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Identifying Stock Prices Using an Advanced Hybrid ARIMA-Based Model: A Case of Games Catalogs

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Abstract: At the beginning of 2020, the COVID-19 pandemic struck the world, affecting the pace of life and the economic behavioral patterns of people around the world, with an impact exceeding that of the 2008 financial crisis, causing a global stock market crash and even the first recorded negative oil prices. Under the impact of this pandemic, due to the global large-scale quarantine and lockdown measures, game stocks belonging to the stay-at-home economy have become the focus of investors from all over the world. Therefore, under such incentives, this study aims to construct a set of effective prediction models for the price of game stocks, which could help relevant stakeholders—especially investors—to make efficient predictions so as to achieve a profitable investment niche. Moreover, because stock prices have the characteristics of a time series, and based on the relevant discussion in the literature, we know that ARIMA (the autoregressive integrated moving average) prediction models have excellent prediction performance. In conclusion, this study aims to establish an advanced hybrid model based on ARIMA as an excellent prediction technology for the price of game stocks, and to construct four groups of different investment strategies to determine which technical models of investment strategies are suitable for different game stocks. There are six important directions, experimental results, and research findings in the construction of advanced models: (1) In terms of the experiment, the data are collected from the daily closing prices of game-related stocks on the Taiwan Stock Exchange, and the sample range is from 2014 to 2020. (2) In terms of the performance verification, the return on investment is used as the evaluation standard to verify the availability of the ARIMA prediction model. (3) In terms of the research results, the accuracy of the model in predicting the prices of listed stocks can reach the 95% confidence interval predicted by the model 14 days after the closing price, and the OTC stocks fall within the 95% confidence interval for 3 days. (4) In terms of the empirical study of the rate of return, the investors can obtain a better rate of return than the benchmark strategy by trading the game stocks based on the indices set by the ARIMA model in this study. (5) In terms of the research findings, this study further compares the rate of return of trading strategies with reference to the ARIMA index and the rate of return of trading strategies with reference to the monitoring indicator, finding no significant difference between the two. (6) Different game stocks apply for different technical models of investment strategies.

Keywords: advanced hybrid ARIMA-based model; time series; game stock; stock price prediction; simulated investment

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1. Introduction

This section mainly introduces the background of the research problem and its motivation in terms of relevant research topics, as well as the study's focus and purpose.

1.1. Background and Motivation of the Research Problem

Since 2020, COVID-19 has spread worldwide, and the world has reported 533,494,106 confirmed cases and 6,326,387 deaths to the WHO as of 15 June 2022, reaching a global fatality rate of 1.19% [1], showing the severity of the pandemic. As a result, countries around the world have implemented high levels of restrictive actions, leading to a global economic recession, impacts on global stock markets, increasing unemployment, etc., which have resulted in negative effects in terms of financial instability. Even some hedge funds have been affected, leaving investors confused and suffering great losses. Thus, this paper addresses the serious influence of the COVID-19 pandemic, as well as exploring some potential benefits in terms of emerging commercial opportunities—especially with respect to financial market issues. Now that governments around the world have implemented restrictions on travel—especially in China—people who stay at home are looking for entertainment to relieve their boredom, and the potential for a new stay-at-home economy via Internet opportunities has emerged, as explored in this study. These phenomena are reflected in the growth of the global game market [2]; thus, the potential prediction of the game software market now represents an interesting research problem, which this study aims to address. In order to stop the spread of the virus, countries continue to implement conditions such as home quarantine and social distancing, encouraging people to stay at home. In this situation, people are quietly changing their entertainment methods, using online games to interactively connect with their friends. As a result, video gaming and Internet traffic have soared to unprecedented levels. Verizon noted a 75% increase in online game traffic in March; in 2022, their annual revenue growth is expected to exceed 30%. In addition, according to a report by the games research institute Newzoo in 2020, the global game market is estimated to be worth USD 159 billion, of which the Asia–Pacific region is the largest market, worth USD 74.8 billion, accounting for 49%. App Annie, a research agency, notes that in 2020, nearly 85% of the revenue of Taiwan's mobile market came from games, with an annual growth of 20%, ranking 7th in the global market [3]. In summary, the consumption of online (Internet) games is rapidly increasing, showing their future importance; thus, the related online games are the focus of this study. Therefore, we take online games companies as our research object, and present a method for the prediction of their future development, with action-oriented significance for financial investment. Indirectly, the prediction of such companies' stocks is a very challenging task, due to the variability and volatility of the stock market under the impact of the COVID-19 pandemic.

Generally speaking, games companies can be divided into three modes of operation: The first mode is the "developer", also known as the "original factory", whose core business is to develop and design their own games. These companies usually have a gross margin of more than 80%, and some even exceed 90%. However, these companies often burn huge sums of money to develop their games' software, leading to a high degree of uncertainty about the outcome of their "research and development". The second mode is "self-produce and marketing", wherein the company produces and sells the game products by itself. The biggest difference from the first kind of developers is that in addition to developing the games, the company also invests more in talents such as marketers, art editors, and front-desk engineers. The advantage is that the industry can be integrated from top to bottom, and the gross profit rate of such companies is usually less than 50%. The third mode is the "agency", wherein the company does not design the games, but makes profits by licensing from developers. Although their gross profit margin is typically lower than that of game developers, such companies are able to calculate their operational costs accurately [4]. Further along the video game supply chain, there are two main areas. One is the game software development and agency companies; these companies have high gross margins and stock price growth, but their revenues are more volatile at the development stage.

The other is the companies that produce the game hardware—such as host chips, memory devices, and e-sports devices—which have relatively low gross profits but relatively stable revenues. When the industry is booming, the customers will consume more products. Furthermore, the global game industry is expected to grow at a compound annual rate of 12% over the next 5 years, according to a report by Business Wire—a company owned by Warren Buffett. It will also drive related industries around the world, including equipment host supply chains, software developers, 3D animation production companies, virtual reality and augmented reality, etc., with a huge annual output value of more than USD 200 billion—which does not include the intellectual property opportunities derived from the characters and stories, e.g., film adaptations, models, anime, and other peripheral products [5]. It is clear that games companies are in a prime position to garner public attention. In particular, as a result of the recent COVID-19 outbreak, these game stocks are particularly favored by investors due to the growth of the stay-at-home economy. It is also for this reason that this study takes the stock price prediction of game companies as the research problem. Interestingly and importantly, it is a core concern for research to address the stock price predictions of game companies in the context of the COVID-19 pandemic in order to identify general areas of interest and learn more about the problem. To effectively identify and solve this key research problem is the motivation of this study. Stock price prediction is a challenging problem because of the complicated variables involved.

However, the stock market is a fantastic place, full of opportunities as well as traps; some people get rich because of it, while others go bankrupt because of it. To be a winner in the stock market, one must be able to objectively use good prediction techniques. For this reason, the construction of effective stock market prediction methods or models is the main motivation of this study. In addition, because stock market prices have the data characteristics of a time series, their early and later data are usually correlated. Thus, the results can often be used to model historical trends, as well as to build immediate warning or prediction models. Moreover, time-series data accumulate over time. In other words, serial data can change rapidly over time, so it is important to be able to respond quickly to the rapidly changing stock prices to identify trends immediately and generate a warning effect, so that investors can avoid risk. Therefore, for the prediction of stock prices, it is possible to start from a time-series data correlation model, and then express the heterogeneity of the time-series data in a pre-constructed mathematical model, finding the characteristics of long-term trends, seasonal change, and irregular change, which can be used to predict future stock price trends [6–8]. In addition, this study utilizes further learning from the relevant literature, where Box and Jenkins (1970) proposed the autoregressive integrated moving average (ARIMA) model to solve the prediction problem of time-series data to which linear regression models are not applicable [9]. In fact, this method can also solve the problem of earlier and later correlation of time-series data, achieving excellent prediction performance. Past examples of time-series data applications can be used to predict the stock prices, sensor data, and remote measuring of application programs. From the construction of predictive models, and from the limited literature discussion, it can be seen that the prediction performance of hybrid models is often better than that of single models [10–18]. Thus, the significant impact of hybrid models for such predictions is addressed in this study.

Based on the above viewpoints, this study aims to establish a set of advanced hybrid ARIMA-based models as an excellent prediction technique for the stock price prediction of game catalog stocks on financial markets. The intent of this study is to predict the price trends of game stocks, hoping to provide a good reference for interested parties—such as relevant stakeholders (especially investors)—to determine the appropriate direction under different perspectives in the context of the current pandemic. In considering prediction performance relative to the literature, this study aims to make a significant contribution to the effective and efficient identification the prices of games catalog stocks on the stock market, achieving financial benefits for stock investors.

1.2. Research Priorities and Objectives

In this study, an advanced hybrid ARIMA-based prediction model is used to predict the prices of game stocks. Based on a limited literature review on the issue of stock price identification of games catalog stocks, the proposed hybrid model has never previously been utilized; thus, this study has good application potential to address this interesting topic for interested parties. The following three research priorities and objectives were implemented to test the availability of the model by means of simulation steps with a superior kind of monitoring indicator and, finally, discuss and draw conclusions from the experimental results and findings, as described below:

(1) Construct the advanced hybrid ARIMA-based models to compare the stock prices predicted in the long, medium, and short term with the actual stock prices, and determine the optimal model. At the same time, use the optimal model to predict the next n days, and use the predicted stock price of n days to form the judgment of an upward or downward trend, so as to provide a warning effect in advance.

(2) Use the optimal model to form a trend judgment and basis for buying, not taking action, or not selling, and use a two-month period as experimental data to compare the rate of return of transactions.

(3) Use the monitoring indicator inquiry system of UNCTAD for the scores of 10 years as the historical data to implement and compare the investment strategies.

The rest of this paper is structured and presented as follows: Section 2 comprises an extensive literature review of the related applications and topics in the stock market for financial fields and games catalog stocks. Section 3 explores the structures and applications of the methodological preliminaries for the ARIMA model. Section 4 shows the algorithms of proposed advanced hybrid ARIMA-based models, along with a simulation with example illustrations for investment strategy designs. Sections 5 and 6 report the analysis and discussion of the empirical results with real cases for the proposed hybrid model, as well as the conclusions, with future insights and future directions for subsequent research.

2. Literature Review

This section mainly explores the stock market in terms of financial fields and stock price, including reviews of the literature on the stock market and game catalog stocks, along with related applications.

2.1. The Stock Market and Its Applications

In the financial field, the stock market is an interesting issue, not only presenting opportunities for financial profiteering, but also entailing high risk. In terms of the stock market, in-depth analysis of transaction data offers profound knowledge with time-series characteristics, and is thus worthy of further research. As with any mathematical time series, such data consist of a series of data points chartered and indexed in chronological order. For their analysis, we can collect data over a specific time period and analyze the sequence of data from the stock market. As for the analysis methods, different techniques for time series have been provided, with good predictive performance. Furthermore, many academics have studied a variety of different prediction techniques outside of stock market prediction in previous studies. For example, Ghoddusi et al. [19] identified some areas of application, including prediction of energy prices, demand forecasting, risk management, and trading strategies. They critically reviewed more than 130 published articles from 2005 to 2018, and found that support-vector machines (SVMs), artificial neural networks (ANNs), and genetic algorithms (GAs) are the most popular techniques used in the prediction of energy economics. Shobande and Akinbomi [20] developed a game theory model to analyze the dynamic competition among Nigeria's leading domestic aviation companies in order to determine the optimal competitive strategies available to the companies to exist in such a complicated operating environment, with superior prediction performance. Furthermore, Shobande and Shodipe [21] forecasted the world population using pure

ARIMA for both short-term and long-term projection and estimation, at the global, regional, and sub-regional levels.

In terms of the related stock market prediction, the exploration of some past studies is valuable. Eapen et al. [22] proposed a novel deep learning model with a CNN (convolutional neural network) and bidirectional LSTM (long short-term memory) for improving stock market index prediction. Afterwards, Shah et al. [23] reviewed the related stock market and its taxonomy of prediction techniques, such as the application of machine learning techniques and other algorithms, which showed great promise. Rao et al. [24] used hybrid linear and nonlinear models to address stock market prediction, while Pang et al. [25] proposed a deep LSTM neural network with an embedded layer and an LSTM neural network with an automatic encoder to carry out stock market prediction. Polamuri et al. [26] first proposed a generative-adversarial-network-based hybrid prediction algorithm (called GAN-HPA); at the same time, the proposed algorithm was compared with a state-of-the-art model—a multi-model-based hybrid prediction algorithm (called MM-HPA)—and then the authors combined GAN-HPA and MM-HPA to build a new hybrid MMGAN-HPA model for improving prediction quality compared to both MM-HPA and GAN-HPA, achieving promising performance in stock price prediction.

Thus, for better prediction performance to increase investment interest, it is important that the approach used for stock market prediction is deeply attractive to objective investors.

2.2. Games Catalog Stock and Its Applications

The games industry is involved in developing, marketing, and selling game hardware and software, and is a large, fast-growing sector with significant long-term expansion potential. The top companies in the industry have benefited from a strong surge in demand during the COVID-19 pandemic. Games industry sales generally performed well early in the COVID-19 pandemic as business shutdowns and social distancing measures limited people's entertainment options. Because games can be played by consumers at home, they have become a popular option. People love all kinds of entertainment, and games offer a broad range of experiences that can be uniquely compelling. The global popularity of games will likely continue to grow in the coming decades, providing leading games publishers with many opportunities to reach new players and expand sales in both developed and emerging markets. For example, Capcom (OTC: CCOEF), Take-Two Interactive (NASDAQ: TTWO), Microsoft (NASDAQ: MSFT), Electronic Arts (NASDAQ: EA), and Nintendo (OTC: NTDOY) stand out as top gaming stocks to buy as long-term investments [27]. Companies that continue adapting to players' demands and shaping their tastes for interactive electronic entertainment are well-positioned to deliver significant returns for shareholders.

In Taiwan, the games industry is also booming—especially mobile games, which accounted for over half of the retail value of video game sales during 2021. Smartphones are now almost ubiquitous in Taiwan, and technical advances mean that the gap between console and mobile games is narrowing. Moreover, the Taiwanese government is relatively supportive of video gaming, recognizing e-sports as legitimate sporting events in 2018 [28]. This has led to a more positive attitude toward investing in game stocks in society. According to the literature [29], the number of users in the video games sector (including mobile games, download games, online games, and gaming networks) is expected to amount to 10.8 million by 2027. User penetration will be 39.1% in 2022, and is expected to hit 45.2% by 2027, while the revenue is projected to show an annual growth rate (CAGR 2022–2027) of 5.63%, resulting in a projected market volume of USD 2.207 billion by 2027.

Although investment in game stocks in Taiwan is becoming more popular, there are still few academic studies about the prices of Taiwanese game stocks. Filling this gap is also one of our motivations.

3. Methodological Preliminaries

This section mainly discusses the main techniques and methods used in the prediction model, including the introduction of the algorithm, related application examples, and monitoring indicators.

3.1. ARIMA Algorithm

(1) Basic composition of the algorithm

The ARIMA algorithm was developed by the statisticians Box and Jenkins (1970) [9]. This algorithm is suitable for data corresponding to fixed time series. Therefore, it has different application examples in different fields, with good predictive performance. The model is mainly composed of three elements—AR (autoregression), AR(p) in short; difference, d in short; and MA (moving average), MA(q) in short—and their formulae are described in detail as follows:

(a) AR: AR(p):

$$y_t = a_0 + \sum_{i=1}^{p} a_i y_{t-i} + \varepsilon_t \tag{1}$$

where a_0 indicates the constant number's intercept, p represents the periods lagging behind (lag), a_i represents the coefficient of y_{t-i}, and ε_t is the white noise.

(b) Difference (d):

$$Y_t - Y_{t-k} = \left(1 - B^k\right) Y_t \tag{2}$$

where the backward shift operator B is used as an operator to remove non-stationarity, where $B^k Y_t = Y_{t-k}$. In the general economic and financial series, we are only interested in d = 0 or d = 1 (i.e., first-order integration); only a few economic time series have d = 2, and integrations of higher order are rarely seen.

(c) MA: MA(q):

$$y_t = a_0 + \varepsilon_t + \sum\nolimits_{i=1}^{q} b_i \varepsilon_{t-i} \tag{3}$$

where a_0 is a constant and is the same as in Formula (1), q represents the periods lagging behind, b_i represents the coefficient of ε_{t-i}, and ε_t is the white noise, which is also the same as in Formula (1).

(2) Model construction

Assuming that the sample data comply with ARIMA's (p,d,q) modes, the next important task is to decide p and q, followed by d. This procedure is called the mode recognition. Parameter estimation must be carried out after the mode recognition. When two or more ARIMA (p,d,q) modes are found to be able to interpret the sample data, the mode analysis must be performed to confirm the fitness and predictive power of the mode.

(a) Stationary series:

Stationarity: Time series evolve over time and need a stable structure, so we require the first-order and second-order dynamic differences of the time series to have a stable structure, and only a time series with a stable structure can be predictable. A time series with a single root is as follows:

$$y_t = \beta_o + y_{t-1} + \varepsilon_t,\ \varepsilon_t \sim^{i.i.d.} N\left(o, \sigma^2\right) \tag{4}$$

After taking the first-order difference:

$$\Delta y_t = y_t - y_{t-1} = \beta_o + \varepsilon_t \tag{5}$$

In this way, it can become a stationary time series, and the random trend can be removed by taking the first-order difference of the time series with a single root. The autocorrelation function (ACF) of a time series is defined as the autocorrelation coefficient of the series (regarded as a function of k, $-\infty$ < k < ∞), which is suitable for judging the order of MA. However, the ACF cannot judge the order of AR, so it should use the partial autocorrelation function (PACF) to do so.

(b) White noise:

White noise (ε_t) must meet three conditions: (i) the expected value is 0; (ii) the variance is the fixed constant; and (iii) the autocovariance is zero. White noise is a time-series random variable with an average of 0.

(c) Fitness Bayesian information criterion:

The Bayesian information criterion (BIC) or Schwarz information criterion (also SBC, SBIC) is a criterion for model selection in finite sets. In line with the Akaike information criterion (AIC), the AIC and SBIC focus on the parametric penalty terms, in which the BIC penalty terms are more significant than those of the AIC. Clement [30] proposed the following formula, which is easier to deal with:

$$BIC = X^2 + k\{ln(n)\} \tag{6}$$

where the smaller the BIC, the better.

(d) ARIMA prediction ability evaluation:

Christodoulos et al. [31] proposed that the common prediction evaluation indices and accuracy test methods of actual values in ARIMA are as follows:

MSE (mean squared error):

$$MSE = \frac{1}{T}\sum_{t=1}^{T}(P_t - Z_t)^2 \tag{7}$$

MAE (mean absolute error):

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|P_t - Z_t| \tag{8}$$

MAPE (mean absolute percentage error):

$$MAPE = \frac{100}{T}\sum_{t=1}^{T}\left|\frac{Z_t - P_t}{Z_t}\right| \tag{9}$$

where P_t indicates the prediction value at time t, the actual value of the model is represented by Z_t, and T is the number of prediction data.

3.2. ARIMA-Related Application Fields

ARIMA has a wide range of applications, and each has a good evaluation performance. Cao [32] studied 30 listed banks in Taiwan and used the cluster analysis method and a time-series ARIMA model to predict and analyze the banks' stock prices. The empirical results showed that the error value of ARIMA prediction was smaller than the error value obtained by using double exponential smoothing, and the accuracy of the stock price prediction was relatively high, which is helpful for researchers to analyze the trends of banks' stock prices [32]. Chen [33] used regression analysis, time series, and neural networks to simulate a monthly closing price prediction model of the Taiwan weighted stock index, and took the four major parameters (i.e., overall economy, international stock market, technical indicators, and Taiwan stock information) that affected the Taiwan weighted stock index as the prediction variables. This research proved that the time-series prediction method is better than the other two methods, followed by regression analysis, while the stepwise regression model is not good at prediction, and the neural network has higher prediction error than the first two methods [33]. Almasarweh and Wadi (2018) used ARIMA to predict the Amman Stock Exchange (ASE) in Jordan to demonstrate ARIMA's predictive ability, and found that ARIMA had good prediction ability for the short-term banking stocks, providing investors with reference direction [34]. Tsai (2014) used regression to test whether the score change of monitoring indicators was consistent with the trend of the stock market, and judged whether the scores of monitoring indicators in the contraction period and the expansion period were different to the trend of the stock market, finding that the scores of monitoring indicators were significantly positively correlated with various stock indices [35]. Zhu et al. (2014) used Taiwan's 50 constituent stocks as the target to conduct a simulated investment with three different strategies to keep gaining and losing, and invested at the closing price on the first business day of every month. After five years of investment, the results showed that the optimal sequence of the three investment strategies was as follows: "contrary investment strategy (unfixed quota at fixed periods)" was the best, "investment strategy of fixed quota at fixed periods" was second, and "momentum investment strategy (unfixed quota at fixed periods)" was poor [36]. Huang et al. [37] compared six investment strategy methods at fixed periods, and the individual stocks' investment research results at fixed periods showed that, in the investment periods of two years and five years, the investment strategy of fixed quotas had obvious advantages compared with the other two investment strategies at fixed periods, and its investment performance was significantly better. Among the above approaches, the performance of the strategy with unfixed quotas at fixed periods was the best. The performance of this investment strategy with fixed quotas was significantly worse than that of the other five investment strategies at fixed periods, including the strategy with fixed quotas at fixed periods [37]. Based on the research design of the relevant literature, this study formulates four investment strategies for comparison: (a) the ARIMA strategy; (b) a monthly strategy with fixed quotas at fixed periods, which is the comparison benchmark; (c) the ARIMA strategy based on the monitoring indicator; and (d) a monthly strategy with fixed quotas at fixed periods based on the monitoring indicators.

In summary, the relevant ARIMA algorithm can be applied in stock market prediction, but there is no research regarding game stocks as the analysis target in the literature, so this study was intended to adopt the relevant ARIMA model to enrich the literature and serve as the academic contribution of this study.

3.3. Monitoring Indicators and Related Applications

A monitoring indicator is also called an "economic signal", which is similar to a traffic signal. Five different signal lights represent the economic monitoring indicators, consisting of nine indices, such as the change rate of monetary aggregates (M1B). The five indicators are red, yellow–red, green, yellow–blue, and blue. The interpretation of each monitoring indicator represents booming, transitional, stable, transitional, and sluggish, respectively. This can change monthly according to the annual change rate of each component item (except for the TIER manufacturing sector composite indicator) to be compared with the test value, and then the score and the light signal can be given based on the light range in which it falls. After summation, it gives the comprehensive judgment score and corresponding monitoring indicator. In particular, the yellow–red and yellow–blue lights are both caution lights, upon seeing which it is advisable to observe whether the subsequent economy will change.

In previous studies of monitoring indicators, scholars noted that the monitoring indicators were closely related to stock prices, as described below. Lin [38] used linear regression analysis to explore whether there was a correlation between monitoring indicators and the price of financial and insurance stocks. The results of empirical research showed that among the factors that constitute the monitoring indicators, the stock price index, customs-cleared exports, and industrial production index had positive relationships with the influence of financial stocks [38]. Tsai [35] used regression to test whether the score change of monitoring indicators was consistent with the trends of the stock market, and judged whether the scores of monitoring indicators in the contraction period and the expansion period were different to the trends of the stock market. The results showed that there was significant positive correlation between the monitoring indicator scores and various stock indices [35].

Based on the results of the abovementioned research, the monitoring indicators are positively correlated with the stock price. Since the monitoring indicators are measured in months, the advanced hybrid ARIMA model proposed in this study was used to predict the monitoring indicators of two months and predict the daily price of game stocks for investment simulation, in order to test whether the monitoring indicators are also correlated with the price of game stocks. This was one of the main purposes of this study, so the experimental results are worthy of consideration.

4. The Proposed Advanced Hybrid ARIMA-Based Model

This section mainly describes the research structure and algorithm flow of the advanced hybrid ARIMA-based model proposed in this study, as well as the simulation of investment strategy design and illustration of practical examples.

4.1. Research Structure and Algorithmic Flow of the Proposed Model

The algorithm of the advanced hybrid ARIMA-based model proposed in this study is described as follows: firstly, 11 game stocks summarized by the Goodinfo website were used, among which 1 listed stock was downloaded from the website of the Taiwan Stock Exchange, while the other 10 were downloaded from the OTC stock trading center. According to the latest issued game stocks, four intervals of datasets from the past seven years (1 July 2014–30 June 2020), three years (1 July 2017–30 June 2020), one year (1 July 2019–30 June 2020), and half a year (1 January 2020–30 June 2020) were selected for confirmation of the optimal ARIMA model. After comparing the predicted values of different data intervals with the actual data, the predicted values closest to the actual values were selected. Next0, the related ARIMA model of these data intervals was used as the optimal model to conduct the investment simulation for two months. The advanced hybrid model proposed in this study mainly includes six research steps and experimental methods, with details as follows:

Step 1: Refer to the information of 11 game stocks listed in Taiwan, including (stock code—company name) 3083 Chinese Gamer, 3086 Wayi, 3293 IGS, 3546 UJ, 3687 OMG, 4946 Cayenne, 4994 X-Legend, 5478 Soft-World, 6111 Softstar, 6169 InterServ, and 6180 GAMANIA, among which only 4994 X-Legend is a listed company, while the rest are OTC companies. Then, intercept the daily closing data from the Taiwan Stock Exchange to establish Excel files of the datasets.

Step 2: According to the latest issued game stocks, confirm the optimal ARIMA model according to the four data subset intervals of 7-year data from July 2014, 3-year data from July 2017, 1-year data from July 2019, and half-year data from January 2020. Calculate the 95% confidence interval with the actual value, and compare whether the predicted value falls into the same interval. Take the number of days falling into the interval as the exact number n (i.e., the predicted value referring to n days).

Step 3: Use the optimal ARIMA model to predict the stock prices of all game stocks in July and August 2020. When the trend is found to be rising, the simulated purchase is based on the actual closing price, but when the trend is found to be falling, the simulated sale is based on the day's closing price, and the rate of return is calculated.

Step 4: Design the investment strategies for different groups, and compare the rates of return of different investment strategies, as shown in Table 1, where they are divided into four groups (A–D). For example, without reference to the predicted value of the optimal ARIMA model, simulate buying and holding the game stocks based on the actual closing price synchronously with Step 3, and simulate the sale of all game stocks based on the day's closing price—as in Step 3—and calculate the rate of return.

Step 5: The control groups (C and D) are the monthly investment with unfixed quotas at fixed periods, which buy and hold at the beginning of the month and sell at the end of the month. With the buying strategy when the prediction score of the monitoring indicator reaches 22 or above, compare the rate of return with groups A and B, respectively.

Step 6: Finally, compare the rate of return and discuss the results.

In order to make readers more aware of the methodological framework of this study, we integrated the research flowchart in graphical form according to the mixed research steps of the above algorithm, as shown in Figure 1 (note: extended sample autocorrelation function (ESACF)):

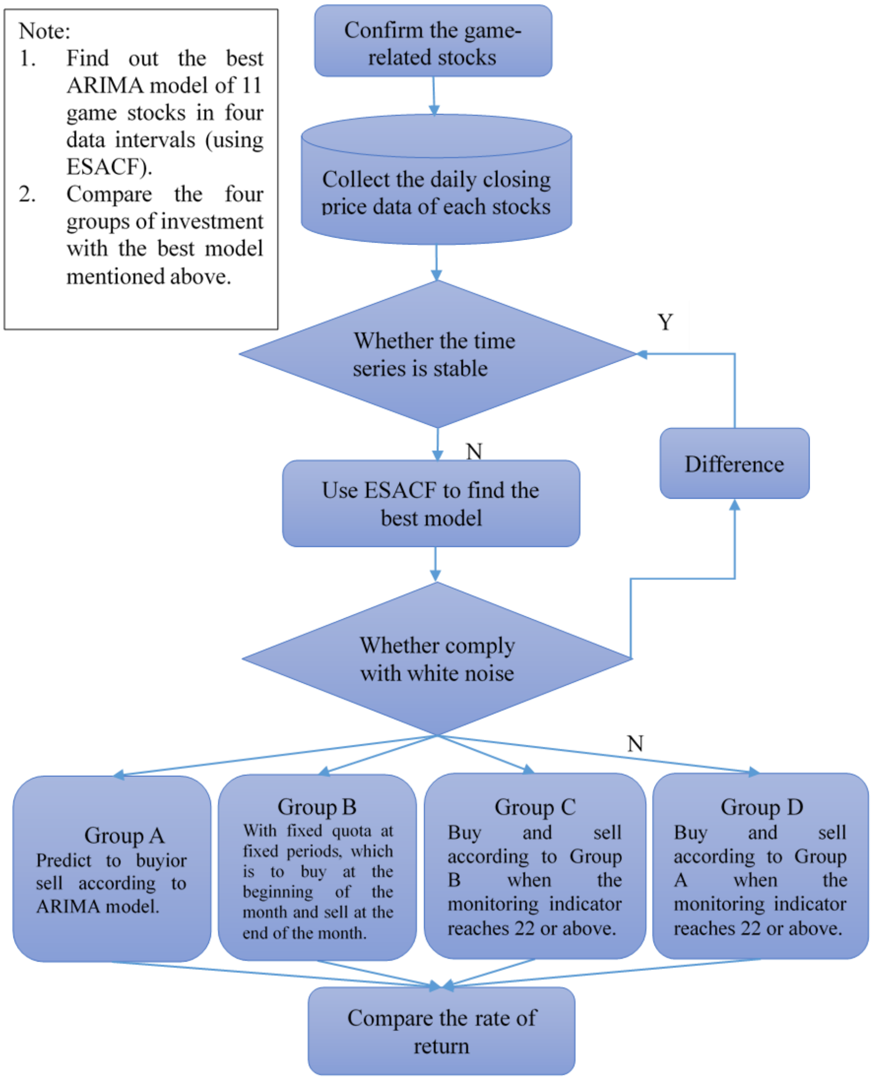

Figure 1. Research flowchart.

4.2. Investment Strategy Design Simulation and Example Illustration

We set up four different investment strategies of groups A–D, including experimental groups and control groups: (1) Groups A (the ARIMA traffic light strategy) and B (the strategy with fixed periods but with unfixed quotas) are the experimental groups, and the buying and selling conditions are set as follows: If the predicted value of the optimal ARIMA model falls into the 95% confidence interval of the actual value for n days in total, the actual closing price shall be changed every day to recalculate the predicted value for the next n days, and the decision can be made to buy, not act, or sell on the next day according to the rise or fall of the predicted value. (2) Group B is also an experimental group that buys at the beginning of the month and sells at the end of the month regardless of the rise or fall in the stock market. (3) Groups C and D are the control groups, which are the extension of groups A and B, respectively. Group C uses ARIMA to predict the score of the monitoring indicators over the next two months. When the score of a monitoring indicator reaches 22 or above, the group buys and holds at the beginning of the month and sells at the end of the month. (4) Group D uses ARIMA to predict the monitoring indicators over two months. When a monitoring indicator reaches 22 or above, group D adopts the same strategy as group A; that is, when ARIMA predicts the stock price rising, it buys, and sells when it predicts the stock price falling. Finally, the best investment strategy can be found by comparing the rate of return of each group during the simulated investment. The above investment strategy is described in detail in Table 1.

Table 1. Investment strategy description.

Investment Strategy	Condition	
	Buy	**Sell**
Group A: ARIMA strategy	Judge the trend by ARIMA: Rise -> buy	Rise -> hold
	Stable -> not buy	Stable -> hold
	Fall -> not buy	Fall -> sell
Group B: strategy with fixed quotas at fixed periods	Buy at the beginning of the month	Sell at the end of the month
Group C: strategy of monitoring indicators + fixed quotas at fixed periods	Buy at the beginning of the month when the indicator prediction reaches 22 or above	Sell at the end of the month
Group D: strategy of monitoring indicators + ARIMA	Judge the trend by ARIMA when the indicator prediction reaches 22 or above: Rise -> buy Stable -> not buy Fall -> not buy	Rise -> hold Stable -> hold Fall -> sell

In order to explain the four different investment strategies more clearly, groups A–D were designed, and an investment simulation was conducted for two months (i.e., July–August 2020), with six important directions as follows:

(1) Firstly, taking the stock of 6111 Softstar as an example, the optimal ARIMA prediction model (ARIMA (1,1,0)) was used to predict the number of days, and the predicted values fell within the 95% confidence interval for three days. Therefore, the prediction for the next three days was made every day as the basis for judging the trends of rise and fall.

(2) In group A, a simulation was conducted to buy and hold at the closing price of 1 July 2020. Since the predicted value of ARIMA showed a rising stock price from 2 July 2020 to 7 July 2020, it continued to hold until selling at the closing price when the predicted value fell on 8 July 2020.

(3) Group B bought on 1 July 2020 and sold on 31 July 2020.

(4) Groups C and D referred to the historical 10-year economic monitoring indicators (from July 2010 to June 2020), and used ARIMA to predict the indicator scores of July and August 2020. Using the optimal ARIMA (0,1,0) model, BIC = 1.829 and $p = 0.809$, we found that the score for July 2020 was 18, while that for August 2020 was 22, and 95% of the predicted values fell within the actual data range, as shown in Table 2. Therefore, group C had no trade in July 2020, buying and holding at the beginning of August 2020 and then selling at the end of the month.

(5) Group D had no trade in July 2020, and traded in August 2020 following the strategy of group A.

(6) Finally, we calculate the actual effects of the whole simulated investment strategy.

For a clear representation of the entire simulated trading process of 6111, the details are shown in Table A1 of the Appendix A (note: to reduce the length of the table and improve its appearance of the table, we included no trading dates for the stock market, and the results were designed according to the investment strategy. Those who do not buy or sell on the day are not shown in Table 2). From Table A1, if we take the 6111 Softstar stock experiment as an example, we can clearly see that the investment performance ranking is group D > group A > group C > group B. This information shows that for 6111 stocks, the hybrid ARIMA and monitoring indicator model is the best, followed by the ARIMA-based model.

Table 2. Comparison of the predicted values of the monitoring indicator and the actual price.

Year–Month	Score of Monitoring Indicator	Forecasting Value	95% Confidence Level
2020–06	19	19	True
2020–07	21	18	True
2020–08	26	22	True

5. Empirical Results and Performance Evaluation

Based on the implementation of the advanced hybrid ARIMA-based model, this section includes the empirical results—the establishment of the optimal model and accurate days, and the rate of return (ROR).

5.1. Empirical Results: Establishment of Optimal Model and Accurate Days

This study aims mainly to establish an advanced hybrid model based on ARIMA, which is an excellent prediction technique for the price prediction of game stocks. In the limited literature discussion, the above hybrid prediction model has never been used for the price prediction of game stocks. Therefore, this study has the benefits and advantages of certain technical methods and applications. In the construction of the advanced model, this study used four intervals of data subsets according to the process shown in Figure 1, with the following key points and highlights: (1) In terms of data collection, there were 11 main game stocks. The data period was from July 2014 to June 2020. (2) In the data experiment, the daily closing price of game-related stocks was applied to the advanced hybrid ARIMA-based model. (3) In the model verification, four different data intervals were used to measure the performance of the hybrid ARIMA-based model in combination with four groups of investment strategies, so as to determine the suitable investment models for individual game stock companies.

After the complete processing of the advanced hybrid ARIMA-based model, *MAE*, *MSE*, and *MAPE* were used to select the first 14 data of the listed game stocks in July 2020, along with the first 3 data of OTC game stocks in the same month. The above prediction data all fell within the confidence range of the actual closing price; among them, in order to reduce the length and the complexity of the chart, only the results of first three stocks were selected, as shown in Tables 3–5 and Figures 2–4. The experimental results can be summarized as follows: the determination of the optimal model is related to the length of the data interval. It can be seen that there are four companies with the best prediction effect in the half-year data interval: 3083, 3546, 4994, and 6111; there are three companies with the best results in the one-year data interval: 3293, 4946, and 5478; for the three-year term, there are three companies: 3086, 3687, and 6180; finally, the seven-year term has one company: 6169. Then, according to the predicted value calculated by the optimal model, it can be seen that the exact number of days (n) falling in the 95% confidence interval of the actual value is different. The exact number of days for 4994 is 14, while the exact number of days for the other stocks is 3. The different data intervals and optimal model experiment results for the 11 stocks are summarized in Table 6, which shows the white noise for $p > 0.05$. The experimental results show that there is no significant decision factor for the size of the data samples and the predicted results, and a smaller sample size may produce a better prediction effect.

Table 3. Comparison of the predicted and actual values of each data interval for 3083 Chinese Gamer.

Date	Actual Value	7-Year ARIMA(0,1,3)		3-Year ARIMA(0,1,1)		1-Year ARIMA(1,1,0)		0.5-Year ARIMA(0,1,0)	
		F.V.	95%	F.V.	95%	F.V.	95%	F.V.	95%
1 July 2020	93.0	90.65	True	90.56	True	90.48	True	90.70	True
2 July 2020	96.8	90.67	True	90.60	True	90.42	True	90.70	True
3 July 2020	95.1	90.66	True	90.64	True	90.41	True	90.70	True

Note: F.V. = forecasting value; 95% = 95% confidence interval.

Table 4. Comparison of the predicted and actual values of each data interval for 3086 Wayi.

Date	Actual Value	7-Year ARIMA(1,1,0)		3-Year ARIMA(0,1,3)		1-Year ARIMA(1,1,1)		0.5-Year ARIMA(0,1,0)	
		F.V.	95%	F.V.	95%	F.V.	95%	F.V.	95%
1 July 2020	18.30	18.70	True	18.52	True	18.61	True	18.42	True
2 July 2020	18.15	18.63	True	18.49	True	18.58	True	18.21	True
3 July 2020	18.70	18.71	True	18.52	True	18.56	True	17.99	True

Table 5. Comparison of the predicted and actual values of each data interval for 3293 IGS.

Date	Actual Value	7-Year ARIMA(0,1,0)		3-Year ARIMA(0,1,0)		1-Year ARIMA(0,1,0)		0.5-Year ARIMA(0,1,0)	
		F.V.	95%	F.V.	95%	F.V.	95%	F.V.	95%
1 July 2020	750	733.3	True	733.2	True	736.2	True	733.0	True
2 July 2020	817	733.6	True	733.3	True	739.4	True	733.0	True
3 July 2020	805	733.9	True	733.5	True	742.6	True	733.0	True

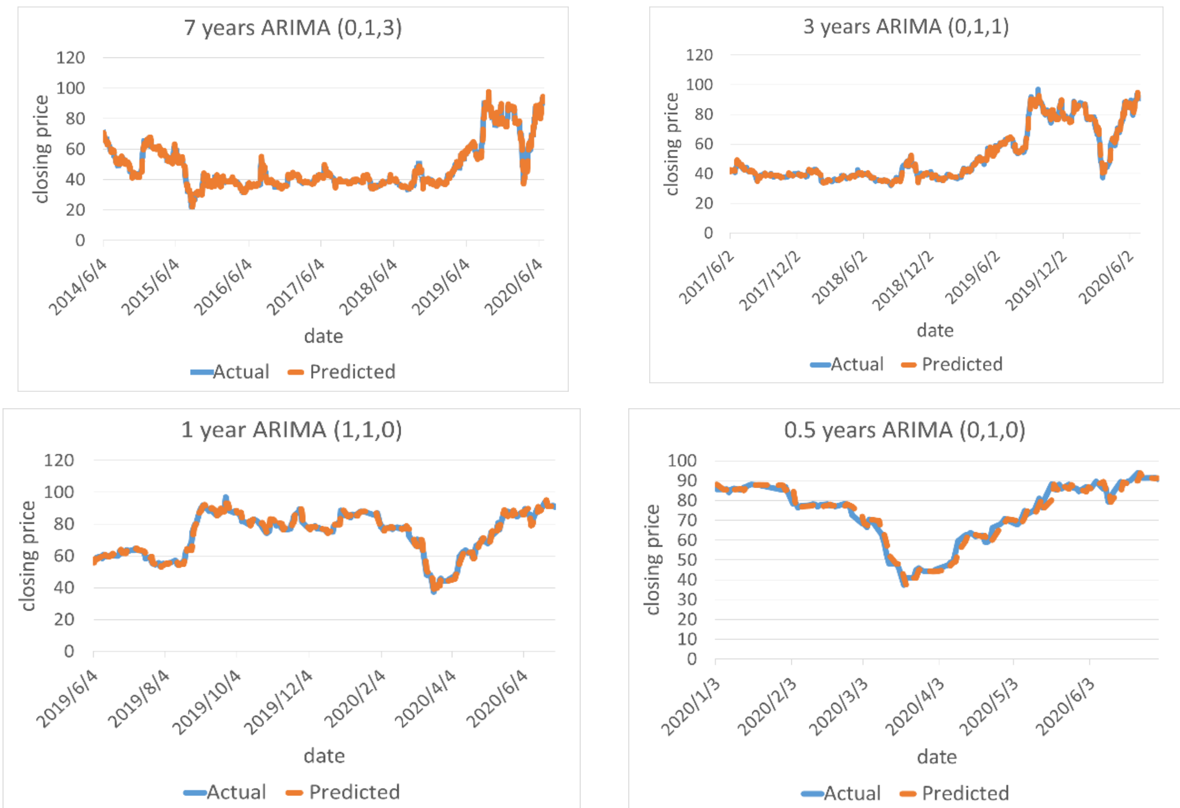

Figure 2. Prediction diagram of the optimal ARIMA models for 7, 3, 1, and 0.5 years for 3083 Chinese Gamer.

Figure 3. Prediction diagram of the optimal ARIMA model for 7, 3, 1, and 0.5 years for 3086 Wayi.

Figure 4. Prediction diagram of the optimal ARIMA model for 7, 3, 1, and 0.5 years for 3293 IGS.

Table 6. Comparison of the optimal ARIMA models in different data intervals.

Code	**7 Years**			**3 Years**			**1 Year**			**0.5 Years**		
	(p,d,q)	**BIC**	**W.N.**	**(p,d,q)**	**BIC**	**W.N.**	**(p,d,q)**	**BIC**	**W.N.**	**(p,d,q)**	**BIC**	**W.N.**
	MAE	***MSE***	***MAPE***	***MAE***	***MSE***	***MAPE***	***MAE***	***MSE***	***MAPE***	***MAE***	***MSE***	***MAPE***
3083	(0,1,3)	0.728	0.566	(0,1,1)	0.863	0.286	(1,1,0)	1.499	0.619	**(0,1,0)** *	1.880	0.256
	4.307	20.938	4.509	4.367	21.428	4.573	4.530	23.017	4.744	4.267	20.620	**4.467**
3086	(1,1,0)	1.295	0.117	**(0,1,3)** *	0.874	0.051	(1,1,1)	1.012	0.061	(0,1,0)	0.183	0.789
	0.297	0.130	1.628	0.247	0.065	**1.346**	0.293	0.100	1.604	0.297	0.174	1.594
3293	(0,1,0)	4.105	0.113	(0,1,0)	4.140	0.171	**(0,1,0)** *	5.383	0.253	(0,1,0)	6.043	0.903
	57.067	4096.550	7.089	57.367	4136.340	7.127	51.250	3366.470	**6.361**	57.667	4176.330	7.164
3546	(0,1,3)	1.417	0.216	(1,1,1)	1.462	0.186	(0,1,3)	1.771	0.366	**(3,1,3)** *	2.752	0.302
	1.903	5.295	1.985	2.027	5.651	2.115	1.720	4.299	1.794	1.557	3.266	**1.626**
3687	(0,1,2)	0.615	0.486	**(1,1,1)** *	0.095	0.172	(0,1,1)	0.815	0.368	(0,1,0)	1.356	0.538
	0.697	1.272	0.011	0.650	1.155	**0.010**	0.683	1.027	0.011	0.713	0.960	0.011
4946	(0,1,6)	0.535	0.675	(0,1,3)	0.503	0.326	**(0,1,2)** *	0.782	0.348	(1,1,1)	−0.980	0.270
	0.147	0.022	0.011	0.060	0.011	0.004	0.043	0.006	0.003	0.057	0.010	0.004
4994	(0,1,2)	1.673	0.715	(0,1,0)	0.733	0.477	(0,1,0)	1.539	0.477	**(2,1,0)** *	1.256	0.276
	2.440	6.590	0.035	2.317	5.853	0.033	2.317	5.853	0.033	2.032	4.400	**0.029**
5478	(0,1,0)	0.994	0.163	(0,1,0)	0.716	0.990	**(0,1,0)** *	0.828	0.904	(0,1,0)	1.665	0.497
	1.300	4.029	1.091	1.313	4.081	1.102	1.187	2.929	**0.998**	1.287	3.975	1.080
6111	(0,1,2)	2.581	0.061	(2,1,0)	2.800	0.478	(2,1,9)	1.964	0.873	**(1,1,0)** *	1.213	0.371
	2.810	11.476	3.308	2.673	10.530	3.146	3.117	12.137	3.685	1.853	4.080	**2.195**
6169	**(0,1,1)** *	0.179	0.866	(0,1,0)	0.564	0.217	(1,1,0)	0.839	0.369	(0,1,0)	1.489	0.308
	0.990	1.491	**1.617**	1.100	1.502	1.785	1.123	1.697	1.843	1.187	1.649	1.943
6180	(0,1,3)	0.617	0.625	**(1,1,3)** *	1.190	0.060	(2,1,1)	0.032	0.694	(0,1,2)	0.791	0.212
	1.410	2.544	0.019	0.980	1.352	**0.013**	1.233	2.147	0.016	1.423	2.329	0.019

Note: W.N. = white noise; * refers to optimal model, and the bold refers to *MAPE* value in optimal model.

5.2. Performance Evaluation of the ROR of the Models

Because the values of *MAE* and *MSE* are related to the prediction error, it is improper to use only *MAE* and *MSE* for cross-dataset comparison. Therefore, we also examined the value of *MAPE*. According to the findings of [39], if the value of *MAPE* is less than 10, the predictive model is classified as highly accurate. As shown in Table 6, the *MAPE* values of the best (optimal) models are between 0.003 and 6.361, all of which are below 10, indicating that these models have high predictive accuracy. Furthermore, since there are few studies using datasets of game catalog stocks in the Taiwan stock market for us to compare our findings with, we deemed it appropriate to design a simulation investment section for inclusion in this study to compare the ROR performance of strategies based on our models with those of other investment strategies. In doing so, we aimed to demonstrate our models' practical value and superior performance.

Among the 11 game stocks, there was one listed stock, along with 10 OTC stocks. In this study, the optimal ARIMA model was used to determine the accurate prediction days (n). The n of 4994 X-Legend was 14 days, while that of the other 10 stocks was 3 days.

Among them, only 3086 Wayi was trading on 11 of the 23 trading days of July 2020, and the trading on the other days was zero. In order to avoid distortion of the predictions, this stock was excluded from the performance comparison.

The predicted index scores of July and August 2020 according to 10-year indicator data were 18 and 22, respectively. Therefore, the simulated transactions of groups C and D did not buy in July 2020. Group C bought at the beginning of August 2020 and sold at the end of August. Group D traded following the ARIMA strategy in August 2020. The results of empirical simulation of 10 game stocks are shown in Table 7. On the whole, the performance of group D was better, followed by group C. In addition, two companies in group A had the best positive ROR: 3293 IGS and 6180 GAMANIA; 5478 Soft-World had the same ROR in both groups A and B, and there were eight companies with a negative rate of return in group A, while there were nine companies with negative rate of return in group B. Therefore, the overall assessment of ROR in group A was better than that in group B, mainly because the stock market price was down from July to August 2020. The ROR results are shown in Table 8, from which the following four important research results can be obtained: (1) In terms of the ROR of investment performance, the performance ranking is group D > group C > group A > group B. Thus, the strategy of the hybrid ARIMA model + monitoring indicators is superior to the individual ARIMA and monitoring indicator strategies. This is an important finding of this study, and validates the results of previous literature showing that hybrid models are superior to individual models. (2) Different game stock companies use different investment strategies, and there is no single strategy suitable for all. (3) Different game stock companies use different data ranges to predict future stock prices.

Table 7. Empirical results of groups A–D's investment strategies.

	Group A	**Group B**	**Group C**	**Group D**
Number of samples	10	10	10	10
Average rate of return	−8.92%	−21.96%	−6.97%	−4.77%
Standard deviation	5.70%	7.93%	5.31%	17.58%
Median	−5.48%	−18.83%	−3.95%	0.00%
Maximum value	20.44%	17.33%	18.80%	21.52%
Minimum value	−44.89%	−74.61%	−45.53%	−43.72%

Note: the shaded blocks indicate significant results.

Table 8. Group comparison table of ROR simulation of game stocks.

Code	**Data Range**	**Best-Fitting Model**	**A-RoR**	**B-RoR**	**C-RoR**	**D-RoR**
3083	0.5 years	ARIMA(0,1,0)	−7.79%	−50.59%	−19.30%	0.00%
3293	1 year	ARIMA(0,1,0)	20.44%	17.33%	18.80%	21.52%
3546	0.5 years	ARIMA(3,1,3)	7.13%	−20.37%	−4.33%	7.64%
3687	3 years	ARIMA(1,1,1)	−20.69%	−19.60%	−3.57%	−19.25%
4946	1 year	ARIMA(0,1,2)	−3.82%	−18.05%	0.00%	3.31%
4994	0.5 years	ARIMA(2,1,0)	−5.44%	−10.86%	2.07%	0.00%
5478	1 year	ARIMA(0,1,0)	−25.73%	−25.73%	−12.80%	−12.80%
6111	0.5 years	ARIMA(1,1,0)	−2.93%	−6.33%	−4.48%	1.11%
6169	7 years	ARIMA(0,1,1)	−44.89%	−74.61%	−45.53%	−43.72%
6180	3 years	ARIMA(1,1,3)	−5.52%	−10.83%	−0.59%	−5.57%
Sum			−89.24%	−219.64%	−69.73%	−47.76%

In addition, the *t*-test analysis of dependent variables shows that the average rate of return of groups A and B is significantly different (t (9) = 2.730, p = 0.023 *, d = 0.597), in that the average rate of return of group A is significantly higher than that of group B. There is no significant difference in the average rate of return between groups A and C (t (9) = −0.660, p = 0.526, d = −0.096). The average rate of return of group A is significantly lower than that of group D (t (9) = −3.137, p = 0.12 *, d = −0.188). The average rate of return of groups B and C is significantly different (t (9) = −4.843, p = 0.001 *, d = −0.650), with that of group B being significantly lower than that of group C. The average rate of return of group B is significantly lower than that of group D (t (9) = −3.488, p = 0.007 *, d = −0.609). There is no significant difference in the average rate of return between groups C and D (t (9) = −0.739, p = 0.479, d = −0.025). Table 9 shows the comparisons of the above *t*-test values and rates of return in each group.

Table 9. *t*-Test results of differences in rate of return.

Groups	Degree of Freedom	*t*-Value	*p*-Value
A:B	9	2.730	0.023 *
A:C	9	−0.660	0.526
A:D	9	−3.137	0.012 *
B:C	9	−4.843	0.001 **
B:D	9	−3.488	0.007 **
C:D	9	−0.739	0.479

*: $p < 0.05$; **: $p < 0.01$.

6. Conclusions

This section presents conclusions based on the experimental results, including the study's findings, contributions, and limitations, as well as future research direction.

6.1. Research Findings

After measuring the optimal ARIMA model for 11 listed (OTC) game stocks, this study has the following major findings: (1) The data interval of the optimal model is six months at most (for four companies), accounting for 36.37% of the total; there are three companies for the three-year and one-year intervals, and one company for the seven-year interval. According to the data interval and prediction results, it can be inferred that a shorter data interval may lead to a better prediction effect; that is, ARIMA is more suitable for short-term stock price prediction. (2) Empirically, for the optimal ARIMA model to predict the game stocks, the stock 3086 Wayi has too many non-trading days, and is therefore excluded. (3) According to the model prediction results of the four groups, *t*-test analysis of dependent variables shows that the average ROR of groups A (predicted to buy and sell based on ARIMA) and B (with fixed quotas at fixed periods) is significantly different. The average rate of return of group A is significantly higher than that of group B, which means that the ARIMA strategy is better than the strategy with fixed quotas at fixed periods as a comparison benchmark. There is no significant difference in the average ROR between groups A and C (the latter based on monitoring indicators + trade with fixed quotas at fixed periods), indicating that the effect of buying and selling based on the ARIMA model is similar to that of buying and selling based on the monitoring indicators, which also proves the applicability of the ARIMA model. (4) In addition, among the four strategies, the best ROR was found for group D—the strategy with the monitoring indicators and ARIMA model—indicating that the strategies using multiple hybrid models are superior to investment strategies using a single model.

6.2. Research Contributions

In terms of the contributions of this study, we must note four key points: (1) In terms of theoretical contribution, the empirical application of the ARIMA model in predicting the prices of Taiwan game stocks proves that ARIMA-based models can be applied to predict the short-term prices of Taiwan game stocks, and that there is no significant difference between the application of ARIMA models and the application of monitoring indicators. (2) In terms of academic contribution, this study provides an example of stock price prediction based on an advanced hybrid ARIMA model, which could be applied to the game stocks, and provides an effective reference index for subsequent research. (3) In terms of practical contribution, the investment strategies A and D of this study can provide reference for investors in game stocks. When an ARIMA model is used to predict the stock price trend, superior investment performance can be achieved. (4) In terms of application, the use of the proposed hybrid ARIMA-based model is rare, and it has not been applied for predicting the prices of game catalog stocks in the limited previous literature. Thus, this study yields a significant application contribution, providing managerial experience in exploring this fascinating issue for interested parties.

6.3. Research Limitations

In terms of research limitations, the following three aspects must be considered: (1) This study does not consider the costs related to stock transaction fees and dividends, and only calculates the ROR of stock price within the simulated time interval, which is limited to July and August 2020. (2) Retraining and retesting must be carried out if our model is applied to different data intervals for training or testing in different periods. (3) If the experimental results of this study need to be applied to different countries or different types of companies, retraining and retesting should also be carried out.

6.4. Future Research Directions

Although the results of this study have some academic and industrial significance, there are still several aspects that can be further strengthened. (1) This study only uses the ARIMA model to predict the price of game stocks. We recommend expanding the research on whether the ARIMA model is also applicable to the stock price prediction of listed (OTC) companies in other industries in the future, as well as comparing it with other investment strategies. (2) This study only takes game stocks in Taiwan as an example. Similar game stocks in different countries could be used as experimental datasets in the future to verify the applicability of the hybrid model. (3) In the future, different data intervals could be expanded to retrain the hybrid model.

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Appendix A The Entire Simulated Trading Process of 6111 Stock

Table A1. Calculation of simulated transactional ROR of 6111 Softstar in 2020 (ARIMA (1,1,0)).

			A	B	C	D	A	B	C	D
Date	**A.V.**	**F.V.**	**Buy/Sell**	**Buy/Sell**	**Buy/Sell**	**Buy/Sell**	**RoR**	**RoR**	**RoR**	**RoR**
1 July 2020	80.8	81.55 82.33 82.86	Buy	Buy						
8 July 2020	84.5	82.84 82.21 81.73	Sell				4.58%			
9 July 2020	82.9	84.98 85.25 85.37	Buy							
10 July 2020	80.1	81.78 80.97 80.38	Sell				−3.38%			
14 July 2020	82.8	84.97 85.38 85.62	Buy							
15 July 2020	81.3	81.76 81.03 80.49	Sell				−1.81%			
17 July 2020	82.1	81.74 81.78 81.75	Buy							
21 July 2020	80.2	78.36 77.26 76.45	Sell				−2.31%			
30 July 2020	80.2	80.78 81.76 82.36	Buy							
31 July 2020	79.3	80.80 81.15 81.33	Sell	Sell			−1.12%	−1.86%		
3 August 2020	78.2	78.92 78.70 78.55		Buy	Buy					
5 August 2020	80.9	80.51 80.60 80.55	Buy			Buy				
6 August 2020	80.2	81.12 81.12 81.04	Sell			Sell	−0.87%			−0.87%

Table A1. *Cont.*

			A	B	C	D	A	B	C	D
Date	**A.V.**	**F.V.**	**Buy/Sell**	**Buy/Sell**	**Buy/Sell**	**Buy/Sell**	**RoR**	**RoR**	**RoR**	**RoR**
24 August 2020	72.5	71.97	Buy			Buy				
		72.35								
		72.37								
25 August 2020	74.8	73.06	Sell			Sell	3.17%			3.17%
		73.13								
		73.05								
26 August 2020	75.8	75.44	Buy			Buy				
		75.55								
		75.50								
27 August 2020	74.9	76.03	Sell			Sell	−1.19%			−1.19%
		76.01								
		75.92								
31 August 2020	74.7	75.47		Sell	Sell			−4.48%	−4.48%	
		75.40								
		75.28								
			Sum				−2.93%	−6.34%	−4.48%	1.11%

References

1. WHO Coronavirus Disease (COVID-19) Dashboard. Available online: https://covid19.who.int/ (accessed on 15 June 2022).
2. TechNews. Available online: https://technews.tw/2020/04/24/the-global-game-industry-is-ushering-in-a-big-change/ (accessed on 24 April 2020).
3. Commercial Times. Available online: https://ctee.com.tw/news/tech/413127.html (accessed on 3 February 2021).
4. Mirror Media (a). Available online: https://www.mirrormedia.mg/story/20200611fin013/ (accessed on 18 June 2020).
5. Mirror Media (b). Available online: https://www.mirrormedia.mg/story/20200611fin011/ (accessed on 18 June 2020).
6. Beran, J. *Mathematical Foundations of Time Series Analysis*; Springer International Publishing: Cham, Germany, 2017. [CrossRef]
7. Štulajter, F. *Predictions in Time Series Using Regression Models*; Springer New York: New York, NY, USA, 2002. [CrossRef]
8. Mills, T.C. *Applied Time Series Analysis: A Practical Guide to Modeling and Forecasting*; Academic Press: London, UK, 2019.
9. Box, G.E.P.; Jenkins, G.M. *Time Series Analysis: Forecasting and Control*; Holden-Day: San Francisco, CA, USA, 1970.
10. Rubio, L.; Alba, K. Forecasting Selected Colombian Shares Using a Hybrid ARIMA-SVR Model. *Mathematics* **2022**, *10*, 2181. [CrossRef]
11. Samee, N.A.; Atteia, G.; Alkanhel, R.; Alhussan, A.A.; AlEisa, H.N. Hybrid Feature Reduction Using PCC-Stacked Autoencoders for Gold/Oil Prices Forecasting under COVID-19 Pandemic. *Electronics* **2022**, *11*, 991. [CrossRef]
12. Wu, J.; Chen, Y.; Zhou, T.; Li, T. An Adaptive Hybrid Learning Paradigm Integrating CEEMD, ARIMA and SBL for Crude Oil Price Forecasting. *Energies* **2019**, *12*, 1239. [CrossRef]
13. Hajirahimi, Z.; Khashei, M. A Novel Parallel Hybrid Model Based on Series Hybrid Models of ARIMA and ANN Models. *Neural Process Lett.* **2022**, *54*, 2319–2337. [CrossRef]
14. Kumar, R.; Kumar, P.; Kumar, Y. Multi-Step Time Series Analysis and Forecasting Strategy Using ARIMA and Evolutionary Algorithms. *Int. J. Inf. Tecnol.* **2022**, *14*, 359–373. [CrossRef]
15. Wu, D.; Wang, X.; Su, J.; Tang, B.; Wu, S. A Labeling Method for Financial Time Series Prediction Based on Trends. *Entropy* **2020**, *22*, 1162. [CrossRef]
16. Islam, S.; Sikder, M.S.; Hossain, M.F.; Chakraborty, P. Predicting the Daily Closing Price of Selected Shares on the Dhaka Stock Exchange Using Machine Learning Techniques. *SN Bus. Econ.* **2021**, *1*, 58. [CrossRef]
17. Shen, J.; Shafiq, M.O. Short-Term Stock Market Price Trend Prediction Using a Comprehensive Deep Learning System. *J. Big Data* **2020**, *7*, 66. [CrossRef]
18. Altarawneh, G.A.; Hassanat, A.B.; Tarawneh, A.S.; Abadleh, A.; Alrashidi, M.; Alghamdi, M. Stock Price Forecasting for Jordan Insurance Companies Amid the COVID-19 Pandemic Utilizing Off-the-Shelf Technical Analysis Methods. *Economies* **2022**, *10*, 43. [CrossRef]
19. Ghoddusi, H.; Creamer, G.G.; Rafizadeh, N. Machine learning in energy economics and finance: A review. *Energy Econ.* **2019**, *81*, 709–727. [CrossRef]

20. Shobande, O.A.; Akinbomi, M.D. Competition dynamics in Nigerian aviation industry: A game theoretic approach. *Future Bus. J.* **2020**, *6*, 11. [CrossRef]
21. Shobande, O.A.; Shodipe, O.T. Re-Evaluation of World Population Figures: Politics and Forecasting Mechanics. *Econ. Bus.* **2020**, *34*, 104–125. [CrossRef]
22. Eapen, J.; Bein, D.; Verma, A. Novel deep learning model with CNN and bi-directional LSTM for improved stock market index prediction. In Proceedings of the 2019 IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC), Las Vegas, NV, USA, 7–9 January 2019; pp. 264–270.
23. Shah, D.; Isah, H.; Zulkernine, F. Stock Market Analysis: A Review and Taxonomy of Prediction Techniques. *Int. J. Financ. Stud.* **2019**, *7*, 26. [CrossRef]
24. Rao, P.S.; Srinivas, K.; Mohan, A.K. A Survey on Stock Market Prediction Using Machine Learning Techniques. In *Machine Learning and Applications, Lecture Notes in Electrical Engineering 2020*; Kumar, A., Paprzycki, M., Gunjan, V., Eds.; Springer: Singapore; Volume 601, pp. 923–931. [CrossRef]
25. Pang, X.; Zhou, Y.; Wang, P.; Lin, W.; Chang, V. An innovative neural network approach for stock market prediction. *J. Supercomput.* **2020**, *76*, 2098–2118. [CrossRef]
26. Polamuri, S.R.; Srinivas, D.K.; Krishna Mohan, D.A. Multi-Model Generative Adversarial Network Hybrid Prediction Algorithm (MMGAN-HPA) for stock market prices prediction. *J. King Saud Univ.-Comput. Inf. Sci.* **2021**, *in press*. [CrossRef]
27. Noonan, K.; The Motley Fool. Best Video Game Stocks to Buy in 2022. Available online: https://www.fool.com/investing/stock-market/market-sectors/communication/video-game-stocks/ (accessed on 13 September 2022).
28. Euromonitor. Video Games in Taiwan. Available online: https://www.euromonitor.com/video-games-in-taiwan/report (accessed on 13 September 2022).
29. Statista. Video Games-Taiwan | Statista Market Forecast. Available online: https://www.statista.com/outlook/dmo/digital-media/video-games/taiwan (accessed on 13 September 2022).
30. Clement, E.P. Using Normalized Bayesian Information Criterion (Bic) to Improve Box-Jenkins Model Building. *Am. J. Math. Stat.* **2014**, *4*, 214–221. [CrossRef]
31. Christodoulos, C.; Michalakelis, C.; Varoutas, D. Forecasting with limited data: Combining ARIMA and diffusion models. *Technol. Forecast. Soc. Change* **2010**, *77*, 558–565. [CrossRef]
32. Cao, R. Stock investment planning and analysis-take listed bank stocks as an example. *Hsuan Chuang J. Manag.* **2004**, *1*, 1–16.
33. Chen, C. A Study for the Forecasting of the Closing Price for TAIEX Once Every Two Months. Master's Thesis, National Cheng Kung University, Tainan, Taiwan, 2006.
34. Almasarweh, M.; Wadi, S.A. ARIMA Model in Predicting Banking Stock Market Data. *Mod. Appl. Sci.* **2018**, *12*, 309. [CrossRef]
35. Tsai, P. Relationship Between Monitoring Indicator Score and Stock Price Index. Master's Thesis, National Chung Cheng University, Chiayi, Taiwan, 2014.
36. Chu, M.; Huang, C.; Tsai, M. The Study of Taking the Strategies of Dollar Cost Averaging and Value Averaging on Investing in the Leading Stocks Taiwan. *Manag. Inf. Comput.* **2014**, *3*, 458–466.
37. Huang, M.; Ma, K.; Chang, W. An Application Method and Empirical Performance Study on Individual Stock with Using Averaging Strategies-Evidences from Taiwanese Stock Markets. *Int. J. Commer. Strategy* **2019**, *11*, 307–334.
38. Lin, Y. Influence of Monitoring Indicator to the Price of Financial and Insurance Stocks. Master's Thesis, National Kaohsiung University of Applied Sciences, Kaohsiung City, Taiwan, 2016.
39. Lewis, C.D. *Industrial and Business Forecasting Methods: A Practical Guide to Exponential Smoothing and Curve Fitting*; Butterworth Scientific: London, UK, 1982.