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**ARTICLE**

# Predicting the Performance of Vietnamese Sugar Mills: An Application of the Grey Verhulst Model

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## ABSTRACT

The sugar industry plays a critical role in the Vietnamese economy, contributing to annual economic growth and job creation. However, the performance of Vietnamese sugar mills has been recognized to be under potential and seems to decline in recent years due to changes in the internal and external environments. Thus, it is necessary to evaluate and predict the performance of companies in this industry to find solutions for their long-run growth. In such a context, this paper aims to predict the performance of Vietnamese sugar mills so that they can improve their profitability for sustainable development in the future. We employed the Grey Verhulst model to analyze data from 16 Vietnamese sugar mills in the 2020–2023 period. The data collected include key financial indicators, such as total assets, cost of goods sold, selling and distribution costs, net profit, and inventory. Firstly, we proved that our proposed forecast model is applicable for the Vietnamese sugar industry with high percentage of reliability and accuracy. Then, using the model, we have predicted the performance of these firms for the period of 2024–2027. Our prediction shows that sugar mills grapple with familiar industry challenges as consumption declines. It is predicted that net profit criteria have the tendency to decline This slowdown places them under significant competitive pressure from foreign sugar producers. Thus, we suggest that sugar mills use our research results to formulate their strategic plan to mitigate the potential risks and position themselves in the market for their long-term profit and sustainable development in the future.

***Keywords:*** Firm Performance; Grey Verhulst Model; Sugar Industry; Sugar Mills

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# 1. Introduction

The sugar sector is of paramount importance in the field of agribusiness, acting as a fundamental pillar for several economies across the globe. The production of sugar encompasses an intricate value chain that starts with the growth of sugarcane or sugar beets and continues to the manufacture of sugar and its generated by-products, including molasses, ethanol, and bioenergy. As it sustains millions of farmers and contributes to rural development, this sector has a substantial impact on agricultural practices. Sugarcane agriculture serves as a major economic driver for rural areas in several developing nations, generating employment opportunities and fostering economic expansion. The industry's need for employment in the stages of planting, harvesting, and processing contributes to the improvement of livelihoods in agricultural regions. Furthermore, the sugar business stimulates progress in agricultural technology, encompassing the creation of crop types with high productivity and the implementation of sustainable farming methods, both of which are crucial for ensuring food security and environmental sustainability. Additionally, the by-products of the business, such as ethanol, play a crucial role in the renewable energy sector by augmenting energy security and diminishing dependence on fossil fuels. Consequently, the sugar sector plays a crucial role not only in food production but also in making a substantial contribution to global energy markets.

In Vietnam, the sugar industry, the second largest industry in the middle region of Vietnam, is a key driver of rural development, supporting agricultural Vietnam's economic growth. Besides a vast global market for sugar, derivatives keep the industry booming. At present, the sugar industry in Vietnam is facing a complex environment characterized by both favorable circumstances and substantial barriers. Following Vietnam's commitment to the Association of Southeast Asian Nations (ASEAN) Asian Trade in Goods Agreement (ATIGA), which substantially cut import duties, domestic production has been greatly affected by competition from cheaper imported sugar, notably from Thailand. Consequently, there has been a significant surge in the importation of sugar, intensifying the challenge for domestic producers to compete effectively. Notwithstanding these obstacles, Vietnam's sugar industry has experienced a certain degree of expansion. According to the Vietnam Sugarcane and Sugar Association (VSSA), there is an anticipated 16.6% growth in domestic sugar production in 2024 compared to the previous financial year [1]. This enhancement can be attributed, in part, to advantageous climatic circumstances and government measures designed to safeguard the local industry, such as the imposition of anti-dumping tariffs on imported sugar. Nevertheless, the sector continues to experience an imbalance between supply and demand since local production only fulfills around 35–40% of the overall demand, requiring substantial imports to compensate for the inadequate supply. Poor competitiveness makes Vietnam's sugar industry unable to supply enough sugar for the domestic market. It is in danger of being wiped out in the domestic market, making Vietnam a complete sugar importer like Malaysia and Taiwan [2]. If that happens, nearly one million workers risk losing their jobs, and sugar areas will have to switch to other crops. Furthermore, the sector is coping with challenges such as the exorbitant expenses of agricultural inputs, the consequences of climate change, and the competition for land utilization with more profitable crops, resulting in a decrease in sugarcane cultivation. The Vietnamese government has responded by taking measures to restore sugarcane cultivation and improve supply chains, but the industry's long-term viability is still dubious.

In such a context, this paper aims to predict the performance of Vietnamese sugar mills for the period of 2024–2027 and suggests these companies use our research results for their strategic planning towards long-term development.

# 2. Research Problem and Context

Mboi, Muturi and Wanjare defined performance management as integral to their performance evaluation metrics; performance measures empower manufacturers to enhance operational efficiency consistently [3]. It also measures enterprise performance and argues that these objectives are necessary because they form the main objectives of enterprises, as stated by Carnero, Martínez-Corral and Cárcel-Carrasco [4]. According to

Liu et al., performance evaluation metrics provide a standardized evaluation method, which is necessary to establish a performance management index system for the food industry [5]. According to Kamble et al., the performance measurement system for industry 4.0-enabled smart manufacturing systems will provide them with the competitive benefits of improved costs, quality, time, flexibility, and optimized productivity [6]. Through forecasting and strategic planning using data from 2020–2023, farmers can benefit from improved yield stability, reduced input costs, and better risk management in the future.

Agribusinesses gain competitive advantage by enhancing product differentiation, optimizing supply chains, and reaching the markets. According to Al Aina and Atan, performance is characterized in various ways. It can be described as "achieving a goal with a specific intention," "the outcomes of an action," "the capacity to achieve or the potential to produce results," or "unexpected results compared to what was anticipated". Additionally, the interpretation of performance can vary depending on who is evaluating the organization's effectiveness [7].

Tseng defined organizational performance as often being assessed using a combination of financial and non-financial indicators to obtain a comprehensive view of its performance [8]. As classified by Nguyen some critical factors utilized for the assessment of performance are financial performance such as total assets, cost of sold capital, selling expenses, and general and administration expenses [9]. Similarly, Wang, Pham and Nhieu found that the total assets, cost of goods sold, gross profit, and expert-based performance are assessed to analyze how well an organization performs and achieves its goals and objectives [10].

This study aims to answer the research question: How can enterprises forecast the performance of sugar factories to help them develop strategies to boost their competitiveness in agribusiness? In this regard, the present study collects relevant information from 2020 to 2023 from 16 sugar mills, and utilizes a mathematical Grey Verhulst model to forecast their performance. The criteria to evaluate performance management from the financial report include total assets [11], cost of goods sold, selling and distribution costs [12], net profit [9], and inventory [13].

To effectively measure the performance of sugar mills, several key measures can be considered:

- Total assets: including both current and long-term assets, are all the resources that a corporation owns and administers [11].
- Cost of goods sold: encompasses the direct expenses incurred in manufacturing the goods sold by a company. This comprises the costs of materials and labor directly involved in the production process, excluding indirect expenditures like distribution and sales force expenses [14, 15].
- Selling and distribution costs: the cost to market a produced product comprises not only the cost to sell, but also the cost to store, pack, and transport the goods, as well as the cost of collecting the sale funds [16].
- Net profit: a company's profit after operational costs, taxes, interest, and depreciation have all been deducted from total sales [17, 18].
- Inventory: inventory performance for firms in sugar manufacturing industries involves several vital metrics, such as raw materials and components served for production [13, 19, 20].

**Figure 1** shows the general scenario of the Vietnamese sugarcane manufacturing process and illustrates the connection between supply/source and demand/customer, which is the fundamental nature of the product lifecycle from sugarcane growers to end customers.

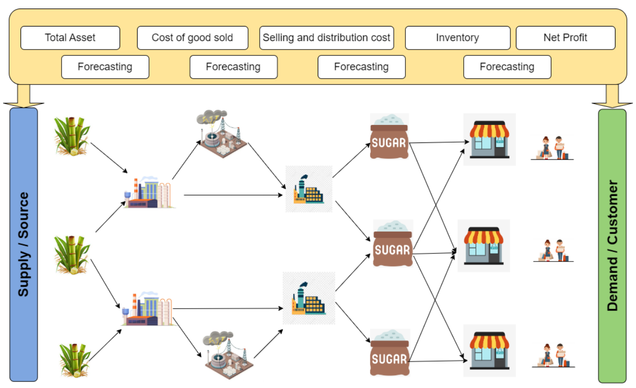


**Figure 1.** The framework of the Vietnamese sugar manufacturing process.

As illustrated in **Figure 1**, once sugarcane is purchased from the farm, it is transported to the factory for sugar processing. However, sugarcane yields numerous additional products, notably electricity from bagasse and mud, by-products of the sugar-crushing process. These materials also serve as valuable resources for fertilizer and animal feed production. The factory processes the incoming sugar into various sugar products (RS: Refined Sugar, White Sugar, and RE: Reducing Sugar—Finished Sugar). Firstly, we predict activities that add value and incur costs or inefficiencies. According to Deng, the Grey prediction model is a crucial aspect of the Grey system theory and effectively addresses uncertain problems with limited data and insufficient information. Based on the number of variables involved, Grey prediction models can be classified into univariate and multivariable models. The univariate Grey prediction model employs a data-driven approach to forecasting [21]. Tang and Lu define the Grey Verhulst model as well-suited for systems characterized by saturated growth with an S-shaped curve or single-peaked characteristics, offering enhanced prediction accuracy [22]. After that, data analytics and predictive Grey Verhulst modeling will be used to forecast future trends in sugar production and find demand for by-products like electricity. Thus, in this research, we collected secondary data from the Vietnamese stock market of sixteen Vietnamese sugar mills from 2020 to 2023 and applied the predictive Grey Verhulst modeling method to forecast future trends in sugar production and find demand for by-products like electricity.

The existing Grey system model encounters limitations as throughput increases in an S-shaped curve or reaches saturation, leading to significant forecasting errors. Such inaccuracies are unacceptable in practical applications. Addressing this issue requires the development of an improved Grey model specifically tailored for port throughput forecasting. Thus, the Grey Verhulst model is employed in this research. As Evans indicated, the entropy method quantifies the uncertainty associated with each variable within a theoretical concept. This approach offers a detailed understanding of the uncertainty, aiming to minimize it as much as possible in the evaluation process, thereby enhancing the objectivity of the analysis [23]. In addition, the forecasting method has been applied in the evaluation of urban carrying capacity by Tang and Lu [22]. Furthermore, Zeng, Ma and Zhou [24] and Zeng et al. [25] also used the estimated method to determine the weight of the specific evaluation indicators of performance management in agribusiness for each year. Deng defined the Grey theory, which made quantitative predictions of the future by modeling limited original data [21]. Wang and Li found that the GM (1,1) model, the Grey Markov model, and the Grey Verhulst model are widely used in Grey forecasting [26]. However, GM(1,1) model can only describe the monotonically changing process of data, and the simulation results have low accuracy [27]. According to Zhao, Shou and Wang, the Grey Markov prediction model needs to divide the data interval, which is relatively subjective [28]. Meanwhile, Grey Verhulst has demonstrated that incorporating the forecasting model into combination forecasting is effective. The Grey Verhulst model can successfully predict mid- to long-term loads, yielding highly accurate forecasting results when applied in this context. According to Tang and Lu, the parameter estimation process is more straightforward than the calculation process of the accurate background value construction method. This method effectively avoids the complexity caused by the background value structure in the Grey Verhulst model and the traditional parameter estimation method of a differential equation converted to a difference equation [22]. The performance management in the agribusiness of the sugar capacity system constructed in this paper is a dynamic system with a particular random fluctuation, which is suitable for using the Grey Verhulst model. Hence, this research introduces a Grey Verhulst model on time series error corrected for the port throughput forecasting.

According to Guo, Song and Ye, there are also many methods for forecasting port throughput, and the Grey system model is one [29]. Because the Grey system model needs little original data, has a simple calculation process, and has higher forecasting accuracy, it has been widely used in the prediction of many research fields. In the previous research, the Grey GM(1,1) model to predict port throughput is imperfect when the throughput increases in the curve with S type or the throughput increment is in the saturation stage. In this case, the throughput forecasting error of the Grey system model will become larger, and the result will be unacceptable in the real world. To solve this problem, we need a new Grey model for port throughput forecasting.

# 3. Methodology

## 3.1. Proposed Framework

To improve the Grey Verhulst model, we applied the effectiveness of the proposed model. We proposed a research framework as demonstrated in **Figure 2**.

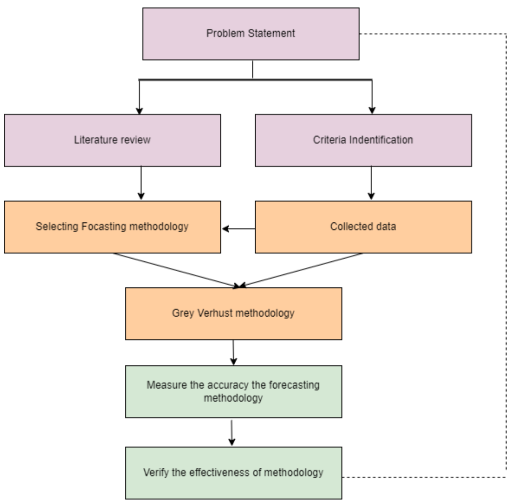


**Figure 2.** The proposed framework.

As shown in **Figure 2**, our process consists of six steps, as follows:

Step 1: Problem statement

Domestically produced sugar products cannot compete in the market. The quantity of sugar manufacturing did not have enough supply for the domestic market, which led to a broken value chain of goods.

Step 2: Literature review and criteria identification affecting the performance management of sugar in Vietnam agribusiness

Developed a Grey Verhulst model that improved the forecasting effectiveness of the stochastic fluctuation data and boosted a practical methodology for forecasting Vietnamese sugar manufacturing performance criteria, designing the fluctuation of four-year forecasting in cases involving samples with a large change in data forecasting.

Step 3: Selecting forecasting methodology and collecting data

This study assesses the future performance of sixteen sugar mills listed on Vietnam's public stock market. The research forecasts future performance trends in the agribusiness sector by analyzing criteria such as total assets, cost of goods sold, selling and distribution costs, net profit, and inventory from 2020 to 2023. The goal is to predict trends to enhance profitability and minimize investment risks for Vietnam's sugar mills.

Step 4: Measure the integrated forecasting model's accuracy to judge its effectiveness in applying the Grey Verhulst models

In this step, we hypothesize that integrating the Grey Verhulst builds a practical model that increases its predictive accuracy.

Step 5: Measure the accuracy of the forecasting methodology to calculate the result and analysis.

Step 6: Verify the effectiveness of the methodology

Regarding the evaluation performance of the forecasting volatility model, based on verifying the results of predicted values that match the actual values, this study adopted the mean absolute percentage error (MAPE) approach to evaluate the forecasting performance of the Grey Verhulst models.

## 3.2. Grey Verhulst Prediction

According to Tang and Lu, Grey prediction is built upon the approach of the Grey forecasting model [22]. In the GM (1,1) model, the first 1 indicates the meaning of one variable, and the next 1 is used to interpret the first order of the Grey differential equation. It is one of the most frequent models used in a series of Grey forecasting models. In this study, we collect data of sixteen Vietnamese sugar manufacturing entities such as total assets, cost of goods sold, selling and distribution costs, owner equity, inventory, net sales, and net profit from 2020 to 2023 based on secondary data from the Vietnam stock market. The authors utilized the Grey Verhulst model to forecast the future performance of Vietnamese sugar manufacturing, aiming to formulate strategies that enhance their competitiveness and foster sustainable expansion amidst increasing openness and integration.

Supposing the original sequence:

$U^0$= [$u^{(0)}$(1),$u^{(0)}$(2),$u^{(0)}$(3),...,$u^{(0)}(n)$], here n $\geq 4$,

$u^{(0)}(k) \geq 0$, k$= 1,\ 2,\ \ldots,\ n$;

The 1-AGO sequence of $U^{(0)}$ is: $U^{(1)} =$ [$u^{(1)}$(1),$u^{(1)}$(2), $u^{(1)}$(3),...,$u^{(1)}(n)$]

Here $u^{(0)}(k) = \sum_{i=1}^{k} u^{(0)}(i)$, $k$ = 1,2,3...,$n$

$Z^{(1)}$ is the mean generation of consecutive neighbors sequence of $U^{(1)}$

Where, $Z^{(1)} = (z^{(1)}$(2), $z^{(1)}$(3),...,$z^{(1)}(n)$

Here $z^{(1)}(k)$ = 0.5[$u^{(1)}(k)$ +$u^{(1)}(k$–1)] $k = 2,3,\ldots,n$

**Definition 1.** *Assumption:*

$$u^{(0)}(k) + az^{(1)}(k) = b\Big(z^{(1)}(k)\Big) \tag{1}$$

*As Grey Verhulst model.*

**Definition 2.** *Assumption:*

$$\frac{du^{(1)}}{dt} + au^{(1)} = b\Big(u^{(1)}\Big)^2 \tag{2}$$

*As the whitenization equation of Grey Verhulst model.*

By calculating Equation (2), we can get

$$u^{(1)}(t) = \frac{au^{(1)}(0)}{bu^{(0)}(0) + \big(a - bu^{(1)}(0)\big)e^{at}} \tag{3}$$

to substitute Equation (2) with the parameter estimated by Equation (1), we can obtain the response function, which can be used in finally forecasting. Obviously, the accuracy of Equation (1) affects directly the final forescast result. In fact, the modeling method above takes $u^{(0)}(t)$ directly as the Grey derivative item of $\frac{dx^{(1)}}{dt}$ , and calculates the area encircled by the fitted curve $u^{(1)}(t)$ and the time axis through the trapezoid formula. Thus, we can obtain $z^{(1)}(t)$. Then substitute Equation (2) with $z^{(1)}(t)$, to optain Equation (3). This method cut if the relationship between difference equation and differential equation, thus it lacks the scientific foundation and theoretical basis.

A new Grey Verhulst model:

According to the Grey model's modeling through, the smooth fitted curve of the 1-AGO sequence is original data is $u^{(1)}(t)$, according to the trapezoid formula, the approximate equation of $u^{(0)}(t+1)$ can be expressed as follows:

$$au^{(0)}(t+1) = u^{(1)}(t) + \frac{1}{2}\left[\frac{du^{(1)}(t)}{dt} + \frac{du^{(1)}(t+1)}{dt}\right] \tag{4}$$

By the definition of accumulating generator, we can obtain:

$$u^{(1)}(t+1) = u^{(1)}(t) + u^{(0)}(t+1) \tag{5}$$

By Equation (2), namely the whitenization equation of the Grey Verhulst model, we can obtain

$$\begin{cases} \frac{du^{(1)}(t)}{dt} + au^{(1)} = b\big(u^{(1)}(t)\big)^2 \\ \frac{du^{(1)}(t+1)}{dt} + au^{(1+1)} = b\big(u^{(1)}(t+1)\big)^2 \end{cases}$$

Adding the two equations of Equations group (5), we can get:

$$\begin{gathered} \frac{du^{(1)}(t)}{dt} + \frac{du^{(1)}(t+1)}{dt} + a\big[u^{(1)}(t) + u^{(1)}(t+1)\big] \\ = b\Big[u^{(1)}(t)^2 + u^{(1)}(t+1)^2\Big] \end{gathered} \tag{6}$$

To substitute Equation (5) with Equation (6), we can obtain

$$\begin{gathered} u^{(0)}(t+1)^2 \frac{a}{2}\big[u^{(1)}(t) + u^{(1)}(t+1)\big] \\ = \frac{b}{2}\Big[u^{(1)}(t)^2 + u^{(0)}(t+1)^2\Big] \end{gathered} \tag{7}$$

We can get a new Grey Verhust model by Equation (7), which is expressed by equation

$$\begin{gathered} u^{(0)}(k+1)^2 \frac{a}{2}\big[u^{(1)}(k) + u^{(1)}(k+1)\big] \\ = \frac{b}{2}\Big[u^{(1)}(k)^2 + u^{(0)}(k+1)^2\Big] \end{gathered} \tag{8}$$

**Theorem 1.** *Supposing $U^{(0)}$ is a non-negative smooth sequence*

*$U^0$= ($u^{(0)}$(1),$u^{(0)}$(2),$u^{(0)}$(3),...,$u^{(0)}$(n))*

*$U^1$ is the 1-AGO sequence of $U^0$, the parameter $\widehat{a} = (a,b)^T$*

*Here,*

$$Y = \begin{bmatrix} u^{(0)}(2) \\ u^{(0)}(3) \\ \ldots \\ u^{(0)}(n) \end{bmatrix}$$

$$B = \begin{bmatrix} -\frac{1}{2}\big[u^{(1)}(1) + u^{(1)}(2)\big] & \frac{1}{2}\Big[\big(u^{(1)}(1)\big)^2 + \big(u^{(1)}(1)\big)^2\Big] \\ -\frac{1}{2}\big[u^{(1)}(2) + u^{(1)}(3)\big] & \frac{1}{2}\Big[\big(u^{(1)}(2)\big)^2 + \big(u^{(1)}(3)\big)^2\Big] \\ \vdots & \vdots \\ -\frac{1}{2}\big[u^{(1)}(n-1) + u^{(1)}(n)\big] & \frac{1}{2}\Big[\big(u^{(1)}(1)\big)^2 + \big(u^{(1)}(1)\big)^2\Big] \end{bmatrix} \tag{9}$$

Equation (9) is the parameter sequence of the new Grey Verhulst model by least-square method

$$\widehat{a} = (a,b)^T = \big(B^T B\big)^{-1} B^T Y \tag{10}$$

Proving is omitted.

**Theorem 2.** *The solution of the whitenization equation of Grey Verhulst model is*

$$u^{(1)}(t) = \frac{1}{e^{at}\left[\frac{1}{u^{(1)}(0)} - \frac{b}{a}(1-e^{-at})\right]} = \frac{au^{(1)}(0)}{e^{at}\left[a - bu^{(1)}(0)(1-e^{-at})\right]} = \frac{au^{(1)}(0)}{bu^{(1)}(0) + \left(a - bu^{(1)}(0)\right)e^{at}} \tag{11}$$

The time response function of Grey Verhulst model is expressed as follows

$$\hat{u}^{(1)}(k+1) = \frac{au^{(1)}(0)}{bu^{(1)}(0) + \left(a - bu^{(1)}(0)\right)e^{ak}} \tag{12}$$

The proof has been left out.

From the solution of the whitenization equation of Grey Verhulst Model, we know that when $t \to \infty$,

If $a > 0$, then $u^{(1)}(t) \to 0$,

If $a < 0$, then $u^{(1)}(t) \to \frac{a}{b}$

Namely, $t$ is big enough, for any $k > t$, $u^{(1)}(t)$ is fully close to $u^{(1)}(k)$, thus, $u^{(0)}(k+1) = u^{(1)}(k+1) - u^{(1)}(k) \approx 0$, the system comes to the death.

### 3.3. Evaluative Precision of Forecasting Models

There are some common approaches to the evaluation of the performance of the volatility model for forecasting. This study adopted five criteria to evaluate the forecasting model of the rice price. Model characteristics include periodicity, randomness, and tendency. To obtain the tendency of the series and the context of the development of natural disasters, this study not only used integration to improve the background value but also increased the accuracy by correcting the model's periodic errors. According to Wang et al.[27] the MAPE is defined as follows:

$$\text{MAPE} = \frac{1}{n}\sum_{k=2}^{n}\left|\frac{u^{(0)}(k) - \hat{u}^{(0)}(k)}{u^{(0)}(k)}\right| \times 100\% \tag{13}$$

where: $u^{(0)}(k)$: the actual value in time period $k$, and $\widehat{u}^{(0)}(k)$: the forecast value in the time period.

The grade of MAPE is divided into four levels shown in **Table 1.**

**Table 1.** The MAPE grade level.

| MAPE | ≤10% | 10–20% | 20–50% | >50% |
|---|---|---|---|---|
| Grade levels | Excellent | Good | Qualified | Unqualified |

We ensure there is no space for errors during the forecasting calculation because forecasting accuracy is important to solve mathematical concerns for future values with incomplete information. Therefore, in this paper, the MAPE is employed to measure the accuracy of the method for constructing fitted time-series values. When MAPE values are small, the predicted values are close to the actual values. This model's application is a relative case study in the agricultural supply chain, particularly for sugar. It enables companies to anticipate future performance, allowing them to plan proactively and reduce risks.

## 4. Results and Disscussion

In this section, we present the forecasting results of the Grey Verhulst model for DMU 1, illustrating the calculations applied to all 16 sugar mill companies. Detailed forecasting results can be found in the **Appendix A.**

Take $U^0 = (914750;\ 1764646;\ 2380345;\ 2887429)$ is the sequence of raw data and $U^{(1)}$ applying for Grey Verhulst models with the simulation such as:

According to Equation (1) $u^{(0)}(k) + az^{(1)}(k) = b\left(z^{(1)}(k)\right)^2$ compute the accumulation generation of $U^0$ and the 1-IAGO sequence of $U^{(1)}$ the equation showed:

$$U^{(1)} = u^{(1)}(1),\ u^{(1)}(2),\ u^{(1)}(3),\ u^{(1)}(4) = 914750;\ 1764646;\ 2380345;\ 2887429$$

The first-order accumulated progression satisfies the following generation of consecutive neighbors sequence of $U^{(1)}$ as follows:

$$z^{(1)}(k) = (1339698;\ 2072495.5;\ 2633887)$$

The parameter $\widehat{a} = (a, b)^T$ and matrix $B$ and constant vector $Y$ are accumulated by means of this:

$$Y = \begin{bmatrix} -1339698 \\ -2072495.5 \\ -2633887 \end{bmatrix}$$

$$B = \begin{bmatrix} -67854 & 1975371.533 \\ -234197 & 4390008.912 \\ -108615 & 7001644.274 \end{bmatrix}$$

After calculating the least squares estimation, we obtain the sequence of parameter $\widehat{a} = (a, b)^T$. According to Equation (11), because of $a < 0$, thus $x^{(1)}(t) \to \frac{a}{b}$

$$
\begin{aligned}
u^{(1)}(t) = & \frac{1}{e^{a0.2676t}\left[\frac{1}{u^{(1)}(0)}-447642(1-e^{-0.2676t})\right]} \\
& = \frac{0.2676u^{(1)}(0)}{e^{0.2676t}\left[0.2676-1196879u^{(1)}(0)(1-e^{-0.2676t})\right]} \\
& = \frac{0.2676u^{(1)}(0)}{b1196879u^{(1)}(0)+\left(0.2676-1196879u^{(1)}(0)\right)e^{0.2676t}}
\end{aligned}
$$

the time response function of Grey Verhulst model and its time response from $u^{(1)}(k+1) = u^{\overline{(1)}}(k+1) - u^{(1)}(k)$ as follows:

$k = 1$; and $u^{(1)}(1) =$ 914,750

$k = 2$; and $u^{(1)}(2) =$ 818,013.89

$k = 3$; and $u^{(1)}(3) =$ 695,302.165

$k = 4$; and $u^{(1)}(4) =$ 543,421.07

$k = 5$; and $u^{(1)}(5) =$ 483,559.99

$k = 6$; and $u^{(1)}(6) =$ 398,643.44

$k = 7$; and $u^{(1)}(7) =$ 324,320.47

$k = 8$; and $u^{(1)}(8) =$ 278,450.7

After determining the simulated values of $U^0$ using the raw series according to the accumulated generating operation by using $u^{(1)}(k+1) = u^{\overline{(1)}}(k+1) - u^{(1)}(k)$. Using the same evaluation and procedures, all predicted values of all companies from 2020 to 2023 are found for DMU1—Vietnamese sugar evaluations shown in **Figure 3**, and sixteen Vietnamese sugar in the table of the Data Availability part.

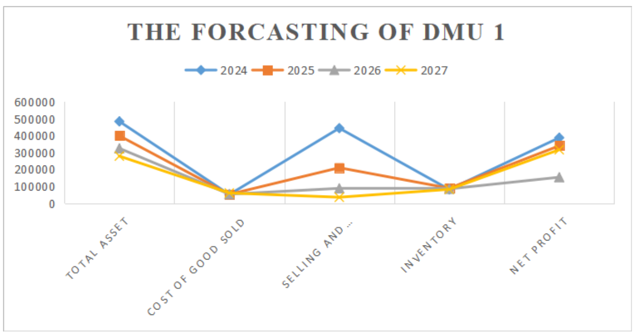


**Figure 3.** Results from the test run of DMU 1 sample.

**Figure 3** shows that the estimated data for the DMU1 from 2024 to 2027 reveals a complex picture marked by challenges and opportunities. The sharp decline from 483,559.99 to 278,450.7 million VND in total assets raises concerns about the company's financial health and long-term viability, a critical concern in the agricultural industry. While this could be partly attributed to industry-wide challenges such as land conversion to more profitable crops, the lift of sugar quotas in 2020 and subsequent trade liberalization could exacerbate this issue by intensifying competition from imported sugar. Given potential internal challenges such as asset divestment or underinvestment, the company must bolster its financial position and consider strategic options like partnerships or mergers within the agricultural value chain. The findings suggest that leveraging technology for precision farming, data analytics, and supply chain management can enhance efficiency and minimize losses in sugar mills. Additionally, implementing risk management and hedging strategies can safeguard against price volatility and unforeseen events. These approaches will help stakeholders navigate market fluctuations and foster sustainable growth within the agricultural value chain.

The volatile net profit trend underscores the uncertainties in the Vietnamese sugar industry. Although a significant profit of 387,206.89 million VND is projected for 2024, subsequent declines to 153,427.11 million VND in 2025 and 2026 are followed by a rebound to 316,225.06 million VND in 2027. These fluctuations reflect the impact of factors such as global sugar price changes, increased competition from trade liberalization, and rising production costs. Additionally, potential decreases in sugar demand from the beverage industry due to stricter alcohol policies and proposed excise taxes on sugary drinks add further complexity. To navigate these risks, DMU1 must adopt proactive financial management strategies, including price risk mitigation through hedging and diversification of its product portfolio. On a positive note, the reduction in selling and distribution costs indicates effective cost-cutting measures or strategic changes in distribution. This trend should be sustained and enhanced through investments in technology and exploration of direct-to-consumer models. However, while stable inventory levels suggest efficient management, they also carry the risk of overstocking or missed opportunities in a volatile market, necessitating improved demand forecasting and adaptable production capabilities.

MAPE was used to evaluate the accuracy of the forecasting model and is shown as follows in the **Tables 2 and 3.**

**Table 3** compares the simulation forecast results from the Grey model and accurate data, showing that

**Table 2.** The simulated forecast results for DMU 1 using the Grey Verhulst.

| Year | Total Asset | | Cost of Goods Sold | | Net Profit | |
|---|---|---|---|---|---|---|
| | Actual Value | Forcasting Value | Actual Value | Forcasting Value | Actual Value | Forcasting Value |
| 2020 | 914,750 | 914,750 | 3768 | 3768 | 278,312 | 278,312 |
| 2021 | 849,896 | 835,338.76 | 4256 | 3,954.87 | 314,970 | 310,406.01 |
| 2022 | 615,699 | 639,209.71 | 4629 | 5,171.01 | 301,548 | 310,668.23 |
| 2023 | 507,084 | 589,129.77 | 4987 | 29,987 | 315,487 | 310,930.68 |

| Year | Selling and Distribution Costs | | Inventory | |
|---|---|---|---|---|
| | Actual Value | Forcasting Value | Actual Value | Forcasting Value |
| 2020 | 599,384 | 599,384 | 99,994 | 99,994 |
| 2021 | 714,971 | 718,264.28 | 99,069 | 100,353.96 |
| 2022 | 742,652 | 736,117.73 | 89,458 | 85,917.90 |
| 2023 | 751,285 | 754,414.94 | 71,648 | 73,558.48 |

**Table 3.** Grey Verhulst methodology for the MAPE of DMU 1. Unit: Percentage

| Year | Total Asset | Cost of Goods Sold | Selling and Distribution Costs | Inventory | Net Profit |
|---|---|---|---|---|---|
| 2020 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 2021 | 1.71 | 7.09 | 0.46 | 1.29 | 1.44 |
| 2022 | 3.89 | 7.91 | 0.87 | 3.95 | 3.02 |
| 2023 | 3.54 | 6.08 | 0.41 | 2.66 | 1.44 |
| Total | 2.29 | 4.23 | 0.43 | 3.95 | 1.48 |

the forecast indices are pretty close to the accurate data. In addition, **Table 2** presents the MAPE simulation results for DMU1 from 2020 to 2023 across sixteen sugar manufacturing companies. The average forecasting accuracy for each criterion was 2.29% for Total Assets, 4.23% for Cost of Goods Sold, 0.43% for Selling and Distribution Costs, 3.95% for Inventory, and 1.48% for Net Profit. Applying the Grey Verhulst methodology significantly improved model precision, achieving forecast accuracy exceeding 90%. This performance earned the Grey Verhulst forecasting method an 'excellent' rating regarding MAPE. Consequently, the Grey Verhulst model proved to be an effective model for forecasting performance criteria, aiding the future performance management of the sixteen companies in this case study. A predictive mathematical model utilizing these forecasts can assist economists in estimating market pressures and developing a more efficient supply chain to manage volatility in the agricultural business market.

The results of the applied Grey Verhulst forecasting model for performance are shown in **Table A1** in the Appendix. Based on the predicted results, sugar mills grapple with familiar industry challenges as consumption declines. Net profit criteria have the tendency to decline This slowdown places them under significant competitive pressure from foreign sugar producers. Performance management is a crucial issue; addressing it requires a coordinated approach that spans raw material sourcing, production, and distribution—a persistent weakness within the sugar mill for many years.

In **Table A1**, DMU 11 in the following years has had a change in investment in total assets in 2024: 5,298,000.92; in 2026, increased by nearly 8%, corresponding to 6,820,410.75 million Dong; in 2027, it reached the highest total expenditure for this criterion, in the forecast period of 7,574,480.15 million Dong. Companies are exploring ways to reduce costs to lower prices, including adopting new technologies that enhance efficiency and lower production expenses. Effective supply chain management throughout sugar mill production is crucial for minimizing labor costs. For the domestic sugar industry to thrive in a competitive environment, it must implement robust strategies and undergo restructuring, focusing on everything from raw material planning and mechanized procurement to production and distribution processes. The results show that companies need to focus on developing production processing technology (increasing total assets) to optimize the performance management model better in the future. The simulation results for the other sugar mill companies can be found in **Table A1** of the Appendix.

In this research, we addressed two key challenges. First, we utilized Grey Verhulst to predict the performance of stochastic volatility in sugar mills. The results are presented in **Table A1** (**Appendix A**), aiding them in developing strategies to enhance their competitiveness in the agribusiness sector. Second, we provided an effective forecasting method tailored for the performance management of Vietnamese sugar producers, including total assets, cost of goods sold, selling and distribution costs, net profit, and inventory. This approach not only improves the accuracy of four-year forecasts in scenarios with significant data fluctuations but also supports sixteen companies in strengthening their weaknesses and achieving tremendous success in Vietnam's agribusiness industry. It is implied in our study that all sixteen companies should strengthen their financial position, optimize operational efficiency, and advocate for supportive policies. Embracing sustainability and engaging with stakeholders across the value chain will further enhance the companies' resilience and long-term prospects in the dynamic Vietnamese sugar market.

# 5. Conclusions

The Vietnamese sugar industry presents a challenging but navigable landscape. Sugar manufacturing can thrive by adopting a proactive and strategic approach, focusing on financial health, diversification into new markets and value-added products, and innovation in agricultural economics. By leveraging favorable policies like anti-dumping measures and FTAs while mitigating risks associated with unfavorable ones like the excise tax, sugar mills can position themselves for success in this evolving market based on the overview forecasting in this research.

This paper employed the Grey Verhulst model to assess its effectiveness in forecasting the performance of stochastic volatility in sugar mills. Specifically, it focused on key financial metrics such as Total Assets, Cost of Goods Sold, Selling and Distribution Costs, Inventory, and Net Profit for sixteen publicly traded sugar mills. By estimating the impact of these volatile criteria on performance, the study aims to assist sugar mills in managing their production process, stabilizing input materials, and allocating risks more effectively. The research findings, derived from the Grey Verhulst model, provide insights into how current performance trends may influence the future performance of sugar mills. The model achieved a MAPE percentage of approximately 5%–10%, indicating its effectiveness and applicability for not only the Vietnamese sugar industry but also farming businesses in Vietnam and globally.

In other words, this research introduces a novel decision-making model, demonstrated through an actual case study, showcasing its applicability and efficacy. The integrated approach offers empirically valuable insights into the sustainable development of the food supply chain industry. Future research could further refine this perspective and develop more integrated approaches to manage increasingly complex supply chains.

However, the criteria used in this study for evaluating management methods may introduce bias in interpreting the research results. Therefore, future research should consider expanding the sample size to a global scale. To improve the specificity of a model forecasting future performance, it is important to incorporate additional evaluation criteria. This includes assessing external factors such as economic indicators, industry trends, and the competitive landscape, all of which can significantly influence future outcomes.

# Author Contributions

Conceptualization, N.-N.-Y.H. and P.M.N.; methodology and formal analysis, N.-N.-Y.H.; data collection, H.-L.L. and H.K.N.; writing—original draft preparation, N.-N.-Y.H., P.M.N. and H.-L.L.; writing—review and editing, P.M.N., H.-L.L.; visualization, N.-N.-Y.H.; supervision, N.-N.-Y.H. and P.M.N. All authors have read and approved the manuscript.

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## Institutional Review Board Statement

Not applicable.

## Informed Consent Statement

Not applicable.

## Data Availability Statement

| DMU | Sugar Manufacturing | Link |
|---|---|---|
| DMU 1 | Son Duong | https://finance.vietstock.vn/MiaDuongSonDuong-ctcp-mia-duong-son-duong.htm |
| DMU 2 | Cao Bang | https://finance.vietstock.vn/CBS-ctcp-mia-duong-cao-bang.htm |
| DMU 3 | Son La | https://finance.vietstock.vn/SLS-ctcp-mia-duong-son-la.htm |
| DMU 4 | Lam Son | https://finance.vietstock.vn/LSS-ctcp-mia-duong-lam-son.htm |
| DMU 5 | Ninh Hoa | https://finance.vietstock.vn/NHS-ctcp-duong-ninh-hoa.htm |
| DMU 6 | Gia Lai | https://finance.vietstock.vn/SEC-ctcp-mia-duong-nhiet-dien-gia-lai.htm?tab=BCTN |
| DMU 7 | Kon Tum | https://finance.vietstock.vn/KTS-ctcp-duong-kon-tum.htm |
| DMU 8 | 333 Dak Lak | https://s.cafef.vn/upcom/s33-cong-ty-co-phan-mia-duong-333.chn |
| DMU 9 | La Nga | https://finance.vietstock.vn/DuongLaNga-ctcp-mia-duong-la-nga.htm |
| DMU 10 | Bien Hoa | https://finance.vietstock.vn/BHS-cong-ty-tnhh-mtv-duong-ttc-bien-hoa-dong-nai.htm |
| DMU 12 | Thanh Cong Bien Hoa | https://finance.vietstock.vn/SBT-ctcp-thanh-thanh-cong-bien-hoa.htm |
| DMU 13 | Soc Trang | https://finance.vietstock.vn/DuongSocTrang-ctcp-mia-duong-soc-trang.htm |
| DMU 14 | Ben Tre | https://finance.vietstock.vn/MiaDuongBenTre-ctcp-mia-duong-ben-tre.htm |
| DMU 15 | Vi Thanh Can Tho | https://finance.vietstock.vn/DuongCanTho-ctcp-mia-duong-can-tho.htm |
| DMU 16 | Kien Giang | https://finance.vietstock.vn/KISUCO-ctcp-mia-duong-kien-giang.htm |

## Conflicts of Interest

All authors disclosed no conflict of interest.

## Lists of Acronyms

| Notation | Interpretation |
|---|---|
| $u^{(0)}(k)$ | the actual value in time period k; $u^{(0)}(k) \geq 0,\ k = 1,\ 2,\ \ldots,\ n;$ |
| $Z^{(1)}$ | the generated mean sequence of consecutive neighbors of X (0) |
| $du^{(1)}(t)$ | the obtained whitening differential equation of the Grey Verhulst model |
| $t \to \infty$ | whitenization equation of Grey Verhust model |
| $\widehat{u}^{(0)}(k)$ | the forecast value in the time period |
| a | the development coefficient |
| b | the Grey action |

## Appendix A

**Table A1.** Forecasting the performance of 16 sugar mills from 2024 to 2027.

| Sugar Mill | | | 2024 | | |
|---|---|---|---|---|---|
| **DMU** | **(I)Total Asset** | **(I)Cost of Good Sold** | **(I)Selling and Distribution Cost** | **(I)Inventory** | **(O)Net Profit** |
| DMU 1 | 183,559.99 | 51,082.46 | 443,707.22 | 81,007.64 | 387,205.9 |

| Sugar Mill | | | 2024 | | |
|---|---|---|---|---|---|
| **DMU** | **(I)Total Asset** | **(I)Cost of Good Sold** | **(I)Selling and Distribution Cost** | **(I)Inventory** | **(O)Net Profit** |
| DMU 2 | 125.01 | 5,109.62 | 58,739.90 | 7,446.79 | 38,105.37 |
| DMU 3 | 105.76 | 1,245.86 | 958,604.70 | 31,638.55 | 97,107.79 |
| DMU 4 | 715,718.70 | 3,214.34 | 776,471.44 | 517,865.6 | 931,424.4 |
| DMU 5 | 537,485.71 | 806,248.69 | 1,352,174.62 | 497,107.5 | 1,076,116 |
| DMU 6 | 2,925,068.68 | 1,326,800.50 | 82,174.62 | 248,001.1 | 2,761,975 |
| DMU 7 | 856,754.89 | 910,833.07 | 156,160.82 | 3,043.19 | 2,320,837 |
| DMU 8 | 426,436.02 | 829,263.01 | 849.93 | 12,294.32 | 168,258 |
| DMU 9 | 474,285.68 | 302,150.12 | 15,330.28 | 33,376.37 | 160,211.4 |
| DMU 10 | 357,490.25 | 415,884.97 | 13,197.17 | 13,251.95 | 662,752.8 |
| DMU 11 | 5,298,000.92 | 402,150.12 | 106,396.07 | 1,140,358 | 5,973,587.3 |
| DMU 12 | 28,738.43 | 930,820.75 | 371,313.47 | 1,033,957 | 25,965.972 |
| DMU 13 | 601,823.91 | 108,326.15 | 4,657.45 | 279,007.4 | 189,927.71 |
| DMU 14 | 1,016,664.72 | 1,599,557.81 | 17,063.52 | 141,417.5 | 2,310,564.8 |
| DMU 15 | 462,337.23 | 52,049.58 | 8,219.21 | 120,492.6 | 95,325.11 |
| DMU 16 | 152,706.65 | 194,982.00 | 11,268.06 | 85,550.38 | 262,178.42 |
| | | | **2025** | | |
| DMU 1 | 68,643.45 | 52,108.98 | 209,703.96 | 88,326.45 | 339,491.2 |
| DMU 2 | 188.42 | 4,910.49 | 64,251.71 | 8,246.322 | 30,666.71 |
| DMU 3 | 165.16 | 1,242.70 | 1,035,966.06 | 32,925.72 | 138,768.6 |
| DMU 4 | 307,617.96 | 3,463.13 | 813,469.17 | 6,245,034 | 1,076,103 |
| DMU 5 | 172,590.41 | 1,326,800.50 | 1,576,749.07 | 429,481.3 | 1,168,025 |
| DMU 6 | 3,098,203.49 | 1,006,248.69 | 77,749.07 | 265,557.9 | 2,884,020 |
| DMU 7 | 934,906.93 | 851,946.33 | 177,919.49 | 286.56, | 2,141,413 |
| DMU 8 | 404,350.08 | 840,545.00 | 707.38 | 12,286.57 | 39,864.81 |
| DMU 9 | 462,652.11 | 366,799.38 | 17,053.83 | 28,579.59 | 204,551.96 |
| DMU 10 | 368,099.59 | 428,933.90 | 18,488.60 | 11,549.65 | 752,165.76 |
| DMU 11 | 4,331,453.23 | 466,799.38 | 128,863.32 | 172,268.3 | 5,960,843.3 |
| DMU 12 | 31,810.87 | 1,042,335.47 | 373,062.74 | 1,519,006 | 21,923.73 |
| DMU 13 | 698,860.88 | 117,156.85 | 5,330.61 | 290,836.1 | 25,784.334 |
| DMU 14 | 1,281,767.98 | 1,685,873.48 | 16,802.61 | 161,623.5 | 3,446,365.6 |
| DMU 15 | 388,312.18 | 68,636.35 | 4,367.65 | 169,326.8 | 70,315.32 |
| DMU 16 | 189,052.52 | 213,911.88 | 11,681.40 | 61,400.06 | 274,695.2 |
| | | | **2026** | | |
| DMU 1 | 24,320.47 | 53,115.38 | 87,777.98 | 84,563.92 | 153,427.2 |
| DMU 2 | 218.98 | 4,644.52 | 66,313.77 | 9,952.01 | 38,040.87 |
| DMU 3 | 201.73 | 1,239.39 | 1,182,663.70 | 36,070.34 | 514,401.1 |
| DMU 4 | 119,651.73 | 4,165.28 | 803,037.75 | 6,191,921 | 241.3 |
| DMU 5 | 52,534.50 | 1,411,798.73 | 1,376,535.33 | 410,171 | 2,730.89 |
| DMU 6 | 2,516,402.99 | 1,111,650.75 | 86,535.33 | 347,801.8 | 396,219.5 |
| DMU 7 | 1,019,964.56 | 779,017.18 | 175,497.59 | 302.52 | 1,123,124 |
| DMU 8 | 443,151.71 | 970,060.10 | 955.41 | 13,902.52 | 12,317.06 |
| DMU 9 | 501,400.59 | 381,922.17 | 18,453.38 | 12,996.9 | 35,869.57 |
| DMU 10 | 426,868.23 | 409,430.93 | 14,576.75 | 9,774.082 | 4,698.752 |
| DMU 11 | 6,820,410.75 | 481,922.17 | 139,185.15 | 1,396,585 | 142,853.4 |
| DMU 12 | 32,744.91 | 11,415,904.00 | 428,544.80 | 1,238,556 | 9,488,586 |
| DMU 13 | 793,185.71 | 102,102.00 | 6,284.18 | 243,214.6 | 21,405.25 |
| DMU 14 | 1,419,886.65 | 1,822,160.19 | 18,761.70 | 195,281.4 | 9,824.396 |
| DMU 15 | 428,600.54 | 85,383.21 | 7,756.40 | 186,820.3 | 11,382,509 |
| DMU 16 | 5,245,247.32 | 185,015.08 | 10,554.96 | 38756.24 | 210,500 |
| | | | **2027** | | |
| DMU 1 | 8,450.67 | 60,046.23 | 34,858.48 | 81,644.94 | 316,224.9 |
| DMU 2 | 232.79 | 4,827.20 | 72,656.67 | 8,808.016 | 31,185.54 |
| DMU 3 | 154.12 | 1,235.93 | 1,079,446.09 | 32,890.92 | 123,910.9 |
| DMU 4 | 44,713.84 | 43,357.58 | 1,005,831.00 | 6,962,667 | 1,029,289 |

| | | | | | |
|---|---|---|---|---|---|
| | | | **2027** | | |
| DMU 5 | 15,727.94 | 1,191,748.51 | 1,467,505.56 | 448,179.9 | 1,060,486 |
| DMU 6 | 2,226,499.81 | 871,235.51 | 97,505.56 | 27,322.92 | 2,864,073 |
| DMU 7 | 1,241,610.99 | 785,297.21 | 159,666.17 | 343.4612 | 2,241,713 |
| DMU 8 | 517,038.39 | 863,298.80 | 1,017.56 | 14,343.46 | 448,675.46 |
| DMU 9 | 416,425.20 | 337,925.76 | 16,326.59 | 39,816.13 | 301,222.69 |
| DMU 10 | 410,213.95 | 448,773.53 | 12,235.06 | 8,067.56 | 784,427.64 |
| DMU 11 | 7,574,480.15 | 51,925.76 | 127,125.25 | 1,175,012 | 592,261.35 |
| DMU 12 | 39,905.40 | 1,147,631.44 | 410,766.73 | 1,105,198 | 24,321.62 |
| DMU 13 | 718,853.23 | 93,874.56 | 8,056.61 | 219,363.9 | 24,439.168 |
| DMU 14 | 1,022,902.373 | 1,947,531.41 | 19,058.90 | 169,332.5 | 20,772,217 |
| DMU 15 | 472,658.40 | 108,157.82 | 7,625.47 | 185,091.3 | 64,814.85 |
| DMU 16 | 221,384.806 | 167,880.64 | 12,927.03 | 22,515.7 | 310,043.8 |

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