performance is evaluated using MAPE on the testing data and through rolling forecasting. MAPE is used to measure the prediction error between actual values and forecasted values. A lower MAPE indicates a lower forecasting error.

The optimization results are evaluated based on three main aspects: nutritional adequacy, total food weight, and estimated menu cost. Nutritional adequacy is assessed by comparing the total energy, protein, fat, and carbohydrate content of the final solution with the predefined minimum targets. Total food weight is calculated as the sum of the quantities of all food ingredients used, while estimated menu cost is calculated using the 30-day forecasted prices.

In addition to the direct evaluation of the optimized solution, backtesting is conducted to assess the robustness of the solution under actual price conditions. In this stage, the recommended menu generated using historical information and forecasted prices is compared with actual price conditions observed in the subsequent period. This evaluation is used to determine whether the solution maintains cost feasibility when exposed to actual price changes.

The final output of the study consists of the composition of food ingredients in grams, total menu weight, energy, protein, fat, and carbohydrate content, as well as the estimated menu cost. The optimization results are intended to serve as a computationally based recommendation for supporting nutritional menu planning for children under five. This study does not involve direct intervention or clinical testing involving children under five; therefore, the clinical effectiveness of the menu in reducing stunting prevalence is beyond the scope of measurement in this study.

RESULTS AND DISCUSSION

Food-Price Forecasting Results

The study used eight food commodities, namely premium rice, broiler chicken, chicken eggs, mackerel, carrots, potatoes, green beans, and beef. Each commodity consisted of 821 daily price observations. Following the preprocessing stage and stationarity testing, the data were used



to develop *Autoregressive Integrated Moving Average* (ARIMA) models. Model performance was evaluated using *Mean Absolute Percentage Error* (MAPE) on the testing data and through *rolling forecast* evaluation.

The evaluation results in Table 2 show differences in predictive performance across commodities. Premium rice and beef produced the lowest testing MAPE values, both at 0.26%. In the *rolling forecast* evaluation, premium rice also achieved the lowest average MAPE of 0.1131%, followed by beef at 0.1990%. The low error values indicate that the historical patterns of these two commodities could be represented relatively well by the ARIMA models used.

Table 2. Forecasting Evaluation Results

Commodity	MAPE Testing	MAPE Rolling Forecast
Premium Rice	0.26%	0.1131%
Beef	0.26%	0.1990%
Mackerel	–	0.3483%
Potatoes	–	0.4456%
Chicken Eggs	3.75%	1.0316%
Broiler Chicken	5.78%	2.6392%
Green Beans	7.90%	2.8570%
Carrots	8.65%	1.5825%

In general, commodities with relatively stable price characteristics tended to produce lower error values than commodities with more dynamic price changes. This difference indicates that the ability of ARIMA to capture price patterns was not uniform across all commodities. Nevertheless, the *rolling forecast* results show that the models were still able to provide relatively good predictions over the evaluation periods, particularly for premium rice and beef.

These evaluation results served as the basis for selecting the best model for each commodity. The evaluated models were subsequently used to generate 30-day price forecasts as inputs for price-dynamics analysis and the menu optimization process.

30-Day Food-Price Forecasting Results

The best ARIMA model for each commodity was subsequently used to generate 30-day price forecasts. The forecasting results were not only used to estimate future prices but also



served as the basis for calculating *return* and volatility for the optimization stage. The 30-day forecasting results are presented in Table 3.

Table 3. 30-Day Food-Price Forecasting Results

Commodity	Forecast Price (IDR/kg)	Return (%)	Volatility (%)
Premium Rice	14,968.42	0.0212	0.0053
Broiler Chicken	31,720.41	-0.0443	0.0085
Chicken Eggs	23,624.10	2.7644	0.4083
Mackerel	35,510.60	-0.0085	0.0016
Carrots	14,331.75	-1.8907	0.0235
Potatoes	15,027.24	-0.8781	0.0232
Green Beans	10,823.80	13.1344	0.5201
Beef	125,328.28	-0.0096	0.0009

Based on Table 3, green beans exhibited the largest projected price increase, with a *return* of 13.1344%. This was followed by chicken eggs, with an increase of 2.7644%. In contrast, carrots experienced the largest projected decline, with a *return* of -1.8907%, followed by potatoes at -0.8781%. Meanwhile, premium rice showed a relatively small change, with a *return* of 0.0212%.

These differences indicate that price dynamics varied across commodities. Green beans had the largest positive *return*, accompanied by volatility of 0.5201%, indicating more dynamic price movements than commodities with lower *return* and volatility values. In contrast, beef had a *return* of -0.0096% and volatility of only 0.0009%, indicating relatively limited price variation over the forecast horizon.

This information has direct implications for the optimization process. Forecast prices were used to estimate future food costs, whereas *return* and volatility were used to represent price movements and uncertainty. Thus, the optimization function considered not only current or historical prices but also projected price conditions for the subsequent period.

Price-Pattern Analysis and Grey Wolf Optimizer Results

Based on the forecasting results, an analysis of price direction and volatility was conducted to identify the price-dynamics characteristics of each commodity. Based on this analysis, green beans and chicken eggs were categorized as commodities exhibiting a *volatile*



uptrend pattern, whereas potatoes and carrots were categorized as having a *volatile downtrend* pattern. The remaining commodities were classified as exhibiting a *sideways* pattern based on the classification criteria applied.

The classification results indicate that commodities with positive price movements do not necessarily exhibit the same level of volatility. For example, green beans had a *return* of 13.1344% and volatility of 0.5201%, whereas chicken eggs had a *return* of 2.7644% and volatility of 0.4083%. This distinction is important in the optimization process because price increases and price instability represent two different characteristics.

Subsequently, the Grey Wolf Optimizer (GWO) was used to determine the relative weights of the three criteria incorporated into the optimization function, namely price, *return*, and volatility. The resulting weights are presented in Table 4.

Table 4. GWO-Derived Criterion Weights

Criterion	Weight
Price	0.676063
<i>Return</i>	0.000000
Volatility	0.323937
Total	1.000000

The optimization results show that price received the largest weight at 0.676063, while volatility received a weight of 0.323937. Meanwhile, *return* received a weight of 0.000000. Therefore, the GWO solution assigned the greatest contribution to the price criterion, followed by volatility, whereas *return* did not provide a direct contribution to the objective value under the optimal weighting solution.

The dominance of the price weight indicates that estimated food expenditure was the primary consideration in the optimization function. Meanwhile, the volatility weight of 0.323937 indicates that price instability was still considered in determining commodity preferences. The zero weight assigned to *return* should be interpreted as a result of the optimization based on the structure of the *fitness* function and the data used, rather than as an indication that price changes are generally unimportant.

Based on these weights, premium rice obtained a score of 0.027237, while beef obtained a score of 0.676064. If the score represents a cost or *fitness* value for which lower values are



preferable, premium rice ranks first and beef ranks last. The interpretation of this ranking, however, depends on the mathematical definition of the score used in the evaluation function.

Menu Optimization Results

The next stage involved determining the menu composition using GWO. The decision variables in the optimization were the quantities of each commodity expressed in grams. The optimization considered nutritional adequacy constraints and estimated costs based on forecast prices.

The minimum nutritional requirements used in the optimization scenario were 1,350 kcal of energy, 20 g of protein, 45 g of fat, and 215 g of carbohydrates. The optimized menu composition is presented in Table 5.

Table 5. Optimized Menu Composition

Commodity	Portion (g)	Cost (IDR)
Premium Rice	272.68	4,081.61
Carrots	0.13	1.83
Potatoes	0.01	0.15
Broiler Chicken	172.46	5,470.42
Mackerel	0.00	0.00
Green Beans	0.03	0.28
Chicken Eggs	0.00	0.00
Beef	0.03	3.36
Total	445.34	9,557.65

The optimization produced a total menu composition of 445.34 g with an estimated cost of IDR 9,557.65. The resulting composition provided 1,502.59 kcal of energy, 49.94 g of protein, 45.02 g of fat, and 215.16 g of carbohydrates. Comparison of these results with the predefined minimum requirements indicates that all nutritional targets were satisfied.

Compositionally, the solution was dominated by premium rice at 272.68 g and broiler chicken at 172.46 g. These two commodities accounted for most of the total menu weight and



served as the primary components of the optimized solution. This dominance indicates that the algorithm did not select ingredients solely on the basis of price but also considered their nutritional contributions toward satisfying the specified constraints.

Premium rice provided the primary contribution to carbohydrate requirements, whereas broiler chicken made an important contribution to protein and fat requirements. Meanwhile, the other commodities appeared only in very small quantities or were not selected. This pattern indicates that the GWO solution tended to allocate larger portions to ingredients capable of providing nutritional contributions efficiently within the cost constraints and the optimized criterion weights.

Overall, the optimization results indicate that integrating forecast prices, price-change characteristics, volatility, nutritional composition, and the GWO *fitness* function can produce a menu composition that satisfies nutritional constraints while providing an estimated cost for the forthcoming period. However, the resulting composition represents a computational optimization solution based on the specified parameters and should not be interpreted as clinical evidence of effectiveness in preventing stunting.

DISCUSSION

The findings demonstrate that integrating food-price forecasting, price-pattern and volatility analysis, and optimization using the Grey Wolf Optimizer (GWO) can provide a computational framework for nutritional menu planning that accounts for food-price dynamics. This approach addresses the need to move menu planning from a *static-price optimization* perspective toward a framework that is more adaptive to price changes. Historical food-price data were first processed using the *Autoregressive Integrated Moving Average* (ARIMA) model to generate 30-day price estimates. These estimates were subsequently combined with information on *return* and volatility before being incorporated into the menu-composition optimization process.

ARIMA Forecasting Performance in Supporting Menu Planning

The evaluation results show that ARIMA achieved relatively low forecasting errors for several commodities, particularly premium rice and beef. Both commodities obtained a testing MAPE of 0.26%, while their average *rolling forecast* MAPE values were 0.1131% and 0.1990%, respectively. These findings indicate that the historical patterns of these two commodities could



be represented relatively well by the ARIMA models. In contrast, commodities such as green beans and carrots produced higher testing MAPE values of 7.90% and 8.65%, respectively, indicating that their price movements were more difficult to predict consistently.

These differences demonstrate that forecasting performance is influenced not only by the forecasting method but also by the characteristics of each individual time series. Commodities with relatively consistent temporal patterns tend to produce lower prediction errors, whereas commodities with more dynamic price movements may generate higher errors. This finding is consistent with previous studies by Rahayu and Utomo (2023) and Gupta and Singh (2024), which demonstrated the applicability of ARIMA for modeling temporal relationships and generating forecasts based on historical time-series patterns.

In the context of this study, forecasting performance has a direct implication for menu optimization. Historical prices are no longer used as the sole representation of food costs but are transformed into estimates of future prices. Accordingly, the ARIMA output functions as a *decision-support input* for the optimization process. This approach extends the application of time-series forecasting beyond prediction accuracy by directly linking forecasting outputs to a nutritional decision-making problem.

Price Dynamics as a Risk Parameter in Optimization

The 30-day forecasting results revealed substantial differences in price dynamics across commodities. Green beans exhibited the largest positive *return* at 13.1344%, followed by chicken eggs at 2.7644%. In contrast, carrots and potatoes showed negative *returns* of -1.8907% and -0.8781%, respectively. These differences indicate that future price conditions cannot be adequately represented by price levels alone but should also incorporate information regarding the direction and magnitude of price changes.

Price-pattern and volatility analysis provides an additional dimension for decision-making. Green beans and chicken eggs were categorized as exhibiting a *volatile uptrend*, whereas potatoes and carrots were categorized as exhibiting a *volatile downtrend*. These classifications provide information about the tendency and instability of price movements that cannot be obtained solely from absolute price values. In menu planning, commodities characterized by an upward price tendency and relatively high volatility can be regarded as having greater potential cost risk than commodities with more stable price movements.



These findings support the use of OHLC-based information for characterizing price movements, as discussed by Tan and Lim (2024) and Hidayat (2023). However, the present study applies this information in a different context. Whereas previous OHLC-based analyses have primarily focused on understanding price-movement characteristics, this study incorporates price-dynamics information as a risk-related input to the menu optimization process. Thus, volatility is not merely treated as a descriptive statistic but as one of the criteria influencing food-commodity selection.

This approach is relevant because food prices are inherently dynamic. A menu that minimizes cost under the price conditions of one period may not remain economically optimal when food prices change. Incorporating estimated prices and volatility characteristics into the optimization process therefore provides a more forward-looking basis for generating menu recommendations that account for anticipated economic conditions.

Integration of Forecasting and GWO in Menu Optimization

The GWO optimization results show that price received a weight of 0.676063, volatility received a weight of 0.323937, and *return* received a weight of 0. The results indicate that the optimization formulation assigned greater importance to price and volatility than to the direction of price movement. The dominant price weight confirms that cost remains the primary consideration in solution construction, while volatility serves as an additional component representing potential price uncertainty.

These findings reinforce previous research on menu optimization that considers nutritional requirements and cost constraints. Ridha (2025) and Sa'adah (2022) demonstrated that optimization approaches can be used to determine combinations of food ingredients while considering nutritional requirements and budget limitations. Similarly, Heryati (2024) and Pratama and Baita (2025) reported the application of optimization approaches to menu and food planning. The present study extends these approaches by incorporating forecasted prices and volatility as dynamic information rather than relying solely on currently observed or historical price conditions.

The use of GWO is also appropriate for a problem characterized by a complex solution space. The combination of eight food commodities, with decision variables representing ingredient quantities in grams, creates numerous possible solutions that must simultaneously satisfy multiple constraints. GWO provides exploration and exploitation mechanisms that



facilitate the search for suitable solutions within such a solution space. This is consistent with Makhadmeh (2024) and Chen (2025), who highlighted the capability of GWO for addressing complex optimization problems.

Nevertheless, the GWO-derived criterion weights also reveal an aspect that warrants further consideration. The zero weight assigned to *return* indicates that this criterion did not contribute to the optimal solution under the current fitness formulation and dataset. This result should not automatically be interpreted as evidence that *return* is unimportant. Rather, it indicates that, under the present optimization configuration, *return* was dominated by the price and volatility criteria. This finding also suggests that the fitness formulation could be further developed to ensure that each dimension of price information contributes meaningfully when theoretically and empirically justified.

Nutritional Feasibility and Cost Efficiency of the Solution

The optimization produced a menu composition with a total portion of 445.34 g and an estimated cost of IDR 9,557.65. The solution provided 1,502.59 kcal of energy, 49.94 g of protein, 45.02 g of fat, and 215.16 g of carbohydrates. Compared with the predefined minimum requirements, all nutritional targets were satisfied. These results demonstrate that GWO was able to identify a feasible solution that satisfied the nutritional constraints while producing a measurable cost estimate.

The optimized composition was dominated by premium rice at 272.68 g and broiler chicken at 172.46 g. The dominance of these two commodities indicates that the algorithm did not simply select ingredients based on their lowest prices but searched for combinations capable of satisfying nutritional constraints within the available solution space. Premium rice contributed primarily to energy and carbohydrate requirements, whereas broiler chicken provided important contributions to protein and fat. Therefore, the final composition reflects the interaction among nutritional composition, forecasted prices, and the fitness function.

These findings are consistent with Ridha (2025), Sa'adah (2022), Heryati (2024), and Pratama and Baita (2025) regarding the use of optimization to obtain food combinations that satisfy nutritional requirements while considering cost. However, the present study extends this approach by introducing dynamic cost information, because the prices incorporated into the optimization were obtained from future price forecasts. Consequently, the resulting solution



does not merely represent the price conditions observed during historical data collection but also incorporates estimated conditions over the 30-day forecast horizon.

Implications for an Adaptive Menu Model

Overall, the findings indicate that the integration of ARIMA and GWO contributes to two interconnected stages of decision-making. ARIMA provides information regarding potential future price conditions, whereas GWO translates this information into decisions regarding food quantities. Price *return* and volatility provide an additional dimension for representing potential changes and uncertainty in food prices. The integration of these components establishes a more adaptive mechanism than optimization approaches based solely on static prices.

This approach also addresses the research gap identified in previous studies. Earlier menu-optimization studies have generally emphasized nutritional composition and cost, whereas food-price forecasting studies have primarily focused on predictive accuracy. The present study connects these two functions within a single decision-making framework. Thus, the forecasting output does not remain merely as a prediction but becomes a direct input into the menu optimization process.

From the perspective of nutritional intervention planning, this approach has the potential to support menu formulation that is more responsive to changing economic conditions. When a commodity is projected to experience a substantial price increase accompanied by relatively high volatility, the optimization system can reconsider its contribution to the resulting menu. Conversely, commodities with more stable prices that can still provide sufficient nutritional contributions may become more favorable within the optimization process. This mechanism provides a conceptual basis for developing adaptive menu decision-support systems.

However, the findings also indicate that the adaptiveness of the model requires further evaluation. The zero weight assigned to *return* suggests that the direction of price movement has not yet been fully reflected in the final solution. In addition, the strong concentration of the solution on premium rice and broiler chicken indicates that the current fitness formulation tends to generate a solution dominated by a limited number of ingredients. From a nutritional-planning perspective, dietary diversity is also relevant. Future developments could therefore incorporate minimum or maximum ingredient proportions, dietary-diversity constraints, or penalty mechanisms to prevent excessive dominance by particular commodities.



Accordingly, the primary contribution of this study is not merely the identification of a single menu composition costing IDR 9,557.65, but the development of a computational framework that jointly connects price forecasting, price-change risk, nutritional requirements, and optimization. This framework provides a basis for generating menu recommendations that can be updated when new price information becomes available. Further evaluation through *backtesting* against subsequent actual prices is required to determine how consistently the generated solutions maintain nutritional feasibility and cost efficiency under the price conditions that actually occur.

CONCLUSION

This study demonstrates that integrating food-price forecasting using ARIMA, price-pattern and volatility analysis, and menu optimization using the Grey Wolf Optimizer (GWO) can generate a nutritional menu composition that accounts for projected food-price dynamics while satisfying predefined nutritional requirements. The 30-day forecasts revealed substantial differences in price movements across commodities, with green beans showing the highest projected increase of 13.1344% and carrots showing the largest projected decrease of 1.8907%. The GWO optimization assigned weights of 0.676063 to price and 0.323937 to volatility, while *return* received a weight of 0. Based on these optimized criteria, the resulting menu composition had a total portion of 445.34 g and an estimated cost of IDR 9,557.65. The solution provided 1,502.59 kcal of energy, 49.94 g of protein, 45.02 g of fat, and 215.16 g of carbohydrates, thereby satisfying all predefined minimum nutritional requirements. Overall, the findings indicate that the proposed framework can integrate forecasted food prices and price-dynamics characteristics into nutritional menu optimization. The framework therefore provides a computational basis for developing menu recommendations that are responsive to projected food-price conditions while maintaining nutritional feasibility. However, the resulting menu should be interpreted as a computationally optimized solution rather than clinical evidence of stunting-prevention effectiveness. Further research should evaluate the framework through systematic backtesting against actual future prices and consider additional constraints related to dietary diversity, ingredient proportions, and age-specific nutritional requirements.



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