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Comparative Analysis of Mathematical Models: A Case Study of Used Smartphone Price Depreciation

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Abstract

The price depression of the smartphone after it becomes used is one of the factors that consumers should consider when buying used smartphones. Therefore, accurate prediction of the price of used smartphones becomes a better insight into marketing strategies, and consumer purchasing decisions. The study aims to compare the performance of the Holt-Winters model damped, logistical decay, and exponential decay to predict the price depression of used smartphones. This research method uses historical data from some used smartphone prices as a basis for analysis. Comparisons between the three models were made to assess the performance of each in representing price depression behavior. Then, a statistical analysis was conducted to determine the most optimal model in predicting the price depression of used smartphones, the optimity of a model measured by the accuracy and speed of the computer performing the model execution. The accuracy measure in this study is the mean square error (MSE) value generated by a model with historical data alignment based on the ratio to the price when the smartphone has not been indicated as usable and the execution speed measure is the time it takes a computer to execute the model. The results show that the Holt-Winters damped model provides the most optimal predictive results compared to the exponential and decay models. This is demonstrated by the lower MSE average value twice as low as compared with the other two models, on the other hand, the holt-winters Damped has the weakness of requiring the longest average execution time of the three models with an average performance speed of 2.7 seconds, but the shortfall is not fatal because the predicted time period in this case is monthly so there is no urgency to advance the speed of seconds rather than accuracy.

Keywords: Depreciation; Exponential decay; Holt-winters damped; Logistic decay; Prediction; Smartphone

1 Introduction

Gadget is one of the major essential needs of modern society, it has undergone significant price changes after becoming used goods [1, 2], including smartphones [3]. This phenomenon is an important focus point, as it can provide in-depth insight into the dynamics of the smartphone market and consumer behaviour towards used items. In rapid technological developments, gadgets often undergo functional changes that make them less in demand after some time of use [4]. The phenomenon of falling prices for used gadgets such as smartphones becomes a major concern, especially in the context of company policies, consumer interests, and asset management [5, 6, 7]. A deep understanding of the price changes of smartphones and other used gadget that tend to fall can provide a better insight into pricing policies, marketing strategies, and consumer purchasing decisions [8, 9, 3]. The objective of this study was to analyse and compare three prediction models, namely Holt-Winters damped, logistic decay, and exponential decay to obtain an optimal model in terms of predicting [10, 11, 12]. The exponential decay model, the logistic degradation model, and the Holt-Winters-damped model have proven to be suitable models for the case of price changes that tend to decline [13, 14, 15]. The Exponential Decay model depicts the process of decaying value at a decreasing rate over time [16], reflecting the natural characteristics of the decay of goods. Meanwhile, logistics decay provides a more complex picture by considering the saturation nature of the change [17], where the decrease of value reaches a certain point and then slows down. Holt-Winters damped, considering the seasonal variables and the effects of the decline that can stifle over time, provides a comprehensive and consistent approach to the phenomena of price fluctuations that may occur in each period [11]. Thus, these three models provide a useful analytical framework to describe and understand the price depression dynamics of gadgets after becoming used goods in a more accurate way. The three models of smartphone price depression prediction, namely exponential decay, logistic decay and Holt-Winters damped, have their respective advantages and limitations. The exponential decay model has the advantage of its simplicity [18, 19], so it is easy to understand and apply [20, 21]. This model is suitable for situations where price declines are stable and predictable [22]. However, it has a limitation in accommodating fluctuations or sudden changes in price dynamics [23]. The logistical decay Model has an advantage in its flexibility [24]. It can reach a saturation point well, so it can describe price depression that is close to zero. Nevertheless, the model has its limitation of complexity [25], which makes it difficult to understand, and requires more data [26]. The Holt-Winters damped model has an advantage of being a more comprehensive solution considering the number of seasons [27]. It is ideal for situations in which prices are experiencing periodic fluctuation. The main objective of the study is to analyse the phenomenon of cases of smartphone price depression after it becomes used, compare the three prediction models, Holt-Winters damped, logistical decay, and exponential decay and identify the most optimal prediction model in predicting price changes of smartphones after they become used in the hope of giving insight for researchers and app developers who have an interest in the field of prediction of used smartphone price depreciation.

2 Research Methods

This research was done using a laptop with AMD RyzenTM 5 5625U processor with RadeonTM Graphics × 12 and a disk capacity of 512.1GB. Used smartphone price depreciation data was taken using the Web Scrapping method manually on the website [28]. The method used in this research is qualitative and statistical with a non-linear least square approach (NLS). This decision is based on the fact that NLS has the ability to adjust mathematical models to observational data that have non-linear relationships [29]. In the analysis of the decline in the price of used gadgets, where the phenomenon of price changes tends to follow nonlinear patterns over time, NLS can estimate the parameters of the model by minimizing the square difference between the predicted results and the actual observational value [30]. With this approach, researchers can optimize the accuracy of models in representing the dynamics of the price decline of gadgets after becoming used goods. Therefore, the use of the NLS method provides an advantage in accurately capturing the complexity of the price changes of the gadget and allows us to obtain accurate, fast, and optimal prediction models [31, 32, 33]. NLS also has a weakness, namely its dependence on the initial values of the parameters [34]. However, these shortcomings can be overcome by choosing careful starting values and understanding the characteristics of the data being analyzed.

2.1 Mathematical Modeling

The mathematical predictive models used are Holt-Winters damped, logistic decay, and exponential decay. Holt-Winters damped is a method of predicting seasonal data [35]. This model uses leverage parameters to limit trend growth in the long term [36], thus producing accurate prediction results [37]. Following is the basic formula of the Holt-Winter damped prediction modelling

$$
\begin{aligned}
\hat{y}_{t+h} &= l_t + \phi b_t + \sum_{j=1}^{m} \left(s_{t-m+j} + \phi b_{t-m+j}\right) \\
l_t &= \alpha(y_t - S_{t-m}) + (1-\alpha)(l_{t-1} + \phi b_{t-1}) \\
b_t &= \beta(l_t - l_{t-1}) + (1-\beta)\phi b_{t-1} \\
s_t &= \gamma(y_t - l_{t-1} - \phi b_{t-1}) + (1-\gamma)s_{t-m} \\
\hat{y}_{t+1} &= l_t + \phi b_t + s_{t-m+1}
\end{aligned} \tag{1}
$$

where $\hat{y}_{t+h}$ is a prediction variable for $t+h$, l_t is a level component at t, b_t is a trend component at t time, s_{t-m+j} is a seasonal component at $t-m+j$, with m as the seasonal period, ϕ is a delay parameter, and α, β and γ ais a parameter softening for level, trend, and seasonal components at the same time [38].

Logistic decay is a predictive method that uses logistic functions to predict data that decreases over time [39, 40, 41]. The following is the basic formula for predicting logistic decays

$$P(t) = \frac{K}{1 + A \cdot e^{-r(t-t_0)}} \tag{2}$$

where $P(t)$ is the total population at t time, K is the maximum capacity of growth limitation, A is a parameter which influences the initial growth rate, r is the growth rate, t_0 is the time at which growth reaches the median value, e is Euler's number, which is the basis of the natural logarithm [42].

Exponential decay is a predictive model that uses exponential functions to predict data that decreases exponentially over time [43, 44]. The following is the basic formula for the prediction modeling of exponential decay

$$f(t) = a \cdot e^{-k \cdot t} \tag{3}$$

where $f(t)$ is the value of the component in time t, a ais the initial component value, k is the rate of depreciation, t is time [45].

2.2 Measuring the level of model optimality

The result of the three modelling then compares with the actual data to measure its accuracy, the variable that becomes determined how accurate is the mean squared error value. Mean squared error (MSE) is an error measure that measures the average square of the difference between observed and predicted values [46, 47]. MSE is often used in statistics and machine learning to measure the performance of predictive models [48, 49]. The formula for MSE is expressed as

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{4}$$

where n is the total data, y_i is the actual value for the i-th data, $\hat{y}_i$ is the prediction value or model output for data i [50].

Optimal or not a model is also measured from the time it takes a computer to execute the three models, the experiments are done as many as five times because the execution time required by the CPU for the same process can vary [51], then take an average to get an accurate result from the three model.

3 Result and Discussion

The data that became the benchmark in this study was the price change on 27 types of smartphones per month after use, here are examples of the datasets processed in this research.

Table 1. Changes in the Price Of 4 Gadgets in Euro Currencies After Became Used Good Per Month

Months	Price			
	Samsung 8	Huawei Mate 10 Pro	Samsung 7 Edge	OnePlus 3T
1	350,00	220,00	350,00	184,50
2	350,00	220,00	350,00	177,84
3	344,23	220,00	353,10	170,74
4	346,00	220,00	353,10	160,51
5	352,03	220,00	353,10	179,10
6	351,91	220,00	356,11	183,96
7	347,50	220,00	354,35	194,13
8	347,72	217,08	320,05	146,04
9	321,72	188,00	306,05	174,52
10	282,43	200,00	317,18	163,88
11	299,79	200,00	312,26	166,71
12	285,00	200,20	303,78	158,28
13	285,00	203,94	290,75	155,74
14	264,25	206,00	286,20	149,61
15	265,91	206,00	266,46	111,06
16	261,75	172,93	250,46	50,00
17	254,65	161,29	219,05	50,00
18	253,22	143,27	210,00	50,00
19	225,00	85,15	168,58	27,50
20	220,00	30,00	169,92	65,00
21	210,00	20,00	177,10	61,40
22	200,00	45,00	182,83	80,00
23	190,00	42,50	168,97	69,33
24	180,00	43,75	160,99	54,00

***Data source**: https://s.id/1ZN05.*

The study is aimed to find the most optimal model between exponential decay, logistic decay, and Holt-Winters damped approaches that is suitable for predicting the depreciation of smartphone prices. The model selection mechanism is done by comparing model-based predictions on 27 types of smartphones in the datasets where the parameters are systematically selected using an optimization approach and based on the historical data.

This prediction is carried out by processing data based on the specified parameters. These parameters are obtained from the results of fitting with the least square method implemented using the scipy library in the python programming language with each model as a reference. For the exponential decay model has two parameters, namely a and k. To obtain these parameters, the program performs an initial guess value with certain condition, for the value of a it is performed by taking the maximum value of the scaled data automatically. While for the value of k, the initial guess of the value starts with a small positive value like 0.1 because the value of the exponential decay will decrease over time. Likewise with other models, the program makes an initial guess under specified conditions.

The initial guess for the Holt-Winters Damped parameters is set with an alpha (a) value of 0.5 in order to give equal weight to the previous and currently observed levels, β at 0.5 for the reason of giving equal weight to the current trend estimate and any changes in trend based on recent data., γ at 0.5 to evenly smooth seasonal effects between recent and past patterns, ϕ at 0.5 which means that this trend will reduce its contribution to the forecast by half over time, l_1 with a value that is the second data point of the actual gadget price scale, b_0 at 0, which means there is no initial trend assuming that the series initially had no up or down movement, $s_0, s_1,, \ldots s_{m-1}$ at a value of 0 assuming there is no strong seasonal pattern from the start of the model. Over time, these values will change as the model is adjusted to actual data. The parameters of logistic decay are determined by the initial guess with the following provisions. K with the maximum value, which is searched automatically by the program, r with a common value which is 0.1 to provide a baseline that can be adjusted during the optimization process, t_0 with the median value, which is determined by the program automatically, A with the minimum value of the scaled values which is determined automatically by the program.

The resulting parameters are then implemented on the appropriate model to see the depreciation trend of smartphone prices in the same period as the data listed in the table. Model performance is checked by comparing the results of the fitted model with actual data. The performance check method uses MSE to measure the accuracy of each model. The following are some results from the modelling in the form of plot timelines.

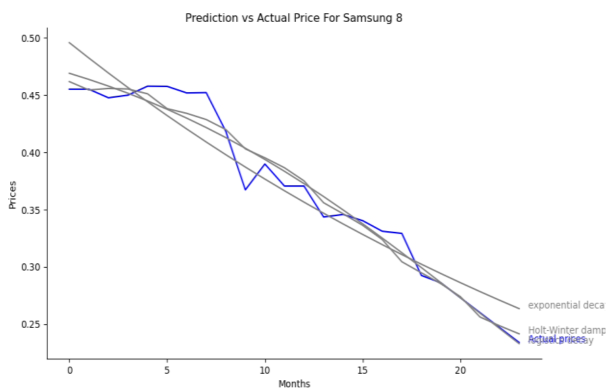

Figure 1. Modeling examples on price changes on used Samsung 8 gadgets

The entire comparative study results obtained by the three models were then collected to measure the accuracy and speed of execution time between the one model and the other, here's the visualization.

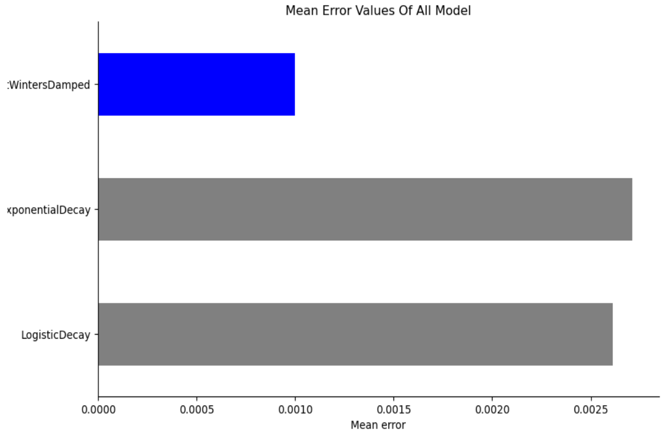

Figure 2. Comparison of average error rates of each model

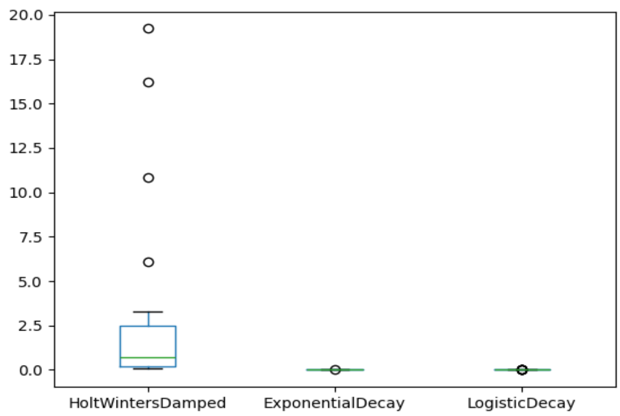

Figure 3. Average execution speed comparison of each model

Based on all the predictions of the above 27 cases, the exponential decay model produced an average MSE of 0.0027, logistic decay of 0.0261, and Holt-Winters damped of 0.0001. Whereas on the execution speed side, the average time to compress an exponential decay from all the above cases was 0,0002 seconds, logistic degradation of 0.046 seconds, and holt-winters Damped 2.7836 seconds. Once rounded, it can be stated that in the case of predicting a fall in the price of used Holt-Winters damped gadgets is the model with the average execution speed of the slowest, this happens because the parameters are more sought and equally more complicated. But this is not a problem because in the case of this study the price decrease occurs in monthly time, on the other hand the level of accuracy is a crucial thing then from that the researchers state that the Holt-Winters damped model is the best model in this case, here is an example of comparing the prediction of the Damped Holt-Winters with actual data on the Samsung 8 smartphone depression case.

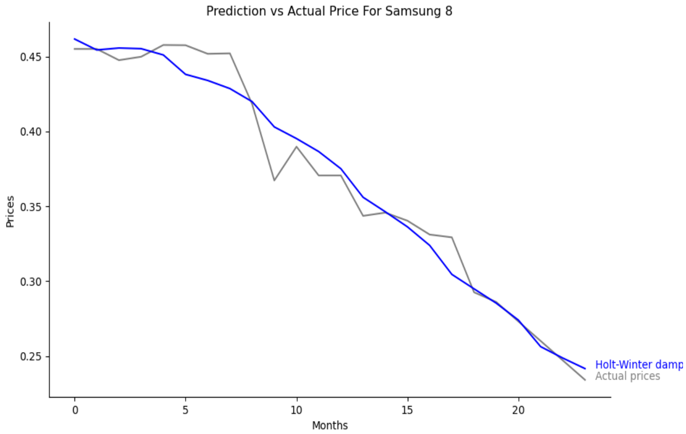

Figure 4. Comparison Of Predictions Holt-Winters Damped With Actual Data Samsung 8

4 Conclusions

Based on the entire process above, it is obtained that if rounded up, the damped Holt-Winters mathematical model has twice the level of accuracy compared to the logistic decay and exponential decay models, the difference in accuracy is quite large making the damped Holt-Winters model the most optimal model, even in terms of time. The slowest execution of this model reaches 2.7 seconds, but in this case, it is not fatal because the predicted time period in the system is monthly so there is no urgency to have such a fast speed. However, logistic decay has the potential to be an optimal model if the predicted cases are real-time based.

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