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Review article

Applicability of genetic algorithms for stock market prediction: A systematic survey of the last decade

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A R T I C L E I N F O

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A B S T R A C T

Stock market is one of the attractive domains for researchers as well as academicians. It represents highly complex non-linear fluctuating market behaviours where traders, investors, and organizers look forward to reliable future predictions of the market indices. Such prediction problems can be computationally addressed using various machine learning, deep learning, sentiment analysis, as well as mining approaches. However, the internal parameters configuration can play an important role in the prediction performance; also, feature selection is a crucial task. Therefore, to optimize such approaches, the evolutionary computation-based algorithms can be integrated in several ways. In this article, we systematically conduct a focused survey on genetic algorithm (GA) and its applications for stock market prediction; GAs are known for their parallel search mechanism to solve complex real-world problems; various genetic perspectives are also integrated with machine learning and deep learning methods to address financial forecasting. Thus, we aim to analyse the potential extensibility and adaptability of GAs for stock market prediction. We review stock price and stock trend prediction, as well as portfolio optimization, approaches over the recent years (2013–2022) to signify the state-of-the-art of GA-based optimization in financial markets. We broaden our discussion by briefly reviewing other genetic perspectives and their applications for stock market forecasting. We balance our survey with the consideration of competitiveness and complementation of GAs, followed by highlighting the challenges and potential future research directions of applying GAs for stock market prediction.

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1. Introduction

The financial market tradings emerged from banking and money transactions to stock market investments and electronic currencies. It introduced a large number of interactivity within money-related transactions [1]. It also has a remarkable effect on the economy wherein, stock market tradings have exemplified several financial aspects. Trading can be considered as a buying and/or selling of instruments such as shares, securities, futures, commodities, to name a few. Careful market tradings can benefit the investors with high returns of their investments, however, trading may not be profitable in all instances; traders may also lose a large number of valuables in the share market. Such contrary behaviour and highly volatile nature of the stock market has attracted researchers, investors, and organizations to develop reliable stock market predictions.

Stock market forecasting primarily includes prediction of stock price and stock trend to derive future market expectations and risks; here, stock trend is the directional movement of stock prices that predicts whether the price would be higher or lower than the previous price value, i.e., whether the trend would be up or down, respectively. On the other hand, such risks can be distributed among various stocks in order to create a portfolio, which is expected to generate an overall profit; optimization of such a portfolio can be a challenging task [2]. Hence, market analysis can be a critical responsibility. The fundamental analysis considers qualitative market information such as organization profiles, strategies along with quantitative stock data information such as price indices, volume, etc. [3]; identification of potential trading using fundamental knowledge demands expertise whereas the technical analysis works with stock features and technical indicators. Prior work on stock market forecasting using computational intelligence largely covered various machine learning, deep learning, and data mining techniques along with opinion mining and sentiment analysis. For such a computation-based approach, selection of an appropriate method can be a major concern, followed by parameter tuning and features identification to enhance the prediction accuracy. Nature-inspired algorithms emerged as a branch, comprising of evolutionary algorithms such as genetic algorithm (GA), differential evolution (DE), as well as swarm intelligence-based methods such as ant colony optimization (ACO), particle swarm optimization (PSO), ant lion optimization (ALO), to name a few. These approaches are designed to computerize the problem-solving capabilities of nature. Various swarm and evolutionary algorithms have been applied to applications belonging to diverse domains [4–8] for algorithmic parameters optimization, feature selection from a large set of variables, classification, as well as near-optimal solution identification for highly complex problems. The potential applications of such approaches to financial domains such as financial crisis prediction using ACO [9], stock market prediction and portfolio optimization using PSO [2], etc. have also been observed. Hence, it is important to study the possible implications of such algorithms on stock market prediction. This article focuses on one of the evolutionary algorithms, GA, and its related perspectives in order to analyse its applicability to stock market forecasting. The rationale behind considering GA is its parallel search ability and treatment capability for complex optimization problems; it is able to address the limitations of neural networks (NNs) such as slow convergence and being stuck in local optima [10]. Hence, a dedicated review article is desirable to demonstrate how GAs can be adapted for financial forecasting. The presented survey addresses the following research questions (RQs) based on the integration of GAs for specific real-world problems associated with stock market prediction.

(RQ1): Why should genetic algorithm, as well as its related perspectives, be applied to stock market prediction?
(RQ2): How can genetic algorithms be integrated with various computational methods for stock market prediction?
(RQ3): What are the different ways in which other approaches can be hybridized with genetic algorithms for stock market prediction?
(RQ4): Which are the other metaheuristic approaches that compete with genetic algorithms and how competitive are they for stock market prediction?

This article provides an organized approach to study GAs, as well as other genetic perspectives, for a focused application on complex stock market forecasting. A systematic overview of this survey article using GAs for stock market prediction is as shown in Fig. 1 and potential solutions to the listed RQs are discussed in the following sections. Based on the no free lunch theorems, it has been proven that "no search algorithm is superior to any other algorithm on average across all possible problems" [11]. Thus, it is of critical importance to understand how GAs and their related genetic perspectives behave to solve the financial forecasting problems; our primary aim to conduct this survey is to understand how the search bias of GAs can be matched with the regularities and patterns present in stock market prediction problems.

1.1. Motivation

GA is said to be representing an efficient global approach for non-linear optimization problems [12]. As compared to random Monte

Acronyms

ACO	Ant Colony Optimization
ALO	Ant Lion Optimization
AMA	Adaptive Moving Average
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
APE	Average Percentage of Errors
ARIMA	Auto-Regressive Integrated Moving Average
ASONN	Adaptive Single-Layer Second Order Neural Network
BERT	Bidirectional Transformer
BGANN	Binarized Genetic Algorithm
BIST	Borsa Istanbul
BOA	Butterfly Optimization Algorithm
BPNN	Backpropagation Neural Network
BSE	Bombay Stock Exchange
CGP	Cartesian Genetic Programming
CLS	Conditional Least Square
CNN	Convolutional Neural Network
CNY	Chinese Yuan
CPNN	Condensed Polynomial Neural Network
CRO	Chemical Reaction Optimization
CS	Cuckoo Search
CSO	Cat Swarm Optimization
DB	Data Base
DC	Data Classification
DE	Differential Evolution
DGSPO	Diverse Group Stock Portfolio Optimization
DSE	Dhaka Stock Exchange
DT	Decision Tree
EFRiR	Evolutionary Fuzzification of Repeated Incremental Pruning To Produce Error Reduction, For Regression
ELM	Extreme Learning Machine
EMA	Exchange Market Algorithm
EMPNGA	Enhanced Multi-Population Niche Genetic Algorithm
ESAX	Extended Symbolic Aggregate Approximation
EUR	Euro
FAMR	Fractional Adaptive Mutation Rate
FFNN	Feed Forward Neural Network
FRBS	Fuzzy Rule-Based System
FS	Feature Selection
GA	Genetic Algorithm
GA-MSSR	Genetic Algorithm Maximizing Sharpe And Sterling Ratio
GD	Gradient Descent
GEP	Gene Expression Programming
GGA	Grouping Genetic Algorithm
GNP	Genetic Network Programming
GP	Genetic Programming
GSE	Ghana Stock Exchange
GWO	Grey Wolf Optimization
HAR	Heterogeneous Autoregressive
HS	Harmony Search
ICA	Imperialist Competitive Algorithm
ICSGA	Improved Cuckoo Search Genetic Algorithm
KB	Knowledge Base
KOSPI	Korea Composite Stock Price Index
LGP	Linear Genetic Programming
LSTM	Long Short-Term Memory
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MF	Membership Function
MINLP	Mixed-Integer Nonlinear Programming
MLP	Multi-Layer Perceptron
MOEA	Multi-Objective Evolutionary Algorithm
MOGP	Multi-Objective Genetic Programming
MSE	Mean Squared Error
NN	Neural Network
NYMEX	New York Mercantile Exchange
PD	Partial Description
PDGP	Parallel Distributed Genetic Programming
PG	Performance Gain
PNN	Polynomial Neural Network
PSO	Particle Swarm Optimization
RB	Rule Base
RBFNN	Radial Basis Functional Neural Network
RF	Random Forest
RIPPER	Repeated Incremental Pruning To Produce Error Reduction
RL	Reinforcement Learning
RMSE	Root-Mean-Square Error
RNN	Recurrent Neural Network
ROI	Return On Investment
RQ	Research Question
RS	Rough Set
SAHS	Self-Adaptive Harmony Search
SAW	Sentiment All-Weather
SAX	Symbolic Aggregate Approximation
SET	Stock Exchange of Thailand
SMA	Simple Moving Average
SMPT	Sentiment Modern Portfolio Theory
SO	Stochastic Oscillator
SONN	Second Order Neural Network
SSR	Sharpe And Sterling Ratio
STGP	Strongly Typed Genetic Programming
SVM	Support Vector Machine
SVR	Support Vector Regression
TMA	Triangular Moving Average
TPMA	Typical Price Moving Average
TSE	Taiwan Stock Exchange
USD	United States Dollar
VMD	Variational Mode Decomposition
VAR	Vector Autoregression

Carlo characteristics, GA has an advantage of the collected information during its sampling operations of the model space. It can be considered as a mechanism that inherits traits from the previously collected information; such approaches can be helpful to address complex optimization targets. The financial market prediction requires understanding the market behaviours for deriving inherent patterns. To

VRM	Vector Representation Model
VWAP	Volume Weighted Average Price
WMA	Weighted Moving Average
WNN	Wavelete Neural Network
WSA	Weighted Superposition Attraction
XGBoost	Extreme Gradient Boosting

attain reliable stock market forecasts, analysis of the available market data and suitability of the prediction approach(es) can play a vital role. The non-linear market behaviour demands adaptable methods to handle fluctuating data [13]. One of the evolutionary approaches, GA, is inspired by inherent parallelism while searching for the fittest solutions; such an approach can be favourable for complex time-series stock market data [14]. Generating a profitable prediction can be beneficial to investors as well as organizations. Various research articles demonstrate applications of different evolutionary computation techniques for financial optimization, however, the advances in genetic perspectives for the financial market demand a detailed study of the state-of-the-art.

In this article, we conduct a focused survey on GA-based stock market prediction approaches. Our primary motivation behind electing GA for such a designated survey is its heuristic search capabilities. Some of the inevitable reasons to adopt GA for various applications including stock market prediction can be listed as follows.

- Reliability and speed in solving difficult problems [15–17]
- Compatibility with current simulations and models [18]
- Search ability in trying to avoid local minima by searching several regions simultaneously [8,19]
- Extensibility [20,21]
- Adaptability to be used in combination with other algorithms [18]
- Not requiring gradient information [19]

The highly complex financial market forecasting can be a challenging task; while several events can influence the stock market, it is of critical importance to understand how the markets can be predicted. The nature-inspired GAs can provide a potential medium to prepare a compatible environment for the prediction model due to its search ability and evolution strategy. Also, GA encoding techniques can be helpful in formulating the given optimization problem. Other genetic perspectives include genetic programming (GP), gene expression programming (GEP), genetic network programming (GNP), to name a few; the variations in GAs along with related approaches have largely been explored for several real-world problems including financial market forecasting. As an extension of GA, GP is a systematic approach to transform the given computational aspects into programs using genetic operations in an iterative manner [22]. The evolutionary nature of GP can be utilized to address the non-linear price movements of the stock markets [23]; it can be adapted as a simulating mechanism for financial trading [24].

Subsequently, GEP can be viewed as an expression tree-based genome representation that is capable of adaptation and evolution [25,26]. It can be viewed as an adaptation of linear structures of GAs as well as tree structures of GPs [27], and hence, it can be further applied to various dynamic problems such as stock market prediction [28]. As compared to the string structure of GA and the tree structure of GP, a network-based genome representation has also been developed as a GNP for modelling dynamic environments [29]. For example, the trading rules can be iteratively updated based on the change in market behaviours which, in turn, can become beneficial for portfolio optimization [30,31]. Here, the re-usability of nodes provides compactness of structure; also, the history of node transitions can affect the current nodes and hence, it can serve as an implicit memory function that can be useful in addressing complex applications [32]. The characteristics of various genetic perspectives can be customized to develop computational approaches that can solve financial problems and thus, it serves as a primary motivation to apply GA, as well as its related perspectives, to stock market prediction (**RQ1**). In this article, we conduct a focused survey with GAs being the centre of interest to address various financial problems such as stock price forecasting, stock trend prediction, optimal portfolio identification, etc. and we discuss different ways in which GAs have been incorporated into financial market applications.

1.2. Survey Strategy

In this survey, we aim to cover the applications of GA in financial markets. To conduct a systematic survey, we carried out a step-wise strategy to collect a set of articles closely related to our main focus of this survey. We initialized our search with Google Scholar website with the search terms “stock”, “prediction”, and “genetic algorithm”. We restricted the articles between years 2013 and 2022 to ensure that the most recent advances could be collected. The search was further modified to include “stock price”, “stock trend”, and “stock market” terms individually with “prediction” as well as “forecasting” terms and the combination of such terms were given along with “genetic algorithm”. We also extended the search with “portfolio optimization” to cover the same as a potential GA application. Further, we detailed our search based on the way in which GAs were applied for specific stock market applications; for this purpose, we considered query terms such as “parameter tuning”, “parameter optimization”, “feature selection”, and “rule selection” to derive application-specific articles. We also searched with “hybrid”, “ensemble”, and “fusion” terms to derive a set of possible applications of GAs. Hence, the initial queries given to Google Scholar search engine were as follows.

- $(stock\ prediction)\ AND\ (genetic\ algorithm)$
- $(stock\ forecasting)\ AND\ (genetic\ algorithm)$
- $(stock\ price)\ AND\ (genetic\ algorithm)$
- $(stock\ trend)\ AND\ (genetic\ algorithm)$
- $(portfolio\ (selection\ OR\ optimization))\ AND\ (genetic\ algorithm)$
- $(stock)\ AND\ (parameter\ (optimization\ OR\ tuning))\ AND\ (genetic\ algorithm)$
- $(stock)\ AND\ ((feature\ OR\ rule)\ selection)\ AND\ (genetic\ algorithm)$
- $(stock)\ AND\ (genetic\ algorithm)\ AND\ (hybrid\ OR\ ensemble)$
- $(stock)\ AND\ (genetic\ algorithm)\ AND\ (fusion)$
- $(stock\ prediction)\ AND\ (genetic\ programming)$
- $(stock\ prediction)\ AND\ (gene\ expression\ programming)$
- $(stock\ prediction)\ AND\ (genetic\ network\ programming)$

It has been observed that the genetic-based computational developments are not only restricted to GAs; therefore, we repeated the search queries by replacing “genetic algorithm” term with “genetic programming”, “gene expression programming”, and “genetic network programming” terms for the said duration, i.e., 2013–2022. To provide a state-of-the-art survey, we also considered the competitiveness and complementation of GAs and therefore, we searched for articles having been discussing other swarm and evolutionary computation techniques along with GAs, such as “particle swarm optimization”, “butterfly optimization algorithm”, “ant colony optimization”, “harmony search”, etc. While a large number of optimization algorithms have been individually applied to stock market prediction, our main consideration with this survey is to demonstrate the significance of GAs and other genetic perspectives; to conduct a fair comparison, we ensured that the selected articles should have compared GAs with other metaheuristics for stock market applications. Among the searched and collected articles, further inclusion/exclusion criteria were also applied; it was observed that the considered search queries also retrieved results including other models based on housing price, oil price, electricity price, cutting-stock problem, to name a few. The applications of GAs

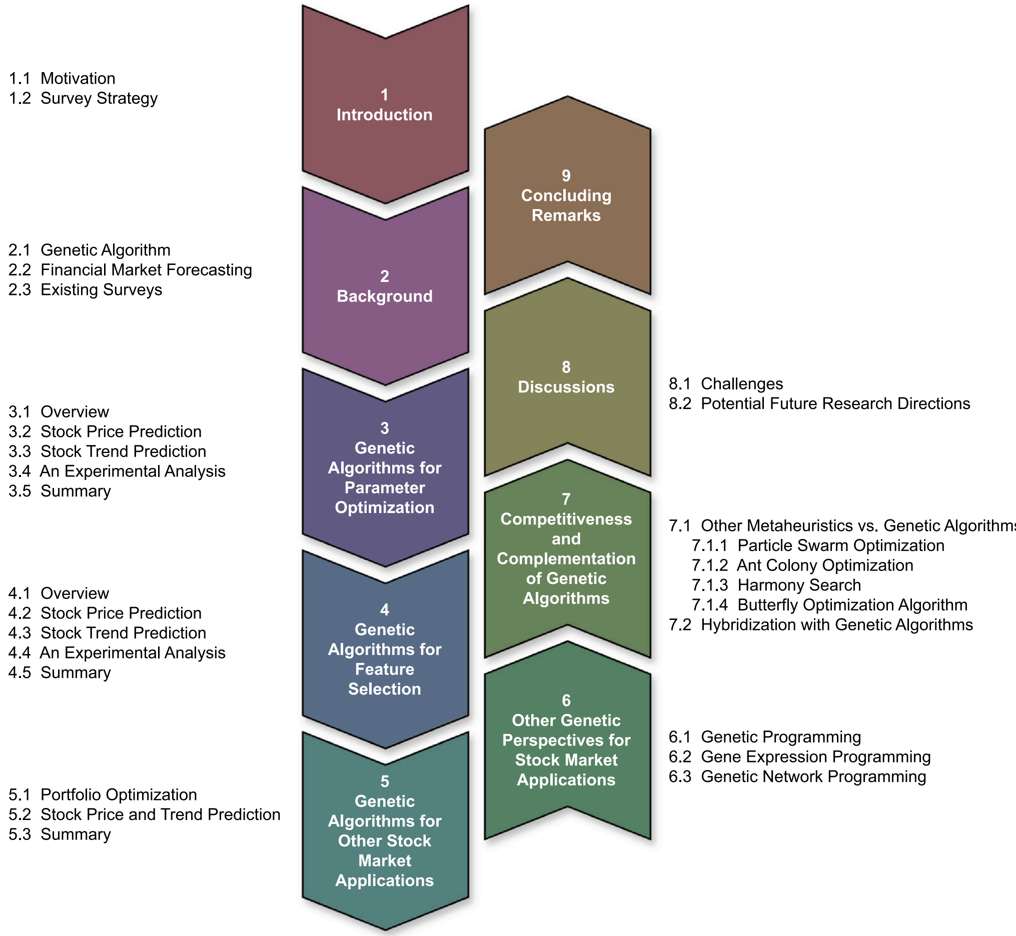

Fig. 1. A systematic overview of GAs for stock market prediction survey.

and related perspectives to markets other than stock market were excluded from our survey whereas the applications to financial market forecasting were included and categorized accordingly. Hence, our aim was to ensure that the articles having major relevance to our survey of interest were included and the articles having deviation from the rationale of conducting this survey were excluded. The final collection of articles were further categorized, reviewed, and included in the specific section of our survey. The year-wise percentage distribution of the considered research articles based on GA and genetic perspectives for various stock market applications in our survey is graphically represented in Fig. 2.

The remaining article is organized as follows: in Section 2, we provide a brief overview of GAs, broadly highlight some of the financial applications addressed using GAs, and showcase how our survey concentrates on stock market applications as compared to the existing surveys; we describe parameter optimization based on GAs and review existing stock price prediction and stock trend prediction-based approaches in Section 3; in Section 4, we discuss how GAs can be used for feature selection and review existing approaches based on stock price prediction and stock trend prediction; we extend our survey based on the applications of GAs for portfolio optimization as well as other financial market applications in Section 5; we explore stock market forecasting addressed using other genetic perspectives in Section 6; we balance our survey with the discussion on competitiveness of other swarm and evolutionary computation with respect to GAs, as well as complementation of GAs, in Section 7; in Section 8, we analyse challenges related to stock markets as well as potential future research directions; we conclude our survey in Section 9.

2. Background

Nature has inspired the development of various evolutionary algorithms. GA is one of the metaheuristics developed to computerize the natural selection procedure so as to generate near-optimal solutions [19]. Due to its ability to work within a dynamic and highly complex environment, many stock market-based forecasting techniques considered GAs for stock price and movement direction prediction [33, 34]. These broad fields can be further exploited based on GA applications such as parameter optimization, feature selection, and classification.

2.1. Genetic Algorithm

The natural selection is claimed to be "the only acceptable explanation for the genesis and maintenance of adaptation" [35]; it can be understood as survival and reproduction of individuals. GA was developed for large search spaces with a fitness objective. The parameter encodings, i.e., chromosomes, are presented in the form of strings that collectively create a population; it carries forward the principle of survival of the fittest and evolves using various genetic operations [36]. Motivation from the biological aspects introduces generation of new offsprings from the parent chromosomes using crossover and mutation operations.

GAs aim to continue evolving so as to attain the fittest possible solutions; the iterative steps of GAs, i.e., selection, crossover, and mutation, can be visualized using Figs. 3, 4, and 5, respectively. Here, for simplicity of understanding and clarity in visualization, the chromosomes of

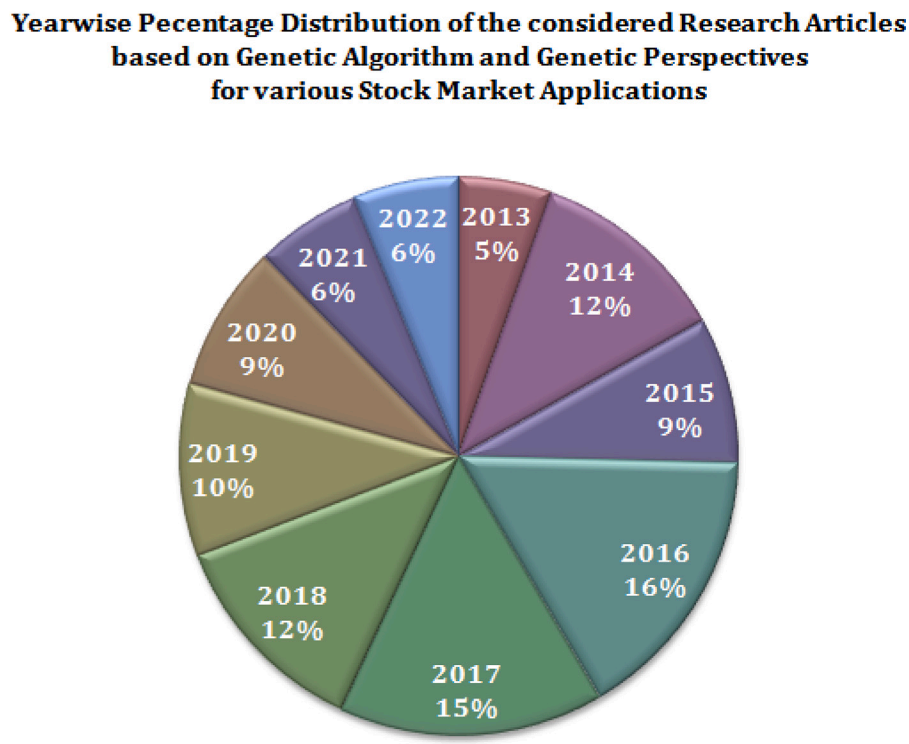

Fig. 2. A graphical representation of year-wise percentage distribution of the considered research articles in our survey.

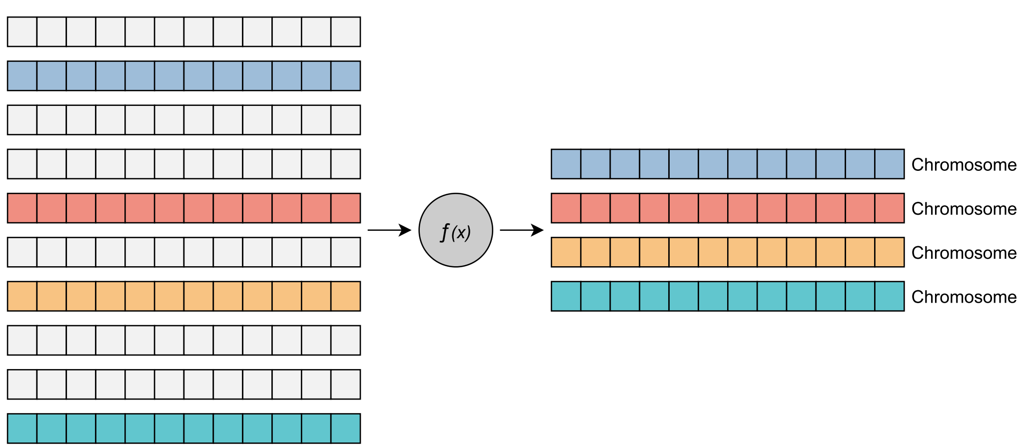

Fig. 3. An illustration of selection operation using genetic algorithm.

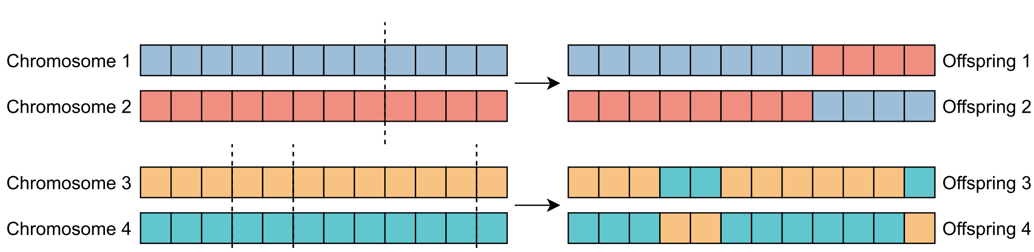

Fig. 4. An illustration of single-point and multi-point crossover operations using genetic algorithm.

interest are highlighted using four colour shades and the uniformity of representation is maintained to illustrate the operations. As it can be seen from the illustrations, the initial population may be selected randomly to represent chromosomes; these chromosome strings, also known as genotypes, are made up of values such that they can be potential solutions to the given problem. In order to select the parent chromosomes from the given population, a fitness function ($f(x)$) is chosen and each chromosome is evaluated to identify fittest solutions;

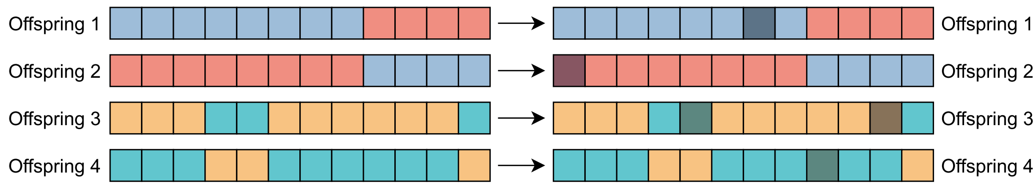

Fig. 5. An illustration of mutation operation using genetic algorithm. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 3 illustrates how chromosomes are selected based on their fitness values. A crossover operation is applied on the selected chromosomes in the next step; based on the way in which the crossover point(s) is(are) selected, the selected parent chromosomes are divided and genes of one chromosome are swapped with that of the other chromosome. In Fig. 4, the crossover points are demonstrated using vertical dashed lines; here, Chromosome 1 and Chromosome 2 present single-point crossover whereas Chromosome 3 and Chromosome 4 denote multi-point crossover. The new offsprings are generated and carried forward for the next step wherein mutation operation is performed. As shown in Fig. 5, certain genes can be mutated with a different value from the set of possible values; these mutated gene positions are illustrated in comparatively darker shades than their previous colours. The fitness of such mutated offsprings can be further evaluated based on the fitness function and a set of chromosomes can be selected to serve as parent chromosomes in the next generation. These operations can be repeated until the termination criterion is met and the fittest possible solution can be adopted for the given problem. It can be observed that through each generation, the genetic representation of the fittest chromosome can vary based on various operations; the randomly selected crossover point(s) can decide the swapping of respective parent strings during crossover whereas one or more points may be flipped or changed during mutation in order to maintain genetic diversity. These operations are performed for avoiding the algorithm to be trapped into local minima due to a large number of chromosome similarities [37]. While predicting through fluctuating stock market characteristics, the targetted approach requires to develop reliable predictions. Such predictions are likely to be influenced by algorithmic parameters, features, and operational aspects. Instead of manually selecting the model and its configurations, bio-inspired approaches can be adopted. Similarly, the natural selection ability of GA can be exploited to solve an optimization problem. It can be suitable for stock prediction because of its capacity to deal with the complexity of a large number of possible combinations [38]. The stock market complexities have attracted various researchers to resolve forecasting problems and GAs have been applied to financial market forecasting applications in distinguished manners. The following section broadly describes the extensibility of GAs to solve various financial problems. Also, it is essential to study the need for a state-of-the-art survey, majorly concentrated on GAs and their applications to stock markets; for this purpose, we review the existing surveys and showcase the importance of conducting this survey. We also provide a comparative discussion on the coverages of the existing surveys as compared to our survey article.

2.2. Financial Market Forecasting

Though our survey majorly focuses on GA-based stock price and stock trend prediction techniques, it is noteworthy to mention that a large number of related financial applications are also addressed using GAs.

In financial aspects, traders may desire to derive reliable predictions as well as interpretable rules that may be followed in order to gain profits from their investment. A time horizon structure, $(1, 5, 22)$, was found to be followed by different applications of heterogeneous autoregressive (HAR) models; it defined 1 day (daily), 5 days (weekly), and 22 days (monthly) trading frequencies for the developed market. Considering that traders belonging to different backgrounds may have diverse investment behaviours, authors proposed to optimize such time horizon structure using GA based on an adaptive HAR model of realized volatility [39]. Subsequently, an nth order fuzzy time-series forecasting model was developed in [40]; authors proposed to apply GA to select fuzzy lagged variables that could significantly explain fuzzy relationships. A recent application optimized fuzzy backpropagation neural network (BPNN) using GA to forecast Indonesian stock exchange composite index [41].

The company finances as well as operations can be analysed using financial ratios. In [42], authors categorized such ratios into liquidity, solvency, growth, cash-flow, operational, profitability, capital structure, and others to predict financial distress using a GA-based wrapper approach. Here, financial distress represented a company's economic inability to fulfil the debt requirements [43] which could be a crucial aspect associated with the financial markets. Similarly, bankruptcy can be a critical situation; it is based on the assessment of the ongoing financial status of the company and determination of the probability of a company facing bankruptcy. A GA-based two-step classification approach was proposed to forecast bankruptcy in [44]; authors proposed to use GA for feature selection of individual classifiers and performed weight-based classifier evaluation for prediction. One of the recent applications of GA was proposed for credit scoring for the financial industry [45]; authors proposed an enhanced multi-population niche GA (EMPNGA) and integrated for feature as well as classifier selection. Other potential application is portfolio optimization using GAs [46], stock usage optimization [47], to name a few. The augmented GA was considered with ANN for forecasting efficiency of monthly stock indices [48]; authors considered eight influential macroeconomic factors and seven commonly observed technical indicators as determinants in their proposed approach. One of the recent approaches integrated constrained gene representation of GA to identify the abnormal situations using outlier time points [49]; authors determined the anomalous time points associated with companies by applying an interpretability model for potential risk assessment. GA was also proposed for conducting a volume weighted average price (VWAP) trading [50]. The applications of GA was also extended to regularized Kalman filter for asset pricing models [51], to extreme gradient boosting (XGBoost) for determining the drift tendency of stock's cumulative abnormal return [52], to name a few. Hence, it can be observed that various optimization, as well as prediction problems of financial domains, are addressed using GAs.

The growing popularity of GAs in the field of solving problems from the financial domains requires a comprehensive survey on GAs, as well as various genetic perspectives; the following sections primarily concentrate on the applications of GAs for stock market forecasting applications, largely covering stock price prediction, stock trend prediction, and portfolio optimization. These sections address **RQ2** based on how GAs can be integrated with different computational approaches for parameter optimization, feature selection, trading rules, and other stock market applications. For the completeness of GAs associated with stock market-related problems, we also include how other swarm and evolutionary computation techniques can complement GAs through fusion, ensemble, and/or hybrid techniques (**RQ3**) and how GAs have a competition against other metaheuristics (**RQ4**).

2.3. Existing Surveys

For complex economics applications, a Pareto-optimal solution can be derived such that the state of the allocated resources cannot be modified without declining one or more criteria. The same can be desired while solving time-series data problems such as stock market prediction. While GAs are associated with a large number of research domains [53], a part of the existing literature reviewed various GA-based methods and their applications for different stock market-related prediction problems.

Various multi-objective evolutionary algorithms (MOEAs) including GA were studied in [54] for financial applications. Based on an evolutionary multi-objective optimization domain, authors considered portfolio optimization problems and other applications such as financial time-series, stock ranking, risk-return analysis, decision-support tools, and economic modelling. Also, potential fields for further research such as appropriate model discovery, data mining, stock price forecasting, as well as risk management were suggested. On the other hand, ANN variations were focused to review stock market predictions in [55]; authors also included GA-based ANN approaches to provide an introductory reviewed material using NNs for the stock market. Another survey on bio-inspired computing for stock market prediction included GAs along with other swarm and evolutionary computation techniques [56]. In [57], authors considered fundamental and technical analyses to analyse the existing forecasting methods; some of the limitations of such methods were identified as well as the need for considering influential input variables such as political and economic factors for reliable stock prediction was discussed. Subsequently, different finance and accounting applications that were addressed using NNs, fuzzy logic, and GA were analysed in [58] over the years 2007–2014; while stock exchanges and portfolio management-related work were significantly presented using computational intelligence, authors also discussed the limited development of hybrid methods for the same. Specifically for portfolio optimization, various techniques were surveyed in [46]; authors directed potential research towards suitable integration of fundamental and technical analyses as well as economical aspects. Other surveys on text mining-based financial market prediction over the years 2000–2016 [59] and time-series prediction [14] were conducted. A survey was dedicated to reviewing diverse applications of GAs in operation management tasks including some of the financial aspects over the years 2007–2017 [60]. Two of the recent surveys were conducted on stock market forecasting based on prediction as well as classification techniques over the years 2010–2018 [61] and based on computational intelligence [62]; though the coverage of topics in these articles were dedicated to stock prediction, a little attention was given to the genetic perspectives. Thus, it is essential to conduct a systematic survey on the applicability of GAs for stock market prediction.

Table 1 demonstrates a comparative analysis of our survey with the existing surveys related to GA and its application to the financial market; various criteria include development of genetic perspectives such as GA, GP, GNP, and GEP in existing surveys along with the year-wise coverage in respective surveys; review of different stock market applications such as price or trend prediction; approaches such as parameter optimization, feature selection, and hybrid techniques, as well as other related aspects in the stock market prediction. Based on GAs and Darwinian approaches, several financial applications including market forecasting were surveyed in [33]; this survey covered articles till year 2015. Subsequently, a bibliometric analysis of GAs was conducted in [53]; also, operational management applications of GAs were reviewed in [60]. Hence, a focused survey on the recent updates, as well as limitations and future directions for GA-based stock price and stock trend prediction requires attention. Therefore our survey primarily focuses on the recent implications between years 2013 and 2022 for GA-based stock market prediction. We believe this concise survey can be useful to study genetics-based evolutionary methods and their applications in the financial markets.

Table 1
Comparative analysis of our survey with existing stock-related surveys based on GA under various criteria: C1 — Genetic algorithm (GA), C2 — Parameter optimization, C3 — Feature selection, C4 — Rule selection, C5 — Stock price prediction, C6 — Stock trend prediction, C7 — Portfolio optimization, C8 — Genetic programming (GP), C9 — Gene expression programming (GEP), C10 — Genetic network programming (GNP), C11 — Other approaches.

Criteria (→) Reference (↓)	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
[54]	✓	✓	✓			✓	✓	✓			
[55]	✓		✓			✓					
[56]	✓	✓	✓		✓						✓
[57]	✓			✓		✓	✓				
[58]	✓		✓			✓	✓	✓			
[46]	✓		✓					✓		✓	
[59]	✓	✓						✓			
[14]	✓	✓	✓					✓			
[60]	✓	✓					✓				
[61]	✓			✓	✓						
Our survey	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

3. Genetic Algorithms for Parameter Optimization

The representative facilities provided by GAs can be extensively adopted by various applications. The chromosomes can be designed to address one of the major concerns in prediction models, i.e., parameter optimization. In this section, we briefly illustrate how GAs can be integrated for tuning and optimizing the parameters; we also review the potential ways in which GAs are adapted for parameter optimization in the field of stock price and stock trend prediction.

3.1. Overview

In computational approaches, selection of the model parameters is a crucial task; a set of parameters can largely affect the performance of the given model [63]. The initial parameter values can be randomly selected or combinations can be made using greedy algorithm [64]. In contrast to random or time-consuming greedy search-based approaches, an adaptive, population-based heuristic search algorithm can be integrated to optimize parameters of the prediction model. GAs are applied to a wide range of forecasting model architectures where parameter-tuning plays a vital role. Here, the chromosomes are designed to represent the given parameter(s); these values can be in the form of binary or real-valued numbers that undergo selection, crossover, and mutation operations. The selection of the parent chromosomes are based on the defined fitness function and new offsprings are generated through iterations. To provide an illustrative representation of chromosomes that present sets of parameters, for example, we consider binary-encoded random strings and demonstrate GA operations using Figs. 6, 7, 8, and 9; here, we take an example of a set of three parameters, presented in binary values, however, real-valued parameters, as well as different number of parameters, can be represented similarly.

As it can be viewed from Fig. 6, the considered binary strings, i.e., chromosomes, are representations of parameters; these chromosomes further undergo crossover and mutation operations as shown in Figs. 7 and 8, respectively, and generate new offsprings. The newly generated offsprings can be similarly presented in the form of sets of parameters as given in Fig. 9; comparison of the same with parameter values before GA operations (Fig. 6) indicates that certain values are modified after one generation. The fitness of these offsprings can be evaluated against the given fitness function and a set of fitter solutions can further serve as parent chromosomes. This process can be carried out until the given termination criterion is met and hence, a set of parameters are derived in the form of the fittest chromosome. The same can be adapted to optimize parameters of various models. While financial markets are largely associated with historical time-series data and an enormous number of ongoing events, identification of appropriate parameters for the considered model and optimization can be carried out using GA.

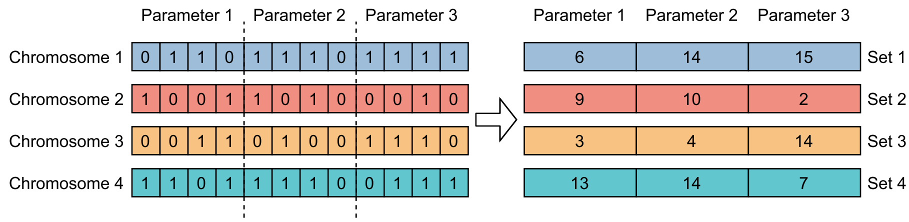

Fig. 6. An illustrative representation of binary-encoded parameter sets after selection using genetic algorithm.

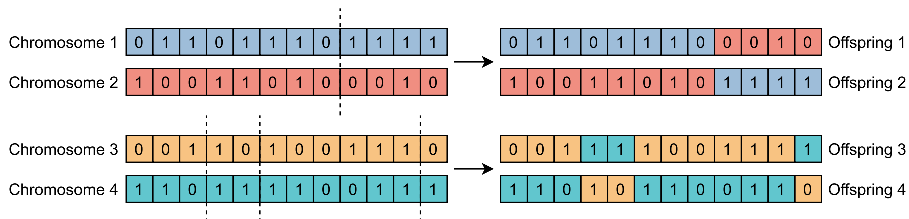

Fig. 7. An illustrative crossover operation between binary-encoded chromosomes using genetic algorithm.

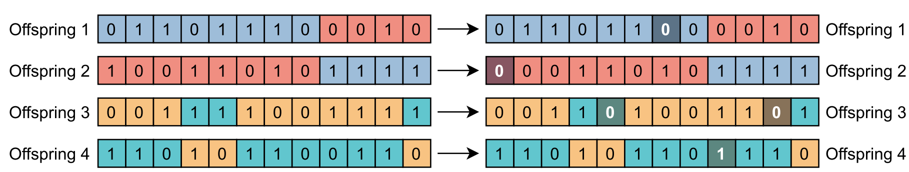

Fig. 8. An illustrative mutation operation within binary-encoded offsprings using genetic algorithm.

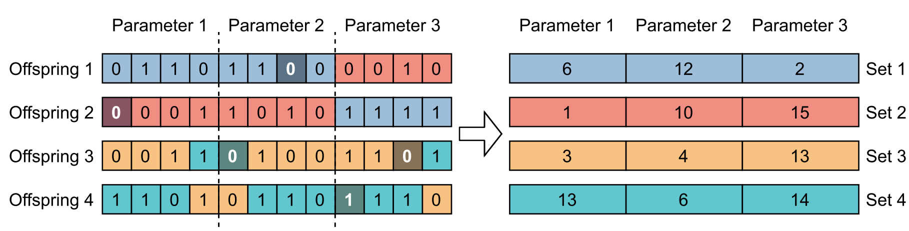

Fig. 9. An illustrative representation of binary-encoded parameter sets after genetic algorithm operations.

3.2. Stock Price Prediction

The stock market provides an opportunity to trade over multiple exchanges; basic information of a specific stock for the trading day generally provides the open and close prices, the highest and the lowest prices attained, and a total number of tradings carried out, i.e., volume. Various technical indicators, for example, simple moving average (SMA), stochastic oscillator (SO), etc. can be derived using such information to analyse the market perspectives. To predict stock price for a short-term period (e.g., inter-day, one-day-ahead), as well as a long-term period (e.g., weekly, monthly), GAs have been adopted in different approaches. GA can be integrated to tune parameters of the prediction models. Considering it as one of the major applications of GAs, we discuss how the ability and compatibility of GAs can be extended for solving complex problems such as stock price prediction.

ANNs have been largely used for stock price prediction. ANN parameters such as neuron weight, bias value, number of hidden layers and number of neurons in each hidden layer can be varied to construct an optimal configuration for the prediction. An automatic design of ANN was carried out using GA, DE, as well as estimation of distribution algorithms (EDA) for several time-series data in [65]; one of the datasets was Dow-Jones industrial average (DJIA) wherein the integration of GA was demonstrated to perform well. Another application of GA was demonstrated with fuzzy time-series in [66] to predict stock prices as well as trend. A collaborative combination of ANN and GA was proposed in [19] with United States dollar (USD) market price, gold coin bubbling price, world price of an ounce of 24 carat gold, and OPEC oil price to be independent network input variables whereas Tehran stock exchange index as a dependent variable. For a hyperbolic tangent sigmoid activation function of ANN, GA with tournament selection and root-mean-square error (RMSE) fitness function, as given by Eq. (1), was adopted to optimize network parameters.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}{N}} \tag{1}$$

where, y_i and $\hat{y}_i$ indicated the actual value and output value of the ith data, respectively; N represented the total number of data wherein the results indicated less than 5% prediction error. Similarly, a GA-based ANN approach was proposed by considering a large number of oscillations experienced by the time-series data [67]. The average data fluctuations for the previously observed days were considered and connection weights were optimized using the neighbourhood replicator; the discretized features were given as inputs to ANN for Dhaka stock exchange (DSE). Some of the drawbacks of a multi-layer perceptron (MLP) such as slow convergence, higher computational overhead, or larger memory requirements could be targetted using a higher order NN approach [68]. The results derived for predicting the last traded price, the lowest price, and the highest price were improved; also, the weekly prediction for last traded price attained an average error rate of 1.038 [67]. One of the recent approaches applied GA to optimize the weights of a feed forward neural network (FFNN) [69]; the optimized model was further used to predict the stock close price.

An adaptive single-layer second order neural network (ASONN) was proposed for one-day-ahead stock close price prediction [70]; it was intended to provide non-linear decision boundaries, fast convergence, and high fault tolerance whereas GA was used to optimize NN parameters due to its large search space capability. With an elitism method, i.e., preservation of the best parent chromosomes in a mating pool, followed by a binary tournament selection and uniform crossover, GA was applied to achieve global optimum NN weight and bias values. The mean absolute error (MAE) of the predicted stock closing price was evaluated using Eq. (2).

$$MAE = \frac{1}{M}\sum_{j=1}^{M}\left(\frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|\right) \tag{2}$$

Here, in Eq. (2), y_i and $\hat{y}_i$ indicated the actual value and output value of the ith data, respectively; M represented number of simulations for the given experiment. Also, the percentage performance gain (PG) was calculated for the proposed second order neural network (SONN) by Eq. (3).

$$PG = \frac{MAE_{existing\ model} - MAE_{SONN\ model}}{MAE_{existing\ model}} \times 100 \tag{3}$$

Subsequently, a single hidden layer FFNN, extreme learning machine (ELM) was adopted with nature-inspired approaches to predict one-day-ahead stock price [71]. For various numbers of inputs, activation functions and the respective number of neurons in the hidden layer were determined using GA, DE, PSO, and weighted superposition attraction (WSA). Here, GA was adopted with a stochastic uniform selection and experiments were carried out among different activation functions; various evaluation metrics were considered wherein the proposed approaches improved the prediction performance.

While NNs have fixed parameters and learn accordingly, polynomial neural networks (PNNs) are capable of exploiting different order polynomials. Also, the number of input variables can vary in partial descriptions (PDs); they are selected so as to provide the optimal classification [72]. Such flexibility can be utilized for complex stock data. A condensed PNN (CPNN) architecture was developed by optimizing the weight vectors and biases using binary encoding-based GA [72] which used elitism and binary tournament selection strategies along with a uniform crossover operator. The proposed CPNN-GA model evaluated fitness as given by Eq. (4) and generated PDs with degree two and four, respectively, for the two hidden layers.

$$fitness = |y - \hat{y}| \tag{4}$$

where, y and $\hat{y}$ indicated the target and the predicted outputs, respectively. Comparison of gradient descent (GD)-based CPNN-GD, MLP-GD, MLP-GA, and radial basis functional neural network (RBFNN) models indicated the efficiency of CPNN-GA.

Due to the long-term dependencies of stock price data, BPNN may not be suitable for financial time-series forecasting. Though a recurrent neural network (RNN)-based long short-term memory (LSTM) approach has achieved significant results in predicting stock price, its slow operational speed and inability to meet market changes could be observed. Such internal gate performances of LSTM were enhanced with GA-based weight optimization in [73]; the proposed approach was applied to predict short-term stock price.

The linear interdependencies of various time-series data can provide useful information. The influence of various stock information, as well as the correlations, can be derived to study the evolution of variable associated with financial market. One of such stochastic processes is vector autoregression (VAR); in [74], authors inherited VAR models for stock closing price and compared the estimation performance achieved using conditional least square (CLS) and GA. The fitness function, mean absolute percentage error (MAPE) was calculated using Eq. (5).

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \tag{5}$$

where, y_i and $\hat{y}_i$ indicated the actual value and output value of the ith data, respectively; N represented the total number of data.

On the other hand, fuzzy rule-based system (FRBS) had shown that it required less number of instances to derive useful predictions [75]. Also, the adaptability of such a system for a highly fluctuating stock market was demonstrated in various studies [75–77]. A case study on stock prediction was developed with Mamdani-type FRBS in [18]. Author proposed to develop a knowledge base (KB) with a set of fuzzy linguistic rules; while rule base (RB) of KB represented symbolic form of such rules, data base (DB) of KB consisted of the sets of linguistic terms as well as the membership information. Hence, an evolutionary fuzzification of RIPPER, i.e., repeated incremental pruning to produce error reduction, for regression (EFRiR) problems was developed; while RIPPER was integrated for rule induction of RB, GA was adopted to optimize DB with triangular membership function (MF). The fitness of the chromosomes, equivalent of FRBSs, was evaluated using MAPE as given by Eq. (5). Author proposed to copy the best 10% of the chromosomes to an elitism set in order to preserve them from being affected by the crossover and mutation procedures. The proposed EFRiR approach was tested against various stock indices.

The stock market fluctuations are one of the major challenges for traders as well as researchers. In order to predict such fluctuations in stock market index, a multi-channel convolutional neural network (CNN)-based approach was proposed in Ref. [78]; authors aimed to optimize the feature extraction module of CNN and therefore, GA was adopted to optimize the hyperparameters. Another application of GA-based parameter optimization was demonstrated on variational mode decomposition (VMD) [79]; authors proposed to integrate GA to optimize the parameters of VMD such that the financial data sequences were decomposed into short-term and long-term trends. These values were provided to an LSTM model to predict the financial price. Thus, a GA-VMD-LSTM (GVL) model was developed and selection of VMD parameters were guided using VMD-loss and parameter choosing rule; authors also adopted BPNN to map prediction-error with chosen factors of the financial data wherein the prediction performances were evaluated using MAE, MAPE, and RMSE metrics. A higher prediction accuracy could be observed due to GA-based enhanced sensitivity of VMD towards the random financial fluctuations [79]. For complicated or dynamic systems, an adaptive neuro-fuzzy inference system (ANFIS) was developed to link NN with fuzzy logic; taking this model into consideration, authors in Ref. [80] proposed to use GA for parameter optimization of ANFIS and used the same for stock index prediction. The proposed GA-ANFIS enhanced the prediction performance as compared to ANFIS without parameter optimization. Recently, double chains quantum GA was proposed to tune learning rates and the optimized parameters were utilized for stock price prediction in [81]; the proposed approach worked with quantum Elman neural network (QENN) model that combined the advantages of machine learning and GA. With the improved results, the authors demonstrated usefulness of internal self-connection signal.

3.3. Stock Trend Prediction

The stock price movement, also called stock trend, can be an important aspect in identifying if the market would be going upward or downward. The trend can be determined using various information and market analyses; as compared to stock price prediction, trend forecasting can be more convenient in making trading decisions wherein the basic concern is likely to be on the market trend instead of the exact amount. Such tradings are likely to take place based on the buy, sell, or hold decisions. Hence, optimization of model parameters using GAs, as well as other methods, can be an important aspect in determining the future market trend.

Based on the wavelet theory, a feed-forward network, namely wavelet neural network (WNN) was developed. It could benefit with automatically separating data components of a time-series [82]. Considering such WNN as a stock market prediction model, authors proposed to derive the optimal parameter weights using GA in [83]. Because of the ability to hold structural changes at higher order, the Morlet wavelet was selected for deriving buy, sell, or hold decisions based on the movement direction of the success rate.

Through extended training time, a large number of parameters, and convergence to local optimum solutions are some of the major limitations of ANNs with BP, this may worsen in the case of operating long-term dependencies of stock market-based time-series data. Because gradient search-based NNs could not perform efficiently for non-linear optimization problems, a GA-based ANN approach was considered for next day stock price movement prediction in [84]. Authors modelled ANN with single input, hidden, and output layers where each chromosome was represented as a string of weights and biases; new populations were created using GA based on the fitness evaluation. Other advances include ANN weight optimization using binarized GA (BGANN) [85] for creating decision-making rules; such rules can provide reference to the investors.

Forecasting stock price has not been limited to historical price data; researchers have started exploiting various news sites as well as social media for stock market prediction. Clustering techniques may also be suitable to analyse such unlabelled data. Social media messages were collected and represented using vector representation model (VRM) in [86]; initial centroids of k-means clustering were selected for three decision classes and GA was applied to optimize the clustering algorithm as an extension of the previous work in [87]. On the other hand, the temporal properties of stock market were explored to determine time window size and LSTM network using GA [88]. Subsequently, a generalized model was proposed using support vector machine (SVM) and GA for next-day stock trend prediction [89]; GA was adopted to find an optimal time window for each technical indicator. Subsequently, the data error penalty coefficient and kernel function of SVM dot kernel that could influence the predictability were optimized using GA in [90]; performance analysis indicated improved prediction accuracy than PSO-based SVM as well as higher profit returns as compared to individual technical indicators. One of the recent advances predicted stock market along with N-day ahead stock prediction using a hybrid ANN with GA [91].

3.4. An Experimental Analysis

The significance of parameter optimization can be viewed with a perspective of experimental evaluation. For this purpose, a sample dataset Hyundai Motor Co. (005380.KS) [88] is considered with data collected between 01-01-2000 and 31-12-2016; Open, High, Low, Close, Volume, simple moving average (SMA), weighted moving average (WMA), relative strength index (RSI), Stochastic %K, and Stochastic %D features are adopted [88]. With 70 population size, single-point crossover with 0.7 rate, and bit-flip mutation with 0.15 rate, MSE fitness function is considered for the experimentation [88]. Here, an LSTM model is adopted with $10 - nh_1 - nh_2 - 1$ architecture and nw window size such that nh_1 and nh_2 indicate the number of nodes in hidden layers 1 and 2, respectively; the aim is to optimize nw, nh_1, and nh_2 using GA and compare the same with other metaheuristics for a fair comparison. Thus, each chromosome represents these parameters in their binary format. With the considered LSTM mode, *tanh* and linear activation functions and Adam optimizer are adopted as described in [88]. While stock price prediction is evaluated using MSE, the trend deterministic R^2 score metric is adopted for stock trend prediction. Comparison of GA with DE, PSO, and ALO for parameter optimization-based stock price and stock trend prediction are demonstrated in Figs. 10 and 11, respectively.

While GA performs better than DE in terms of MSE as well as R^2 score, the swarm intelligence-based PSO and ALO have better prediction performances. While parameter optimization has been an important factor, such demonstrations can be useful in identifying the significance of the selected metaheuristics and how the same can be utilized to overcome limitations of the other approaches.

3.5. Summary

Parameters of a given model can have a significant impact on the model's performance. While manual selection or greedy approach may not be suitable in order to tune such parameters, various optimization algorithms can be adapted for solving the parameter optimization problem. The financial market applications are challenging due to a large number of uncertainties associated with such markets; also, the potential influences can introduce fluctuations in the market behaviours. In order to deal with such situations, it is important to develop prediction models that can serve robust solutions; such solutions can highly be dependent on the selection of model's hyperparameters. Among the several hyperparameter tuning approaches, GA can be utilized due to its ability to search for near-optimal solutions from a large search space. This section provides an illustrative representation on how GAs can be adapted for parameter optimization; the applications of GAs for the stock price, as well as stock trend, prediction are reviewed with the recent advances in the literature. A summary of the reviewed articles on GA-based parameter optimization for stock price prediction and stock trend prediction is given in Table 2. Here, specifications on the considered GA operations and representations are provided along with the stock market forecastings and corresponding results.

4. Genetic Algorithms for Feature Selection

GAs offer a way in which chromosome strings can be presented to indicate specific aspects. One of the important factors of a prediction model is the input features [95]; while these features can be manually selected, it is essential to understand the impact of such features on the prediction model and its overall performance. Therefore, GAs can be adopted for feature selection; it can be a useful approach in automatically deriving important features from the available pool of features and other properties. In this section, we demonstrate how GA chromosomes can be utilized to indicate which features can be chosen; we further review the applications of GA-based feature selection approaches in stock price prediction and stock trend prediction.

4.1. Overview

Features play a vital role in the model's learning phase; useful information can be derived from features and hence, it is a critical task to select a set of meaningful features. In stock market, various technical indicators can be derived from the available stock data to understand the market characteristics; also, several related data can be appended with the existing properties to assist the market analysis. Identification of such features can be helpful for stock market prediction. Among the widely available list of possible features, manual analysis and selection of features may be a challenging approach; there have been various methods proposed for feature selection that can be broadly applied based on the type of data and other available information. Some of the main reasons why feature selection is essential can be understood with the concepts of redundancy and dimensionality. It may be possible that the set of features would be having two or more features that are redundant to each other and hence, they do not add any new information; such features would result in increasing the size of the feature set which, in turn, increases the dimensionality of operable data and complexity of the model. Therefore, the redundant features should be eliminated and the dimensionality should be reduced in order to have a concise set of features. Also, features that do not

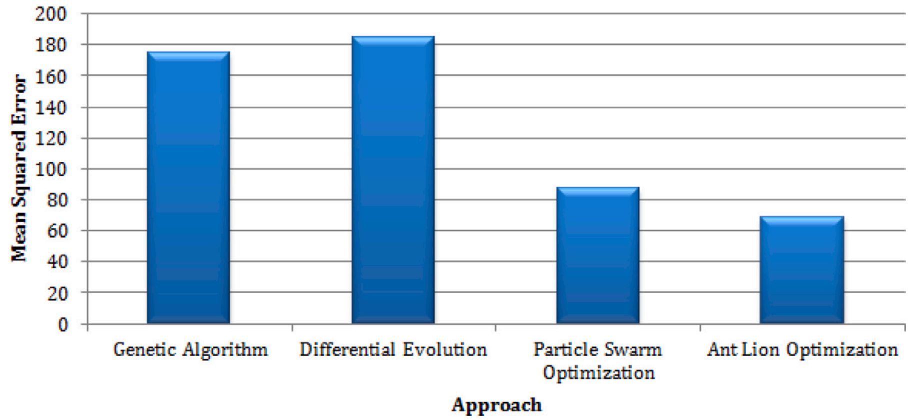

Fig. 10. An experimental comparison of GA, DE, PSO, and ALO for stock price prediction through parameter optimization.

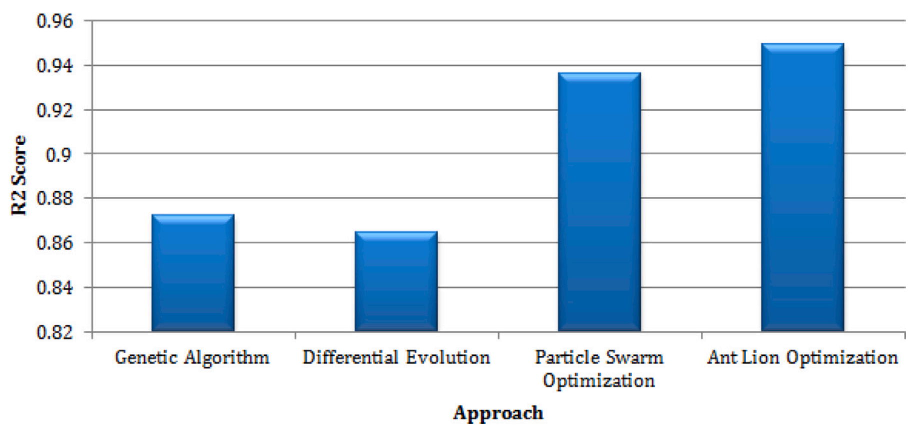

Fig. 11. An experimental comparison of GA, DE, PSO, and ALO for stock trend prediction through parameter optimization.

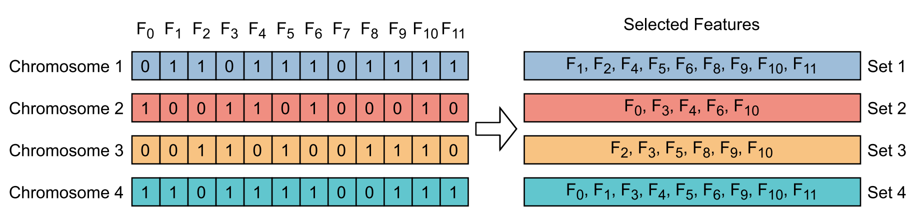

Fig. 12. An illustrative representation of binary-encoded feature sets after selection using genetic algorithm.

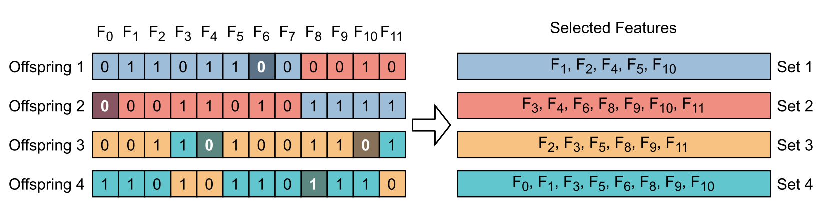

Fig. 13. An illustrative representation of binary-encoded feature sets after genetic algorithm operations.

provide much information can be eliminated from the consideration. Instead of a manual selection, various computational approaches should be integrated to deal with feature selection; these approaches may calculate the correlation among features, importance of features, or other information and a set of features can be obtained. GA is one of the metaheuristics that can be applied for feature selection.

In continuation to the previously presented GA operation illustrations, we demonstrate one of the ways in which feature selection can be carried out using GA in Figs. 12 and 13. Here, we consider an initial set of 12 features, represented with $\mathrm{F}_0, \mathrm{F}_1, \dots, \mathrm{F}_{11}$. Each binary-encoded chromosome denotes whether the specific feature is selected; for example, Chromosome 1 in Fig. 12 shows 0s for features F_0, F_3, and F_7 which means these features are to be eliminated from consideration, whereas 1s for the remaining features indicate the inclusion of these features; the selected set of features for each chromosome is also presented for a clear understanding. These chromosomes undergo crossover and mutation operations as given by Figs. 7 and 8, respectively. At this stage, a new set of features can be observed in Fig. 13 such that

Table 2
Summary of GA-based parameter optimization for stock price and stock trend prediction.

Paper	Approach	Chromosome	Selection	Crossover	Mutation	Fitness	Dataset	Prediction	Result
[65]	ANN, GA	Number of nodes, learning factor, weights	Elitism	Single-point	Rate: 0.07	MSE	DJIA	Close price	RMSE: 0.11
[66]	Fuzzy time-series, GA	Not specified	Tournament	Single-point; rate: 0.8	Rate: 0.01	RMSE	TAIEX	Closeprice	Average RMSE: 79.7; average directional accuracy: 0.5830
[19]	ANN, GA	Not specified	Tournament	Not specified	Rate: 0.3	RMSE	Tehran stock exchange	Stock index	Less than 5% prediction error
[67]	ANN, GA	Weight	Not specified	Rate: 0.6	Rate: 0.015	MSE	DSE	Stock price	Improved last traded, maximum, minimum price predictions
[69]	FFNN, FA	Weight, bias	Roulette wheel	Single-point; rate: 0.8	Rate: 0.01	RMSE/MAPE	PT Adhi Karya Tbk	Daily stock price	Best MAPE less than 10%
[70]	ASONN-GA	Weight, bias	Elitism, binary tournament	Uniform; rate: 0.5	Rate: 0.003	Absolute difference: target and estimated output	BSE, DJIA, NASDAQ, FTSE	Close price	PG: 9.24% than MLP, 6.15% than RNN; MAE: 0.0131
[71]	ELM, GA, DE, PSO, WSA	Not specified	Stochastic uniform for GA	Rate: 0.8	Rate: 0.2	Not specified	IBM, Citibank	One-day-ahead price	Higher forecasting accuracy
[72]	CPNN-GA	Weight, bias	Elitism, binary tournament	Uniform; rate: 0.5–0.6	Rate: 0.02–0.05	Absolute difference: target and estimated output	BSE, DJIA, NASDAQ, FTSE, TAIEX	Close price	Improved prediction
[73]	LSTM, GA	Not specified	Not specified	Not specified	Not specified	Sum of squared errors: target and estimated output	Bovespa index	Short-term price	Improved speed than LSTM
[74]	VAR, GA	VAR parameter	Roulette wheel	Rate: 0.8	Rate: 0.1	MAPE	ADHI, WIKA, WASKITA, PTPP	Close price	Low predictive forecast error as compared to CLS approach
[18]	Mamdani-type FRBS	KB	Elitism, binary tournament	Rate: 0.7 to 0.95	Rate: 0.03 to 0.2	MAPE	Taiwan stock exchange, Tehran stock exchange, others	Stock price	Improved prediction performance
[78]	CNN, GA	CNN hyper-parameters	Not specified	Rate: 0.7	Rate: 0.25	Hit ratio	KOSPI	Stock index fluctuation	Higher prediction accuracy than ANN and CNN
[79]	VMD, GA, LSTM	Data-fidelity constraint α, Lagrangian multiplier τ, number of nodes K, convergence tolerance level ε	Roulette wheel	Adaptive crossover-strategy	Adaptive mutation-strategy	VMD-loss	As provided by [92–94]	Close price	Reduced MAE, MAPE, and RMSE
[80]	ANFIS, GA	Premise parameters (c, σ) and consequent parameters (r_i, q_i, p_i)	Not specified	Rate: 0.4	Rate: 0.01	MSE, RMSE	NASDAQ	Stock market indices	Improved MSE, RMSE, and R-squared as compared to ANFIS
[83]	WNN, GA	Not specified	Not specified	Rate: 0.7	Not specified	Weight; error	Shenzhen Composite Index, S&P500	Buy, sell, hold decisions	Reduced MAPE; Accuracy: 83.78%

(*continued on next page*)

Table 2 (*continued*).

[84]	GA-ANN	Not specified	Not specified	Rate: 0.7	Rate: 0.2	MSE	Nikkei 225 index	Next-day trend	Improved hit ratio
[86]	K-means, GA	Not specified	Elite	Not specified	Not specified	Sum of squared distances: cluster elements and their centroid	Social messages	Buy, sell, hold decisions	Accuracy: 89.31%
[85]	BGANN	Weight	Not specified	Not specified	Not specified	Profit	Nifty bank	Decision-making rules	Improved error rate than SVM, NN, ARIMA
[88]	GA-LSTM	Time window size; number of LSTM cells	Not specified	Rate: 0.7	Rate: 0.15	MSE	KOSPI	Stock trend	Improved MSE, MAE, MAPE than benchmark
[89]	SVM, GA	Time window size; feature selection variable	Probabilistic	Rate: 0.4	Rate: 0.1	Rate of return	Microsoft, Nike, Goldman Sachs, Intel	Next-day stock trend	Improved trading compared to volume–weight SVM
[90]	SVM, GA	Not specified	Not specified	Not specified	Not specified	Not specified	SET	Buy, sell, hold decision	Average accuracy: 78.22%; improved return profits
[91]	ANN, GA	Not specified	Roulette wheel	Multi-point	Two-point	Inverse of root mean square of errors	DOW30, NASDAQ100	Trend, N-day ahead stock	Better performance than ANN

Offspring 1 eliminates F_0, F_3, F_6, F_7, F_8, F_9, and F_{11} features from consideration and selects only the remaining features. Such changes can be observed with other offsprings; the same can be evaluated against the considered fitness function and the fittest solutions can be derived for further generations. Thus, GA can be integrated for feature selection. Among various potential applications, financial market forecasting considerably requires identification of a set of useful features; such features can be historical stock market data, derived technical indicators, associated stock information, as well as fused features. In order to have an efficient selection of features, several approaches have adopted GAs because of their ability to obtain potential solutions from the large search spaces.

4.2. Stock Price Prediction

The identification of useful features is an essential part for reliable prediction. The stock price prediction can be significantly affected by the set of features adopted during the model's learning phase. Therefore, it is important to utilize the market information and select a set of features that hold informative details; such features can be effectively selected using GAs.

For stock close price prediction, GA and rough set (RS) theory were utilized along with fuzzy time-series model in [96]. GA was exploited to derive the universe of discourse and partition interval length based on the observed characteristics of stock trend; fuzzy logic rules and corresponding weights were generated for the fuzzified observations using RS. Authors applied defuzzification to derive the predicted stock index price. Experiment on Nikkei Index data for the year 2014 indicated higher prediction accuracy of the proposed approach than that of fuzzy time-series without GA and RS.

The applicability of LSTM models is well-known for the time-series stock market predictions; one of the recent advances proposed to integrate GA for selecting a set of features and used the same with LSTM for stock price prediction [97]. Authors considered a set of 40 factors, i.e., features, and applied GA to determine the importance ranking of these factors; subsets of top 30, 20, 10, and 5 factors influencing the stock price were further selected and provided as input features to the LSTM model. The performance improvement and robustness of the proposed approach were shown using MSE metric [97].

4.3. Stock Trend Prediction

The stock movement direction can be categorized using the index values. Instead of predicting the exact price value, price hike or drop movement can be determined for a short-term, as well as long-term, period; this can also be helpful in deriving trading rules. GA-based approaches have been integrated for feature selection to predict the stock trend; such features are desired to study the inherent characteristics of stock market movements. The effective problem-solving ability of GA can be exploited to find a reliable set of features that can be given as input to the prediction model.

While a large number of technical indicators exist, a GA-based three-layered feed-forward ANN approach was proposed to prepare a set of diverse features in [98]. Authors collected daily close price of stock exchange of Thailand (SET50) and experimented with technical indicators of varying time span lengths to predict stock price index trend; an average improvement of 12.4% was achieved as compared to the previous work with ANN [99].

On the other hand, individuals having financial background are likely to adopt fundamental analysis whereas others may opt for technical methods such as filtration for feature selection. A wrapper method was selected for extracting useful features along with an extended GA in [100]. Authors experimented with CSI 300 daily stock data and classified stock trend using SVM. The capabilities of GA in selecting a set of features were explored along with SVM kernel parameters in Ref. [101]. Authors integrated GA and SVM to develop a homogeneous ensemble classifier namely, GASVM, to predict 10-day ahead stock trend. The comparison of the proposed GASVM with the existing decision tree (DT), NN, RF, and (ensembled) 15 SVM (ESVM) based on 14 features derived from Ghana stock exchange (GSE); the results indicated considerably higher prediction performance with the proposed GASVM [101].

The trading rules have been referred to by a large number of individuals, however, optimization of such rules can be a challenging task. In order to build such trading strategies using trading rule features, a RoboTrading system was proposed with GA maximizing sharpe and sterling ratio (GA-MSSR) method [102]. Authors proposed to use SSR, i.e., sharpe and sterling ratio, to derive risk-adjusted return; the proposed approach integrated GA with the consideration that

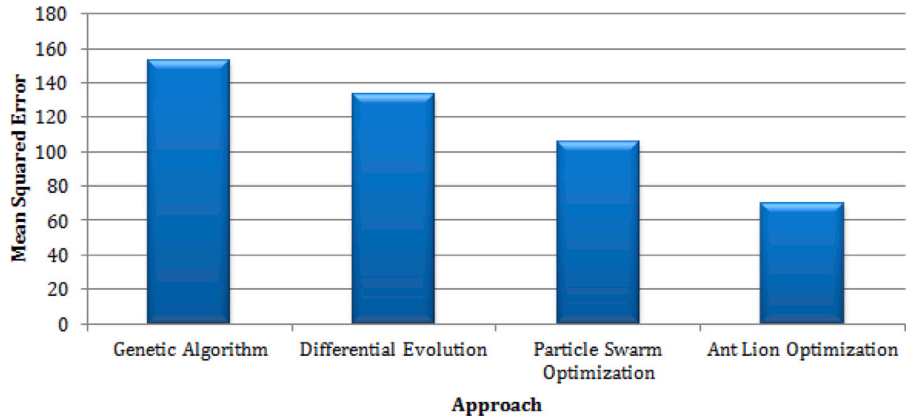

Fig. 14. An experimental comparison of GA, DE, PSO, and ALO for stock price prediction through feature selection.

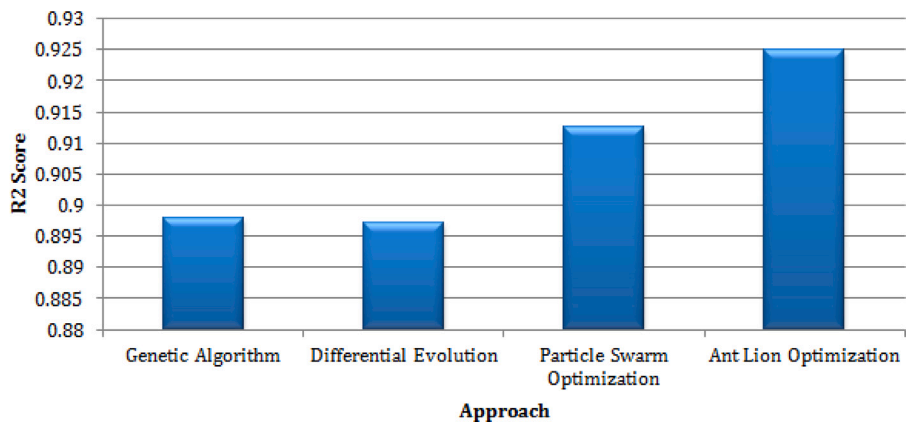

Fig. 15. An experimental comparison of GA, DE, PSO, and ALO for stock trend prediction through feature selection.

maximization of such a fitness score can maximize the profit with a certain level of risk management. The results indicated that the features derived using the trading rules could provide information on evaluating the price movement trend over a long period of time; the proposed formulation of trading strategies optimize the performance [102]. Recently, the concept of distributed lag analysis was considered in [103] and GA was adopted to select a set of useful features for stock trend prediction using random forest (RF).

4.4. An Experimental Analysis

The significance of parameter optimization can be viewed with a perspective of experimental evaluation. For this purpose, as explained earlier, dataset 005380.KS is considered with data collected between 01-01-2000 and 31-12-2016; Open, High, Low, Close, Volume, SMA, WMA, RSI, Stochastic %K, and Stochastic %D features are adopted [88] with chromosomes representing these features. Here, the considered LSTM model is adopted with $10 - 15 - 7 - 1$ architecture and 10 window size, *tanh* and linear activation functions and Adam optimizer as described in [88]. While stock price prediction is evaluated using MSE, the trend deterministic R^2 score metric is adopted for stock trend prediction. Comparison of GA with DE, PSO, and ALO for feature selection-based stock price and stock trend prediction are demonstrated in Figs. 14 and 15, respectively.

As it can be seen, GA and DE perform quite similar whereas PSO and ALO have comparatively better prediction performances. It can be viewed as a potential expansion of considering the advances of other swarm intelligence-based metaheuristics for integration with GA as well as other evolutionary computation algorithms for an improved prediction. Also, the significance of selecting features using such approaches can provide potential enhancement in the stock market forecasting.

4.5. Summary

Apart from parameter optimization, the application of GAs for feature selection or feature extraction can be applicable for stock market forecasting. From a pool of available features representing specific aspects of the stock, it is a challenging task to select unique, informative features that can further aid the prediction model. This section provides an illustrative example on how GAs can be adapted for this task; the same is also supportive to financial markets. The reviewed articles indicate the performance enhancements received due to GA-based feature selection approaches. A summary of the reviewed articles with a primary focus on GA-based feature selection for stock price, as well as stock trend, prediction is given in Table 3.

5. Genetic Algorithms for Other Stock Market Applications

There have been a large number of possibilities in which various perspectives can be demonstrated using GA chromosomes; the chromosomes are a representative form of a group of genes such that an individual gene can indicate a specific value. These values may belong to binary or continuous numbers; they may also be presented with trading rules. In case of having a portfolio optimization, such chromosomes can operate on the percentage of selected stocks or their weightage. Thus, the varieties offered by chromosomes can be potential solutions to several stock market applications.

5.1. Portfolio Optimization

Various aspects of a portfolio may include stock selection, capital allocation, group trading, investment trading and hence, optimization

Table 3
Summary of GA-based feature selection for stock price and stock trend prediction.

Paper	Approach	Chromosome	Selection	Crossover	Mutation	Fitness	Dataset	Prediction	Result
[96]	Fuzzy, GA, RS	Universe of discourse	Not specified	Not specified	Not specified	MSE	Nikkei index	Close price	Smaller RMSE
[97]	LSTM, GA	Features	Roulette	Rate: 0.8	Rate: 0.003	r^2 determination coefficient	China construction bank, CSI 300 stock	Stock price	Reduced MSE
[98]	ANN, GA	Binary strings	Tournament	Arithmetic	Not specified	Accuracy	SET50 index	Trend	Average accuracy: 63.6%
[100]	GA-Adaboost-GA-PWSVM	Not specified	Not specified	Not specified	Not specified	Accuracy	CSI 300	Trend	Stable performance
[101]	Ensemble SVM, GA	Features, classifiers	Tournament	Rate: 0.85	Rate: 0.10	Not specified	GSE	10-day ahead stock trend	Improved performance than DT, RF, and NN
[102]	GA-MSSR	Feature weights	Not specified	Rate: 0.4	Rate: 0.5	SSR	Currency pairs EURUSD, GBPUSD, AUDUSD, USDJPY, USDCAD, and USDCHF	Trading strategy for 5-min intraday data	Improved results
[103]	RF, GA	50 features	Roulette wheel	Single-point	Bit-flip	Not specified	S&P500, NIKKEI 225, CAC40, DAX	Stock trend	Accuracy: 80%

of strategy parameters and security weights. For recommending a portfolio, GA properties may be utilized to optimize trading-based parameters and/or strategy [104].

While suggesting a specific trading strategy may not interest all the investors, recommending a group of trading strategies was proposed in [105] to provide a variety of options to potential investors. The aim of optimizing such a portfolio strategy was to maximize returns and minimize risk based on the weights of individual groups. A grouping GA (GGA) was adopted where chromosomes consisted of group, weight, and technical indicators-based trading strategy; the fitness function was determined using portfolio return, associated risk, and balances of group and weight. An experiment on stock data collected over years 2011 to 2016 indicated positive returns as well as risk-avoiding ability. Subsequently, GGA was implemented for group trading strategy portfolio by representing chromosome as group, strategy, and weight parts whereas the fitness value using balances of group as well as weight, portfolio return, and risk factors in [106]. Another GGA-based approach was proposed for diverse group stock portfolio optimization (DGSPO) [107]; authors designed group diversity factor in order to have diversification of stocks from various industries and the same was adopted as a fitness function.

Because a group stock portfolio contains similar stocks in the same group, investors can substitute stocks within the same group. Such dynamic grouping was proposed using GGA with grouping, stock, and portfolio were selected as part of chromosomes [108]. The groups were created by considering stock price series and reducing the high dimensionality using symbolic aggregate approximation (SAX) and extended SAX (ESAX). Also, a stability factor was developed using cash dividends of stocks. Authors had selected modified portfolio satisfaction, group balance, and series distance as the first fitness function and along with that, price balance and unit balance as the second fitness function; they evaluated chromosome and individual quality, respectively. The proposed approach improved return on investment (ROI) and group similarity and the trade-off was found as well.

Various approaches have used clustering techniques to group stock-related information. In [109], authors developed various portfolios with cluster analysis of investor information; the investors belonged to foreign, institutional, or individual types. For each type, weight optimization was performed on the selected stocks using GA. Authors experimented with 90 companies having the highest market capitalization from the Korea composite stock price index (KOSPI 200); high returns were achieved with this approach.

Using support vector regression (SVR), decision-making day stock close price was predicted and portfolio was optimized using GA based on the investment profit and risk factors [110]. The trading data were implemented to calculate stock transactions and overall investment profit. On the other hand, an agglomerative clustering was adapted with GA to apply diversification-based portfolio optimization [111]; authors considered cardinality, quantity, and transaction cost constraints in a possibilistic mean-semi-absolute deviation portfolio optimization model. Authors proposed to derive seven financial ratios of each asset and prepared a feature vector to further identify linkages between data; the best cluster of assets was further identified using agglomerative clustering whereas GA was used to determine the weights of the chosen stocks using fitness as given by Eq. (6) [111].

$$fitness = \Bigg[\frac{\lambda}{2} \sum_{i=1}^{n} \Big[b_i - a_i + \frac{1}{3}(\alpha_i + \beta_i)\Big] w_i - (1-\lambda) \left\{ \sum_{i=1}^{n} \frac{1}{2}\Big[a_i + b_i + \frac{1}{3}(\beta_i - \alpha_i)\Big] w_i - \sum_{i=1}^{n} k_i \| w_i - w_i^0 \| \right\} \Bigg] \tag{6}$$

where, the proportion invested in asset i on the existing portfolio was given by w_i^0 and by w_i for others; r_i denoted the return rate of asset i; k_i indicated the constant rate of transaction cost for risky asset i; λ specified the investor risk tolerance such that $0 \leq \lambda \leq 1$; n was the number of assets.

A price-based portfolio selection approach was considered using fuzzy stochastic price scenario [112]. For Bombay stock exchange (BSE) stocks, ratio factors were evaluated which indicated future fuzzy prices and returns were calculated. Authors included transaction cost with capital budget and applied fuzzy GA to attain long-term and short-term returns. On the other hand, an NN-based approach was proposed to forecast stock returns and to measure the associated risk [113]; authors utilized this approach to further optimize portfolios with low, medium, and high risks for risk-averse as well as risk-taker investors using GA. One of the recent approaches used priority index along with GA to optimize stock portfolios [114]; authors proposed to derive priority index scores of the selected stocks and further, determined the percentage of investment to the selected stocks using GA. Also, a wealth creation parameter was considered to evaluate its role in portfolio returns. A different length GA-based clustering approach was proposed in Ref. [115] wherein vertical as well as horizontal clusterings were applied to generate a limited number of stocks. Authors clustered stocks based on their returns per unit of risk for each day, i.e., through vertical clustering, and clustered the algorithm centroids on a timely manner, i.e., through horizontal clustering. Also, the Markowitz model was integrated for weight identification of stocks belonging to the portfolio; the results indicated higher performance using the proposed GA-based clustering approach [115].

Portfolio profitability is one of the desirable aspects; to make a profitable decision, higher-order moments are taken into consideration by many investors. Using the third and fourth order moments in statistics, i.e., skewness and kurtosis, respectively, the portfolio selection problem was addressed in study [116]; authors proposed to include two-stage clustering, RBFNN, and GA for multi-objective optimization, data-driven asset selection, and return prediction tasks. The results indicated enhanced performance using the proposed hybrid approach as compared to the traditional mean–variance model [116]. One of the recent approaches proposed sentiment all-weather (SAW) and sentiment modern portfolio theory (SMPT) models in order to obtain the market conditions using Twitter sentiments [117]; authors used Google's bidirectional transformer (BERT) model for this task. Using different objectives, GA was adopted to optimize the models such that the cumulative returns, as well as sharpe ratio, could be maximized and volatility could be minimized. Authors also developed a robo-advisor based on the proposed models and portfolio management approaches [117].

5.2. Stock Price and Trend Prediction

It can be observed that a large number of GA applications belong to the optimization of hyperparameters of various prediction models. The significance of such tuning can be noticed from the prediction results; while a considerable amount of performance improvement has been attained, the same can be further supported by selecting and/or extracting useful features. These features may be based on fundamental analysis as well as technical analysis. On the other hand, trading rules play a vital role in determining what actions can be taken with the targeted stock; such rules can be derived along with other hybrid applications using GAs. This section conducts a review on other such applications of GAs for stock price, as well as trend, forecasting.

In stock markets, different trading strategies are followed by various investing parties. The expectation is to gain higher profits and hence, traders may look forward to the financial behaviours, economic characteristics, associated news and events, as well as various public opinions. Such factors can be helpful in developing various trading rules. For the crude oil futures market, authors proposed to develop trading rules based on moving average (MA) indicators [118]. For this purpose, SMA, weighted MA (WMA), exponential MA (EMA), adaptive MA (AMA), typical price MA (TPMA), and triangular MA (TMA) were considered. The trading rules defined short and long periods wherein the fitness of these rules were evaluated using excess return rate as given by Eq. (7); GA-based new trading rules were generated for the given period.

$$Ra = Ral + Ras + Rf - Rbh \tag{7}$$

where, Ral and Ras represented returns of long position and short position respectively; Rf indicated risk free return whereas Rbh specified return rate of the buy-and-hold strategy which took the long position throughout the period [118].

GAs are capable of searching through large search spaces, however, potential limitations such as being trapped into local optima may be solved by integrating other metaheuristic approaches. Such an ensembled version can be useful in improving the prediction models. The stock markets represent diverse characteristics; hence, the selection of a single algorithm may not suffice. To address this issue, a cooperative optimization framework was developed with GA and chemical reaction optimization (CRO) in [119]. Author proposed to apply GA and CRO as constituent algorithms and optimized the weights of an MLP model; the information of the generated solutions was shared, i.e., migrated between the algorithms and the best solution was adopted. The proposed framework demonstrated performance improvement using average percentage of errors (APE) metric as given by Eq. (8).

$$APE = \frac{1}{N}\sum_{i=1}^{N}\frac{|y_i - \hat{y}_i|}{y_i} \times 100 \tag{8}$$

where, y_i and $\hat{y}_i$ indicated the actual value and output value of the ith data, respectively; N represented the total number of data.

For complex stock market data, SVM can provide linear model mapping for high-dimensional non-linear data. This can be useful to create hyperplane(s) for providing distinction among the classes. Hence, a GA-ensembled SVM method was proposed in [120] with the Gaussian RBF as the kernel. Authors predicted the trend of one-week-ahead stock price of the Bovespa index of Brazilian stock exchange. To enhance the performance accuracy, other stock indices such as S&P 500, Dow Jones industrial average, FTSE 100, DAX, Nikkei 225, and Hang Seng were examined along with USD, Euro (EUR), and Chinese Yuan (CNY) currencies; the proposed approach outperformed Bagging, AdaBoost, RF, and SVM with RBF kernel.

Such stock tradings are likely to be dependent on the predicted price movements. The future direction can be derived using association rule mining; however, such classification may encounter issues in handling numerical data and internal relations. To address these limitations, relation representation models may be constructed. Hence, a GA-based approach was proposed to construct optimized relations among technical indicators in [121]; association rules were generated to classify the stock price change into positive, negative, or no change based on the difference between close price of a trading day and next day's open price.

Subsequently, an intelligent hybrid trading system using RSs and GA was proposed in [122]. The conditional attributes and decision attributes, i.e., up or down, were generated using RS analysis. To ensure that GA could efficiently work with high-dimensional stock data and to reduce the search space, reduction techniques were performed with RSs and optimal as well as sub-optimal trading rules were discovered. The degree of applicability of such a system was experimented with KOSPI 200 dataset; training with six-month period and 50 decision rule sets could deliver the highest annualized return rate. With an increasing demand of algorithmic trading, it is important to understand how GA as well as other evolutionary algorithms can enhance the trading strategies; an approach was proposed by combining two GAs to find the best optimization and trading window for a trading strategy in [123].

A recent approach proposed information fusion-based GA approach for stock price and trend prediction [124]. With a motivation to integrate genetic diversity and survival capabilities of various organisms, authors proposed GA with inter-intra crossover and adaptive mutation (ICAN) to optimize parameters of an LSTM prediction model and select a set of features. The prediction performance of GA with ICAN indicated remarkable improvement using MSE, MAE, MAPE, and R^2 score metrics.

5.3. Summary

Apart from the specific applications of GAs such as hyperparameter tuning and feature selection, this section precisely concentrates on the other potential ways in which GAs are integrated with financial market forecasting. These applications include the usability of chromosomes for a variety of representations such as portfolio, stocks, groups, trading rules, percentage of stock information, to name a few. The adaptability of GAs with other approaches can also be viewed from their potential applicability to various stock market predictions, as well as portfolio optimization, problems. A summary of the reviewed articles based on GA for various stock market applications is provided in Table 4.

Table 4
Summary of GA-based approaches for various stock market applications.

Paper	Approach	Chromosome	Selection	Crossover	Mutation	Fitness	Dataset	Prediction	Result
[105]	GGA	Group, weight, trading strategy	Elitist	Two-point	Swap	Group balance, weight balance, profit factor, risk factor	Source unspecified	Group trading strategy portfolio	Improved results
[106]	GGA	Group, weight, trading strategy	Elitist	Two-point; rate: 0.8	Swap; rate: 0.003	Group balance, weight balance, portfolio return, risk factor	Source unspecified	Group trading strategy portfolio	Improved results with stop-loss and take-profit points
[107]	GGA	Grouping, stock, stock portfolio	Elitist/Roulette wheel	One-point, random	One-point	Group diversity	30 and 31 stocks from Taiwan stock exchange (TSE)	Portfolio optimization	Performance and diversity improvement
[108]	GGA	Group, stock, portfolio	Elitist	Two-phase	Two-phase	Two functions with SAX, ESAX	Taiwan stock exchange	Portfolio optimization	Improved stock price series similarity; higher ROI
[109]	GA, k-means clustering	Weight	Rank-based	Rate: 0.5	Rate: 0.06	Equal, market capital, minimum variance, and sharpe weights	KOSPI 200	Portfolio optimization	Improved stock selection and capital allocation
[110]	SVR, GA	Not specified	Not specified	Rate: 0.5	Rate: 0.15	Objective function	Source unspecified	Portfolio optimization	Improved annularized returns of investment
[112]	Fuzzy, GA	Not specified	Binary tournament	Single-point	Bitwise	Objective function	BSE	Portfolio selection	Maximum short-term, long-term returns
[111]	Agglomerative clustering, GA	Not specified	Roulette	Heuristic	As given by [125]	Eq. (6)	40 stocks from S%P 500	Portfolio optimization	Higher average return and sharpe ratio
[113]	Neural network, GA	Weight	Roulette wheel	Two-point; rate: 0.9	Adaptive feasible; rate: 0.05	Mean–Variance–Skewness	5 indices (66 stocks) from Iran's stock market	Risk, return; portfolio optimization	Close results with Mean–Variance–Skewness with weight constraints model
[114]	Priority index, GA	Percentage of each selected stock	Roulette wheel	Arithmetic; rate: 0.6	Shift in genes values; rate: 0.4	Portfolio return/Portfolio standard deviation	S&P 500	Portfolio optimization	Optimal portfolio making up to five months significance of wealth creation parameter
[115]	Clustering, different length GA, Markowitz model, PSO	Cluster	Binary tournament	Probabilistic uniform	Probabilistic	Objective function	61 Indian stocks	Portfolio optimization	Optimized portfolio with vertical as well as horizontal clustering
[116]	Clustering, RBFNN, GA	Asset weights	Roulette	Rate: 0.5	Rate: 0.01	Objective function	SSE 50 index	Asset selection, return prediction	Better higher-order moments than traditional mean–variance model
[117]	SAW, SMPT, GA, BERT	Not specified	Not specified	Rate: 0.5	Rate: 0.2	Based on cumulative returns, sharpe ratio, and volatility	SPDR ETFs	Portfolio optimization	Robo-advisor

(*continued on next page*)

Table 4 (*continued*).

[118]	SMA, WMA, EMA, AMA, TPMA, TMA, GA	Not specified	Based on the highest fitness	Rate: 0.7	Rate: 0.05	Based on excess return rate	Crude oil prices of New York Mercantile Exchange (NYMEX) futures	Trading rules	Performance improvement
[119]	MLP, CRO, GA	Weight, bias	Elitism; binary tournament	Uniform; rate: 0.6	Rate: 0.002	Average percentage of errors (APE)	S&P-100, DJIA, NASDAQ, FTSE 100, TAIEX	Time series	Average APE: 0.7690
[120]	GA, SVM	Binary; floating-point	K-tournament (K = 3); elitist	Scattered; BLX-Alpha-Beta	Flip bit; non-uniform	Classification accuracy	Bovespa index	Weekly trend	Improved prediction
[121]	Association rule mining, GA	Technical indicators rules (64-bit)	Not specified	Single-point	Flip bit	Not specified	DJIA	Trend	Accuracy: 95%
[122]	GA, RS	Reduct, number of cut points, candidate cut points	Elitist	Rate: 0.5	Rate: 0.06	Sharpe ratio	KOSPI 200	Trading rules	Returned the highest annualized return rate
[123]	GA	Optimization and trading window; moving average period	Proportion-ate; rank; tournament	Rate: 0.7; 0.8; 0.9	Rate: 0.25; 0.3	Not specified	BM&F Bovespa	Algorithmic trading profit	Enhanced trading strategy
[124]	GA, LSTM	Window size as well as number of nodes in hidden layers 1 and 2 of LSTM in part I, ten features in part II	Fitness-based	Single-point; rate: 0.7 for part I, 0.8 for part II	Bit-flip; rate: 0.15 for part I, 0.003 for part II	MSE for part I, R^2 score for part II	KOSPI, 000660.KS, 005380.KS, 005490.KS, 005930.KS, 012330.KS, 017670.KS, 0939.HK, 3188.HK	Stock price and trend	Lower MSE, MAE, MAPE; higher R^2 score

6. Other Genetic Perspectives for Stock Market Applications

The genetic processes have evolved to provide solutions to unstructured and complex problems. Along with GAs, other genetic perspectives have also been considered to provide a potential environment for stock market prediction. This section briefly considers such implications and reviews existing work for financial market forecasting. It also analyzes the rationale for applying genetic perspectives to stock market prediction (**RQ1**).

6.1. Genetic Programming

Genetic programming (GP) can be considered as an implication of GA to a computer program population; while GA optimizes a linear representation of the fixed-length, GP can operate tree representation of a variable size [11]. Similar to GA, the operations involved in GP include selection, crossover, and mutation; traditional representation of parse tree structures can be evaluated recursively [11,126,127]. The fitness function represents the cost function that may be defined based on the desired output; it evaluates the score derived using the parse tree. The randomly created initial populations have random parameter specifications and further child structures; while full method contains equal lengths from the root to a leaf, grow method may not satisfy this criterion. Based on the fitness value, individuals are selected for reproduction. Similar to that in GA, a crossover rate is decided for creating the next generation and new structures may be introduced with mutation applied to a small part of the population.

To derive an optimal representation of GP, many variants have also been introduced. The state space size and multi-dimensional type constraints may be considered as some of the primary limitations of GP; a strongly typed GP (STGP) was proposed as a type constraint variation of GP [128] where the root node returned the type of the actual problem definition whereas each non-root node returned the type required by its parent node. Other constraining structures such as enforcing specific structure, grammar-based constraints, and bias have also been developed [24]. Subsequently, the graphical representations of trees introduced graph-based GP which were extended for the parallel distributed GP (PDGP) for highly parallel programs [129]. Due to the basic linear representations of computer programs and the requirement of tree-based compilers and/or interpreters motivated developing a linear GP (LGP) of fixed as well as variable length trees [130]. The directed acyclic graph representation of a program was introduced using Cartesian GP (CGP) [131]; the genes associated with CGP genotype specify information regarding data and operations of nodes. The fixed-length genotypes may have variable-length programs, also known as phenotypes and the mappings among them define CGP characteristics; a function look-up table plays an important role for gene computations. Other variations of GP involve probabilistic GP, mixture of grammars and probabilities, multi-objective GP (MOGP), grammatical evolution [24], to name a few. The selection of an appropriate GP variant would be dependent on the target application and the prediction models associated with it.

One of the major advantages of GP structures is that they do not create invalid states in a majority of the cases [132,133]; the inherent variable length demonstrates flexibility for complex, non-linear data such as financial market. Also, the limitations such as dealing with different data types or constraints can be addressed using different tree structures of GP variants itself [134,135]. Hence, GP-based approaches have been adopted for pattern identification, risk assessment, forecasting stock market using various trading rules, and optimization. It uses an artificial evolution within a system for developing a computational program automatically. Such an approach can be largely applied to various fields including financial markets [134,135]. Stock market index movement and corresponding portfolio selection are some of the potential applications; trading rule generation, parameter optimization, and regression-based techniques can be enhanced with GP.

6.2. Gene Expression Programming

One of the limitations of GP such as handling constraint-based relation with different data types whereas the inability of GA to guarantee optimality require integration and extension of these genetic perspectives to develop stable optimization approaches. Gene expression programming (GEP) is developed to incorporate fixed-length linear chromosomes as that in GA and branched tree structures with varying sizes and shapes as that in GP [27]. To predict short-to-medium term fluctuations in the stock market, a parameter tuning method using GP and GEP was proposed in [136]; authors proposed fractional adaptive mutation rate (GEP-FAMR) Elitism to balance between mutation rate and chromosome fitness and hence, improving overall prediction accuracy. Subsequently, a mutual funds-based investment strategy was guided using trading rules generated with GEP [137]; the proposed approach combined single asset time-series as well as portfolio management to generate trading rules which were suitable for a dynamic market.

6.3. Genetic Network Programming

A string structure of GA and a tree representation of GP, i.e., a genome, can be considered as the foremost difference between GA and GP [11]; similarly, genetic network programming (GNP) can be differentiated based on the network-like genome structure. It was proposed as a new evolutionary computation method to overcome the efficiency issue of GP [29]. It consists of judgement and processing nodes that correspond to terminal nodes and that in GP, respectively; GNP also consists of mutation and crossover operators. The trading signals can be helpful to indicate whether specific stocks should be bought, sold, or not traded; such an approach was developed using fuzzy GNP with reinforcement learning (RL) [138]. A recent study proposed GNP-based approach with weighted inter-section class association rule mining for stock market prediction [139].

Other variations such as neuro-genetics, genetic engineering, and hybrid methods can be applied for specific tasks in stock market prediction.

7. Competitiveness and Complementation of Genetic Algorithms

In the current literature studies, various metaheuristic methods are applied to solve stock market-related prediction problems. While our primary review is based on the adaptability of GAs for stock price and stock trend prediction, it is worth mentioning how other swarm and evolutionary computation approaches are used to compete or even improve the results achieved using GAs. In order to provide a balanced survey, we discuss the participation of other methods and compare them with GAs; we also discuss how GAs complement other algorithms to improve the prediction models. Such analysis may be useful in developing fusion-based approaches to derive concrete stock market prediction methods.

7.1. Other Metaheuristics vs. Genetic Algorithms

While a significant amount of stock market prediction work has been carried out using GAs, other swarm and evolutionary approaches have demonstrated performance improvement as compared to GAs. This section briefly addresses **RQ4** to determine the competitiveness of GAs with respect to other metaheuristics for stock market prediction.

7.1.1. Particle Swarm Optimization

A large number of nature-inspired optimization approaches have been developed and explored for stock market forecasting; particle swarm optimization (PSO) is one of such metaheuristics which was inspired by the swarm intelligence of bird flocks searching for corn. PSO presents the social movement of the particles associated with a swarm that move towards a global best position in the search space [140]. One of the primary reasons for adapting PSO for time-series data is its capability to deal with continuous data [141].

PSO is integrated with various methods to improve its forecasting abilities for non-linear stock markets. Based on the principle of centre of mass, PSOCoM was proposed to support the cognitive behaviour of the particles [142]. The long-term, as well as short-term predictions, were carried out using this approach; comparisons using mean squared error (MSE) indicated faster convergence of PSOCoM than that of GA. One of the ANN-based hybrid approaches, an improved cuckoo search GA (ICSGA), was proposed in [143] for stock price prediction. Though PSO derived the most accurate predictions, the proposed ICSGA could also improve the performance as compared to CS, ICS, as well as GA.

Another approach based on hyperparameter tuning using grid search approach, GA, as well as PSO, was proposed for an SVM model in Ref. [144]; authors proposed to optimize parameters of various kernel functions using these three methods and evaluated stock price prediction. The results indicated higher performances attained by GA as compared to PSO and grid search methods; a remarkable performance enhancement was attained for radial basis kernel function using GA-optimized SVM parameters [144]. One of the recent advances integrated MLP-GA and MLP-PSO for Borsa Istanbul (BIST) 100 index movement prediction [145]; the results indicated close results with MLP-PSO having slightly higher performance than MLP-GA, however, both the approaches attained close results on the prediction performances for Gaussian function as well as $tanh(x)$ [145].

7.1.2. Ant Colony Optimization

Inspired by the behaviours of real-ants, an ant colony optimization (ACO) approach was developed with artificial ants. The pheromone trails provided by such ants were developed to further optimize the given search space [146]. Several variations of ACO have also been introduced to find potential global solutions. Considering financial markets, such an optimization approach can be helpful in deriving an optimal set of features, model parameters, etc.

For the financial crisis prediction, an ACO-based feature selection (ACO-FS) and ACO-based data classification (ACO-DC) methods were proposed [9]. Further, authors proposed to compare feature selection performance of ACO-FS with feature selection based on GA, PSO, and grey wolf optimization (GWO) methods; among these methods, GA-based feature selection required the highest cost whereas the proposed ACO-FS resulted in the minimum cost. On the other hand, performances of various classifiers were evaluated for these feature selection methods wherein the ACO-based financial crisis prediction model outperformed [9].

7.1.3. Harmony Search

Harmony search (HS) is a music-based metaheuristic approach with the aim to search for a state of harmony [147]. Such optimality can be incorporated for an optimization problem. It is also referred similar to the choice of best-fit individuals in GA [148].

While ANNs have been largely applied for stock market prediction, various optimization techniques can be included to support the feature selection process and hence, performance improvement. One of such approaches was proposed in [149] where authors proposed to select a set of features from the given list of technical indicators using HS and GA. The selected features using HS and GA were individually provided to ANN to predict stock price using HS-ANN and GA-ANN, respectively. The comparison indicated smaller MAPE using HS-ANN as compared GA-ANN; the proposed hybrid models could attain higher performance as compared to individual ANN. Subsequently, HS was proposed for ANN training phase in [150] to predict the stock price of various companies; the optimization performance was compared by incorporating ANN with imperialist competitive algorithm (ICA), GA, and PSO algorithms. The results indicated performance improvement using ANN-HS model. A cuckoo search (CS) and self-adaptive HS (SAHS)-based model was proposed in [151] to optimize the weight of orders for stock index. Authors compared the results with traditional HS, GA, SAHS, and cat swarm optimization (CSO) wherein the proposed SAHS indicated higher fitness than others.

7.1.4. Butterfly Optimization Algorithm

The food searching and mating behaviours of butterflies based on their fragrance intensity were considered as a motivation to develop butterfly optimization algorithm (BOA) for global optimization [152].

For an optimal parameter tuning of an SVR, BOA-SVR was proposed in [153] for stock market prediction using daily close price. Comparison with SVR parameters optimization using various metaheuristics showed that BOA-SVR achieved higher accuracy as compared to GA-SVR; however, it must be noted that the computational expensiveness of GA-SVR was less as compared to BOA-SVR.

7.2. Hybridization with Genetic Algorithms

To overcome the limitations of one approach, one or more complementing methods can be hybridized to attain higher performance accuracy. GAs have also been integrated for such hybrid approaches along with other metaheuristics for stock price as well as stock trend prediction. Thus, this section addresses **RQ3** and reviews the potential ways in which the performances of GAs have been enhanced by hybridization with other approaches for stock market prediction.

Based on the existing ensemble models, it was argued that the linear weighted approach might not be suitable for stock prices-based nonlinear time-series data. For a stock e-exchange price prediction, Elman network, gated recurrent NN (GRNN), and WNN with SVM NN were considered in [154]; authors optimized the model parameters with improved PSO (IPSO) using decimal and binary PSOs, i.e., DePSO and BiPSO. For IPSO, GA-based crossover and mutation operations were introduced for particles' performance enhancement. Hence, the training speed of PSO and global search capability of GA were integrated and the proposed approach, ANNs-PSO-GA, significantly improved stock indices forecasting with high volatility and noise. The parameter optimization capabilities of GA were also demonstrated with SVR for short-term trend prediction of a stock open price in [155]; the GA-SVR calibration model provided an accurate prediction as compared to grid search-based GRID-SVR and PSO-SVR. A regression-based model, auto-regressive integrated moving average (ARIMA) was appointed for predicting stock price in [156]; the forecasting approach was enhanced using the important regressors derived using GA. Similarly, a hybrid NN with PSO and GA was proposed for predicting the market clearing price on an hourly basis [157]. Considering the higher time duration requirement for execution using GA, authors proposed to integrate an exploitation-based algorithm to improve the optimization efficiency of GA [158]; thus, the exchange market algorithm (EMA) was combined with GA as EMGA to enhance the search strategy for stock market optimization problems. Authors considered the balanced and fluctuating conditions of stock markets and optimized the stocks for stockholders. The results indicated effective optimization capabilities using EMGA [158]. Another important aspect in stock market is optimization of index funds; for a subset of stocks, an index tracking portfolio aims to match the performance of the benchmark index [159]. For this purpose, a hybrid model based on GA and mixed-integer nonlinear programming (MINLP) was proposed in study [159]. Authors integrated GA for selecting stocks that could be considered for index tracking portfolio and adopted MINLP for estimating the weights of such stocks; results showed the ability of the proposed approach in creating an index fund with a close return rate as that of the market with considerably lower risk [159].

The primary focus of our survey is on stock price and stock trend prediction along with portfolio optimization. Therefore, the competing and complementing approaches discussed in this section are mainly associated with these applications of stock markets; interested researchers may be directed to explore further information on diverse financial applications and the suitability of various metaheuristics.

8. Discussions

In this article, we have reviewed the recent advances for stock market prediction based on variations and extensions of genetic perspectives. An overview of linking genetic perspectives with stock market prediction is given in Fig. 16. A graphical representation of our survey presents various genetic perspectives and other algorithms that are hybridized with such approaches for stock market prediction applications. It also provides a list of potential stock market applications. Though we have primarily considered stock price and stock trend forecasting techniques using GAs, such approaches can also be integrated for other finance-based applications such as portfolio optimization [46], market volatility prediction [160], trading strategy [34], bankruptcy prediction [44,161], foreign exchange tradings [162,163].

Here, several experimental analyses have been carried out to demonstrate how GA-based parameter optimization as well as feature selection approaches may result for stock price and trend prediction. As it can be seen through Figs. 10, 11, 14, and 15, GA and DE approaches have near-similar prediction performances; as they both belong to evolutionary computation, their approach to solve the given problem through evolution can be viewed to have considerable prediction results. On the other hand, two swarm intelligence-based algorithms, i.e., PSO and ALO have also been experimented and compared with GA and DE; while these methods have reduced errors even further, their implications to stock market prediction can be viewed for potential expansion. While the comparisons have been carried out for a sample dataset with primary set of features as well as model, an existing article has proposed information fusion-based approach with inter-intra crossover as well as adaptive mutation operations [124] wherein single chromosome contains two parts to focus on parameter optimization as well as feature selection problems together. As given in this article, the dataset considered here for the experiment has showcased an improved performance as compared to ALO; this indicates that the superiority of GA can be demonstrated through fusion. Through the detailed analysis of various aspects, it can be understood that prediction performance can be largely dependent on the dataset considered, features, preprocessing techniques, selection of prediction model as well as its hyperparameters, optimization algorithm, tuning of parameters, the target application, to name a few. As the experimental environment constraints may change, it is likely to observe variation in the forecasting results. Also, the computational complexity can play a vital role in identifying an appropriate choice of experimental set-up. According to the No Free Lunch theorem, the average performance of all such optimization algorithms is likely to be equal [164,165] and hence, it is of an utmost importance to determine the essential matters associated with the problem of interest and to determine the superior optimization algorithm to obtain desirable forecasting results. It can be observed that various genetics-based methods have been hybridized with other algorithms to build optimal models; such models have been utilized for stock market prediction applications. Though a significant amount of work has been carried out using such evolutionary algorithms, the existing challenges, as well as potential future research directions in the field of GA-based stock market prediction, are worth mentioning.

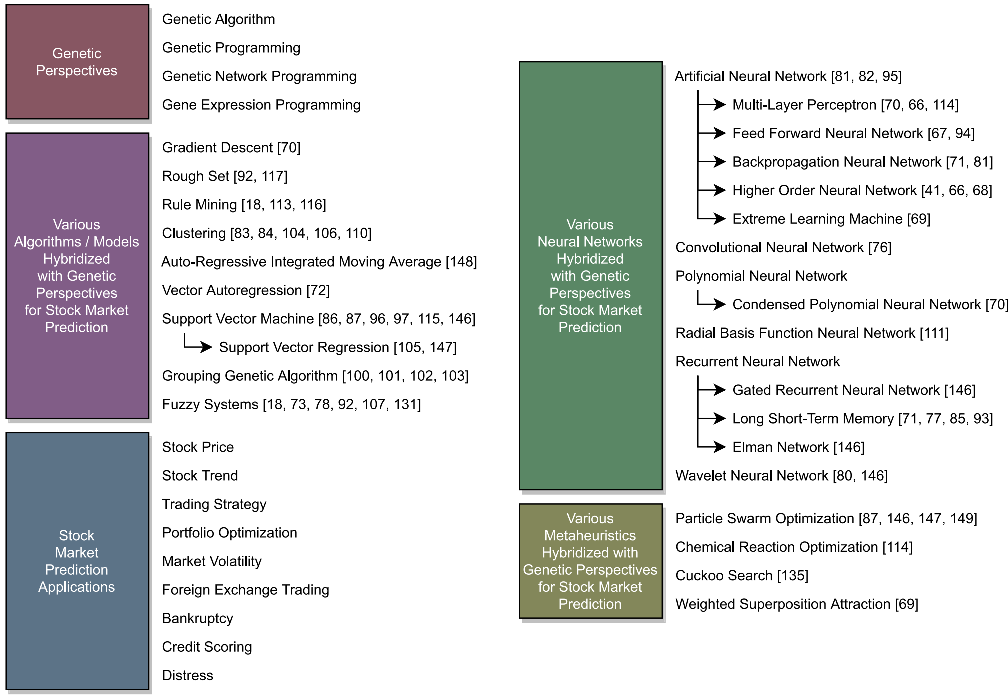

Fig. 16. An overview of linking genetic perspectives with stock market prediction.

8.1. Challenges

GA has been developed as a natural selection-based optimization approach; although it has the ability to search through large solution spaces, it may not guarantee to find an optimal solution [166]. On the other hand, it may require a longer duration to converge as well as it may get trapped into local optima.

To develop a GA-based approach, various parameters need to be defined and represented for the given problem. This process requires identification of appropriate population size, fitness function, selection strategy, crossover and mutation rates. Also, defining stopping criteria for the approach can be application dependent. Such factors must be well-attributed to attain better solutions. The limitation of degeneracy, i.e., multiple chromosomes representing the same solution, can degrade the possibility of having efficient solutions and therefore, finding optimal patterns in the complex stock market using GA may not converge completely and the derived solutions may lack optimality [167]. Also, the required execution time using GAs is generally high which, in turn, can have an adverse effect on its efficiency [158].

An enhanced approach, GP, was developed as an iterative tree-based representation. It can be considered for generating trading signals, however, stock price prediction has not been significantly addressed. However, GP encounters limitations while working with constraint-based complex relationships. This may be a concern for portfolio optimization tasks where different assets and their correlations with other influential factors need to be considered for optimal portfolio construction. Also, other genetic perspectives such as GP, GEP, GNP are relatively less explored for the field of financial markets.

It can be observed from the reviewed literature that the rationale behind selection of a specific strategy is not clearly anticipated. Though specifications about the selection approach, crossover and mutation methods, as well as their rates, are provided, the intuition(s) behind such adopted combinations are given less attention. Similarly, one or more datasets are taken for the experiment, however, the rationale behind choosing a specific dataset as well as the time duration for which the experiment is carried out are not clearly mentioned. Hence, a comparative study among such diversely carried out experiments may be difficult.

Some of the other challenges may include identification of influential facets of the stock market and incorporation of the financial aspects. The non-linear behaviours can be analysed with the associated social, economical, political, national as well as international, and emotional factors of traders, investors, and related parties. Also, little attention has been given to economics-related fiscal matters. Identification and inclusion of such real-world features and derivation of their application using metaheuristics may be beneficial for the stock market prediction.

8.2. Potential Future Research Directions

To develop reliable stock market predictions, the existing limitations need to be addressed. Some of the potential future research directions may be considered as follows.

It has been observed that beyond the large search space capability, GAs suffer premature convergence in a local optimum. GAs may be adapted with alternate tuning which may aid to avoid such premature convergence [168]. An improvement was proposed to reduce the definition interval and calculate crossover probabilities with a scale factor [168]. Authors showed these factors to have a direct influence on speed as well as convergence of a GA; similar enhancements may also be developed for operators such as mutation.

Though standard selection strategies are largely followed, the same may not be suitable for the given problem definition. Understanding the targeted stock market dataset and inherent characteristics may be useful in selecting appropriate algorithm variables. Also, developing a rationale behind choosing a specific operator may be beneficial for deeper understanding, re-development, and enhancement of the proposed work. Subsequently, other approaches can be integrated based on the market characteristics to identify useful features through integration of coefficient of variation-based properties for enhanced forecasting performances [169]. On the other hand, the data can be fused to extract useful information through quantization [170] and the same can be further provided to the optimized prediction model for stock price and trend prediction.

Though different aspects of the financial market have been considered, other influential factors may have been given limited attention; for example, opinion-based forecasting, sentiment analysis for market trend identification, the impact of social media and/or news. Such events may introduce drastic changes in the market trend; other learning approaches have evaluated stock market under such influence, however, limited research works have applied GA and/or GP-based techniques for improving the predictions, which can be one of the promising future directions. A series of experimental analyses can be carried out in the future for demonstrating the impact of GA as well as its subsequent variants in solving stock market prediction challenges. Also, the companies having been listed on multiple stock exchanges can provide important information about the market behaviours [13,171]. Such factors can be further explored using GAs as well as other metaheuristics to recommend potential investment strategies. It can be considered as another potential directive where genetic perspectives can be utilized for multiple exchanges to enhance portfolio diversification.

The slower convergence or possibility of being trapped into local minima using GAs may be improved by enhancing multi-objective or parallel approach [172]. Also, the genetic operators can be fine-tuned for developing stronger optimization models. It may also be considered to hybridize GAs with other swarm and evolutionary computation for stock market prediction [154]. It can be observed that fusion techniques have a significant implication on stock market predictions [173]; the flexibility of various genetic perspectives can be utilized for potential fusion with other metaheuristics to further enhance the prediction performance.

9. Concluding Remarks

Investment in a stock market demands knowledge of market behaviours, trading strategies, technical as well as fundamental analyses. It can be beneficial as well as detrimental and trading should be carried out carefully. Because of the complexity and non-linearity of the stock market, many researchers have proposed prediction techniques for future stock prices, movement direction, portfolio selection, profit returns, and various relevant aspects. In this article, we have studied GA-based recent advances in stock price and stock trend prediction. The applicability of these techniques has been broadly categorized into parameter optimization, feature selection, and hybrid approaches including classification and regression. We have studied how such algorithms have been applied to forecast stock market behaviour. It can be observed that GAs have been applied to a large number of stock market-related forecasting applications, whereas other genetic perspectives have been limited to specific domains such as trend prediction and portfolio optimization.

The stock market fluctuations are likely to occur throughout the trading period. Such variations and related patterns may be significant in understanding the market behaviour and hence, predicting future stocks. It could be observed that patterns-based market analysis could be further evaluated and optimized using genetic approaches. Also, factors associated with outcomes of an investment such as risk assessment, as well as stock exchange-based internal aspects may be considered to develop an efficient prediction system. Along with the market analysis, investors' profiles can be helpful for constructing a personalized prediction. Though we have restricted our survey to stock price and stock trend prediction, portfolio optimization may be one of the interesting research topics. It can be seen that only a few evolutionary computation methods have been integrated with GA; the performance may be improved by controlling the shortcomings of one approach with the help of another approach(es). Stock market data is continuous whereas GA works with binary string representation; to enhance the prediction accuracy, other bio-inspired approaches such as PSO can be integrated to deal with such continuous data. Hence, the existing competitiveness of such metaheuristics and complementation of GAs have also been presented as part of our survey. We have reviewed the shortcomings of GAs and discussed potential future research directions. It can be observed that the development of ensembled approaches is useful to construct reliable stock prediction models.

This article is aimed to provide a focused survey covering GAs and related genetic perspectives such as GP, GNP, GEP with recent updates from years 2013 to 2022 as well as challenges and future directions. Also, experimental analyses have been provided to compare and demonstrate the usefulness of GA; the same can be useful in further expansion of integrating other metaheuristics as well as proposing fusion-based techniques. It may encourage interested researchers in extending the research work for solving potential issues in predicting stock market. The inherent relationships and dependencies within stock markets may be useful for market analysis. Deep learning has given promising results for stock predictions [174], however, it could be observed that a limited number of deep learning-based techniques were applied with GA and/or GP optimization; detailed study of such potential extensions may bring improvement in stock trend prediction.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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