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Review

Exploring Time-Series Forecasting Models for Dynamic Pricing in Digital Signage Advertising

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Abstract: Audience attention is vital in Digital Signage Advertising (DSA), as it has a significant impact on the pricing decision to advertise on those media. Various environmental factors affect the audience attention level toward advertising signage. Fixed-price strategies, which have been applied in DSA for pricing decisions, are generally inefficient at maximizing the potential profit of the service provider, as the environmental factors that could affect the audience attention are changing fast and are generally not considered in the current pricing solutions in a timely manner. Therefore, the time-series forecasting method is a suitable pricing solution for DSA, as it improves the pricing decision by modeling the changes in the environmental factors and audience attention level toward signage for optimal pricing. However, it is difficult to determine an optimal price forecasting model for DSA with the increasing number of available time-series forecasting models in recent years. Based on the 84 research articles reviewed, the data characteristics analysis in terms of linearity, stationarity, volatility, and dataset size is helpful in determining the optimal model for time-series price forecasting. This paper has reviewed the widely used time-series forecasting models and identified the related data characteristics of each model. A framework is proposed to demonstrate the model selection process for dynamic pricing in DSA based on its data characteristics analysis, paving the way for future research of pricing solutions for DSA.

Keywords: time-series forecasting; dynamic pricing; digital signage advertising; data characteristics; model selection

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1. Introduction

Audience attention is a factor that has the most significant impact on the pricing decision of Digital Signage Advertising (DSA) [1]. Generally, the higher the attention level received by a digital signage advertisement, the higher the profit expectancy. Various environmental factors can influence the audience attention level, including location popularity, temperature and air humidity, weather condition, social class of the surrounding community, and others [2]. These factors are important in determining the pricing decision for DSA to maximize revenue and increase advertising effectiveness.

The current pricing solutions of DSA show some deficiencies in obtaining the optimal pricing decision. Commonly, the pricing mechanisms applied to DSA are the fixed-price strategy or the auction-based pricing strategy [1,3]. In a fixed-price strategy, the advertising spot in a specific digital signage is charged with a fixed predetermined price. It can be in the form of direct sales or a guaranteed contract from the service provider. The price is commonly established based on the audience attention level of an advertisement spot. However, the changes of attention level toward the spot in time due to the changes in the surrounding environmental factors are not considered, resulting in sub-optimal pricing. In an auction-based pricing strategy, the price varies based on contextual information such as the location and time, the number of detected mobile devices nearby, and others. This information is used as the factors to generate a bid, and the advertising spot will be sold to the highest bidders. This approach is beneficial in the sense of better utilizing the resources of the service provider. However, using such a scheme might be inefficient for the advertiser because it requires time-consuming bidding actions. Thus, dynamic pricing solutions need to create a significant benefit to the service provider as well as the advertiser [4].

With recent technology advancements, more dynamic pricing solutions are emerging, applying time-series forecasting methods to predict future activities based on historical data [5]. They provide a strong foundation for time-series forecasting dynamic pricing solutions using statistical, AI, and hybrid models [6,7]. There are several ways to categorize the time-series forecasting models. Wang suggested three main categories of time-series forecasting methods as statistical models, Artificial Intelligence (AI) models, and hybrid models [6]. On the other hand, Neha Sehgal and Krishan classified the time-series forecasting models as stochastic models, AI models, and regression models. However, both the regression and stochastic models are using similar statistical inferences to establish the relationship between the price and other relevant factors. Hence, both stochastic and regression models are classified under the subcategories of statistical models in our review. Figure 1 elucidates the classification tree of the seven most widely used time-series forecasting models on price estimation.

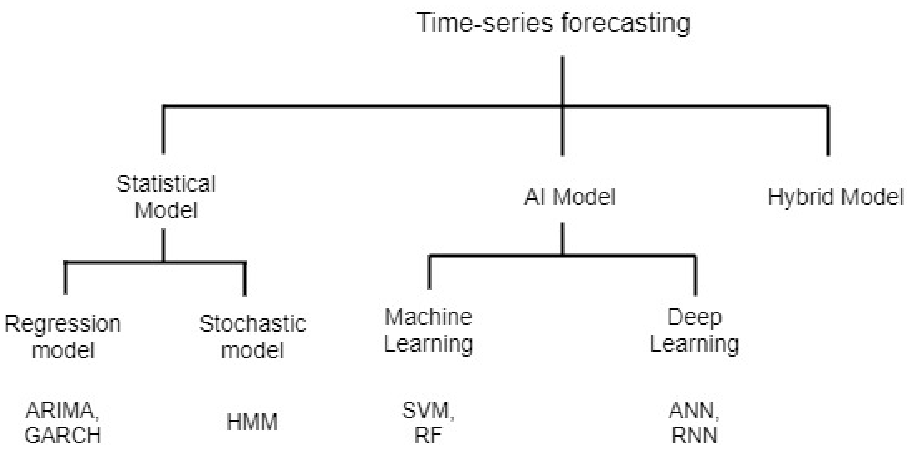


Figure 1. Classification tree of price forecasting models.

The existing price forecasting methods that applied the time-series forecasting models are exemplified in different domains for its applicability. However, as a real-world problem is often complicated, no single model can perform the best in every situation [8]. With an increasing number of models, the model selection decision is also difficult, especially when vital information and knowledge are insufficient. Hence, a model selection framework is crucial for identifying a suitable approach for different data characteristics. From the review, there are four relevant essential data characteristics: namely, data linearity, stationarity, volatility, and the size of the dataset. These data characteristics are essential factors in selecting the optimal forecasting model for pricing decisions, particularly in its usage and interpretability in DSA.

This review aims to structurally analyze the data characteristics of different time-series forecasting models, along with a proposed framework for the optimal model selection of dynamic pricing in DSA. The main contributions of this paper are summarized as follows:

- To review the widely used time-series forecasting models, providing an abstract of the different models that can potentially be applied for dynamic pricing.
- To discuss the relationship of data characteristics to the time-series forecasting models from each category.
- To investigate the applicability of the model selection framework based on the data characteristics of the dataset in DSA.

This paper is divided into four sections. Section 2 presents the review of time-series forecasting models based on the data characteristics. Section 3 shows a summary of the suitable data characteristics for the time-series forecasting models and a proposed framework for optimal model selection based on the data characteristic analysis of DSA. Conclusions are drawn in Section 4.

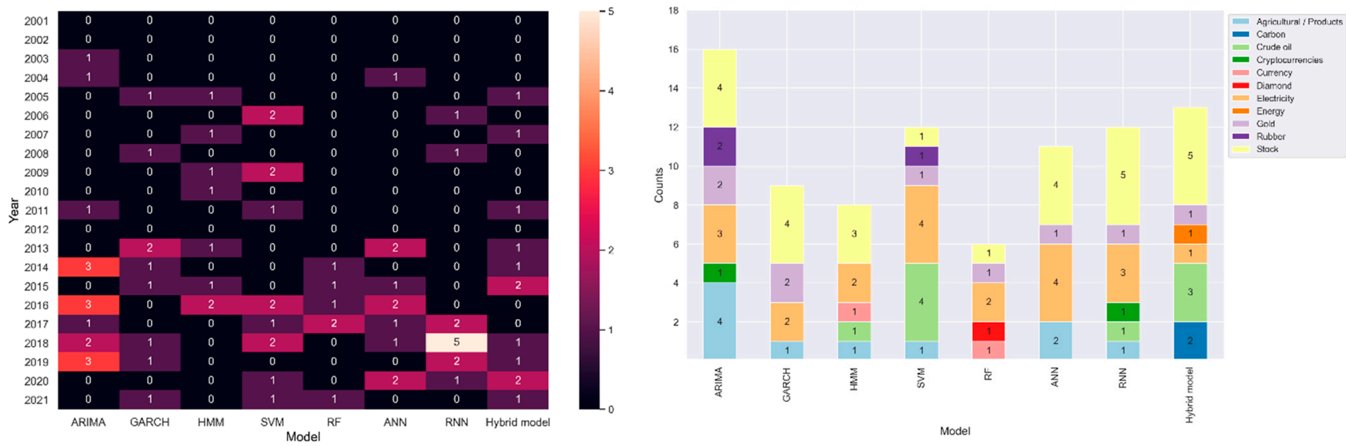
2. Review on Time-Series Forecasting Studies

Time-series forecasting is used to predict future activities based on current historical data [9]. Commonly, the time-series data have the following characteristics: linearity, stationarity, and volatility. Linearity refers to the linear relationships of the time-series data to the time [10]. Stationary time-series data can be recognized as a property that does not depend on the time [11]. Generally, non-stationary time-series data include observations with trend and seasonality. The trend indicates the general movement of the data in each observed time frame without considering the data seasonality. Seasonality indicates a periodic fluctuation, which can be affected by time, magnitude, and direction. Volatility refers to the unexpected rise or fall of time-series data, which is also known as heteroscedasticity, where the time-series data variance comprises rapid changes between extremely high and low values [12]. As there are many available time-series forecasting models, the optimal model selection could be difficult. Thus, the above-mentioned data characteristics are essential in selecting an optimal time-series forecasting model, as the different models have different capabilities in handling different data characteristics. Apart from the three data characteristics, we included the size of the dataset as another consideration in selecting the optimal model, as it can influence the model performance, as will be seen shortly.

The evolution of seven time-series forecasting models over the past two decades was studied to discover the popular models for dynamic pricing. Table 1 shows the listing of the studies. Figure 2 illustrates the distribution of the studies, showing the evolution of the model application in different domains. The Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) regression models, as a subcategory of the statistical models, have been applied since 2003. The regression model applications spanned over two decades. Stochastic models, such as Hidden Markov Model (HMM), have been used since 2007. The application of this model does not show any spike during the studied period. However, it was noted that the application of both regression and stochastic models were enhanced or combined with other approaches, such as the AI model, into the hybrid models starting from the 2010s to complement its shortcomings.

Table 1. Review on time-series forecasting studies for dynamic pricing from 2001 to 2021.

Category	Model	Count	Time Range	References
Regression Model	ARIMA	14	2003–2019	[13–27]
	GARCH	9	2005–2021	[12,28–35]
Stochastic Model	HMM	8	2007–2016	[36–43]
Machine Learning	SVM	12	2005–2021	[44–55]
	RF	6	2006–2021	[56–61]
Deep Learning	ANN	10	2004–2020	[62–70]
	RNN	12	2006–2020	[71–82]
Hybrid Model	Regression + Stochastic	1	2017	[83]
	Regression + ML	4	2005–2021	[84–87]
	Regression + DL	6	2014–2021	[88–93]
	Stochastic + DL	1	2007	[94]
	DL + DL	1	2020	[95]



(**a**) The distribution of models from 2001 to 2021 (**b**) The model applications in different domains

Figure 2. The evolution of time-series forecasting models in different domains over two decades.

Machine Learning (ML) models (of the AI models) have been applied since 2006, including Random Forest (RF) and Support Vector Machine (SVM). It was noted that these approaches were becoming more widespread in the 2010s as AI receives more attention. In addition, Deep Learning (DL) models, as a subcategory of the AI models, including Artificial Neural Network (ANN) and Recurrent Neural Network (RNN), were introduced in the early 2000s, although not much attention was given to the application of DL models until the 2010s. From the review, the application of DL models in the 2000s was less than the application of the regression and stochastic models, as shown in Figure 2a. During that time, researchers were investigating new ways to improve the model performance. Thus, different combinations of hybrid models have been proposed and presented. More attention was given to the hybrid models from the 2010s due to their robustness and the availability of computing resources.

Notably, the stock and electricity markets have always been a focus of time-series forecasting, as shown in Figure 2b. Different models have a relatively higher application count in these two fields, which is likely due to the market complexity that is highly volatile. It is also noted that the application of time-series forecasting is extending to other domains for dynamic pricing recently. The following section introduces the statistical model, AI model, and hybrid model for dynamic pricing solutions.

2.1. Statistical Model

A statistical model is a mathematical model that can be used for time-series forecasting [96]. It is classified into two categories of regression and stochastic models.

2.1.1. Regression Model

A regression model is a statistical technique that is used for finding the relationship between the data. It is widely applicable as it is simpler to compute [5,10]. This model can establish the relationship between the time-series data and the predicted price. The most popularly used regression models, including Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH), are introduced in this section.

Autoregressive Integrated Moving Average (ARIMA)

ARIMA is a linear regression model that works efficiently with stable correlated time-series data [82]. It can be applied to time-series forecasting problems in any domain based on the principle of univariate analysis. The model works well on stationary time-series data. The theoretical background of ARIMA is explained in [97].

Some studies have exemplified the applicability of ARIMA in forecasting time-series in different domains such as cryptocurrencies [13], stock [14–16], rubber and latex [17,18], agricultural and e-commerce products [19–21,27], gold [22,23], and electricity [24–26] from 2003 to 2019 and demonstrated exceptionally promising results. From the studies made, ARIMA has difficulty when handling non-stationary time-series data, as it is trying to model the changes based on the historical time-series data with linearity assumptions when performing forecasting. It is noticed that the following factors will affect the model performance: sudden fluctuation [23], nonlinear and non-stationary time-series data [21], and multi-step ahead forecasting [98]. There are other variations of ARIMA introduced, such as ARIMA with the independent variable (ARIMAX) [17] and Seasonal ARIMA (SARIMA) [18] for multivariate modeling and seasonal time-series data problems, respectively. It is noticeable that ARIMA produces an exceptional performance when the data are linear and stationary. Table 2 summarizes the studies applying the ARIMA.

Table 2. ARIMA time-series forecasting from 2003 to 2019.

Domain	Author	Dataset	Model	Result
Cryptocurrencies	Mittal et al., 2018 [13]	Cryptocurrencies (2013 to May 2018)	ARIMA	Accuracy of 86.424
Stock	Ayodele et al., 2014 [14]	New York Stock Exchange and Nigerian Stock Exchange	ARIMA	R^2 of 0.0033 and 0.9972
	Rotela Junior et al., 2014 [15]	Bovespa Index (January 2000 to December 2012)	ARIMA	MAPE of 0.064
	Setyo, 2017 [16]	Indonesia Composite Stock Price Index	ARIMA	MAPE of 0.8431
Rubber	Sukanya and Vichai, 2016 [17]	Bangkok and World natural rubber price (January 2002 to December 2015)	ARIMAX	MAPE of 1.11
Latex	Chalakora and Vichai, 2018 [18]	Central Rubber Market of Hat Yai, Thailand	SARIMA	MAPE of 24.60 and RMSE of 14.90
Agricultural and e-commerce product	Verma et al., 2016 [19]	Agricultural Produce Market Committee, Ramganj (May 2003 to June 2015	ARIMA	MAPE of 6.38
	Jadhav et al., 2017 [20]	Price of cereal crops in Karnataka (2002 to 2016)	ARIMA	MAPE of 2.993, 1.859, 1.255 paddy, ragi, and maize, respectively
	Carta et al., 2018 [27]	Amazon product's prices, with Google Trends data used as exogenous features	ARIMA	Achieves the lowest average MAPE of 4.77
	Anil Kumar et al., 2019 [21]	Price in market Kadiri, India (January 2011 to December 2015)	ARIMA	MAPE of 2.30
Gold	Banhi and Gautam, 2016 [22]	Multi Commodity Exchange of India (November 2003 to January 2014)	ARIMA	MAPE of 3.145
	Yang, 2019 [23]	World Gold Council (July 2013 to June 2018)	ARIMA	Relative error of less than 1.2%
Electricity	Contreras et al., 2003 [24]	Spanish and Californian electricity market of 2000	ARIMA	Mean errors of less than 11%
	Mingzhou et al., 2004 [25]	California power market of 1999	ARIMA	MSE of 0.1148
	Tina et al., 2011 [26]	EPEX power exchange	ARIMA	MAPE of 3.55

Generalized Autoregressive Conditional Heteroscedasticity (GARCH)

GARCH is refined from the ARCH model, as proposed by Bollerslev [99]. This model overcomes the weaknesses of the ARCH model, as the ARCH model is of a very high order with huge number of parameter estimations [12]. GARCH is widely applied for economic and financial series forecasting. This model was found to have higher efficiency in forecasting when working with data of high volatility compared to ARIMA. The latter is limited in the autoregressive heteroscedasticity (ARCH) effect and is of linear time-series data, as it is assumed that the future value is in a linear relationship to time [12,100].

From the review, GARCH has been deployed in different domains for forecasting data with high volatility, such as the prices of gold [28,29], stocks and the financial market [30–33], agricultural products [34], and power and electricity [12,35] from 2005 to 2021. GARCH is proven to have better performance than ARIMA if the data have high volatility. This can be verified by conducting the Lagrange Multiplier (LM) test [28,34]. The results indicate that ARIMA cannot predict well due to the volatility of the data. There are different refinements of GARCH, including Exponential GARCH (EGARCH) [12] (capturing asymmetric volatility of the data) and nonparametric GARCH (NPGARCH) [33] (removing the parameterized assumptions, which indicates that the data are in the relationship of square linear and stochastically volatile). Overall, GARCH is suitable for data with high volatility. However, for cases where the time-series data have a linear relationship, this model may not be able to model the time-series data well compared to the ARIMA approach. Table 3 summarizes the review on the studies of GARCH.

Table 3. GARCH time-series forecasting from 2005 to 2021.

Domain	Author	Dataset	Model	Result
Oil	Lama et al., 2015 [12]	Cotlook A (April 1982 to March 2012)	GARCH, EGARCH	EGARCH achieved the best performance with RMSE of 14.41
Gold	Ping et al., 2013 [28]	Kijaang Emas prices (July 2001 to September 2012)	GARCH	MAPE of 0.809767
	Yaziz et al., 2019 [29]	Malaysia gold price (January 2003 to June 2014)	ARIMA, GARCH, ARIMA-GARCH	ARIMA-GARCH achieved the most optimal result with a price error less than 2
Stock	Xing et al., 2021 [30]	West Texas Intermediate (January 2015 to May 2018) and CSI300 (May 2015 to 2016)	GARCH with nonlinear function	AIC of −1119.77 and −11373.6 for CSI300 and WTI dataset
	Tripathy and Raahman, 2013 [31]	Bombay Stock Exchange and Shanghai Stock Exchange (1990 to 2013)	GARCH	AIC of −5.512662 and −5.260705 for BSE and SSE dataset
	Erica et al., 2018 [32]	Adaro energy share price (January 2014 to December 2016)	GARCH	MAPE of 2.16
Power	Hong Li et al., 2008 [33]	Power price in California of 2000	NP-GARCH, GARCH, ARIMA	NP-GARCH achieved the lowest MPE of 3.62 and 4.86
Agricultural Product	Bhardwaj et al., 2014 [34]	Gram price in Delhi (January 2007 to April 2012)	GARCH, ARIMA	GARCH achieved the best performance with an average error of less than 2
Electricity	Garcia et al., 2005 [35]	Spanish and Californian Power Market (September 1999 to November 2000) and (January 2000 to December 2000)	GARCH	FMSE of less than 6 and 69 for Spanish and Californian market

2.1.2. Stochastic Model

The stochastic model is widely applied for time-series forecasting [7] to draw inferences of the characteristics of the time-series data [5]. Different from the regression model, the inferences made using the stochastic model are based on the principles of probabilities. On the other hand, the regression model is used to identify the linear relationship between the time-series data and the price outcome. One of the stochastic models, Hidden Markov Model (HMM) is explained in this section.

Hidden Markov Model (HMM)

HMM was first introduced in 1996 by Baum and Petrie [101]. HMM is a double stochastic process that introduces the hidden states with the unobservable underlying stochastic process. HMM has been applied to time-series forecasting in different domains such as forecasting prices of stock and option [36–38], commodity market [39], electricity [40,41], crude oil [42], and currency exchange rate [43] from 2007 to 2018. As the real-life market is complex and highly volatile with nonlinear relationships, HMM helps model the time-series data with the hidden states. The model can find the hidden states of the time-series data to improve its forecasting capability and accuracy [102]. HMM is suitable for data with high volatility, as hidden states of the model can simulate different volatility regimes. In addition, the model considered the times-series data correlation in interpreting the data characteristic. Hence, the model is suitable for dynamic pricing when the time-series data are non-stationary and high in volatility. It is noticed that HMM has a better performance compared to regression models such as GARCH when the data are high in volatility and has a larger sample size [38,103]. HMM can also outperform some Deep Learning (DL) models due to its utterly probabilistic state architecture [36,104]. In addition, the model does not require a huge amount of training data as DL models do. In short, HMM is suitable for nonlinear and highly volatile data, as it can capture the changes of every time step well. Table 4 summarizes the studies using HMM.

Table 4. HMM time-series forecasting from 2007 to 2018.

Domain	Author	Dataset	Model	Result
Stock	Hassan and Nath, 2005 [36]	Four airline stock indexes	HMM	MAPE of less than 6.850 for included stocks
	Hassan, 2009 [37]	Six different stock prices	Fuzzy logic model and HMM	MAPE of less than 4.535
	Dimoulkas, 2016 [38]	Nordic BM	HMM, ARIMA	HMM has the best accuracy of 73%
Commodity	Date et al., 2013 [39]	Financial market commodity prices	HMM	RMSE of 0.08502
Electricity	Valizadeh Haghi and S. M. Moghaddas Tafresgu, 2007 [40]	Spanish spot market of 2005	HMM	
	Jianhua Zhang et al., 2010 [41]	Electricity market data of August 2009	HMM	MAPE of 4.1598
Oil	Bon and Isah, 2016 [42]	WTI dataset for oil prices of 2015	HMM	
Financial	Shaaib, 2015 [43]	Foreign currency exchange rate of Euro against USD (April 2007 to February 2011)	HMM, ANN	HMM achieved the best performance with MSE of less than 0.04

2.2. Artificial Intelligence Model (AI)

Artificial Intelligence (AI) refers to a machine that can mimic or act like a human when provided with the human-like capabilities such as perception, manipulation, communication, learning, and problem-solving [105]. Comparing to the statistical models, the AI model learns from past data to improve its performance instead of identifying the optimal parameters based on probability as in the statistical models. In addition, the AI models are widely applied in time-series forecasting to identify the hidden data patterns to make an accurate approximation [8]. Two subcategories of AI models are the Machine Learning (ML) models and Deep Learning (DL) models.

2.2.1. Machine Learning Model (ML)

ML models can produce reliable predictions by identifying the hidden patterns of the historical data for trends and relationships [106]. It can be used for time-series forecasting as it can extract the information from the time-series data during the learning process and learn from the extracted information to perform future forecasting [107]. The two most widely applied machine learning approaches are Support Vector Machine (SVM) and Random Forest (RF).

Support Vector Machine (SVM)

V. Vapnik first proposed Support Vector Machine (SVM) in 1995 [108]. SVM is a type of learning algorithm proposed to improve the neural network's generalizability to achieve the global optimum solutions. SVM was first introduced for classification tasks, and it is extended for regression and time-series forecasting problems with excellent outcomes [47,109].

SVM has been applied in various domains for price forecasting, such as crude oil [44–47], rubber [48], gold [49], and electric [50–53], agricultural [54], and stock [55] from 2005 to 2021. SVM can avoid the over-fitting problem and model the nonlinear relationships stably, as it applied the risk minimization principle in training. SVM has been tested and compared to statistical models such as ARIMA and has shown a better performance [47,49]. The interpreted result suggests that SVM performs better for capturing nonlinear relationships and in handling irregularities than statistical models. However, SVM has lower transparency with very high dimensionalities, where the score of the results cannot be represented as a simple parametric function [110]. The model also requires many steps to get to the best parameters to fit the model. Nevertheless, SVM generally will not work well on a large dataset, as it is constrained by time and memory optimization [111]. From the review, the SVM is robust in modeling the nonlinear data. Table 5 shows the studies on the SVM models.

Table 5. SVM time-series forecasting from 2005 to 2021.

Domain	Author	Dataset	Model	Result
Crude oil	Xie et al., 2006 [44]	WTI crude oil price (January 1970 to December 2003)	SVM, ARIMA, BPNN	SVM has the best performance with RMSE of 2.1921
	Qi and Zhang, 2009 [45]	OPEC, DJAIS and AMEX oil index	SVM	Error rate of 16.23%
	Khashman and Nwulu, 2011 [46]	WTI crude oil price (2002 to 2008)	SVM, ANN	SVM has the highest correct prediction rate of 81.27
	Yu et al., 2017 [47]	WTI crude oil price	SVM, ARIMA, FNN, ARFIMA, MS-ARFIMA, Random walk, SVM	SVM has the best performance with highest Diebold–Mariano test score

Table 5. *Cont.*

Domain	Author	Dataset	Model	Result
Rubber	Jing Jong et al., 2020 [48]	Bulk latex	ARIMA	ARIMA-SVM achieved the lowest MAPE of 0.3535
Gold	Makala and Li, 2021 [49]	World Gold Council (1979 to 2019)	SVM, ARIMA	SVM achieved the best result with an RMSE of 0.028
Electricity	Swief et al., 2009 [50]	PJM (March 1997 to April 1998)	SVM	MAPE of 1.3847
	Mohamed and El-Hawary, 2016 [51]	New England ISO (2003 to 2010)	SVM	MAPE of 8.0386
	Saini et al., 2016 [52]	Australian Electrical Market	SVM	MAPE of less than 1.78
	Ma et al., 2018 [53]	ERCOT	SVM	MAPE of 6.57
Agricultural	Akın et al., 2018 [54]	Raisin World Export dataset	SVM, ANN	SVM is better than ANN with an accuracy of 0.888
Stock	Kumar et al., n.d. [55]	Financial time-series data	SVM, RF	SVM outperform the RF by 1.04% of hit ratio

Random Forest (RF)

Random Forest (RF) is an ensemble method formed by many decision trees that are used for both classification and regression processes, which was introduced by Breiman in 2001 [112]. RF has been applied in time-series forecasting for dynamic pricing, including forecasting the prices of power load [56] and electricity [57], diamond [58], exchange rate [59], gold [60], and stock [61] from 2006 to 2021. RF works better for data with high volatility and randomness, such as exchange rate, and it has outperformed the SVM [59]. In addition, RF can work faster and better on large training samples, with the training time significantly faster than the SVM. However, some studies have shown that RF performed worse than the regression models in modeling linear data [55,113]. In short, it is suitable for nonlinear, stationary, and highly volatile data. Table 6 included the studies of the RF models.

Table 6. RF time-series forecasting from 2006 to 2021.

Domain	Author	Dataset	Model	Result
Load	Lahouar and Ben Hadj Slama, 2015 [56]	Tunisian Company of Electricity and Gas (January 2009 to August 2014)	RF, ANN, SVM	RF has the lowest MAPE of less than 4.2302
Electricity	Mei et al., 2014 [57]	NYISO	RF, ANN, ARIMA	RF has the lowest MAPE of 12.05
Diamond	Sharma et al., 2021 [58]	Kaggle	RF, Decision Tree, Lasso, Ada Boost, Ridge Gradient Boosting, Linear Regression, Elastic Net	RF has the lowest RMSE of 581.905423
Exchange rate	Ramakrishnan et al., 2017 [59]	Department of Statistic Malaysia, World Bank, Malaysia Palm Oil Council, Malaysian Rubber Export Promotion Council, Federal Reserve Bank	RF, NN, SVM	RF has the lowest RMSE of 0.018

Table 6. *Cont.*

Domain	Author	Dataset	Model	Result
Gold	Liu and Li, 2017 [60]	DJIA, S&P500, USDX	RF	RF showed a promising result in predicting the different datasets, with prediction performance up to 0.99
Stock	Khaidem et al., 2016 [61]	Samsung, GE and, Apple stock	RF	Accuracy of higher than 86.8396

2.2.2. Deep Learning Model

Unlike the ML model, the DL model is inspired by the human neurological structure, and it is composed of a collection of neurons that are connected between layers to form a network [114]. However, both ML and DL models learn from the data to improve their performance. In addition, the DL model works exceptionally well compared to the statistical methods in nonlinear data forecasting [114]. Artificial Neural Network (ANN) and Recurrent Neural Network (RNN) are explained in the following section.

Artificial Neural Network (ANN)

Warren and Walter proposed the ANN in 1943 [115], which is a computational model inspired by the human biological nerve system. It is composed of layers of connected neurons. ANN has been applied in many domains for time-series forecasting, including the forecasting of prices for the agricultural product [62], electricity [63–66], gold [67], and stock [68–70] from 2004 to 2020. The application of ANN is more robust than the statistical models in capturing the trends and seasonality of the data—the non-stationarity of the data [62]. ANN is proven to work better than the statistical model with the time-series data that are nonlinear, stationary, and have sudden changes through the layering hierarchy [70]. Despite its superior result, the one significant drawback of ANN is its black-box nature [116]. The computational process of ANN is complex, and how the model decides is hardly understandable. There is also the risk of overfitting when there are too few data observations. The model will only memorize the unique data features, which means that it does not learn the underlying relationship of the data, resulting in lower generalizability. Table 7 summarizes the studies of ANN time-series forecasting.

Table 7. ANN time-series forecasting from 2004 to 2020.

Domain	Author	Dataset	Model	Result
Agricultural	Jha and Sinha, 2013 [62]	Soybean price from SOPA, rapeseed-mustard from Delhi	ANN, ARIMA, TDNN	ARIMA obtained better result for soybean price forecasting with an RMSE of 5.43, hybrid ARIMA-TDNN has better performance with an RMSE of 3.46
Electricity	Yamin et al., 2004 [63]	Californian power market (January 1999 to September 1999)	ANN	MAPE of less than 9.23
	Ozozen et al., 2016 [64]	EPIAS (2014 to 2015)	ANN, ARIMA, ARIMA-ANN	The hybrid model achieved an MAPE of 4.08
	Ranjbar et al., 2016 [65]	Ontario power market (January 2003 to December 2003)	ANN	MAPE of 9.51
	Sahay and Singh, 2018 [66]	Historical power data (2007 to 2013)	Backpropagation algorithm	MAPE of 6.60

Table 7. *Cont.*

Domain	Author	Dataset	Model	Result
Gold	Verma et al., 2020 [67]	Gold price from investing site, (January 2015 to December 2018)	GDM, RP, SCG, LM, BR, BFGS, OSS	GDM algorithm has the lowest MAPE of 4.06
Stock	Laboissiere et al., 2015 [68]	CEBR3, CSRN3	ANN	MAE of 0.0009 and 0.0042 for CEBR3 and CSRN3
	Prastyo et al., 2017 [69]	Daily stock closing prices from Wanjawa and Lawrence	ANN	RMSE of 0.1830
	Wijesinghe and Rathnayaka, 2020 [70]	Colombo stock exchange	ANN, ARIMA	ANN has the lowest MAPE of 0.1783

Recurrent Neural Network (RNN)

RNN is a variation of ANN [117] with a feedback architecture that contains a feedback loop for later layers of the network to go back to the input layer. RNN has been proven to be a suitable method for time-series forecasting, as exemplified by the studies in forecasting the prices of stock [71–75], Bitcoin [76], fuel [77], gold [78], electricity [79–81], and agricultural [82] from 2006 to 2020. The introduced hidden state in RNN with the ability to memorize previous information helps improve its forecasting capability, even though the data scale is more extensive [82]. Long short-term Memory (LSTM) is introduced also as a refinement of RNN in remembering values for longer or shorter times [72]. From the reviews, RNN has shown an excellent result in nonlinear time-series forecasting as compared to the statistical model. RNN can model both the nonlinear and high volatile data well. Therefore, RNN would be a good choice for time-series forecasting for the above-mentioned data characteristic, provided that there are sufficient data observations. Table 8 shows the summarized review on the studies of RNN for time-series forecasting.

Table 8. RNN time-series forecasting from 2006 to 2020.

Domain	Author	Dataset	Model	Result
Stock	Sun and Ni, 2006 [71]	Yahoo Finance (April 2005 to August 2005)	RNN	Accuracy of 0.9784
	Li and Liao, 2017 [72]	China stock market (2008 to 2015)	RNN, LSTM, MLP	LSTM has the highest performance with an accuracy of 0.473
	Wang et al., 2018 [73]	Yunnan Baiyao stock data	LSTM	Accuracy of 50–65%
	Sima et al., 2018 [74]	Yahoo Finance (January 1985 to August 2018)	LSTM, ARIMA	ARIMA and LSTM achieved an RMSE of 5.999 and 0.936, respectively
	Du et al., 2019 [75]	American Apple stock data of 2008	LSTM	MAE of 0.155
Cryptocurrency	Tandon et al., 2019 [76]	Coin Market Cap website	LSTM, RF, Linear Regression	LSTM has the best performance with an MAE of 0.1518
Fuel	Chaitanya Lahari et al., 2018 [77]	Historical data from major metropolitan cities	RNN	Accuracy of above 90%
Gold	S and S, 2020 [78]	World Gold Council	LSTM	RMSE of 7.385

Table 8. *Cont.*

Domain	Author	Dataset	Model	Result
Electricity	Mandal et al., 2007 [79]	PJM	RNN	MAPE of less than 10
	Zhu et al., 2018 [80]	New England ISO and PJM	LSTM, SVM, DT	LSTM has the best performance with an MAPE of lower than 39
	Ugurlu et al., 2018 [81]	Turkish electricity market of 2016	LSTM, GRU, ANN	GRU has the best performance with an MAE of 5.36
Agricultural	Weng et al., 2019 [82]	Beijing Xinfadi Market (August 2015 to July 2018)	RNN, ARIMA, BPNN	The RNN achieved the best performance with the lowest AAE of 0.49, 0.21, 0.15

2.3. Hybrid Model

Hybrid models are generally a combination of two or more models from the statistical and AI categories. The hybrid model is usually more robust than the single models, as it combines and complements the advantages of a single model to improve the forecasting accuracy. The hybrid model is widely used in different domains for dynamic pricing schemes, including the domain of stock [83–85,94,95], crude oil [86,88,89], energy [90], carbon [87,91], electricity [92], and gold [93] from 2004 to 2021. Different combinations have been proven to successfully integrate the advantages of different models to improve the performance. For example, ANN-GARCH [93] accepted data nonlinearity and volatility. The proposed model demonstrated a significant advantage in modeling highly non-stationary and non-linear time-series data by outperforming any of the single models. From these studies, the hybrid model is proven to have better forecasting capability for time-series data.

Although the hybrid model has demonstrated a promising outcome, such a model is usually highly complex and computationally intensive [118]. The determination of the models for combination is often tricky and challenging, as it requires an in-depth understanding of each method. Thus, a strong background of different models should be mastered and well-understood to decide on a suitable hybrid architecture. The hybrid models also have lower flexibility, since it is specifically designed to handle a particular problem. Table 9 shows the reviewed studies for the hybrid models.

Table 9. Hybrid model time-series forecasting from 2004 to 2021.

Domain	Author	Dataset	Model	Result
	Tang and Diao, 2017 [83]	WIND database (January 2010 to September 2016)	HMM-GARCH	RMSE of 0.0238 and 0.0075
Stock	Pai and Lin, 2005 [85]	Ten stocks dataset (October 202 to December 2002)	ARIMA, SVM, ARIMA-SVM	Hybrid model has the lowest MAE for the included ten stocks
	Raiful Hassan et al., 2007 [94]	Daily stock price of Apple, IBM, and Dell from Yahoo Finance	ANN-GA-HMM	MAPE of 1.9247, 0.84871, and 0.699246 for the stock, respectively
	Wang and Guo, 2020 [84]	Ten stocks dataset (2015 to 2018)	DWT-ARIMA-GSXGB	RMSE of less than 20.3013 for the worst case, the general cases have an RMSE of less than 0.3
	Chen et al., 2020 [95]	Yahoo Finance (September 2008 to July 2019)	MLP-Bi-LSTM with AM	MAE of 0.025393

Table 9. *Cont.*

Domain	Author	Dataset	Model	Result
Crude oil	Shabri and Samsudin, 2014 [88]	Brent crude oil prices and WTI crude oil prices	ANN, WANN	WANN has the best performance with MAPE of 1.31 and 1.39 for Brent and WTI dataset
	Zhang et al., 2015 [86]	WTI and Brent crude oil (January 1986 to 2005) and (May 1987 to June 2005)	EEMD-LSSVM-PSO-GARCH	MAPE of 1.27 and 1.53 for WRI and Brent dataset
	Safari and Davallou, 2018 [89]	OPEC crude oil prices (January 2003 to September 2016)	ESM-ARIMA-NAR	MAPE of 2.44, obtained the lowest error compared to other single models
Energy	Bissing et al., 2019 [90]	Iberian electricity market (February to July 2015)	ARIMA -MLR and ARIMA-Holt winter	ARIMA-Holt Winter has better performance with an MAPE of less than 5.07 for different day forecasting
Carbon	Zhu and Wei, 2013 [87]	European Climate Exchange (ECX) of December 2010 and December 2012	ARIMA-LSSVM	RMSE of 0.0311 and 0.0309 for DEC10 and DEC12
	Huang et al., 2021 [91]	EUA futures from Wind database	VMD-GARCH and LSTM	VMS-GARCH has the best performance with first ranking in terms of RMSE, MAE and MAPE
Electricity	Shafie-khah et al., 2011 [92]	Spanish electricity market of 2002	Wavelet-ARIMA-RBFN	Error variances of less than 0.0049
Gold	Kristjanpoller and Minutolo, 2015 [93]	Gold Spot Price and Gold Future Price from Bloomberg (September 1999 to March 2014)	ANN-GARCH	MAPE of 0.6493 and 0.6621

3. Discussion

After reviewing the different time-series forecasting models presented in Section 2, it can be concluded that the data characteristics analysis is an important step in deciding the optimal model for forecasting, as each of them performs better on particular data characteristics. Consequently, in order to determine the optimal model selection for DSA, data characteristics analysis is performed. This section presents a summary of the suitable data characteristics for the models introduced in Section 2, which is followed by the DSA data analysis and a proposed framework for optimal model selection based on the result analysis.

3.1. Summary of Suitable Data Characteristics for the Included Models

In the review of the seven forecasting models, the importance of the different data characteristics in the optimal model selection for price forecasting is emphasized. Table 10 shows the suitability of data characteristics for each model. Each model has varying performance for the different data characteristics. The large dataset is generally built up with more than 100,000 observations, and the small dataset has fewer observations. This section presents a summary of the strengths and weaknesses of the models.

Table 10. Optimal model selection with its suitable data characteristics.

Model	Linear	Nonlinear	Stationary	Non-Stationary	Volatile	Non-Volatile	Large Dataset	Small Dataset
ARIMA	✓		✓			✓		✓
GARCH		✓		✓	✓			✓
HMM		✓		✓	✓		✓	
SVM		✓		✓		✓		✓
RF		✓		✓	✓		✓	
ANN		✓		✓		✓	✓	
RNN		✓		✓	✓		✓	

First, for regression models, ARIMA is suitable for linear and stationary data, whereas the GARCH model has a better performance when the data are high in volatility and is adaptable to non-stationary data. However, when the data have a linear relationship, ARIMA will have a better performance than GARCH. The stochastic model, HMM, introduced the hidden states that can simulate different volatility regimes. Therefore, it has better performance than a regression model such as GARCH when the data are high in volatility and there is a larger sample size. However, it should be noted that the hidden parameters of HMM are difficult to determine, and the algorithm will probably stop at a local maximum before reaching the most satisfactory result. Hence, this results in lower accuracy in price forecasting.

As one of the ML models, SVM is more effective than statistical models such as ARIMA and GARCH in the sense of its better capability of working with the nonlinear, non-stationary, and highly volatile data. Unlike the regression models, SVM is not limited to working with data having a linear relationship or high volatility, the algorithm is convex optimized. This means that it can find the global optimum of the result. Therefore, it is better than HMM in reaching the most promising result. It can generalize well to previously unseen data, overcoming the existing problems such as forecasting a sudden fluctuation. However, if the dataset is too large, SVM might not perform well due to the memory and optimization constraints. The main advantage of RF compared to SVM is its ability in handling massive datasets. RF has a good capability of avoiding overfitting by limiting the generalization error with an important requirement of a large dataset with less noise. However, when estimating the linear data, RF might have lower performance as compared to SVM and ARIMA due to its random behavior, and the prediction is computed based on the average values.

DL models such as ANN and RNN are both neural network models inspired by the human neuro system. They have a few pros and cons in common, such as good generalizability and good performance on nonlinear and non-stationary data modeling. However, these models are also black box in nature, which results in low model transparency. Both DL models have shown better results compared to ML models when the dataset size is sufficient for training. Among ANN and RNN, RNN has demonstrated a better result than ANN in forecasting data with high volatility.

Moreover, the hybrid model has demonstrated its robustness as a model that combines two or more models, complementing the advantages of the single model. Therefore, a hybrid model can better model the underlying relationship and obtain a more accurate result than any single model. In the case that any single model cannot take care of the different data characteristics, the application of the hybrid model is more appropriate.

The discussed models are generally being applied widely in different areas and have achieved outstanding results. Moreover, different comparative studies have pointed to the suitability of a particular model on certain data characteristics. In conclusion, this section has comprehensively shown the suitable data characteristics for each model.

3.2. *DSA Data Analysis and Proposed Framework for Optimal Model Selection*

As the data characteristics can influence the model performance, a study is conducted based on a collected dataset of DSA. As the attention level toward signage can greatly influence the pricing decision, the dependency and relationship of the environmental factors related to the attention level should be carefully considered. The environmental factors included in this study are location, weather, and temperature. These factors have significant impacts on the attention level and the final pricing decision [2]. Table 11 shows two examples of how the environmental factors impact the attention level and consequently the pricing of the DSA.

Table 11. Environmental factors and its impact on the attention level and pricing of DSA.

Factors	Example	Attention Level	Price
Location	High popularity, High rating of surrounding public facilities, business	Increase ↑	Increase ↑
Weather and temperature	Raining, extremely high or low temperature and air humidity	Decrease ↓	Decrease ↓

Realizing the environmental factors impacts on the pricing decision, the collected dataset is composed of three attributes including the temperature, air humidity level, and the popularity index of the surrounding business environment based on the two environmental factors, as shown in Table 11. They were collected from 13 locations of digital signage in Malaysia using data scraping methods from April to June 2021. The temperature and humidity data were obtained from OpenWeather API, while the popularity index was scraped from Google Maps.

These data characteristics are used to measure the index representing the attention level, which indirectly affects the price forecast of the DSA. Thus, this study aims to investigate the collected DSA data characteristics daily, monthly, and as a whole. The signage being analyzed was selected randomly. The signage with ID 1000, which was located at Negeri Sembilan, Malaysia, with coordinates (101.9119, 2.70179) was investigated in the study. The results for other signages were not presented in this article to avoid repetitive information.

3.2.1. Location

The location is the most applied factor in the traditional pricing scheme for DSA, such as a fixed price strategy and auction-based pricing mechanism [1]. The geographical environment and facilities surrounding the digital signage are the most crucial factors, as they strongly affect the accessibility and visibility of the digital signage, determining the audience attention level. For example, a higher rating of surrounding businesses can increase the crowd of a particular location, which indirectly increases the attention level toward the advertisement. Thus, the more prosperous a location is, the higher the attention level that can be obtained to improve the effectiveness of the advertisement. The different days and times also have a direct impact on the crowd size of the location. For example, the crowd on weekends will commonly be higher than the working days. Hence, it increases the demand for a DSA spot and results in higher prices. These indexes are indeed imperative in affecting the pricing decision. Considering its relationship with the attention level that can be obtained, the higher the value of these indexes, the higher the price.

Figure 3 illustrated the comparison of the popularity indices of the signage with ID 1000 for 24 h on weekdays and during the weekend. The popularity indices show different peak hours of the weekdays and weekend. Notably, the popularity index is higher on weekends compared to weekdays. Thus, this exemplifies the assumption that the signage will be attracting higher attention levels during the weekend than on weekdays, resulting in higher prices for DSA.

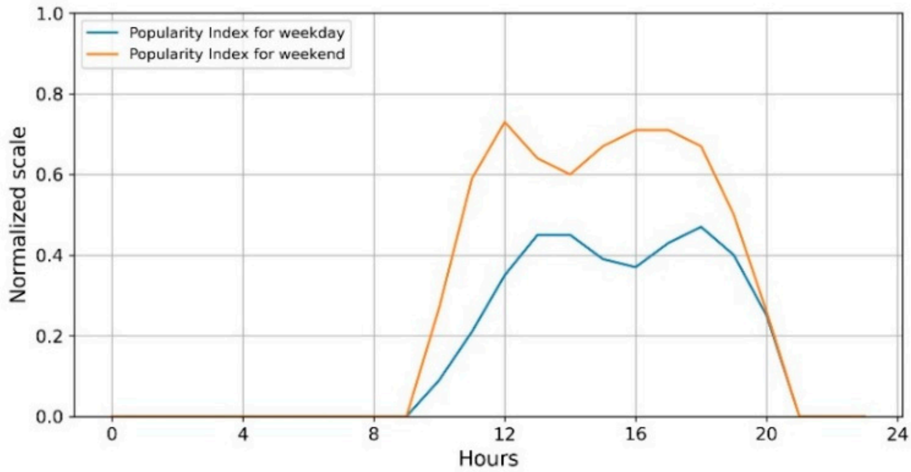


Figure 3. Popularity index comparison over 24 h for both weekdays and weekends.

There is clearly a seasonal trend in the monthly and whole-dataset plots of the DSA data, as shown in Figures 4 and 5. This represents a non-stationary data characteristic. Generally, both figures show the same seasonal trend, with the popularity index rising and falling cyclically, affecting the amount of audience attention that can be grabbed. Thus, a dynamic pricing scheme can be applied for DSA to maximize profit.

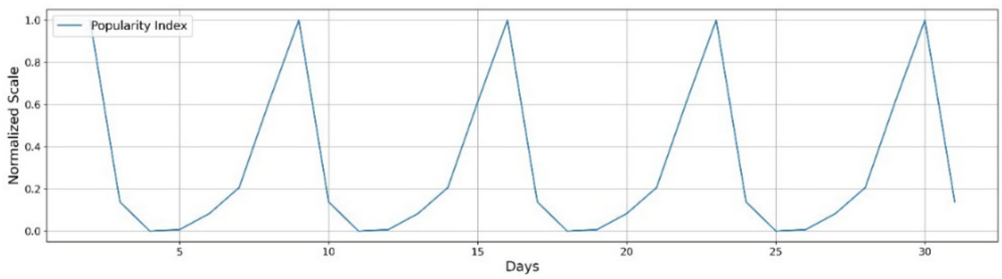


Figure 4. Popularity index changes in 30 days.

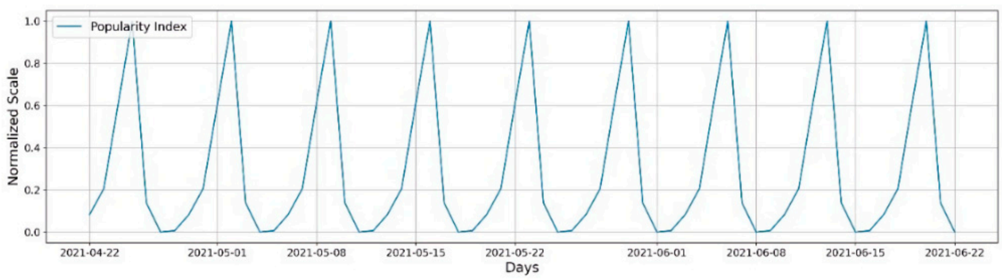


Figure 5. Popularity index changes for the whole dataset.

3.2.2. Weather and Temperature

The weather and temperature have a significant impact on the crowd size of a location, especially for outdoor environments. The changes in the weather include changes in the air humidity and temperature [119]. The weather can have many changes in a short duration. With fast-changing weather, an hourly update to precisely calculate the prices of an advertising spot can be performed. As bad weather will negatively affect outdoor activities and events, this will result in lower prices of the advertisements at those spots.

The temperature and air humidity data are analyzed. The data are complementary to each other. When the values of air humidity go down, the values of temperature go up. Figure 6 shows the changes in temperature and air humidity over 24 h on a randomly selected day to illustrate how these attributes change in a day. The data show an irregular movement in a longer time frame of 30 days and in the plot for the whole dataset, as shown in Figures 7 and 8, respectively. Generally, the temperature and air humidity show a movement that is contradictory to each other. The weather can affect the crowd size. An extremely high or low temperature will result in the crowd of a location to decrease. Notably, the environmental factors show a different data characteristic.

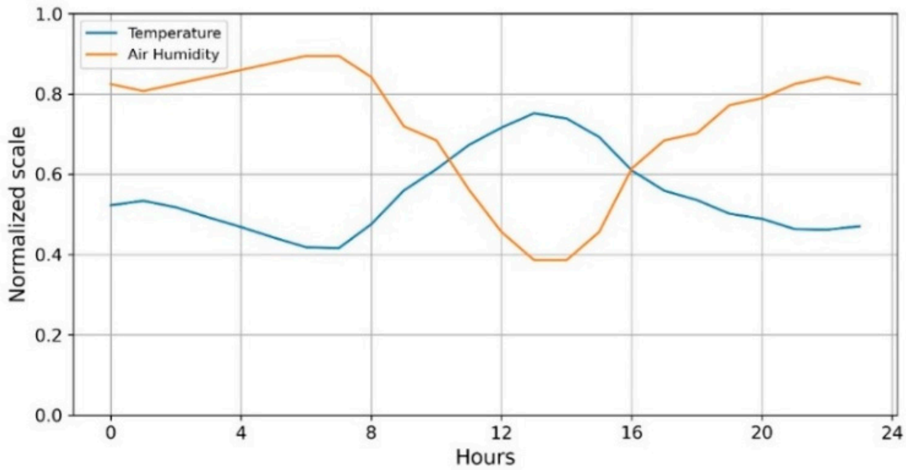


Figure 6. Temperature and air humidity in 24 h.

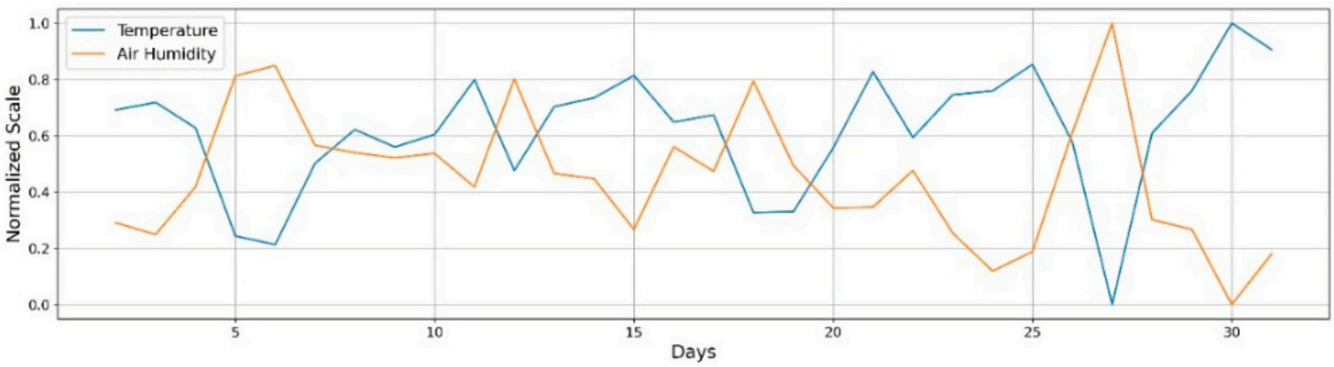


Figure 7. Temperature and air humidity in 30 days.

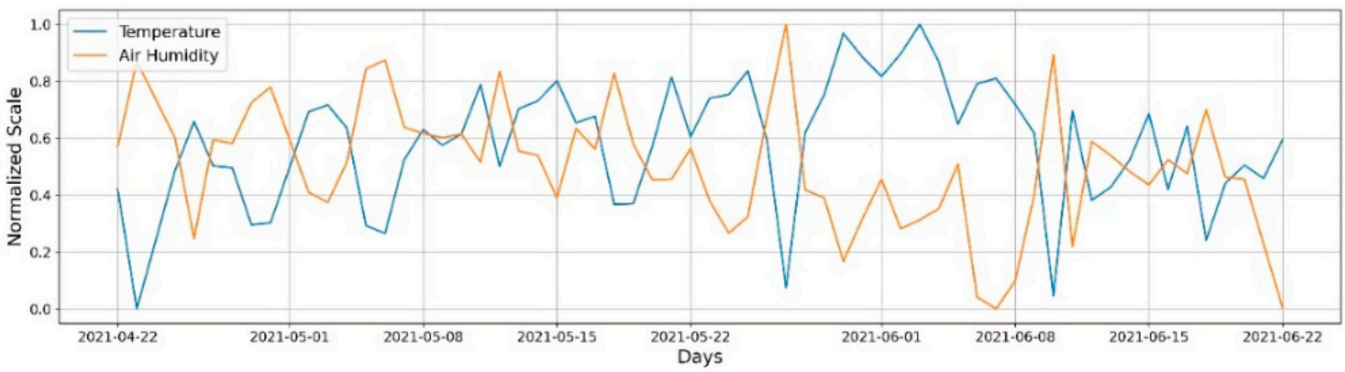


Figure 8. Temperature and air humidity for the whole dataset.

Therefore, we observe that the data for each factor of the DSA show different characteristics. Based on the review studies, a framework is developed to analyze the data for optimal model selection. A list of procedures and tests can be used to determine the data characteristics. A linearity test can be conducted through data visualization using a scatter plot by observing if the point cluster forms a diagonal line. The data stationarity can be checked by using the Augmented Dickey–Fuller (ADF) test [120]. A Lagrange Multiplier (LM) test is used to check the existence of the ARCH effect to assess the volatility in the dataset [5]. The p-values of both ADF and LM tests are used to indicate if the null hypotheses of the test are accepted to determine the stationarity and volatility of the data. In addition, dataset size is determined based on the number of observations in the dataset. Based the result from each test, the optimal price-forecasting method for each case can be determined. Note that the hybrid model is not included in the framework, as the hybrid models are the combination of two or more single models targeting different data characteristics, depending on the specific forecasting problems handled. Figure 9 illustrates the proposed framework, with the corresponding tests to determine the optimal model selection.

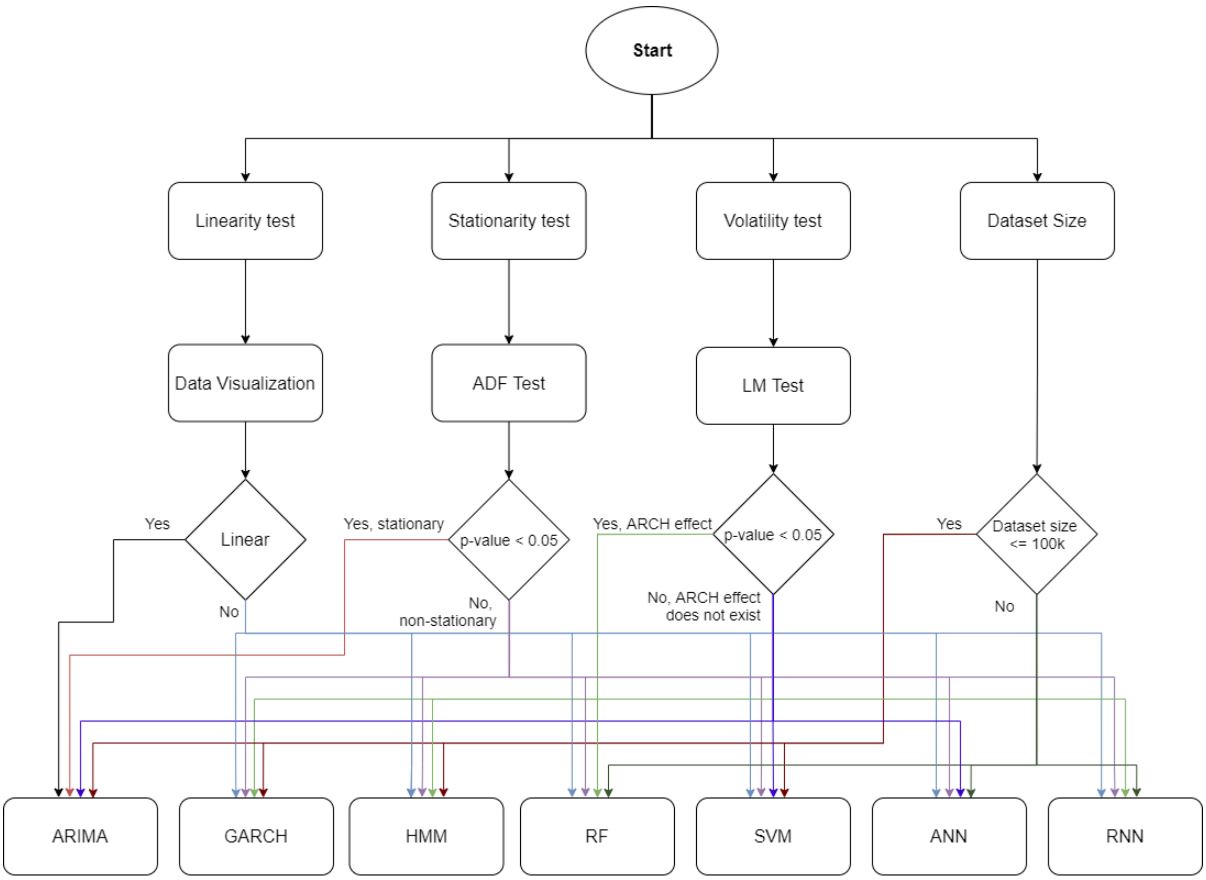
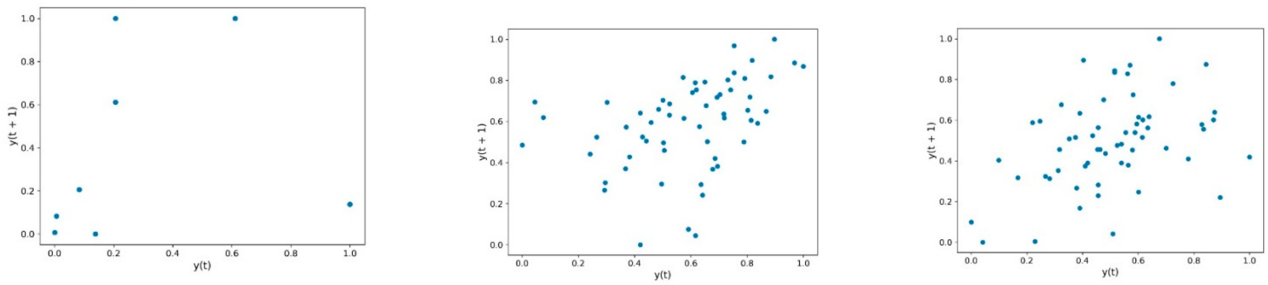


Figure 9. Proposed framework for optimal model selection.

From the above analysis, it is noticeable that each data point has different movements in time. The linearity, stationarity, and volatility tests for the environmental factors of the DSA dataset are performed to examine the data characteristics for each. Following the steps as illustrated in Figure 9, Table 12 shows the test results. Figure 10 shows the data visualization of the linearity test for the popularity index, temperature, and air humidity data. Based on Figure 10b,c, it is noticeable that the temperature and air humidity data show a linear relationship, respectively, as the points cluster along the diagonal line.

Table 12. Data characteristics tests and results.

Environmental Factor		Linearity	Stationary	Volatility	Dataset Size	Selected Model
Location	Popularity index	No	No	No	≤100 K	SVM
Weather	Temperature	Yes	Yes	No		ARIMA
	Air humidity	Yes	Yes	No		ARIMA



(**a**) Popularity index (**b**) Temperature (**c**) Air humidity

Figure 10. Scatter plot for popularity index, temperature, and air humidity.

From the interpreted results, SVM is the optimal model for modeling the popularity index, while ARIMA is suitable for modeling both temperature and air humidity. Multiple models can forecast the respective environmental factors instead of using a single model to fit all the factors. As the environmental factors affect the attention level and consequently the pricing decisions, using multiple models for different data characteristics is better in forecasting the future values of the data for pricing decisions. In our case, where the pricing label is not available, a rule-based system can be applied by setting a threshold value for each environmental factor to generate the price. This can help effectively forecast the important factors that will affect the attention level and pricing decision for DSA. With the optimal models used, a better pricing decision can be made.

4. Conclusions and Future Work

This paper presented a list of widely used time-series forecasting models for dynamic pricing based on an extensive literature review. These models have been proven to have outstanding achievement in different domains. From the review, each model has its strength in dealing with different data characteristics. The advantages and disadvantages of each model are discussed and presented. In addition, the relationships between the models and the different data characteristics are investigated to suggest the optimal model selection for the price forecasting of DSA. From there, an optimal model selection framework is proposed based on the data characteristics analysis of DSA data. This structured review provides a solution of dynamic pricing using time-series forecasting, paving the way for future research on dynamic pricing in DSA.

For future work, an experimental study shall be carried out to examine the applicability of the proposed optimal model selection framework. More time-series data shall be collected to conduct the experimental study for dynamic pricing in DSA to investigate the effectiveness of the optimal model selection framework. Moreover, a customer behavioral targeting approach can be considered in identifying their preferences for better advertising effects [121].

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