Hybrid symbiotic organisms search feedforward neural network model for stock price prediction

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Abstract. The prediction of stock prices is an important task in economics, investment and financial decision-making. It has for several decades, spurred the interest of many researchers to design stock price predictive models. In this paper, the symbiotic organisms search algorithm, a new metaheuristic algorithm is employed as an efficient optimization method for training feedforward neural networks. The training process is used to build a better stock price predictive model. The Straits Times Index, Nikkei 225, NASDAQ Composite, S&P 500, and Dow Jones Industrial Average indices were utilized as time series data sets for training and testing the proposed predictive model. Three evaluation methods namely, Root Mean Squared Error, Mean Absolute Percentage Error and Mean Absolution Deviation are used to compare the results of the implemented model. The computational results obtained revealed that the hybrid Symbiotic Organisms Search Feedforward Neural Networks showed outstanding predictive performance when compared to the hybrid Particle Swarm Optimization Feedforward Neural Networks, Genetic Algorithm Feedforward Neural Networks and ARIMA based models. The new model is a promising predictive technique for solving high dimensional nonlinear time series data that are difficult to capture by traditional models.

Keywords: Stock price prediction; symbiotic organisms search algorithm; particle swarm optimization; feedforward neural networks, ARIMA.

1. Introduction

Stock market prediction is the act of trying to determine the future value of a company stock or other financial instruments traded on an exchange. Successful prediction of a stock's future price does not yield profit first but serves as a guide to investors who will use the prediction to guard their investments. The efficient-market hypothesis suggests that stock prices reflect all currently available information and any price changes that are not based on newly revealed information thus are inherently unpredictable [1]. Other schools of thoughts disagree, and these individuals rely on various methods and technologies to gain insight on future price information [2].

The value of a stock price is influenced by the earnings per share, firm’s book value, price earnings ratio and dividends per share. Although these factors are the fundamental units influencing the base stock price, the market also reflects a power over a specific stock price at any point in time. This is due to the constant pull and push of demand and supply within the market, this fluctuation may be due to trader’s personal preference, events portrayed by the news, strategic approaches to stock exchange or perceptions based on other traders behaviour. These fluctuations may be estimated based on past behavioural patterns of a particular stock to an extent. However, random events that force the stock to behave out of its norm are very difficult to predict. These occurrences are what experienced traders look for in maximising their profits. As such, any insight on these anomalies prove to be highly valuable to any trader within the market [3].

Traditionally, stock price forecasting has been carried out using time series analysis [4]. With the emergence of Artificial Neural Networks (ANNs), this form of analysis could be effectively performed at scale with higher levels of accuracy and accountability for un conceived variables [5, 6, 7]. Furthermore, non-hybridized time series models are outperformed by ANNs and Auto Regressive Integrated Moving Average (ARIMA) hybrids [8]. Evaluation of the prediction accuracy of these approaches are undertaken through the computation of the Root Mean-Squared Error (RMSE) and the Mean Absolute Percentage Error (MAPE). However, this evaluation should represent how much financial value each possesses, as such performance is measured by profitability, consistency and robustness [9].

In this paper, an efficient hybrid symbiotic organisms search (SOS) algorithm, which is combined with an artificial neural network is developed to solve the stock price prediction problem. The goals of this paper is therefore, to demonstrate the applicability of the SOS algorithm to train a machine learning technique in this case the ANN.
and to also show that the new hybrid method is able to obtain better predications when compared with other existing methods that have been applied to solve the same problem. To further validate the superior performance of the SOS algorithm, the ARIMA based model, Particle Swarm Optimization (PSO) algorithm, and Genetic Algorithm (GA), of which the last two are well-known global optimization metaheuristics are implemented in parallel to test the superior of the proposed hybrid SOS algorithm.

The rest of the paper is organized as follows: Section 2 presents related work, which involves using FFNN and hybrid models that consist of both metaheuristic algorithms and FFNN to perform stock price forecasting. The motivation and methodology of the proposed prediction approach and three other implementation models are discussed in Section 3. Section 4 presents the experimental results using recent time-series datasets. Finally, the concluding remarks is given in Section 5.

2. Related Work

In the past decade, the application of artificial intelligence and machine learning techniques such as ANNs have been used for the forecasting of Straits Time Indices (STI). Several literatures tend to focus on portfolio optimisation which is the act of selecting which stocks to invest your money in, given a finite capital and finite set of available stocks [10,11]. This however is not the focus of this study, although it is a main focus point when considering utilising machine learning techniques for optimising return on investment.

In [9], the use of multiple methods for the prediction of stock prices was investigated. The authors used the stock prices of five different companies which were obtained from Yahoo Finance. The four different forecasting methods investigated were: ARIMA model, ANNs, Holt’s Winters (a statistical forecasting method for seasonal time-series data) and time-series linear model (TSLM). It was found that the Holt’s Winters model produced the best overall forecasting accuracy compared to the other methods [9]. In [12], the SOS algorithm was proposed for training a feedforward neural network (FNN). The computational results from the training with SOS were compared to other results obtained from similar training of FNN using other metaheuristic search algorithms, such as the culture search(CS), genetic algorithm (GA), particle swarm optimisation (PSO), mean-variance optimisation (MVO), gravitational search algorithm (GSA), and biogeography-based optimisation (BBO). The results showed that the SOS trained the FNN the best for the task at hand [12].

The study conducted in [13] used both the PSO and backpropagation algorithm to train a FFNN for time-series forecasting. There were four types of time-series data used, these are sunspots (number of sunspots observed over a period of time), exchange-rate (the USD to INR exchange rate), earthquake (seismogram readings over time) and airline (the number of airline passengers). The results obtained were compared to results from other methods used to predict time-series data, such as the PSO-only trained FFNNs, backpropagation trained FFNNs, and the Box-Jenkins models (which are statistically based models for predicting time-series data). Experimentation from the study showed that the PSO-only models were notably better than the backpropagation only models and that the hybrid approach (PSO-backpropagation) was better than the Box-Jenkins models [13].

The feedforward neural networks variants proposed in [14] were used for stock market data (NAV of SBI mutual fund) prediction and evaluation of the performances of three different methods for adjusting the network weights during training: the resilient backpropagation method, the Levenberg-Marquardt (also referred to as Bayesian regularisation) method and the scaled conjugate gradient method. It was observed that the Bayesian regularisation method was the best at being able to generalise on the given data compared to the other training methods [14]. The study in [15] used the PSO algorithm to optimise the weights of an artificial neural network, which was used to forecast the exchange rate of the Straits Times Index (STI) time series data. The results obtained were very promising and interesting.

Therefore, building on the identified gap from the above related literature, the current study tries to replicate the earlier proposal made in [15] where the PSO algorithm was utilised for training neural networks. The current study, however, considers the employment of a more recent metaheuristic algorithm for the training of FFNNs with the main goal of building a more robust and efficient stock price predictive model. In the next section, two of the main algorithms that inspired the current work, namely SOS and PSO are briefly discussed. Thereafter, the implementations of four hybrid models including, SOSFFNN, PSOFFNN, GAFFNN, and ARIMA model are explained.

3. Motivation and Methodology

The symbiotic organisms search algorithm simulates the symbiotic interactions within a paired organism relationship that are used to search for the fittest organism [17, 30]. SOS iteratively uses a population of candidate
solutions to promising areas in the search space in the process of seeking the optimal global solution. In the initial
ecosystem, a group of organisms is generated randomly for the search space. Each organism represents one
candidate solution and is associated with a certain fitness value, which reflects the degree of adaptation to the
desired objective. The generation of new solutions is governed by three phases: the mutualism phase,
commensalism phase and parasitism phase. The nature of the interaction defines the main principle of each phase.
Interactions benefit both sides in the mutualism phase; benefit one side and do not impact the other in the
commensalism phase; benefit one side and actively harm the other in the parasitism phase. Each organism interacts
with the other organism randomly through all phases. The process is repeated until termination criteria are met.
Interested researchers are therefore referred to the work presented in [17] for an in-depth understanding of the
fundamental design concept and computational representation of the three SOS global optimization search phases.
Moreover, several applications of SOS and its improved variants exist in literature, where notable performances
of the algorithm are reported [23-29].

The SOS algorithm was chosen because it has never been applied to the stock price prediction problem, so it is
something new and will add value to the research in this field. Another reason for choosing SOS is that its
operations require no specific control parameter. There are many advantages of SOS that also factored into the
decision to consider this algorithm for the training of FFNN. The algorithm avoids the risk of compromised
performance due to improper parameter tuning. This is the case since the only parameters that need to be set are
the size of the population/ecosystem and the maximum number of evaluations. Other algorithms such as the
Genetic Algorithm (GA), Differential Evolution (DE), PSO, Mine Blast Algorithm (MBA), and Cuckoo Search
(CS) require the tuning of at least one more than one specific algorithm control parameters in addition to these two
parameters. The SOS algorithm uses three interaction strategies, mutualism, commensalism, and parasitism, to
gradually improve candidate solutions. This makes the algorithm simpler and quicker to implement since no time
needs to be spent on choice of operators. An organism (candidate solution) in this algorithm is represented by a
vector of size 2, where the values are the open and close stock prices for a company. This representation was
chosen since it is the easiest way to represent all the necessary data and to be able to manipulate the data to get
the best solutions.

The PSO algorithm used is the global best PSO hybridized with a neural network. In this algorithm the
neighborhood of each particle is the entire swarm. A swarm consists of a collection of particles, where each
each particle is a candidate solution. The particles are then evolved where each particle’s position and velocity are
changed according to its own experience and that of its neighbors. Each particle can communicate with every
other particle, and each particle is attracted to the best particle found by any member in the swarm. Each particle
is a point in an n-dimensional space and contains the set of all the weights in the neural network and the bias. The
algorithm stops when the maximum number of iterations has been reached. The position of the i th particle is
represented as \( x_i = (x_{i1}, x_{i2}, ..., x_{in}) \) and these components of position represent the individual weights and bias.
The velocity of the i th particle is represented as \( v_i = (v_{i1}, v_{i2}, ..., v_{in}) \). There are no operators as such for this
algorithm instead it uses a fitness function with updates of positions and velocities to find near optimal solutions.

The PSO algorithm has been chosen as a candidate competitive algorithm for the proposed SOS algorithm because
it is a common algorithm used for stock price predictions. It is a good algorithm to compare SOS with since the
results for the PSO implementation with neural networks has produced notable results for stock price prediction.
It does not use operators such as mutation and crossover which makes it simpler and easier to implement. The
search can be carried out by the speed of the particle. During the development of several generations, only the
most optimist particle can transmit information onto the other particles, and the speed of the searching is very
fast. The global best PSO model has been chosen since it converges faster than the I-best or the local best PSO
models. This is due to the larger particle interconnectivity of the global best PSO model. However, global best
PSO can easily be trapped in local minima, so more focus has to be given to exploration rather than exploitation
during training. This is done by changing the PSO parameters such as higher values for the maximum velocity
and inertia weight.

3.1. Modelling and program design

The model implementation for this study was coded in C# using Microsoft Visual Studio 2017 as the IDE. The
program has a GUI interface where each of the three hybrid algorithms and ARIMA model can be run and the
results displayed upon completion of the program run. The dataset used for training and testing contains data from
25 April 2015 to 25 April 2019 [16, 19, 20, 21, 22]. All the algorithms used the same dataset so that the
performance comparisons between the algorithms would be more meaningful. All the algorithms were run on the
same computer for 1000 iterations with a population size of 30. The details of the SOS, PSO, and GA with neural
network algorithms and the ARIMA model are presented next.
3.2. Hybrid symbiotic organisms search algorithm with feedforward neural networks

In order to improve the SOS algorithm, it is hybridized with a feed forward artificial neural network (FFNN). The idea of hybridizing SOS with a neural network was motivated by similar implementation method presented in [15], in which the PSO was hybridized with a neural network. Therefore, since hybridizing PSO with a neural network seemed to be a very common experience in the literature, it sparked interest on how SOS would perform if it was hybridized with a neural network. When it comes to stock price prediction there can be many companies involved and neural networks have good scalability to large datasets and work well with high dimensions. Neural networks also have the ability to model non-linear complex relationships and real-world stock market prediction is complex, so the application of neural networks will be beneficial. This hybridization works by using the SOS algorithm to train the neural network by finding the optimal weights and bias for the network in a similar way to the PSO algorithm was used to train FFNNs in [15]. The visual representation of the SOS and FFNN hybridized architecture is given in Figure 1.

![Fig. 1. Architecture of the feedforward network trained by the metaheuristic algorithms](image)

The neural network comprises of a single input layer with 2 nodes, a hidden layer with 8 nodes and an output layer with 2 nodes. A vector represents each organism or candidate solution. It contains the weights from the hidden layer to the output layer and the bias value for the network. This vector has a length of 34. The representation of the vector is illustrated as shown in Figure 2.

![Fig. 2. Solution representation for the hybrid algorithm](image)

A – weights linking the input layer nodes to the hidden layer nodes
B – weights linking the hidden layer nodes to the output layer nodes
C – the values for the bias

The algorithm is trained independently for each dataset comprising of 1259 instances. The dataset was split into 80% for training and 20% for testing. Thereafter, the data was normalized after the train-test split. A population size of 30 is used and the algorithm is run over 1000 iterations. The algorithm takes two inputs: the open value
and the close value for a stock and it predicts these two values for the next day. The RMSE is used as the fitness function in this algorithm since the goal is to minimize the error of the prediction, so an error formula is an appropriate fitness function. The proposed SOSFFNN algorithmic structure is shown in Algorithm 1, while the flowchart is illustrated in Figure 3.

**Algorithm 1:** Hybrid SOS with feedforward neural networks

1. Initialize a population of size 30, composing of individuals described in Figure 1 (above). Each cell of the individuals is randomly initialized to values that are between 0 and 1.
2. REPEAT for each individual in the population
   3. Initialize the weights of the neural network with the corresponding weights contained by the individual
   4. REPEAT for each training instance
      5. Input the instance in the FFNN to obtain an output
      6. Calculate RMSE for the output and the expected output
      7. END
   8. Calculate the Average of RMSE values which will serve as the fitness value of the individual
   9. END
10. REPEAT
11. Increase number of iterations by 1
12. REPEAT for each individual $X_i$ in the population
13. Set the best individual $X_{best}$ to the individual with the lowest fitness value
14. MUTUALISM PHASE
15. Select an individual $X_j$ randomly
16. Determine a mutual relationship vector $\text{Mutual\_Vector} = (X_i + X_j) / 2$
17. Determine the benefit factors $BF1$ and $BF2$, where the benefit factors are either 1 or 2
18. Modify $X_{i\_new}$ and $X_{j\_new}$ based on their mutual relationship
   $X_{i\_new} = X_i + \text{rand}(0,1) * (X_{best} - \text{Mutual\_Vector} * BF1)$
   $X_{j\_new} = X_j + \text{rand}(0,1) * (X_{best} - \text{Mutual\_Vector} * BF2)$
19. Calculate the fitness of $X_{i\_new}$ and $X_{j\_new}$ by using lines 3 to 8
20. IF $X_{i\_new}$ fitness value is less than $X_i$
21. Replace $X_i$ with $X_{i\_new}$
22. END
23. IF $X_{j\_new}$ fitness value is less than $X_j$
24. Replace $X_j$ with $X_{j\_new}$
25. END
26. END
27. COMMENSALISM PHASE
28. Select an individual $X_i$ randomly
29. $X_{\_new} \leftarrow X_i + \text{rand}(-1,1) * (X_{best} - X_j)$
30. Calculate the fitness of $X_{\_new}$
31. IF $X_{\_new}$ fitness value is less than $X_i$
32. Replace $X_i$ with $X_{\_new}$
33. END
34. END
35. PARASITISM PHASE
36. Select an individual $X_j$ randomly
37. Create a parasite ($X_{\text{parasite}}$) from $X_i$
38. Calculate the fitness of $X_{\text{parasite}}$
39. IF $X_{\text{parasite}}$ fitness value is less than $X_j$
40. Replace $X_j$ with $X_{\text{parasite}}$
41. END
42. END
43. UNTIL number of iterations are equal to 1000
3.3. Hybrid particle swarm optimization with feedforward neural networks

The second model implementation is the employment of the PSO hybridized with a feed forward neural network. The neural network consists of an input layer that has 2 nodes, a hidden layer that has 8 nodes and an output layer that has 2 nodes. The inputs are opening value for a stock and a closing value for a stock for a day. The network outputs the predicted opening and closing values for the stock for the next day. In this algorithm a swarm is initialized with 30 particles where each particle is represented by a vector of size 34 that holds all the weights for the network as well as the bias value. The swarm is also initialized with random velocities. The \( \min X \) and \( \max X \) values are set to -1 and 1. The fitness function used is RMSE so that the error between the predicted values and the actual values can be minimized. The positions and velocities are updated for every iteration. The inertia value is set at 0.9, the two constants \( c_1 \) and \( c_2 \) are both set at 2 and the probability of death is 0.01. The algorithm runs...
until the maximum number of 1000 iterations are reached. The best positions after the PSO is run provides the optimal weights for the neural network to be able to predict the output values.

3.4. Hybrid genetic algorithm with feedforward neural networks

The third model implementation is the Genetic Algorithm hybridized with a feed forward neural network. The operators used includes the Roulette Selection, Uniform Crossover with a crossover rate set to 0.5, and Uniform Mutation with a mutation rate set to \(1/(\text{Length of individual}) = 1/34\). The population comprised of 30 individuals that were randomly initialized, and each individual is a vector of size 34. Elitism was used in selection for the population for the next generation, where the best individual is kept for the next generation. The fitness function used for this algorithm is the RMSE because we aim to minimize the error between the actual and predicted values. This algorithm was allowed to run for a maximum of 1000 iterations, and the best individual served as the optimal weights for the neural network to predict the output values.

3.5. Autoregressive integrated moving average model

The fourth model is an Autoregressive Integrated Moving Average model. This implementation was done with an assistance of using the Extreme Optimization Numerical Libraries for .NET [18]. This library was built to assist developers to program financial, engineering and scientific applications. Two ARIMA models were used, one to forecast the Open Stock Values for each day and the other was to forecast the Close Stock Values for each day.

3.6. Evaluation metrics

A testing strategy that is used is the Mean Absolute Percentage Error (MAPE), which is a measure of the prediction accuracy of a forecasting method in statistics, for example in trend estimation. It is a very common testing strategy for stock price prediction algorithms and many organizations focus primarily on MAPE when assessing forecast accuracy. Most people are also more comfortable when dealing with percentage terms which makes this error easy to interpret. The formula is given in equation 1.

\[
MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|
\]  

(1)

where \(A_t\) is the actual value of the stock price and \(F_t\) the forecast value from the algorithm. The absolute value in this calculation is summed for every forecasted point in time and divided by the number of fitted points \(n\). Multiplying by 100% makes it a percentage error. A drawback of this method is that it cannot be used for data that has zero values since this could result in a division be zero error. This model is used nonetheless because it is highly unlikely that the price of a stock will be zero. Due to the pitfalls in MAPE, it is used in conjunction with other evaluation techniques like MAD. With MAPE the lower the percentage error the better.

Another common evaluation metric to test forecasting accuracy is the Root Mean Squared Error (RMSE). The RMSE is frequently used measure of the differences between values predicted by a model or an estimator and the values observed. This technique is used mainly when there is variance in the data, and it makes use of standard deviation which is good when it comes to mathematical operations. RMSE is the square root of the average of squared differences between prediction and actual observation. It expresses the average model prediction error in units of the variable of interest. The metric can range from 0 to infinity and is indifferent to the direction of error. The formula for RMSE is given in equation 2.

\[
RMSE = \sqrt{\frac{1}{n} \sum_{j=1}^{n} (y_j - \hat{y}_j)^2}
\]

(2)

where \(n\) is the number of values, \(y_j\) is the forecast and the variable \(\hat{y}_j\) is the mean error. Since the errors are squared before they are averaged, the RMSE gives a relatively high weight to large errors. This means that the RMSE should be more useful when large errors are particularly undesirable. RMSE avoids the use of taking the absolute value, which is not wanted in many mathematical calculations. It is a negatively-oriented score, which means lower values are better.

The last testing metric discussed is the Mean Absolute Deviation (MAD). Other than MAPE, MAD is the most popular metric for evaluating forecast accuracy. The mean absolute deviation of a dataset is the average distance between each data point and the mean. This strategy measures variance just like MSE but lacks the strong statistical relationship MSE has. MAD has the advantage of being easier to understand among people who are not
specialists in the field, and this is partly due to the fact that the error has the same dimension as the forecast. The formula for calculating MAD is represented in equation 3.

$$MAD = \frac{1}{T} \sum_{t=1}^{T} |e_t - \hat{e}_t|$$

(3)

where \(T\) is the number of time periods, \(e_t\) is the forecast error in period \(t\) and the last term denoted by \(\hat{e}_t\) is the mean error for period \(t\). The metric MAD is used in conjunction with MAPE to help overcome the pitfalls of MAPE and give a better overall view of the results. The three testing metrics are used to ensure that the error of the forecast can be seen using different evaluation to make it easier to determine which forecasting algorithm produces the best results. This combined evaluation technique allows for a better comparison between the algorithms, so that a more informed decision can be made.

4. Experimental Results

All the algorithms were run on the same MSI computer to allow for better comparison of the results. The computer specifications are indicated as follows: Processor: Intel® Core™ i7-7700HQ, CPU @ 2.80GHz, Installed Memory (RAM): 12.0 GB, Graphics Card (GPU): Nvidia GTX1050, System Type: 64-bit Operating System, x64-based processor Operating System: Windows 10 Home. Each algorithm was run 10 times and the average of the results was recorded. All the simulation results presented in this paper was generated using the stock price prediction GUI simulator shown in Figures 4 and 5. Similarly, an illustration example run of hybrid SOS with feedforward neural network is also in Figure 6.

4.1 Results and discussion

The dataset used in this research are the Straits Times Index [16], Nikkei 225 [19], NASDAQ Composite [20], S&P 500 [21], and Dow Jones Industrial Average [22] financial stock data. Three hybrid models, i.e. GAFFNN, SOSFFNN, and PSOFFNN were executed 20 times for each dataset. The ARIMA model in this case is used as the control predictive model, based on its popular adoptions in the literature. Different combination of parameters was investigated for the ARIMA model. The combination of parameters that achieved the best results across all
datasets were used to compare with the results of the hybrid metaheuristic models. The parameters of the ARIMA model are defined as follows: $p$ – the lag order, $d$ – the degree of differencing, $q$ – the order of moving average.

The results for each execution were evaluated using RMSE, MAD and MAPE. These evaluation metrics was applied to the open and close stock values independently. Thereafter, the final RMSE, MAD and MAPE values was calculated by taking the average evaluations obtained for the open and close stock values for each execution. Table 1 to 5 below displays the results obtained by the ARIMA model using different parameters on the above-mentioned datasets. Figure 6, shows the proposed system user friendly interface sample result generation for the developed standalone stock price prediction application framework. The test result is a generation from the Nikkei 225 data set using hybrid SOSFFNN algorithm.

![Stock Price Prediction](image)

Fig. 6. Stock price prediction user interface with a graph displaying the open values prediction forecast of the SOS hybrid model on the Nikkei 225 dataset

Table 1: Results of the ARIMA model with different parameters executed on the Straits Times Index (STI) dataset

| $(p, d, q)$ | RMSE   | MAPE   | MAD    |
|------------|--------|--------|--------|
| $(1, 0, 0)$| 0.51496| 726.47592| 0.47442|
| $(1, 0, 1)$| 0.47060| 679.52866| 0.43000|
| $(2, 0, 0)$| 0.47093| 679.88486| 0.43034|
| $(0, 0, 1)$| **0.27339**| **449.00106**| **0.23612**|
| $(0, 0, 2)$| 0.27285| 449.12424| 0.23544|
| $(1, 1, 0)$| 0.58764| 799.56756| 0.54576|
| $(0, 1, 1)$| 0.58756| 799.84806| 0.54567|
| $(1, 1, 2)$| 0.58765| 799.58167| 0.54577|
| $(2, 1, 0)$| 0.58779| 799.72292| 0.54591|
| $(2, 1, 2)$| 0.58763| 799.55608| 0.54574|
| $(2, 1, 1)$| 0.58765| 799.58166| 0.54577|
Table 2: Results of the ARIMA model with different parameters executed on the Nikkei 225 dataset

| (p, d, q) | RMSE          | MAPE                  | MAD            |
|-----------|---------------|-----------------------|----------------|
| (1, 0, 0) | 0.257656952   | 2357.559386           | 0.222398109    |
| (1, 0, 1) | 0.223440401   | 2179.917297           | 0.187451798    |
| (2, 0, 0) | 0.369366712   | 2862.846678           | 0.32351028     |
| (0, 0, 1) | **0.199942531** | **1468.738496**       | **0.163198376** |
| (0, 0, 2) | 0.199744769   | 1468.634883           | 0.163052049    |
| (1, 1, 0) | 0.328223844   | 2684.223466           | 0.28749196     |
| (0, 1, 1) | 0.328222336   | 2684.217399           | 0.287490387    |
| (1, 1, 2) | 0.328244527   | 2684.306579           | 0.287513567    |
| (2, 1, 0) | 0.32822739    | 2684.237797           | 0.28749565     |
| (2, 1, 2) | 0.328243377   | 2684.302004           | 0.287512356    |
| (2, 1, 1) |              |                       |                |

Table 3: Results of the ARIMA model with different parameters executed on the NASDAQ Composite dataset

| (p, d, q) | RMSE          | MAPE                  | MAD            |
|-----------|---------------|-----------------------|----------------|
| (1, 0, 0) | 0.255949      | 769.0082205           | 0.194733137    |
| (1, 0, 1) | **0.235651**  | 724.0124868           | **0.181368113** |
| (2, 0, 0) | 0.452104      | 1059.278054           | 0.37432056     |
| (0, 0, 1) | 0.36518       | 368.9350407           | 0.32365794     |
| (0, 0, 2) | 0.365181      | **368.9269246**       | 0.323462226    |
| (1, 1, 0) | 0.258114      | 772.5081537           | 0.196327618    |
| (0, 1, 1) | 0.258459      | 773.0649823           | 0.19658466     |
| (1, 1, 2) | 0.259033      | 773.993644            | 0.197013238    |
| (2, 1, 0) | 0.259202      | 774.2607697           | 0.197138868    |
| (2, 1, 2) | 0.258456      | 773.0491356           | 0.196583485    |
| (2, 1, 1) | 0.259133      | 774.1481284           | 0.197087301    |

Table 4: Results of the ARIMA model with different parameters executed on the S&P 500 dataset

| (p, d, q) | RMSE          | MAPE                  | MAD            |
|-----------|---------------|-----------------------|----------------|
| (1, 0, 0) | 0.20447068    | 1669.778185           | 0.156086969    |
| (1, 0, 1) | 0.442889447   | **652.305845**        | 0.401816475    |
| (2, 0, 0) | 0.259992093   | 1941.203308           | 0.196922849    |
| (0, 0, 1) | 0.390232405   | 801.2790239           | 0.355453868    |
| (0, 0, 2) | 0.3901787     | 801.2263174           | 0.35537639     |
| (1, 1, 0) | 0.203828916   | 1666.116668           | 0.155597012    |
| (0, 1, 1) | **0.203713539** | 1665.432994           | **0.155510929** |
| (1, 1, 2) | 0.204357768   | 1669.29952            | 0.155991186    |
| (2, 1, 0) | 0.204953521   | 1672.773333           | 0.156434643    |
| (2, 1, 2) | 0.204083968   | 1667.673622           | 0.155787515    |
| (2, 1, 1) | 0.204362647   | 1669.323426           | 0.155994957    |
Table 5: Results of the ARIMA model with different parameters executed on the Dow Jones Industrial Average dataset

| (p, d, q)   | RMSE         | MAPE          | MAD            |
|------------|--------------|---------------|----------------|
| (1, 0, 0)  | 0.199051     | 4912.181919   | 0.154297985    |
| (1, 0, 1)  | **0.190526** | 4531.451637   | **0.153318065**|
| (2, 0, 0)  | 0.291742     | 6146.048597   | 0.239788249    |
| (0, 0, 2)  | 0.394909     | **2107.870186**| 0.361829727    |
| (1, 1, 0)  | 0.200285     | 4947.555069   | 0.154654101    |
| (0, 1, 1)  | 0.200212     | 4946.549816   | 0.154600909    |
| (1, 1, 2)  | 0.200821     | 4955.118616   | 0.155047078    |
| (2, 1, 0)  | 0.201839     | 4969.060447   | 0.155820802    |
| (2, 1, 2)  | 0.200679     | 4953.147935   | 0.154942359    |

The ARIMA models with parameters p = 1, d = 0, q = 1 produced good results for all datasets. Table 6 presents the best result, average and standard deviation by the hybrid models for the STI dataset, and the result achieved by the ARIMA model for the STI dataset. The SOSFFNN model obtained the lowest RMSE, MAPE and MAD values. However, all algorithms achieved RMSE and MAD value very close to zero, indicating very small prediction error. Judging by the Average MAPE values, the SOSFFNN was the only algorithm that received a MAPE value that is below 100%.

Table 6: Results obtained by the various algorithm executed on the Straits Times Index (STI) dataset

|               | RMSE            | MAPE            | MAD             |
|---------------|-----------------|-----------------|-----------------|
| Best result   | PSOFFNN 0.098514582 | GAFFNN 0.08554277 | SOSFFNN 0.056947606 | ARIMA 0.27339 |
| Average       | 0.153291915     | 0.15695206      | **0.068066492** | 0.27339      |
| Standard Deviation | 0.036538728 | 0.03731014      | 0.009085544     | -             |

|               | PSOFFNN 140.70341544 | GAFFNN 68.6739057 | SOSFFNN 61.00968446 | ARIMA 449.00106 |
| Best result   |                      |                  |                  |                |
| Average       | 181.5528373         | 162.905379       | **79.4198888**   | 449.00106     |
| Standard Deviation | 90.60608094 | 54.4678486      | 31.70291803      | -             |

The SOSFFNN model also obtained the lowest RMSE, MAPE and MAD values on the Nikkei 225 dataset as seen in Table 7. The MAPE values for all algorithms are well above 100%, but the hybrid SOS algorithm received an average MAPE that is much lower than the other three models in this comparison. The MAPE values being above 100% simply means that the errors obtained are much greater than the actual values.
The hybridized PSO model best results on the S&P 500 dataset were the lowest amongst all other models, which can be seen above in Table 8. The best result received an MAPE value that was well below 100%, whereas the other model obtained MAPE values well above 100%. However, the SOS hybrid model achieved the best average results for RMSE, MAPE and MAD on this dataset. The results finding of the PSO hybrid model reveals that PSO can also achieve remarkable results with better parameter tuning, i.e. population size and number of max iterations. The RMSE and MAD values for all algorithms are close to zero, with the hybrid models obtaining values extremely closer to zero than compare to the ARIMA model.
Table 9: Results obtained by the various algorithm executed on the NASDAQ Composite dataset

|        | RMSE | MAPE | MAD  |
|--------|------|------|------|
|        | PSOFFNN | GAFFNN | SOSFFNN | ARIMA |
| Best result | 0.084575 | 0.081267 | 0.0847377 | 0.235651 |
| Average | 0.1700351 | 0.115943 | 0.1044186 | 0.235651 |
| Standard Deviation | 0.08755651 | 0.01794 | 0.0388474 | - |

More so, the PSO hybrid model was able to achieve the best result which was the lowest RMSE and MAD values for the NASDAQ Composite dataset as shown above in Table 9. However, these values were slightly lower than those values of the hybridized SOS algorithm. But, the hybrid SOS model best result for MAPE was the lowest amongst the rest, in fact it was the only MAPE value below 100%. Ultimately, the SOS hybrid model achieved the lowest average RMSE, MAPE and MAD results. Table 11 displays the results obtained by the different models on the Dow Jones Industrial Average dataset. The hybrid SOS model achieved the best results. All algorithms produced MAPE values well above 100%, but the SOS hybrid model produced the lowest amongst the others. The RMSE and MAD values are close to zero, hence indicating an achievement of low prediction errors.

Table 11: Results obtained by the various algorithm executed on the Dow Jones Industrial Average dataset

|        | RMSE | MAPE | MAD  |
|--------|------|------|------|
|        | PSOFFNN | GAFFNN | SOSFFNN | ARIMA |
| Best result | 0.079243065 | 0.0874652 | 0.07653209 | 0.190526 |
| Average | 0.188904686 | 0.1152931 | 0.09272649 | 0.190526 |
| Standard Deviation | 0.087414082 | 0.0184702 | 0.01034236 | - |

The forecast of next day predictions for both open and close stock values of each day are presented in Figures 7 to 26 for the different datasets. The y-axis depicts the normalized stock values (open/close), and the x-axis represents the different days in the chronological order. Figures 7 to 10 displays the predictions obtained by the various algorithms on the Straits Times Index dataset. The ARIMA model forecast in Figure 7 over predicts all the open and close stock values, whilst the hybridized models produced exceptional predictions shown in Figures 8 to 10. The hybridized models were able to successfully predict the fluctuation trends. However, Figure 10 shows...
the forecasts predicted by the SOS hybridized model. The predicted values received were the closest to the actual forecast values. Hence, it held the best average evaluation results amongst all models. The ARIMA model performed way better on Nikkei 225 dataset shown in Figure 11. The predicted values were much closer to the actual stock values, and it also shows some effort made to fit the actual forecast fluctuation trend. The hybridized approaches predictions in Figures 12 to 14 yet again displays remarkable performance achieved on the Nikkei 225 dataset. More so, the SOS hybrid model continued to produce outstanding predictions as shown in Figures 14. The predicted values appear to be sitting very closely to every true stock value.

The ARIMA model predictions in Figure 15 shows that its performance has dropped significantly when applied on the S&P 500 dataset. The hybridized models’ forecasts, in Figures 16 to 18, also showed some struggle in predicting the next day stock values, i.e. PSO hybridized model in Figure 17 under predicted the closing stock values by a substantial amount. The GA and SOS hybridized models produced fairly good forecast results as shown in Figures 16 and 18 respectively. Overall predictions on the S&P 500 dataset shows that the SOS model produced better predictions compared to the other algorithms. The ARIMA model forecast on the Dow Jones Industrial Average and the NASDAQ Composite dataset are displayed shown in Figure 19 and 23 respectively. These models attempts to output predicted values to follow the actual forecast fluctuations. Whilst, the remaining hybridized models were able to successful predict the fluctuation trends for both datasets. The SOS hybrid model displays the best results on both datasets as shown in Figures 22 and 26, with the GA hybrid model performance following behind. The PSO hybrid model forecast, in Figure 25, battled to predict the closing stock values on the NASDAQ Composite dataset. Therefore, the visual graph representation has shown that the hybrid SOS models are capable to predict excellent results on the various stock market datasets.

Fig. 7. Graphs displaying the open stock values (left graph) and close stock values (right graph) prediction forecast obtained by the ARIMA model on the Straits Times Index dataset

Fig. 8. Graphs displaying the open stock values (left graph) and close stock values (right graph) prediction forecast obtained by the GAFFNN model on the Straits Times Index dataset
Fig. 9. Graphs displaying the open stock values (left graph) and close stock values (right graph) prediction forecast obtained by the PSOFFNN model on the Straits Times Index dataset.

Fig. 10. Graphs displaying the open stock values (left graph) and close stock values (right graph) prediction forecast obtained by the SOSFFNN model on the Straits Times Index dataset.

Fig. 11. Graphs displaying the open stock values (left graph) and close stock values (right graph) prediction forecast obtained by the ARIMA model on the Nikkei 225 dataset.
Fig. 12. Graphs displaying the open stock values (left graph) and close stock values (right graph) prediction forecast obtained by the GAFFNN model on the Nikkei 225 dataset.

Fig. 13. Graphs displaying the open stock values (left graph) and close stock values (right graph) prediction forecast obtained by the PSOFFNN model on the Nikkei 225 dataset.

Fig. 14. Graphs displaying the open stock values (left graph) and close stock values (right graph) prediction forecast obtained by the SOSFFNN model on the Nikkei 225 dataset.
Fig. 15. Graphs displaying the open stock values (left graph) and close stock values (right graph) prediction forecast obtained by the ARIMA model on the S&P 500 dataset.

Fig. 16. Graphs displaying the open stock values (left graph) and close stock values (right graph) prediction forecast obtained by the GAFFNN model on the S&P 500 dataset.

Fig. 17. Graphs displaying the open stock values (left graph) and close stock values (right graph) prediction forecast obtained by the PSOFFNN model on the S&P 500 dataset.
Fig. 18. Graphs displaying the open stock values (left graph) and close stock values (right graph) prediction forecast obtained by the SOSFFNN model on the S&P 500 dataset.

Fig. 19. Graphs displaying the open stock values (left graph) and close stock values (right graph) prediction forecast obtained by the ARIMA model on the Dow Jones Industrial Average Index dataset.

Fig. 20. Graphs displaying the open stock values (left graph) and close stock values (right graph) prediction forecast obtained by the GAFFNN model on the Dow Jones Industrial Average Index dataset.
Fig. 21. Graphs displaying the open stock values (left graph) and close stock values (right graph) prediction forecast obtained by the PSOFFNN model on the Dow Jones Industrial Average Index dataset.

Fig. 22. Graphs displaying the open stock values (left graph) and close stock values (right graph) prediction forecast obtained by the SOSFFNN model on the Dow Jones Industrial Average Index dataset.

Fig. 23. Graphs displaying the open stock values (left graph) and close stock values (right graph) prediction forecast obtained by the ARIMA model on the NASDAQ Composite dataset.
Fig. 24. Graphs displaying the open stock values (left graph) and close stock values (right graph) prediction forecast obtained by the GAFFNN model on the NASDAQ Composite dataset

Fig. 25. Graphs displaying the open stock values (left graph) and close stock values (right graph) prediction forecast obtained by the PSOFFNN model on the NASDAQ Composite dataset

Fig. 26. Graphs displaying the open stock values (left graph) and close stock values (right graph) prediction forecast obtained by the SOSFFNN model on the NASDAQ Composite dataset

5. Conclusion

The hybrid SOSFFNN model was developed and tested based on the existing hybridization of PSO and FFNNs study. Additional comparison that involves the implementation of hybrid GA with FFNN and ARIMA model were carried out to further validate the superior performance of the hybrid SOSFFNN algorithm. The hybrid SOSFFNN outperformed hybrid PSOFFNN, GAFFNN and ARIMA model by noticeable margins. The shortcomings of the SOSFFNN has been identified to be attributed to the increased implementation complexity given by the combination of two already complex algorithms. Future improvements of SOS with FFNN could
include training on a much larger data set or data sets with much higher complexity levels. This could then be adapted to incorporate multi-objective parameters between relative stock prices that may influence another stock’s price. Finally, a model consisting of a FFNN with a hybridization that utilizes the SOS optimization algorithm shows promise in the area of stock price prediction and supersedes those of the PSO, GA, ARIMA model implementations. However, the added complexity of a FFNN may prove to be an area that requires greater fine-tuning to achieve a better predictive accuracy.

References

[1] Pownall, Grace, Charles Wasley, and Gregory Waymire. "The stock price effects of alternative types of management earnings forecasts." Accounting Review (1993): 896-912.
[2] Pai, Ping-Feng, and Chih-Sheng Lin. "A hybrid ARIMA and support vector machines model in stock price forecasting." Omega 33, no. 6 (2005): 497-505.
[3] Seetharaman, A., Indu Niranjan, Nitin Patwa, and Amit Kejriwal. "A Study of the Factors Affecting the Choice of Investment Portfolio by Individual Investors in Singapore." Accounting and Finance Research, no. 3 (2017): 153.
[4] Montgomery, Douglas C., Lynwood A. Johnson, and John S. Gardiner. Forecasting and time series analysis. New York etc.: McGraw-Hill, 1990.
[5] Refenes, Apostolos Nicholas, Achileas Zapranis, and Gavin Francis. "Stock performance modeling using neural networks: a comparative study with regression models." Neural networks, vol. 7, no. 2 (1994): 375-388.
[6] Schöneburg, Eberhard. "Stock price prediction using neural networks: A project report." Neurocomputing, vol. 2, no. 1 (1990): 17-27.
[7] White, Halbert. "Economic prediction using neural networks: The case of IBM daily stock returns." (1988): 451-458.
[8] Pai, Ping-Feng, and Chih-Sheng Lin. "A hybrid ARIMA and support vector machines model in stock price forecasting." Omega 33, no. 6 (2005): 497-505.
[9] Ponnam, Lakshmi Tharun, V. Srinivasa Rao, K. Srinivas, and Vamsi Raavi. "A comparative study on techniques used for prediction of stock market." In Automatic Control and Dynamic Optimization Techniques (ICACDOT), International Conference on, pp. 1-6. IEEE, 2016.
[10] Konno, Hiroshi, and Hiroaki Yamazaki. "Mean-absolute deviation portfolio optimization model and its applications to Tokyo stock market." Management science, vol. 37, no. 5 (1991): 519-531.
[11] Trippi, Robert R., Preface By-Lee, and K. Jae. Artificial intelligence in finance and investing: state-of-the-art technologies for securities selection and portfolio management. McGraw-Hill, Inc., 1995.
[12] Wu, Haizhou, Yongquan Zhou, Qifang Luo, and Mohamed Abdel Basseit. "Training Feedforward Neural Networks Using Symbiotic Organisms Search Algorithm." Computational intelligence and neuroscience 2016 (2016).
[13] Adhikari, Ratnadip, and R. K. Agrawal. "Hybridization of Artificial Neural Network and Particle Swarm Optimization Methods for Time Series Forecasting." International Journal of Applied Evolutionary Computation (IJAEC) 4, no. 3 (2013): 75-90.
[14] Jabin, Sauriya. "Stock market prediction using feed-forward artificial neural network." growth 99, no. 9 (2014).
[15] Junyou, Boo. "Stock Price forecasting using PSO-trained neural networks." In Evolutionary Computation, 2007. CEC 2007. IEEE Congress on, pp. 2879-2885. IEEE, 2007.
[16] Straits Times Index dataset
https://stooq.com/q/d/?s=%5ESti&c=0&d1=20140425&d2=20190425 [Last accessed 26 April 2019].
[17] Ezugwu, Absalom E., and Doddy Prayogo. "Symbiotic Organisms Search Algorithm: theory, recent advances and applications." Expert Systems with Applications (2018).
[18] https://www.extremeoptimization.com/Default.aspx. [Last accessed 12 December 2018].
[19] Nikkei 225
https://finance.yahoo.com/quote/%5En225/history?period1=1398463200&period2=1556229600&interval=1d&filter=history&frequency=1d [Last accessed 26 April 2019].
[20] NASDAQ Composite dataset
https://finance.yahoo.com/quote/%5EXIX/history?period1=1398463200&period2=1556229600&interval=1d&filter=history&frequency=1d [Last accessed 26 April 2019].
[21] S&P 500 dataset
https://finance.yahoo.com/quote/%5EGSPC/history?period1=1398463200&period2=1556229600&interval=1d&filter=history&frequency=1d [Last accessed 26 April 2019].
[22] Dow Jones Industrial Average dataset
https://finance.yahoo.com/quote/%5EDJI/history?period1=1398463200&period2=1556229600&interval=1d&filter=history&frequency=1d [Last accessed 26 April 2019]