

Real-Time Production-Forecasting Using GSS-Optimized Holt DES: An Empirical Comparison with ARIMA

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Abstract

Kurnia Plastic Factory depended on manual documentation of transactions and production scheduling, leading to postponed reporting, erroneous completion projections, and inadequate decision-making. This research created an online point-of-sale system featuring automated predictions for production duration and assessed its forecasting precision and computational efficacy in comparison to a statistical standard. The system was constructed utilizing the Extreme Programming style, the Laravel framework, PHP, and MySQL. Holt Double Exponential Smoothing technique was refined through the application of the golden section search algorithm. Functional testing verified that all 19 features functioned as intended, whereas user acceptance testing attained a success percentage of 94.74%. The assessment of forecasting efficacy was conducted by rolling one-step-ahead projections utilizing 255 observations of production duration documented from 2023 to 2025. The autoregressive integrated moving average model with parameters of one, one, and one surpassed the optimum smoothing technique in all accuracy measures, recording a mean squared error of 1.69, a mean absolute error of 1.05, and a mean absolute percentage error of 34.99%. The refined smoothing technique necessitated an average processing duration of 2.36 milliseconds, in contrast to 35.77 milliseconds for the fixed-order statistical model. The prediction endpoint yielded a response time of about 154.20 milliseconds. The smoothing technique was preserved due to its automatic parameter adjustments for each request, resulting in reduced processing expenses, even though it exhibited diminished forecasting precision. These results revealed a compromise between predictive precision and computational efficacy in production scheduling.

Keywords- ARIMA, Extreme Programming, Golden Section Search, Holt Double Exponential Smoothing

1. INTRODUCTION

Manufacturing supports economic growth by increasing production capacity and meeting market demand [1], so manufacturers must keep production planning efficient to stay competitive. Inaccurate completion estimates cause late deliveries, poor machine utilization, and lower customer satisfaction, while information systems increasingly support production, inventory, and decision-making [2]. In plastic manufacturing, such estimates are hard to produce manually because output depends on machine capacity, setup time, and unplanned downtime. Kurnia Plastic Factory illustrates this problem. Production data, machine operations, and customer orders are recorded separately in notebooks, receipts, and spreadsheets. Interviews with the owner and order records from 2023 to 2025 show that the factory handles about 5–8 orders per month, that 60–70% of them finish 1–3 days later than estimated, and that compiling a production report takes roughly a week.

Forecasting from historical order data is a natural way to improve these estimates. Holt Double Exponential Smoothing (Holt DES) updates a level and a trend component with every new observation, which makes it light enough for per-order forecasting [3]. However, its accuracy is sensitive to the smoothing parameters α and β [4]. Manual tuning or brute-force search over fixed candidate values is costly and does not guarantee an optimal pair, particularly when the parameters must be re-tuned as new transactions accumulate.

Previous studies leave a clear gap. Point-of-sale (POS) studies concentrate on transaction recording, user-perception evaluation, or adoption, without any forecasting [5], [6], [7] Holt DES and other exponential smoothing variants have been applied to household statistics, e-commerce sales, and gold prices [8], [9], [10]. and ARIMA with simple exponential smoothing has been used for raw-material planning. In the studies we reviewed (25 relevant papers from Google Scholar, 2021–2026), none applied Holt DES to

production completion time, tuned α and β automatically, embedded the forecast in a live POS workflow, or compared it with ARIMA as a benchmark.

This study addresses that gap by developing a web-based POS system for Kurnia Plastic Factory using Extreme Programming (XP), whose iterative cycles suit changing operational needs [11]. The objectives are (1) to design and implement the system; (2) to embed production-duration forecasting using Holt DES, with α and β optimized automatically by Golden Section Search (GSS), a derivative-free method that narrows the search interval using the golden ratio; and (3) to evaluate the forecasts against ARIMA with a rolling one-step-ahead scheme, using accuracy metrics [12] and computation time. The contributions are a working POS system with built-in forecasting and a reusable comparison procedure that shows the accuracy deployability trade-off of self-tuning smoothing methods in real-time operations.

2. METHODS AND DATA

The practical research will integrate this study with the experimental technique. This study aims to design and implement a web-based Point of Sales (POS) system for Kurnia Plastic Factory to automate the recording of transactions and production schedules, to integrate an automated process of forecasting duration of production in the system using Golden Section Search (GSS) optimised Holt Double Exponential Smoothing (Holt DES), and to empirically test the reliability of the forecasting method against a well-known statistical benchmark (ARIMA) in a rolling one-step-ahead scheme. This article discusses the method the factory utilised to handle production and transactions that were previously performed manually. The research approach is presented in four main steps, as indicated in Figure 1. These are problem recognition, system design, system evaluation and outcome analysis.

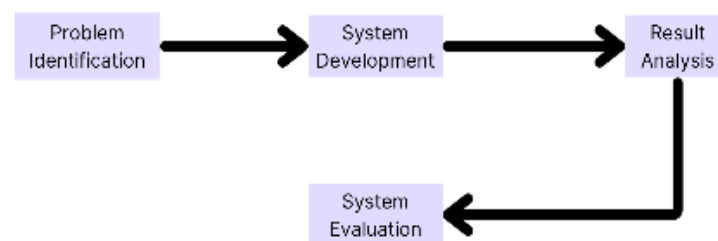


Figure 1 Research Method

2.1.1 Problem Identification

This stage identifies the operational problems of Kurnia Plastic Factory via primary and secondary data. Primary data were collected from six semi-structured interviews (1–2 hours each) with the factory owner between June and August 2025. The interviews covered topics such as transaction management, production scheduling, delivery-time forecasts, available machinery, and requested software capabilities. Interviews indicated that production durations were documented manually by hand, leading to frequent gaps between expected and actual delivery dates and problems maintaining transaction data. Field notes were sorted by theme, translated into functional and non-functional specifications, then aggregated across sessions to 19 system requirements. Secondary data was collected from a literature assessment on POS systems, Holt DES forecasting and the Laravel framework that formed the research gap indicated in the Introduction. One restriction is that just an owner was interviewed, therefore the requirements are from one stakeholder and do not reflect the demands of production personnel or customers.

2.1.2 System Development

This stage adheres to the Extreme Programming (XP) framework, comprising five iterative phases: Planning, Design, Programming, Testing, and Release, executed over six cycles within a three-month development timeframe. During the planning stage, system specifications and user narratives were established according to the 19 criteria. During the design phase, a system model was developed utilising Use Case Diagrams and Activity Diagrams that represent the two access roles recognised for this system:

Admin and Manager. The framework was constructed on Laravel 8, PHP, and MySQL, operating on a local server administered through *Laragon* to suit the current Windows 7 infrastructure at the factory. In the programming stage, the Holt DES algorithm, with parameters dynamically modified by GSS, was incorporated into the order generation process to forecast production timelines, and the Counting Sort algorithm was embedded in the dashboard to pinpoint top-selling items. The Testing and Launch stages are further upon in Phase 3 and the subsequent implementation protocols.

2.1.3 Result Analysis

This system underwent assessment through three distinct approaches specially utilised in this research. Initially, Black Box Testing was performed by assessing each of the 19 system functionalities enumerated according to established input-output scenarios, without scrutinising the underlying code architecture. Secondly, User Acceptance Testing (UAT) was performed by the plant owner utilising a questionnaire that assessed the identical 19 elements, each evaluated on a 1–5 Likert scale (as outlined in Table 6); the overall success rate was calculated by dividing the actual total score by the maximum achievable score. Third, the precision of the forecasts was evaluated independently through the Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), symmetric MAPE (sMAPE), and Mean Absolute Scaled Error (MASE), by juxtaposing the production completion times estimated by the Holt DES model refined with GSS against the actual recorded times and the ARIMA standard, employing a one-step-ahead rolling methodology with 204 training data points and 51 test data points as delineated in Section 2.3.3.

2.1.4 System Evaluation

In this step the results of the three evaluation methods described in Section 2.1.3 were collated to decide if the produced system satisfied the research goals outlined in Section 1. Black Box testing verified that all 19 functions function as specified. The UAT success rate was to get a minimum classification of “very good” ($\geq 80\%$) according to the standard Likert-based interpretation scale employed in this investigation [13]. The UAT outcome is user approval, not proof of accuracy of forecasting, which was based primarily on error metrics against the ARIMA benchmark. In an effort to directly address the third study objective, the MAPE, sMAPE and MASE[14] values were tested against the ARIMA benchmark findings, to determine the empirical dependability of the GSS optimised Holt DES technique for real time deployment. This evaluation also revealed system weaknesses such as the untested multi-user scenario, which are discussed in the Discussion and used to guide recommendations for future work. The researchers employed an Extreme Programming systems development approach. This way works well because one of the agile approaches is to be adaptable and maintain open lines of communication with the users, since apps might change anytime [15].

2.2.1 Planning

During the planning phase, prerequisites were collected via discussions with the factory proprietor [16]. and an examination of existing literature regarding the evolution of POS systems and the Laravel framework. The interviews revealed that manual processes hindered the tracking of sales and production advancements, reports were delayed, identifying best-selling products was cumbersome, and there was no dependable approach to predict completion timelines. The results were synthesized into 19 prioritized system specifications. The operational procedure, encompassing product entry, sales documentation, and report creation, was depicted in a flowchart [17] [18]. The program is a web-based system developed using Laravel, PHP, and MySQL on a Laragon local server, featuring two distinct roles: Administrators possess complete access, whereas Managers are restricted to five functions (analyzing statistics, overseeing sales and waiting-list information, exporting sales data, and generating receipts).

2.2.2 Design

The design phase concentrates on creating an interface and structure that comply with the 19 system requirements that were determined during the planning phase, while also following suitable and repeatable modelling rules that make clear how the system's data interacts with one another. The system design, including the database structure, user interface layout, and business process flows, is modelled using use-case and activity diagrams. As shown in Figure 3, the outcome is a collection of use-case diagrams with eight use cases spanning the Admin and Manager roles.

2.2.3 Coding

The Point of Sale system was developed utilising the Laravel framework due to its flexibility, inherent security attributes, and user-friendliness. The design specifications generated in the earlier phase were converted into code via pair programming and continuous integration, with ongoing refactoring implemented to ensure the codebase remains organised and sustainable. The development spanned three months, culminating in operational modules such as login/registration, dashboard, item/machine management, transaction management, waiting list, production forecasting, and sales reporting. The Counting Sort algorithm has been included into the dashboard module to evaluate recorded sales data and prioritise things based on total sales, so enhancing the system's functionality from mere transaction logging to decision support analytics for recognising top-selling products.

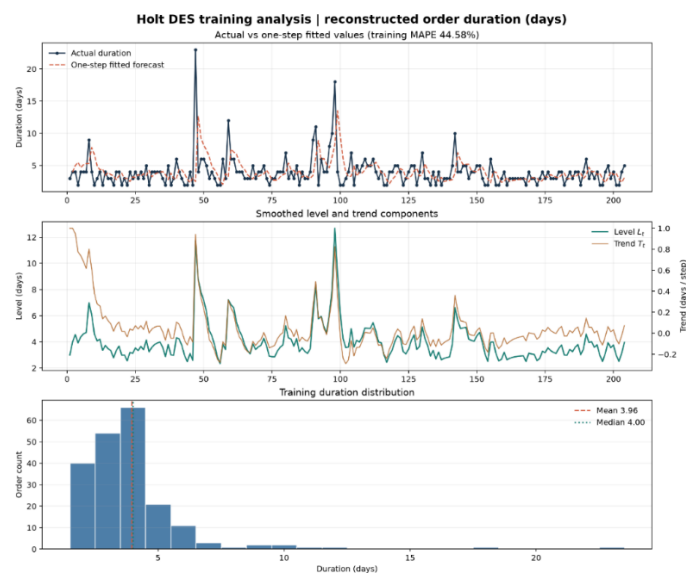


Figure 2 Holt DES training analysis

Tabel 1 Manual Calculation Holt DES

t	Y _t	F _t	L _t	T _t	APE(%)
1	3	-	3.0000	1.0000	-
2	4	4.0000	4.0000	1.0000	0.00
3	4	5.0000	4.5496	0.9499	25.00
4	2	5.4995	3.9228	0.7743	174.97
5	4	4.6971	4.3837	0.7394	17.44

Tabel 2 Descriptive statistics and trend tests of the training series

No	Item	Score
1	N	204

2	Period	2023-01-13 to 2025-03-10
3	Mean / median / SD	3,96 / 4 / 2,34 days
4	Min-max	2-23 days
5	Outliers (1,5×IQR, batas 1,5-5,5)	23 orders
6	Linear Regression	slope -0,0034 days/observation, p = 0,219
7	Mann-Kendall	p = 0,412; Sen's slope= 0

2.2.4 Testing

System testing was carried out in two phases, both directly on the implemented system as detailed in section 2.2.3. The 19 implemented functionalities were confirmed by black-box testing based on pre-defined input-output assumptions without investigating the internal code structure. The plant owner then conducted User Acceptance Testing (UAT) with the same set of features to verify that the system satisfied its operational criteria, which were scored on a 1–5 Likert scale; specific ratings are shown in Table 6. Feedback received in this phase was incorporated before launch. The forecasting capabilities were assessed independently from the functional and usability testing, utilising the MSE, MAE, MAPE, sMAPE and MASE metrics detailed in Section 2.3.3 to verify their performance against the ARIMA benchmark.

2.2.5 Release

The evaluated system was implemented on the factory's local server, constructed with Laravel and MySQL, and operated on the factory's current Windows 7 hardware, enabling the owner to utilise it for daily operations. Training occurred on January 5, 2026, encompassing essential functions including product input, transaction recording, buyer oversight, production time assessments, and analysis of top-selling items, supplemented by documented operating protocols to aid in staff orientation. Feedback obtained directly from the owner during this stage concerning system efficacy and opportunities for enhancement is encapsulated in the Discussion part and forms the foundation for suggestions for subsequent endeavours in the Conclusion section.

2.3.1 Golden Section Search Optimization Procedure

For the second research purpose, this paper applies Golden Section Search (GSS) [19] to optimize automatically the smoothing parameters of the Holt DES such that there is no need for manual tuning of the parameters. GSS is a derivative free optimization method for unimodal functions. It computes the objective function, the training MAPE, at two interior sites chosen according to a golden ratio and iteratively reduces a search interval $[a,b]$ by keeping the sub-interval with the lesser error. GSS is one-dimensional while Holt DES has two parameters thus the optimization is done sequentially in three stages: (1) α optimize in $[0,1]$ while β is fixed at its initial value 0.1; (2) β optimize in $[0,1]$ using the α obtained in stage 1; (3)- optimize α again in $[0,1]$ using the β obtained in stage 2. The stages stop when the interval width falls below $\varepsilon = 1 \times 10^{-4}$. This took roughly 20 iterations per stage, 60 in total. Thus the final pair (α, β) it represents a solution that is determined coordinate by coordinate and may not be the global optimum of the error surface defined by two parameters. The training MAPE is not assured to exhibit unimodality in either parameter. During each iteration, the two internal points are derived as follows:

$$x_1 = b - r(b - a) \quad (1)$$

$$x_2 = a + r(b - a) \quad (2)$$

Where $r = (\sqrt{5} - 1) / 2 \approx 0.618$ represents the golden ratio constant, and a and b signify the present lower and upper limits of the search interval. During each iteration, the objective function $f(x)$, which denotes the training MAPE generated by the Holt DES model with x as a prospective parameter value, is assessed at x_1 and x_2 :

$$\text{if } f(x_1) < f(x_2), \text{ then } b = x_2; \text{ otherwise } a = x_1 \quad (3)$$

This comparison eliminates the sub-interval least likely to contain the minimum, and the process repeats until the interval width falls below a predefined convergence threshold ϵ :

$$|b - a| < \epsilon \quad (4)$$

2.3.2 Holt Double Exponential Smoothing Model

The parameters α and β derived from GSS are utilized in the Holt DES model to predict order fulfillment duration. Let Y_t represent the recorded duration (in days) for the t -th order, where $t = 1, 2, \dots, n$ sequentially indexes the orders based on their order date. L_t and T_t denote the level and trend after observing Y_t , and F_t denotes the one-step-ahead forecast of Y_t made using information up to order $t - 1$. Initialization ($t = 1$). The model is initialized with the first two observations:

$$L_1 = Y_1 \quad (5)$$

$$T_1 = Y_2 - Y_1 \quad (6)$$

The level is set to the first observation, and the trend is set to the first observed change. No forecast is produced at $t = 1$, so the first forecast is F_2 . At least two observations are required. Recursion ($t = 2, \dots, n$). At each step, the forecast is computed first, using only the level and trend from the previous step. The observation Y_t is then used to update the components:

$$F_t = L_{\{t-1\}} + T_{\{t-1\}} \quad (7)$$

$$L_t = \alpha \cdot y_t + (1 - \alpha) \cdot (L_{\{t-1\}} + T_{\{t-1\}}) = \alpha \cdot y_t + (1 - \alpha) \cdot F_t \quad (8)$$

$$T_t = \beta \cdot (L_t - L_{\{t-1\}}) + (1 - \beta) \cdot T_{\{t-1\}} \quad (9)$$

The forecast error is $e_t = Y_t - F_t$, and the absolute percentage error is $APE_t = |Y_t - F_t| / Y_t \times 100$. The training MAPE reduced by GSS is the average of APE_t over $t = 2, \dots, n$. Forecasting a new order. After the last archived order n , the forecast h steps ahead is

$$F_{\{n+h\}} = L_n + h \times T_n \quad (10)$$

and the system uses $h = 1$ when creating new order. The values $0 \leq \alpha, \beta \leq 1$ control the weight given to recent observations. Because T_1 depends on the first two observations, the initial trend may be unstable; its influence decays within the first observations.

Worked example. Using $\alpha = 0.4504$ and $\beta = 0.1113$ with $y_1 = 3$ and $y_2 = 4$, the initialization gives $L_1 = 3$ and $T_1 = 1$. For $t = 2$, $F_2 = 3 + 1 = 4$, $L_2 = 4$, $T_2 = 1$. For $t = 3$ ($y_3 = 4$): $F_3 = 4 + 1 = 5$, $L_3 = 0.4504(4) + 0.5496(5) = 4.5496$, and $T_3 = 0.1113(4.5496 - 4) + 0.8887(1) = 0.9499$. The complete calculation is presented in Table 1.

Where L_t denotes the smoothed level at time t , T_t the trend estimate at time t , and Y_t the actual production duration at time t . The forecast k periods ahead is then computed as:

$$MAPE = (1/n) \times \frac{\sum |Y_t - F_t|}{Y_t} \times 100\% \quad (11)$$

2.3.3 Forecasting Data and Evaluation Procedure

This segment outlines the data processing approach employed to assess the GSS-optimized Holt DES model in comparison to the ARIMA. The historical dataset consists of 255 completed order observations (production duration in days) gathered from the Kurnia Plastic Factory archives from 2023 to 2025. The dataset was sequentially partitioned into 204 training instances (80%) and 51 testing instances (20%). A preliminary examination of the 204 training observations (Table 2, Figure 2) showed no significant monotonic trend (linear regression slope = -0.0034 days per observation, $p = 0.219$; Mann–Kendall $p = 0.412$). The series is nevertheless non-stationary: the ADF test on the original series gave $p = >0.05$, and stationarity was achieved only after first-order differencing ($d = 1$). Together, these results describe a series without a deterministic long-term trend but with persistent level shifts caused by occasional long-duration orders. Such a series calls for models that update their level adaptively as new orders arrive, which Holt DES does through its recursive level and trend components and ARIMA(1,1,1) through differencing. Neither model is assumed to be superior a priori; both are evaluated on the same rolling one-step-ahead scheme. The assessment process was carried out in three separate computational phases:

Step 1: GSS Parameter Optimization and Holt DES Calculation

As demonstrated at $t = 2$, $L_2 = 0.4504(4) + (1 - 0.4504)(3 + 1) = 4.0000$ and $T_2 = 0.1113(4 - 3) + (1 - 0.1113)(1) = 1.0000$, yielding a forecast for $t = 3$ of $F_3 = L_2 + T_2 = 5.0000$ days. Comparing F_3 to the actual observation $Y_3 = 4$ yields an absolute error of 1.0000 day.

Step 2: ARIMA Benchmark Identification Procedure

A statistical benchmark was created using an ARIMA model trained on the same 204 training data points. First, the Augmented Dickey-Fuller (ADF) test was performed on the original series and the p-value was greater than 0.05 which meant that the series was non-stationary. First order differencing ($d=1$) was employed and ADF test verified the stationarity ($p<0.05$). Then we looked at the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the differenced series. Both graphs showed strong single lag spikes before being shut off, showing autoregressive order $p=1$ and moving average order $q=1$. Thus, ARIMA(1,1,1) was selected as the best statistical baseline model based on the smallest training Akaike Information Criterion (AIC) and residual diagnostics.

Step 3: One-Step-Ahead Comparative Evaluation To assess the deployability of both models in a real-time transactional system, a rolling one-step-ahead forecasting technique was conducted over the 51 test observations. For each test step t , the two models produced a forecast at $t+1$. Once the actual value $Y_{(t+1)}$ was available, the data window was modified to incorporate $Y_{(t+1)}$ and the next forecast was generated. The rolling scheme for Holt DES yielded a test MSE of 2.3048 and an MAE of 1.1753. For a specific test observation with near zero actual production duration ($Y_t=2.0$ days), Holt DES predicts $F_t=4.22$ days with a single-point absolute percentage error of 111%, a phenomenon that artificially inflates standard MAPE and that warrants the inclusion of sMAPE (33.33%) and MASE (0.6817). Using the same rolling framework, ARIMA(1,1,1) produced a test MSE of 1.6920 and MAE of 1.0513.

3. RESULTS AND DISCUSSION

3.1 Design Result

The use case diagram created in the system design stage contains 2 actors, namely Admin and Manager based on the planning outcomes that have been authorized. Access to any feature of the system means both actors have to complete the login/registration process. The Admin actor has access to all system including product and buyer management, transaction processing, machine and waiting list management, production time forecasting and sales reporting. In contrast, the Manager actor is allowed to access a limited set of five features such as checking the sales statistic, managing data buyers/transactions, managing waiting list orders, exporting data transactions into excel and printing receipts from transactions. This division of access by position is indicative of the factory's mode of operation. The day to day transactional and administrative work is handled solely by the Admin and the Manager only needs monitoring level visibility of sales and production performance. Figure 3 presents the whole structure of the use case diagram with in total 8 use cases.

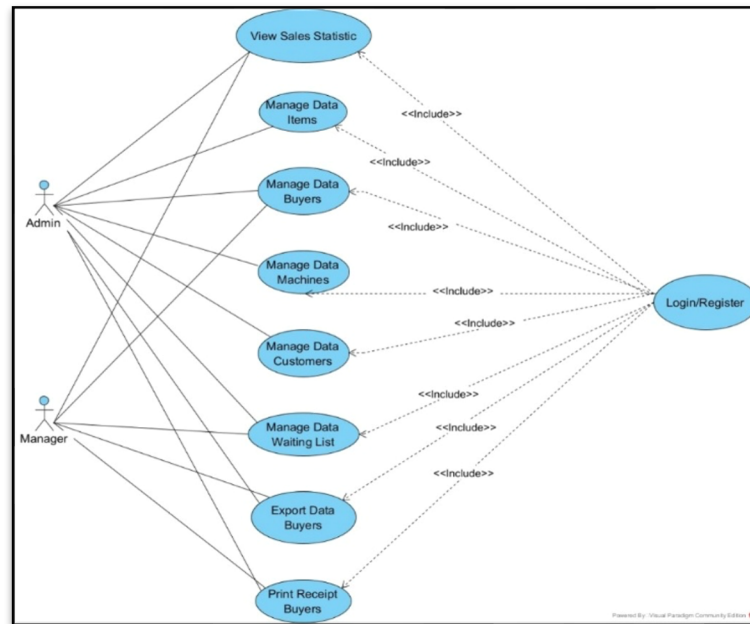


Figure 3 Use Case Diagram of System

3.2 Coding Result

The system was developed as a web application featuring modules for user authentication, a dashboard, management of items and machinery, transaction processing, a queue system, production forecasting, and sales analytics.

Figure 4 Form For Adding New Transaction

Figure 4 Form for initiating a new transaction, the forecasting functionality is integrated within the Add Order form. Upon the administrator's selection of the client, item, machine, and quantity, the system acquires the historical production times, executes Holt DES utilizing the GSS-optimized parameters, and presents the projected completion date on the form prior to order submission. If all necessary machines are occupied, the system alerts the administrator to add the order to a queue, and the order is transferred to the buyers list when a machine is freed.

3.3 Computational Performance and In-Transaction Feasibility

The assessment of computational feasibility was conducted on the local development system outlined (Intel Core i3-1215U, 8 GB RAM, PHP 8.1.10 on Laragon 6, utilizing ARIMA executed in Python). Each measurement was conducted 100 times following the exclusion of an initial warm-up run, utilizing

the 204 training observations as input. Table 3 presents the execution duration, Table 4 details the GSS iterations, CPU, and memory consumption, while Table 5 outlines the overall response time of the forecasting endpoint

Table 3 Execution time of forecasting methods

No	Measurement	Mean (ms)	Max/worst case (ms)	SD (ms)
1	Holt DES + GSS (total)	2.359	3.401	0.176
2	GSS optimization only	2.341	3.329	0.173
3	Holt forecast only	0.018	0.072	0.006
4	ARIMA (1,1,1), fixed order (fitting + forecast)	35.766	172.814	17.652
5	ARIMA with AIC search over 32 candidate orders (search + fitting + forecast)	2,675.058	4,315.501	321.035

Table 4 GSS iterations, CPU, and memory usage

No	Item	Holt Des + GSS (PHP)	ARIMA(1,1,1)fixed order (Python)	ARIMA with AIC (Python)
1	GSS iterations per run	60	n/a	n/a
2	Process CPU usage	99.30%	89.12%	95.02%
3	Peak memory	6 MiB	144.395MiB	144.395MiB

Table 5 End-to-end response time of the forecasting endpoint

No	Measurement	Value
1	Valid Responses	100/100 (HTTP 200)
2	Average Response Time	154.203 ms
3	Worst Case Response Time	250.728 ms
4	Sample standard deviation	20.566 ms

The Holt DES with GSS optimization was able to complete a full prediction, including the parameter optimization, at an average time of 2.36 ms (worst case 3.40 ms), as shown in Table 3. In contrast, 99% of this time (2.34 ms) was spent in GSS and the final one-step forecast took 0.02 ms. As indicated in Table 4, GSS performed exactly 60 iterations in each run (three sequential stages of around 20 iterations each). Fixed-order ARIMA(1, 1, 1) took 35.77 ms on average (worst case 172.81 ms), about 15 times longer than Holt DES, but still well below one second. Re-identifying the order by AIC over 32 candidates took 2,675.06 ms on average (worst case 4,315.50 ms), more than 1,000 times longer than Holt DES.

As would be expected for single-threaded computing, process CPU consumption was consistently close to one logical processor (89–99%), therefore it did not distinguish between the approaches. Although the two numbers are not directly comparable, peak memory was lower for Holt DES (6 MiB vs. 144.40 MiB). The Python value represents the peak working set of the entire process, including the interpreter and its numerical libraries, while the PHP value represents the peak allocation of the forecasting routine. With a mean response time of 154.20 ms (worst case 250.73 ms, SD 20.57 ms; Table 5), the forecasting endpoint ultimately supplied correct valid responses. About 1.5% of this time is spent on the prediction computation itself (2.36 ms); the remaining time is spent processing requests and retrieving data. As a result, both approaches are computationally viable for in-transaction use. What sets Holt DES apart is that it adjusts its parameters at each request without requiring a new runtime or order re-identification. Network delay and concurrent multi-user load are not included in these tests, which were taken on a local development server from a single client using sequential queries.

3.4 Testing Result

Before the application is sent to the factory owner, system testing is conducted first to make sure the system is working well and meets the required specifications for use. This testing is conducted directly by the factory owner, who submits the final application results for testing. This system testing is performed using the black box approach. User Acceptance Testing is evaluation performed by end users who directly engage with the system to ascertain whether its functionalities align with their specified requirements. This UAT testing comprises five categories: SS (Strongly Agree), S (Agree), CS (Somewhat Agree), KS (Disagree), and TS (Strongly Disagree) [20][21]. Nineteen statements are employed to assess the system's fundamental functions utilising a 1–5 Likert scale. The subsequent formulas and evaluation outcomes from the respondents are as follows:

Table 6 UAT Scores

No	Statements	Expected Results	Score (1-5)
1	Order Waiting List	Automatic orders are entered into the waiting list table.	5
2	Automatic Machine Selection	The machine dropdown only displays items.	4
3	Add Shipping Costs	The invoice displays shipping costs if filled in.	5
4	Add Other Costs	The invoice displays additional costs.	5
5	Reset Machine ID	Machine IDs are sorted from smallest to largest.	4
6	Items – Machines Integration	Item data is stored and linked to the machine.	5
7	Export Buyers to Excel	Excel files are downloaded according to the data.	4
8	Buyer Data Sorting	Data is displayed per month with 50 data points.	5
9	Print Notes	A new tab appears with the invoice ready to print.	5
10	Customer Details	Detail page appears with name, contact, address, purchase history	5
11	Monthly Excel Export	Excel is filled with data according to the month	5
12	Waiting List to Buyers	Data disappears from the waiting list and appears in the buyer	5
13	Login & Register	User successfully registers and logs in	5
14	Dashboard	Displays total sales for 1 month & graph	5
15	CRUD Items, Machines, Customers	Data changes according to action	5
16	Automatic calculation of total item price	Successfully calculated automatically after entering the total quantity of items	5
17	Production Time Forecasting	The system displays an estimated production completion time based on historical data when a new order is created.	4
18	Forecasting Accuracy Evaluation	Error metrics are computed on the 51 test observations with a rolling one-step-ahead scheme, and MASE is below 1.	4

19	System Compatibility on Windows 7	The system runs properly with Laravel 8 and MySQL on a Windows 7 PC without errors.	5
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A. Strongly Agree	= 5 x 14
B. Agree	= 4 x 5
C. Somewhat Agree	= 3
D. Disagree	= 2
E. Strongly Disagree	= 1
Total Score	= 70+20
	= 90

And the total calculation of the X value (highest value) and Y value (lowest value) is done as follows:

$$\begin{aligned} \text{MAX} &= \text{Highest Score} \times (\text{number of statement} \times \text{number of respondents}) \\ &= 5 \times 19 \\ &= 95 \end{aligned}$$

$$\begin{aligned} \text{MIN} &= \text{Lowest score} \times (\text{number of statements} \times \text{number of respondents}) \\ &= 1 \times 19 \\ &= 19 \end{aligned}$$

The UAT success rate is calculated using the following formula:

$$\begin{aligned} \text{Success Rate} &= \frac{\text{Actual Total Score}}{X} \times 100\% & (12) \\ &= \frac{90}{95} \times 100\% = 94.74\% & (13) \end{aligned}$$

The User Acceptance Test (UAT) employed a 1-5 Likert scale across 19 system criteria, yielding a cumulative score of 90 out of a possible 95, equivalent to 94.74%. This result indicates that the factory owner accepts the system's functions and usability, with a "very good" evaluation. It does not measure forecasting accuracy, which is assessed separately through the error metrics (MSE, MAE, MAPE, sMAPE, and MASE) in Section 2.3.3. Fourteen criteria, covering inventory management, equipment, buyers, the waiting list, and sales reports, received the highest score of 5, while five criteria were rated 4, notably machine selection, sorting, Excel export, and the forecasting-related features (items 17 and 18). The scores for the forecasting items reflect the user's perception of the feature, such as its ease of use and the clarity of its output, and not the accuracy of the predictions, which was lower than that of the ARIMA benchmark. These results suggest that the system is suitable for use in plastic manufacturing operations, with room for improvement in the forecasting-related features.

3.5 Discussion

The primary contribution of this research consists of three elements lacking in prior studies: automated optimization of smoothing parameters, forecasting integrated inside a real-time transaction framework, and empirical evaluation against a statistical standard. The Golden Section Search (GSS) method automatically adjusts α and β , achieving convergence far more efficiently than comprehensive parameter exploration [22], so an expected completion date is displayed whenever a new order is created. This differs from prior Holt DES studies, which were standalone socio-economic or commodity forecasts [23] or manual parameter selection in external programs like RStudio. To assess the accuracy of this embedded approach, GSS-optimized Holt DES was benchmarked against ARIMA using the same rolling one-step-ahead scheme (204 training, 51 test observations); Table 7 contrasts this evaluation with two comparable research.

Table 7 Evaluation Comparative

Aspect	This Study	Fadillah & Hendrastuty (2025)[24]	Nafisah et al. (2025)[25]
Domain	Plastic production duration (Kurnia Plastic Factory)	Weekly helmet stock (Toko Eko Helm)	Monthly <i>songkok</i> production (Tebu Mas Gresik)
Methods Compared	Holt DES (GSS-optimized) vs. ARIMA	ARIMA(2,1,0) & ARIMA(1,1,0) as best single models (without comparison to other methods)	ARIMA(1,1,1) vs. Simple Exponential Smoothing (SES)
Parameter Optimization	Golden Section Search (automated, $\alpha = 0.4504$, $\beta = 0.1113$)	Manual grid based on ACF/PACF + lowest AIC	Manual grid based on ACF/PACF + SES α tuning
Evaluation Scheme	Rolling one-step-ahead, train/test 204/51	Static forecast 4 weeks ahead (without explicit train/test split)	Static forecast 5 months ahead (without explicit train/test split)
Accuracy Metrics	MSE, MAE, MAPE, sMAPE, MASE	MSE, AIC	MAE, MSE, MAPE
Best Performing Model	ARIMA(1,1,1) (MSE 1.6920 vs. Holt DES 2.3048)	ARIMA (selected as a single model, not compared)	ARIMA(1,1,1) (MAE 17.43 vs. SES 18.02)
Deployment Context	Real-time, per-order forecast within POS transaction system	Periodic batch, supporting manual procurement decisions	Periodic batch, supporting manual raw material planning
Contribution Focus	Trade-off between accuracy vs. real-time implementation feasibility	Stock prediction accuracy for procurement	Production prediction accuracy for raw material planning

ARIMA(1,1,1) outperformed Holt DES on all five metrics, consistent with both reference studies that found ARIMA superior to its alternatives. Holt DES nevertheless beat a naive persistence baseline (sMAPE 33.33%, MASE 0.6817), which is robust to the near-zero actual values that inflate MAPE. Unlike the reference studies, which produced periodic (weekly or monthly) forecasts for manual procurement decisions, this system needs a forecast each time a single order is submitted. In that setting ARIMA's periodic re-identification (stationarity testing, differencing, ACF/PACF-based order selection) is impractical. Holt DES is therefore retained not for statistical superiority but for its balance of accuracy and deployability in real-time embedded forecasting, a scenario neither reference study assessed.

This study has several limitations. First, the system runs on legacy Windows 7 hardware, which restricts it to Laravel 8 and prevents migration to newer, more secure framework versions. Second, Holt DES had higher error than ARIMA, so its forecasts should be treated with caution when production durations vary widely and need continued error monitoring after deployment. Third, parameter optimization and evaluation used the owner's manual 2023-2025 records, so the GSS parameters and the ARIMA benchmark should be re-estimated as digitally recorded data accumulates. Fourth, UAT involved a single respondent and concurrent multi-user performance was not tested. Finally, because the series shows no significant long-term trend, Holt DES's trend component may add noise, and a trend-free single exponential smoothing baseline was not evaluated.

4. CONCLUSION

This research created a web-based Point of Sale (POS) system for Kurnia Plastic Factory utilizing the Extreme Programming (XP) technique. The system facilitates product oversight, customer data acquisition, financial dealings, machine performance tracking, and a queue management feature,

supplanting the factory's manual documentation with a cohesive digital process. Black Box Testing validated that all 19 evaluated functions performed as expected, while User Acceptance Testing (UAT) had a success percentage of 94.74%. The UAT outcome signifies user approval of the system and does not imply predictive precision. Holt's Double Exponential Smoothing (Holt DES) was employed for estimating production time, with its smoothing parameters ($\alpha = 0.4504$, $\beta = 0.1113$) automatically optimized by Golden Section Search (GSS), eliminating the necessity for manual adjustments. In the test set including 51 observations, assessed using a rolling one-step-ahead methodology, Holt DES attained a mean squared error (MSE) of 2.3048 and a mean absolute error (MAE) of 1.1753. Its MASE of 0.6817 is beneath 1, signifying reduced error compared to a simplistic one-step benchmark.

In comparison to the ARIMA(1,1,1) benchmark, Holt DES exhibited inferior accuracy across all metrics (test MSE 2.3048 versus 1.6920; MAE 1.1753 versus 1.0513; MAPE 40.50% versus 34.99%), hence the suggested method should not be considered more precise. Its benefit resides in operational compatibility. The GSS-optimized Holt DES necessitated an average of 2.36 ms per forecast over 100 runs (with a maximum of 3.40 ms), including parameter re-tuning, whereas the fixed-order ARIMA(1,1,1) took 35.77 ms (with a worst-case of 172.81 ms), and re-identifying the ARIMA order via AIC used 2,675.06 ms. Both options are sufficiently rapid for transactional applications, hence the benefit of Holt DES lies in its automatic re-tuning without the need for order re-identification, a reduced memory usage (6 MiB compared to 144.40 MiB, albeit these numbers are not directly comparable), and inherent compatibility with the PHP stack. The forecasting endpoint had an average response time of 154.20 ms, with a maximum of 250.73 ms, during local testing.

The practical implication is that small firms with limited infrastructure can include a self-tuning forecasting approach in a transactional system, accepting a minor loss in accuracy for simpler deployment. This study has some limitations: the data set is based on the owner's manual records, a rather significant forecast error (MAPE = 40.50%) exists, the system was implemented on outdated infrastructure (Laravel 8), and the UAT did not involve concurrent multi-user access. Future work includes hardware and framework version upgrades, multiple users simultaneously testing, re-estimation of the GSS parameters and the ARIMA benchmark with the accumulation of digitally recorded production data, exploration of hybrid strategies using ARIMA for periodical batch retraining and Holt DES for instant single-order predictions, and integration of WhatsApp Business API notifications.

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