Archives of Computational Methods in Engineering (2021) 28:2133–2164
https://doi.org/10.1007/s11831-020-09448-8

ORIGINAL PAPER

A Comprehensive Survey on Portfolio Optimization, Stock Price and Trend Prediction Using Particle Swarm Optimization

Ankit Thakkar[1] · Kinjal Chaudhari[1]

Received: 23 October 2019 / Accepted: 1 June 2020 / Published online: 19 June 2020

Abstract

Stock market trading has been a subject of interest to investors, academicians, and researchers. Analysis of the inherent non-linear characteristics of stock market data is a challenging task. A large number of learning algorithms are developed to study market behaviours and enhance the prediction accuracy; they have been optimized using swarm and evolutionary computation such as particle swarm optimization (PSO); its global optimization ability with continuous data has been exploited in financial domains. Limitations in the existing approaches and potential future research directions for enhancing PSO-based stock market prediction are discussed. This article aims at balancing the economics and computational intelligence aspects; it also analyzes the superiority of PSO for stock portfolio optimization, stock price and trend prediction, and other related stock market aspects along with implications of PSO.

Abbreviations

ABB	Adaptive Bollinger Bands
ABC	Artificial Bee Colony
ACC	Acceleration
ACO	Ant Colony Optimization
APSO	Adaptive Particle Swarm Optimization
AMA	Adaptive Moving Average
ANN	Artificial Neural Network
BA	Bat Algorithm
BAS	Beetle Antennae Search
BB	Bollinger Bands
BBPSO	Bare-Bones Particle Swarm Optimization
BC	Boundary Constraint
BEA	Bat Echolocation Algorithm
BFO	Bacterial Foraging Optimization
BiPSO	Binary Particle Swarm Optimization
BP	Back-Propagation
BR-ANN	Bayesian-Regularized Artificial Neural Network
BSE	Bombay Stock Exchange
BSO	Beetle Swarm Optimization
CAPM	Capital Asset Pricing Model
CARRX	Conditional Autoregressive Range
CCEF	Cardinality-Constrained Efficient Frontier
CCMV	Cardinality-Constrained Mean-Variance
CCPSO	Competitive Co-evolutionary Particle Swarm Optimization
CLPSO	Comprehensive Learning Particle Swarm Optimization
CPSO	Constriction factor-based Particle Swarm Optimization
CRPSO	Cooperative Random learning Particle Swarm Optimization
CS	Cuckoo Search
CSO	Cat Swarm Optimization
CV	Cross-Validation
CVaR	Conditional Value-at-Risk
CV-PSO	Continuous Velocity Particle Swarm Optimization
DDPSO	Dimension-Decreasing Particle Swarm Optimization
DePSO	Decimal Particle Swarm Optimization
DMA	Dynamic Model Averaging
DMS	Dynamic Multi-Swarm
DPSO	Drift Particle Swarm Optimization
DRT	Dynamic Random Topology
DSSPSO	Dynamic Search Space Particle Swarm Optimization
EEMD	Ensemble Empirical Mode Decomposition
EHO	Elephant Herd Optimization

Kinjal Chaudhari
17ftphde21@nirmauni.ac.in

Ankit Thakkar
ankit.thakkar@nirmauni.ac.in

[1] Department of Computer Science and Engineering, Institute of Technology, Nirma University, Ahmedabad, Gujarat 382 481, India

EMA	Exponential Moving Average
EO	External Optimization
EPSO	Evolutionary Particle Swarm Optimization
ETF	Exchange Traded Fund
EUA	European Union Allowance
FCM	Fuzzy C-Means
FMOPSO	Fuzzy simulation-based Multi-Objective Particle Swarm Optimization
FPSO	Fuzzy clustering-based Particle Swarm Optimization
FTB	Financial Tool-Box
FWNN	Fuzzy Wavelet Neural Network
GA	Genetic Algorithm
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GC	Granular Computing
GD	Gradient Descent
GRNN	Generalized Regression Neural Network
GSA	Gravitational Search Algorithm
GSM	Global Stock Market
HFLANN	Heuristic Functional Link Artificial Neural Network
HGSA	Hybrid Gravitational Search Algorithm
HMOPSO	Hybrid constraint-handling Multi-Objective Particle Swarm Optimization
HS	Harmony Search
IA	Immune Algorithm
ICS	Improved Cuckoo Search
IMF	Intrinsic Mode Function
IPO	Initial Public Offering
IPSO	Improved Particle Swarm Optimization
IVFCM	Interval-Valued Fuzzy Cognitive Map
IWM	Improved Wavelet Mutation
KOSPI	Korea Composite Stock Price Index
lnMC	Log of Market Capitalization
LS-SVM	Least Square Support Vector Machine
LSSVR	Least Squares Support Vector Regression
LSTM	Long Short-Term Memory
MA	Moving Average
MACD	Moving Average Convergence/Divergence
MAD	Mean Absolute Deviation
MF	Mutual Fund
MLP	Multi-Layer Perceptron
MM	Minimax
MOEA/D	Decomposition-based Multi-Objective Evolutionary Algorithm
MOLPSO	Many Optimization Liaisons Particle Swarm Optimization
MOM	Momentum
MOPSO	Multi-Objective Particle Swarm Optimization
MSE	Mean-Squared Error
MS-IDPSO	Multi-Swarm of Improved self-adaptive Particle Swarm Optimization
M-V	Mean-Variance
NARX	Non-linear Autoregressive with Exogenous input
NBC	Naïve Bayes Classifier
NN	Neural Network
NPSO	Normalized Particle Swarm Optimization
NSE	National Stock Exchange
NSGA-II	Non-dominated Sorting Genetic Algorithm-II
NYSE	New York Stock Exchange
OBVA	On-Balance Volume Average
PAA	Piecewise Aggregate Approximation
PBMV	Prediction-Based Mean-Variance
PLS	Partial Least Squares
POCS	Portfolio Optimization based on Clonal Selection
POCSPS	Portfolio Optimization based on Clonal Selection integrated with Particle Swarm Optimization
PRS	Performance-based Reward Strategy
PSO	Particle Swarm Optimization
RBF	Radial Basis Function
ROC	Rate of Change
RRA	Relative Risk Aversion
RRL	Recurrent Reinforcement Learning
RSI	Relative Strength Index
RT	Random Topology
SAX	Symbolic Aggregate Approximation
SD	Standard Deviation
SET	Stock Exchange of Thailand
SFIS	Sequential Forward Input Selection
SMA	Simple Moving Average
SML	Security Market Line
SQP	Sequential Quadratic Programming
SR-MOPSO	Self-Regulating Multi-Objective Particle Swarm Optimization
SSE	Shanghai Stock Exchange
SSO	Simplified Swarm Optimization
STO	Stochastic Oscillator
S-V	Semi-Variance
SVM	Support Vector Machine
SV-PSO	Sparse Velocity Particle Swarm Optimization
SVR	Support Vector Regression
TMA	Triangular Moving Average
TPSO	Turbulent Particle Swarm Optimization
TRB	Trading Range Breakout
TVPSO	Time Variant Particle Swarm Optimization
UC	Unconstrained
UEF	Unconstrained Efficient Frontier
VaR	Value-at-Risk

VMD	Variational Mode Decomposition
VR	Variable Ranking
VwS	Variance with Skewness
WM	Wavelet Mutation
WMA	Weighted Moving Average
WNN	Wavelet Neural Network
WPSO	Inertia Weight-based Particle Swarm Optimization
WRS	Weight Reward Strategy

1 Introduction

The financial market trading of various securities has attracted a large number of investors. A generalized and, in a majority of the cases, the primary goal of investing in the financial market(s) is to gain maximum profits. It offers a wide scope to the constantly changing capital market frictions and therefore, to the individuals associated with it [1]. As compared to conventional financial approaches such as savings or fixed deposits, investment in the capital market may raise opportunities for increasing the expected returns [2]. While careful investment and trading can be beneficial, such markets may worsen and bring loss of valuables as well. This induces that stock valuation should be carried out before the investment; it can be considered as the process of identifying intrinsic stock price value [3]. The stock valuation can be assessed to classify stock positions on the security market line (SML), i.e., an expected rate of return of each security in capital asset pricing model (CAPM) [4]. There have been various theories associated with an investment, portfolio, arbitrage pricing, option pricing, interest rates, as well as the economic choice [5]. For realistic trading in the financial market, knowledge and acquisition of such aspects can be helpful; in contradiction to that, a large number of traders primarily rely on their analyzing abilities and experiences [6, 7].

Stock market equity is shown to be one of the long-run determinants of per capita GDP, i.e., gross domestic product [8]. It can play a crucial role in regulating a country's economic output. The economics can be divided into microeconomics and macroeconomics [9, 10]; while the former is concerned with the study of individuals and businesses, the latter can be associated with decisions taken by countries and their implications on the economy as a whole. The inherent non-linear nature of economy market requires detailed analyses to make reliable trading. It can be categorized into fundamental analysis and technical analysis [11–13]. The fundamental analysis is based on quantitative tools as well as qualitative indicators of a company such as its profile, managerial policies, marketing strategies, products and their intrinsic values; this kind of an approach requires expertise and detailed market study. On the other hand, the technical analysis is based on the inherent patterns of the targetted instrument such as its price, volume, market trading; such information can be utilized to derive crucial points, oscillations, and other technical aspects. Though such analysis can be carried out using various technical indicators, knowledge of fundamental concepts can be integrated for a reliable financial market study [14]. This kind of study can be employed for stock market-based predictions, for example, assets allocation-based portfolio construction, one-day-ahead stock price prediction, to name a few.

An equity market or a stock market aggregates trading activities of financial instruments; trading include buying, selling, and issuance of various assets publicly as well as privately. The markets serve as platforms for interaction and trading of stocks, bonds, physical assets, and derivatives such as options, futures, forwards among potential buyers and sellers. While a primary market issues new securities on an exchange, investors buy and sell the securities they own in the secondary market; stocks can be traded on either of these markets. Stock-related concepts can be primarily grouped into stock price, stock price movement, i.e., trend, and stock portfolio; analyzing and examining the stock market to forecast its expected returns have been a subject of interest for financial traders as well as academic researchers to develop reliable prediction models. It can be useful in determining trading aspects, stock returns as well as futures, market volatility and liquidity, foreign exchanges, transaction rules, and other applicable measures that can predict the probable future value of a company's stocks. Therefore, the calculation of the risk associated with expected return and/or profit is crucial. While investment corresponds to buying securities or assets for stable, generally long-term returns with moderate risk association, speculation can be related to executing risky and short-term financial transactions to gain higher profits [15, 16]. Depending on the intention, fundamental and/or technical analysis can be carried out to forecast the expected market returns. This has introduced the need for applying computational approaches to solve financial problems such as stock price prediction, optimal portfolio selection, asset allocation, price movement direction forecasting, market behaviour prediction. Such problems require studying a large number of historical data, company profiles, different transactions and associated factors to derive important information such as market trend, effects of the inflation rate or influence of the news; various machine learning as well as deep learning approaches have been adapted to solve complex financial problems [17, 18]. On the other hand, data mining, text mining, and other sentiment analysis-based techniques have also been explored to study the economy market and related social, financial, and content information [19, 20]. An optimal model configuration can be helpful to improve the resultant accuracy; hence, various nature-inspired metaheuristic approaches have also been integrated to dynamically optimize such methods.

Swarm intelligence and evolutionary algorithms have been developed with the primary objective of optimizing various real-world problems [21, 22]. A large number of nature-inspired algorithms have been proposed such as genetic algorithm (GA), ant colony optimization (ACO), particle swarm optimization (PSO), to name a few [23, 24]; these approaches have covered a vast range of applications and have also been expanding their applicability in various domains [25]. In case of limited availability of actual information and/or resources, the aim of finding a partial solution that can help to optimize the given problem requires such a metaheuristic approach [26]. One of the complex, non-linear time-series prediction problems is based on the dynamic financial markets; to address the same, a large number of optimization approaches have been integrated with machine learning, deep learning, data mining, as well as sentiment analysis-based approaches. While different methods have been used for financial market predictions, the continuous value data of the stock market have been significantly exploited using PSO due to its applicability and adaptability for continuous data [27]. In this article, we have pursued a comprehensive survey on the integration of PSO within various stock market aspects such as portfolio optimization, stock price prediction as well as stock trend forecasting. We have studied the implications of PSO in optimizing other stock market-related concepts such as trading, futures, returns, etc. The main objective is to develop a detailed understanding of critical stock markets, analyzing PSO-based existing approaches, and identifying correspondence among these methods and stock market predictions. While a large number of metaheuristic approaches have been compared for their robustness in complex problem-solving, PSO has demonstrated rapid convergence ability in the large search space [28]. The global optimum position attained by the particle agents can be significantly exploited to generate initial solutions; integration of such approach with other methods can be benefited from PSO's convergence abilities. The limitation of being trapped into local optima may be overcome using other approaches such as GA [28]. PSO can be applied for continuous data, such as financial time-series data, as well as other dynamic and complex optimization problems, such as portfolio optimization. Though some of the existing literature works have reviewed PSO-based stock-related predictions, it is essential to expand the horizons within stock markets with recent works that have been addressed using PSO. Hence, we carefully develop our survey to explore the widespread applications of PSO in complex stock market prediction.

1.1 Stock Market Computations

It is desirable to study financial concepts associated with stock market before exploring different prediction techniques. The technical analysis plays a vital role in stock market predictions; it is used to observe inherent patterns of the stock price and forecast trading rules. Technical indicators based on such trading rules have resulted in significant positive return [29]; historical stock price data can be exploited to derive various technical indicators. Also, the impacts of conducting technical analysis on the resulted forecasting have been evaluated for various stock markets [29, 30]. Evidence has shown that fluctuations and recurrent patterns of the stock trend could be derived using technical indicators such as moving average (MA), relative strength index (RSI); such indicators can be constructed using historical stock price data.

The continuously updating stock price information can be recorded using a stock ticker. Such reports can be useful in determining the current market scenario as well as the interests of different traders in specific stocks or financial securities. The historical stock data generally consist of date or timestamp, open, high, low, close, as well as volume information about the stock. For an intraday trading, the timestamp data may be integrated for deriving stock market data at a specific interval, such as minutes, hours; date information can be useful for interday trading over one day or longer. While the opening or open price indicates the price at which the particular stock was first traded upon the opening of an exchange on a trading day, the closing or close price indicates the last traded price for the same; the highest and the lowest prices on which the stocks are traded on an exchange within the specific trading day are denoted using high and low, respectively; the total number of share trading carried out for specific security on an exchange in a trading day is given by volume. When a company gets listed on an exchange, its security trading information can be derived; in the case where a company gets listed on multiple exchanges, such historical data can be separately collected from respective exchanges. The purpose of expanding business dimensions can be served with the company's stock trading on such exchanges. Some of the examples include New York Stock Exchange (NYSE), Nasdaq stock market (NASDAQ), Shanghai Stock Exchange (SSE), Shenzhen Stock Exchange, Bombay Stock Exchange (BSE), National Stock Exchange (NSE), to name a few. Stock data of the companies listed on such exchanges can be selected for predicting future stock price and/or trend.

Based on the historical data of stock exchanges, various technical indicators can be derived to utilize the stock patterns for prediction. Such indicators and their graphical representations can be adopted to determine useful information about stock patterns. A brief overview of some of the technical indicators and the computation method for the same is given in Table 1 (referred from [31]). These formulas are defined to evaluate technical indicator at time *t* for a time period *n*; the stock price has been denoted with *X*, e.g., stock close price. Such indicators can be plotted to analyze the stock patterns.

1.2 Existing Surveys on PSO-Based Financial Applications

The stock market has been a subject of interest for different purposes. Integration of metaheuristics within learning algorithms have been frequently studied and their applications to the stock market have been observed. Though PSO-based stock market predictions have been reviewed in the past, the recent advancements in the given field and broader perspectives towards PSO and its financial applications have demanded a critical comprehensive survey. We aim to prepare this survey with the primary orientation towards providing a detailed review of PSO-based applications in stock markets; we believe that understanding of the financial market concepts can accommodate clarity in approaching the same using computational methods. Hence, we have tried to balance between economics and computer science while discussing PSO-based stock market prediction aspects.

One of the early surveys on PSO provided an overview of PSO developments and taxonomy, followed by a range of PSO applications [32]; the survey mentioned that PSO flexibility could be used for economic, financial, business as well as engineering, medical, and other applications. A survey on machine learning-based financial time-series prediction briefly included PSO-based stock prediction [33]. Another review article provided the evolution of PSO algorithm and indicated financial forecasting as one of the applications [34].

A comparison-based survey for the financial domain was carried out for artificial neural network (ANN), PSO, and GA in [35]; authors discussed portfolio management, credit evaluation, as well as financial prediction and planning within the financial market domains. Subsequently, PSO advances were categorized into modification, population topology, hybridization, extension, theoretical analysis, and parallel implementation in [36]; to cover various domains of applications, authors also reviewed the financial time-series prediction. Considering that the review literature that has majorly been limited around approaches such neural networks (NNs), GA, PSO, ACO, authors in [37] discussed the principles, developments, and applications of various heuristic, metaheuristic, and hyper-heuristic bio-inspired methods; however, the list of applications included the financial aspects addressed by bio-inspired algorithms other than PSO.

Computational intelligence-based various financial market applications were explored in [17]; authors provided a financial trading framework with forecasting using ANNs, support vector machines (SVMs), hybrid mechanisms, as well as their optimization models including PSO, GA, artificial bee colony (ABC). On the other hand, impacts of different bio-inspired approaches were reviewed in [38] for stock market prediction; such optimization methods were compared over stock market domains such as stock market prediction and portfolio optimization. Subsequently, swarm intelligence-based different ANNs were surveyed for optimizing stock market price in [39]; comparisons showed that the swarm intelligence approaches with ANNs could improve stock price predictions as compared to other machine learning approaches. A detailed survey was carried out on swarm intelligence for dynamic optimization problems such as discrete, continuous, constrained, multi-objective, and classification in [22].

One of the recent surveys on swarm intelligence studied PSO-based portfolio optimization for various portfolio models [27]; the implications of different swarm intelligence methods on portfolio optimization and potential extensions in the field were analyzed as well. Based on the covariance risk factor in mean-variance (M-V) portfolio optimization model, authors developed a survey on deterministic models and applications in [40]; the techniques included exact solutions, approximate solutions, as well as hybrid approaches. As compared to the scope of earlier surveys, we have restricted our study within PSO-based financial aspects to provide an exhaustive survey. We believe this study can be beneficial for developing broader perspectives of PSO in financial markets. The comparison of the coverage of relevant topics in the existing surveys and our survey is shown in Table 2.

The remaining article is organized as follows: we have conceptually discussed PSO and a brief overview of time-series as well as financial market-related PSO applications in Sect. 2; we have elaborated the significance of portfolio optimization and various models, followed by PSO-based parameter optimization, modelling, and hybrid approaches for portfolio construction and optimization in Sect. 3; we have considered stock price prediction techniques where PSO has been applied for parameter optimization as well as hybrid methods in Sect. 4; we have reviewed the existing works in stock trend prediction based on parameter optimization and feature selection using PSO in Sect. 5; implications of PSO on other stock market concepts such as trading rules and strategies, returns, futures, etc. have been briefly reviewed in Sec. 6; stock market prediction using PSO and its variants, various features and linkages to potential stock market applications, limitations of the existing methods, challenges and future directions for potential enhancement have been discussed in Sect. 7; we

Table 1 Summary of Technical Indicators

Technical Indicator	Computation Formula [31]	Description
Simple Moving Average (SMA)	$SMA_n(t) = \frac{1}{n}\sum_{i=1}^{n} X(t-i+1)$	An average price of the given time period
Weighted Moving Average (WMA)	$WMA_n(t) = \sum_{i=1}^{n} \frac{(n-i+1)\cdot X(t-i+1)}{n-i+1}$	More emphasis on the recent prices compared to the older prices of the given time period
Exponential Moving Average (EMA)	$EMA_n(t) = \alpha \cdot X(t) + (1-\alpha)\cdot EMA_n(t-1)$ where, smoothing factor, $\alpha = \frac{2}{n+1}$ and $EMA_n(1) = X(1)$	Quicker responses to the recent price of the given time period
Triangular Moving Average (TMA)	$TMA_n(t) = \frac{1}{n}\sum_{i=1}^{n} SMA_i$	Weights placed on the middle prices of the time period
Momentum (MOM)	$MOM_n(t) = X(t) - X(t-n+1)$	Amount by which the stock prices have altered over the time period
Acceleration (ACC)	$ACC_n(t) = MOM_n(t) - MOM_n(t-n+1)$	Market driving force
Relative Strength Index (RSI)	$RSI_n(t) = 100 - \frac{100}{1+RS_n(t)}$ where, $RS_n(t) = \frac{\sum_{i=1}^{n} Gain(t-i+1)}{\sum_{i=1}^{n} Loss(t-i+1)}$; here, $Gain(t) = X(t) - X(t-1)$, if $X(t) > X(t-1)$ and 0, otherwise; $Loss(t) = X(t) - X(t-1)$, if $X(t) < X(t-1)$ and 0, otherwise	Magnitude comparison between recent gains and recent losses
Moving Average Convergence/Divergence (MACD)	$MACD(t) = MA_u(t) - MA_v(t)$ where, MA_u and MA_v indicate short and long moving averages (MAs), respectively	Correlation between a short MA and a long MA (note: MA is calculated similar to SMA)
Signal Line	$SignalL(t) = MA(MACD)$	Suggestion of a change in trend
Rate of Change (ROC)	$ROC_n(t) = \frac{X(t)-X(t-n+1)}{X(t-n+1)} \times 100$	Comparison between current price and previous price from a selected time period ago
William's %R	$\%R_n = -100 \times \frac{HH_n - Close}{HH_n - LLn}$ where, HH_n and LL_n indicate the highest high price and lowest low price within time period (n), respectively	Price normalization
Stochastic	$\%K = \frac{X_n - L_m}{H_m - L_m} \times 100$ where, X_n is treated as the recent close price, H_m and L_m denote the highest and the lowest prices traded within previous m trading days (generally, $m = 14$), respectively; $\%D = 3 - day\ SMA\ of\ \%K$	Signals of over-purchasing, over-selling, or deviation; $\%K$ refers to slow stochastic indicator whereas $\%D$ refers fast stochastic indicator
Bollinger Bands (BB)	$UpperBand_n = MiddleBand_n + (\alpha \cdot SD_n)$; $LowerBand_n = MiddleBand_n - (\alpha \cdot SD_n)$ where, $MiddleBand_n = MA_n$, SD denotes standard deviation, and α denotes the factor for SD	Upper and lower envelope bands around the price

Table 2 A comparative analysis of our survey with the existing PSO-based surveys under various criteria: C1- PSO, C2-Portfolio, C3- Stock price, C4-Stock trend, C5- Trading, C6-Returns, C7- Foreign exchange, C8- Hybrid, C9- Other financial aspects, C10- Stock market conceptualization

Criteria (→) Reference (↓)	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
[32]	✓								✓	
[33]	✓		✓							
[34]	✓								✓	
[35]	✓								✓	
[36]	✓						✓			
[37]	✓									
[17]	✓		✓							
[38]	✓		✓	✓				✓		
[39]	✓		✓	✓				✓	✓	
[22]	✓									
[27]	✓	✓				✓			✓	
[40]	✓	✓						✓	✓	
Our survey	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

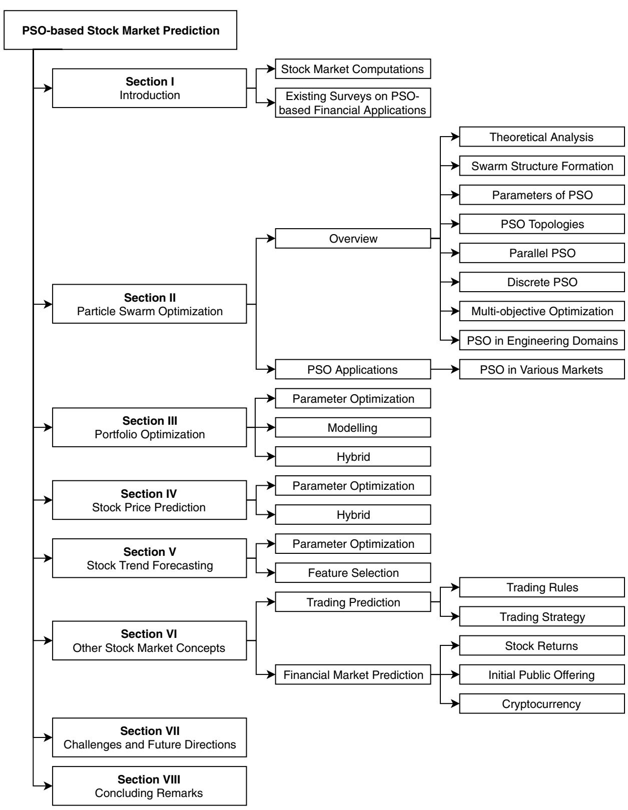

Fig. 1 An overview of the coverage and categories of PSO-based stock market prediction

have concluded our survey on PSO-based stock market-related forecasting and discussed the research aspects that may be considered for future research in Sect. 8. An overview of the coverage and categories of PSO-based stock market prediction that has been considered in this survey is shown in Fig. 1.

2 Particle Swarm Optimization

Nature consists of an enormous number of interactions within itself and with other creatures. Behaviours, as well as various activities of such creatures, have inspired researchers to develop artificial life theory in computational intelligence. The initial concept of exploiting the compatibility of social interactions instead of individual cognitive was developed for computational intelligence in [41].

The proposed PSO approach was inspired by the analogues of bird flocks that searched for corn. PSO is a swarm intelligence-based optimization approach that meets the primary five principles that can be applied for creating artificial swarm viz. proximity, quality, diverse response, stability, and adaptability [28, 42]. Here, the proximity principle specified simple PSO calculations based on time and space; the quality aspect demanded that a swarm should be able to sense and respond to the environmental changes; based on the diverse response-ability, the swarm should not have restricted scope so as to support diverse response principle; though the swarm should be stable enough not to change its behavioural mode with each change of the environment, it should be adaptable in order to change its behaviour, if that was worth.

2.1 Overview

PSO was initially proposed as an emulation of the social movement behaviour such as that of birds flock or fish school [41]. The swam entities were generalized with the term particles having a small amount of mass and volume, followed by velocity and acceleration. Thus, a particle swarm theory was developed to determine how particles move toward the global best position. Such entities were placed in the search space; the problems and/or functions were evaluated based on the movement of particles through the search space.

In a D-dimensional search space of PSO, each particle i can be represented with three vectors viz. current position $X_i = (x_{i1}, x_{i2}, ..., x_{iD})$, particle's optimal position, i.e., previous best position $P_i = (p_{i1}, p_{i2}, ..., p_{iD})$, and velocity $V_i = (v_{i1}, v_{i2}, ..., v_{iD})$; the optimal swarm position, i.e., global best position $g_{best} = (g_1, g_2, ..., g_D)$ is known to all m particles. For iteration $t + 1$, velocity and position coordinates of each particle are updated as given in Eq. (1) and (2), respectively [28, 43]; in order to restrict the particle velocity within a defined boundary, V_{min} and V_{max} are defined as the minimum and maximum allowable velocities, respectively. An iteration of PSO-based particle movement has been demonstrated in Fig. 2.

$$V_{id}^{t+1} = \omega \times V_{id}^{t} + c_1 \times rand() \times (P_{id}^{t} - X_{id}^{t}) + c_2 \times rand() \times (g_{best_d}^{t} - X_{id}^{t}) \quad (1)$$

$$X_{id}^{t+1} = X_{id}^{t} + V_{id}^{t+1} \quad (2)$$

where, ω is the inertia weight; c_1 and c_2 present acceleration constants; $rand()$ generates a random value within the interval [0, 1]; the velocity ranges within $[V_{min}, V_{max}]$. In Eq. (1), the first term, $\omega \times V_{id}^{t}$, denotes the influence of particle velocity in iteration t based on which it conducts inertial moving from the current position; subsequently, the second term, $c_1 \times rand() \times (P_{id}^{t} - X_{id}^{t})$, has the cognitive acceleration factor associated with the particle's own experience which determines its movement whereas the last term, $c_2 \times rand() \times (g_{best_d}^{t} - X_{id}^{t})$, corresponds to the particle's movement that is inspired by the movement of other

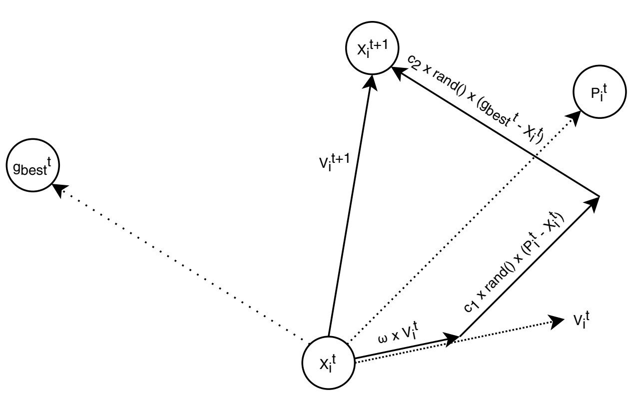

Fig. 2 An iterative particle movement in PSO (referred from [28])

particles and hence, based on the social acceleration factor [28]. Various modifications have been proposed in order to enhance the convergence ability and wide range of applicability of PSO.

An early survey on PSO, presented in [34], reviewed its evolution, variations, the stability aspects, as well as convergence abilities, including applications. In one of the recent literature studies, authors have provided an overview of PSO and its advances in [28] wherein various kinds of research works carried out for PSO were categorized into eight aspects: theoretical analysis-based PSO mechanisms, structural change-based performance analysis, impact of parameter settings, impact of topology selection, parallel PSO, discrete PSO, multi-objective optimization, and PSO for engineering domains.

2.1.1 Theoretical Analysis

It refers to the concepts and principle of PSO algorithm; the interactions among various particles and the effectiveness of the overall concept can be analyzed. Study of the evolution of PSO's theoretical aspects can be utilized to understand its stability through various enhancements. According to [28], the research problems were divided into individual particle's moving trajectory, convergence, and evolution and distribution of the swarm. To adapt PSO for stock market prediction problem, compatibility between the problem domain and PSO-based conceptual environment should match.

2.1.2 Swarm Structure Formation

The particles are capable of updating their structures in order to improve the performance; the formation of overall swarm in order to find the optimum position over a large-scale search space can be important aspect in optimization. Various swarm structures can be considered based on multi-sub-populations, learning object selection, velocity update formula and strategy, dynamic position and speed updation; these variations of PSO can be combined with other techniques for improving multi-modal problems and population diversity, as explained in [28].

2.1.3 Parameters of PSO

The inherent properties of such particles include position and velocity which help them to move towards an optimal position. Parameters such as inertia weight, learning factors, limits of speed and position, initial population and its size can be varied to attain the benefits of PSO within the given problem environment. For the given stock prediction model, such parameters need to be carefully selected. It can be helpful for global exploration as well as local exploitation.

2.1.4 PSO Topologies

The swarm of particles is associated with individual particles within the swarm; interaction in terms of local as well as global optimum positions can be useful to guide the swarm movement. Hence, the topology can be correlated with the neighbouring particle behaviour [28]. Such topologies can be static or dynamic which may be determined using particle index or with the topological distance among particles; utilization of such topologies can increase neighbourhood-based experience.

2.1.5 Parallel PSO

The operability of PSO can be conducted in a parallel manner to reduce the time complexity [44]; such technique can be enhanced using the system's capability to derive feasible solutions within a limited time period. The same can be helpful for a real-time application such as stock market prediction.

2.1.6 Discrete PSO

Based on the problem domain, PSO can provide continuous or discrete solutions to optimize the encoding ability of the integrated approach. One of the continuous data examples is time-series data of the stock market which demonstrates the continuous characteristics of stock values. Discrete PSO, on the other hand, can be useful for solving binary problems such as instance selection for a time-series classification problem.

2.1.7 Multi-objective Optimization

An optimization approach can be applied to independently targetting functions to obtain an optimal value. It can be widely used in deriving Pareto optimal solutions of the problems for which finding a perfect solution is likely to be impossible because of the object conflictions [28]. Stock portfolio optimization can be considered as one of such problems that aim at achieving a near-optimal solution.

2.1.8 PSO in Engineering Domains

Based on diverse provisions of PSO and its variants, it can be applied to a large number of engineering as well as medical domain applications [28]. Integration of PSO with other learning-based approaches as well as ensembled evolutionary algorithms has been extensively explored [25]. Also, interdisciplinary problem domains such as financial markets can be ensembled with such metaheuristic approaches to attain higher result outcomes.

2.2 PSO Applications

The simplicity and problem-solving ability of PSO and its variants have been adapted in various domains to target complex optimization problems. PSO-based applications have been extended to electric power systems [45], wireless sensor networks [46], data clustering [47, 48], cruise cabin price forecasting [49], cloud computing [50], road pavement roughness prediction [51], low material wastage based on rectangular shape packing into circular container [52], travelling salesman problem [24], earthquake prediction [53], to name a few. It can be determined that PSO's convergence ability can be integrated in a wide range of applications. Though our survey is restricted to PSO-based stock market prediction, we also summarize other financial market concerns, as well as time-series data, that have been addressed using PSO.

2.2.1 PSO in Various Markets

Economic discussions and financial market concepts can be expanded over an extensive variety. PSO has been incorporated to optimize and/or predict a variety of financial topics.

Technical indicators have been introduced in financial markets to assist market trend analysis. They have been exploited in various approaches to forecast future stock price movements and hence, to provide an appropriate trading signal, i.e., buy, sell, or hold. A stock trading system was proposed to optimize the weights of several technical indicators using multi-objective PSO (MOPSO) in [54]. The percentage profit and Sharpe ratio functions were considered with the end-of-day market data; the technical indicators optimization using MOPSO outperformed that using non-dominated sorting GA-II (NSGA-II). Here, Sharpe ratio is useful to derive the return of an investment as compared to the associated risk; it can be considered as an average return earned in excess of the risk-free rate per unit of volatility or total risk [55]. A PSO-based trade credit financing approach was proposed to obtain optimal selling price, replenishment number and schedule along the fluctuating demand [56]; the replenishment was stock restoration at the former level. Here, the credit period could be understood as the time duration provided to the buyers in order to simulate the demand, reduce some of the inventories, or increase the market share. For generalized type demand, a two-level trade credit policy-based approach applied PSO for pricing and time-varying demand and cost in [57].

The market fluctuations follow volatility clustering principle; such clustering was denoted as one of the reasons for degraded prediction performance of many generalized autoregressive conditional heteroskedasticity (GARCH) models. Therefore, authors proposed to apply PSO with an adaptive fuzzy-GARCH model to predict the stock market volatility in [58]. PSO was integrated to provide rapid convergence by optimizing membership functions. GARCH has also been used to measure stock market volatility; one of the enhancements consists of including range with GARCH, i.e., a conditional autoregressive range (CARRX) model for dynamic volatility. In [59], CARRX was used with least squares support vector regression (LSSVR) and adaptive PSO (APSO) to forecast the financial market volatility. The investment behaviours as well as stock category can be evaluated based on the quality of association rule mining; PSO-based optimal threshold values were predicted in [60]. Subsequently, turning point recognition, which is one of the deciding factors for buying or selling stocks, was predicted using a PSO ensembled SVM approach in [61]. Another application of PSO includes the creation of a profitability-based optimal trader for each market trader by optimizing adaptive Bollinger bands (ABB) parameters using PSO [62].

Apart from the financial stock markets, portfolio optimization technique could be developed for creating an investment profile in the electricity market as well; it was proposed to be helpful in deriving the amount of power that could be negotiated so as to increase the profits associated with the available market types [63]. While the prices were predicted using ANN, these expected prices were adapted for portfolio optimization using an evolutionary PSO (EPSO). Another approach using EPSO to provide electricity market participation prediction was proposed in [64]. Similarly, PSO-based hybrid approach for a simplified resolution using an exact method was proposed for solving the participation problem in multiple electricity markets [65]. Based on the electricity price prediction, a portfolio optimization model with risk measurement was proposed using PSO in [66]. In case of such markets where decisions should be made within a short time period, the simplified exact resolution was combined to determine the initial PSO solutions and hence, to derive optimized portfolio for an electricity market [67].

For biodegradable products, consideration of the degree of freshness, elasticity of demand against price, as well as sensitivity of demand towards the degree of freshness could be useful in determining the factors influencing product prices. PSO-based ANN approach was proposed for dynamic price strategy forecasting for such perishable products in [68]. On the other hand, one of the popular agricultural products, soybeans, was considered for futures price prediction using dynamic model averaging (DMA) with PSO in [69]; PSO was used to optimize two forgetting factors and a decay factor of DMA. The proposed DMA-PSO showed prediction enhancement for Chinese soybeans futures price forecasting.

Based on the time-varying characteristics of international crude oil prices, a hybrid method was proposed to forecast its future price in [70]. Authors adopted ensemble empirical mode decomposition (EEMD) approach to decompose the time-series into intrinsic mode functions (IMFs) and residual terms; the non-linear components were predicted using least square SVM (LS-SVM) with PSO (LSSVM-PSO) whereas the time-varying components were forecasted using GARCH model. The combined predicted values could achieve higher performance accuracy. While the time-series data concept was initially referred to as the stock market data, its adaptability has been expanded to the industrial environment as well. In [71], authors introduced industrial safety prediction; the long short-term memory (LSTM) was aggregated with PSO and gradient descent (GD) to obtain optimal parameters.

3 Portfolio Optimization

Investment in a non-linear financial market may introduce uncertainty; risk aversion behaviour of humans would impel them to attempt towards reducing such unpredictability. For different investment schemes that are expected to be providing a similar return, a risk-averse investor is likely to select the scheme with lower risk. Because individuals repeatedly invested to create a panel of risk aversion estimates, a correlation between relative risk aversion (RRA) and wealth was found in [72]. This can be helpful in understanding how an individual may choose to invest in different securities as well as hold a market portfolio. In order to maintain transparent trading within capital markets, disclosure of portfolio information is mandatory; such clarification can also affect the performance as well as the liquidity of the disclosed stocks [73].

A portfolio can be considered as a group of financial assets such as securities, stocks, funds, or cash equivalents; in order to maximize the expected return and to minimize the associated risk, portfolio diversification has been adopted by a large number of investors. Majority of the risk-averse investors do not engage in the market with risky assets; various studies have discussed emotions such as fear and their influences on risky investment attitudes, selection of portfolios, as well as returns [74]. Investors follow specific models and act accordingly to rebalance the portfolio in case of facing price fall, for example, the traditional Merton model considered purchasing risky assets whereas a fear-based model preferred selling out risky assets [75]. Hence, identification of one's attitude towards risk management, selection as well as optimization of a suitable portfolio, and consideration of the corresponding model is a crucial task. It can be seen that risk is in-built with higher returns. The modern portfolio theory focuses on how risk-averse investors may select a portfolio that would generate maximum expected returns [5]. Various models include M-V, variance with skewness (VwS), semi-variance (S-V), mean-absolute deviation (MAD), value-at-risk (VaR), minimax (MM), and conditional VaR (CVaR).

Portfolio optimization can be broadly categorized into portfolio construction, selection, and management tasks. The unconstrained (UC) portfolio optimization has been extended by incorporating various constraints to ensure realistic portfolio management [27]. Boundary constraints (BC) introduced a limit on the lower as well as upper limits to ensure that the investment amount lies within a certain range; this can be helpful in reducing the costs associated with small portions in a portfolio. Cardinality constraints considered limiting the maximum allowable number of securities that can be held in a portfolio so as to assist easy management. Transaction costs determine the amount payable for purchases, sales, and revisions of securities; such costs can significantly affect the expected outcomes and hence, must be incorporated for realistic portfolios. The transaction lots of each security could be rounded to the nearest integer value by adding constraints on the minimum or maximum transaction units. Constraints such as budget, floor and ceiling have also been considered to construct practical portfolios.

In order to demonstrate the applicability of PSO for stock market portfolio optimization, we have briefly categorized it into parameter optimization, modelling, and hybrid approaches including PSO with other nature-inspired algorithms.

3.1 Parameter Optimization

Identification of optimal parameters for the given model can significantly improve the prediction performance. While a large number of machine learning, as well as deep learning techniques, have been used for portfolio optimization, PSO and its variants have been adapted to optimize the parameter values.

An index fund can be considered as a type of mutual fund with a portfolio; such a portfolio is constructed to track the components of a financial market index. Such funds maintain their benchmark index irrespective of the market state. The co-movement of stock returns varies over time based on the investors' operations [76]. Hence, a hybrid model was proposed for portfolio optimization by adopting such time-scale features in [77]. The time-scale features were decomposed using maximum overlap discrete wavelet transform; weights of each scale were optimized using PSO as given by the optimizing objective function in Eq. (3) [77].

$$minimize \;\; \lambda_\alpha|\hat{\alpha}-0| + \lambda_\beta|\hat{\beta}-1| \tag{3}$$

where, $\hat{\alpha}$ and $\hat{\beta}$ indicated the ordinary least-squares regression intercept and slope; $\lambda_\alpha, \lambda_\beta \geq 0$ defined weighting values. As compared to the Canakgoz's approach, the average values of $|\alpha| = 0.00048$ and $|1-\beta| = 0.10378$ improved the proposed approach [77]. The weighted time-scale features were used to create homogeneous clusters of securities, followed by constructing an optimal portfolio for index tracking.

To solve the constrained portfolio optimization problem, prediction-based mean-variance (PBMV) model was proposed to predict the expected returns instead of using the mean of past returns [78]. The variance of errors associated with the expected portfolio returns was taken as the risk measure. Hence, the risk and return were determined using a low complexity heuristic functional link ANN (HFLANN) where the structure weights were determined using PSO. On the other hand, the portfolio optimization task was carried out using self-regulating multi-objective PSO (SR-MOPSO). For the given portfolio problem, objectives were defined as Eq. (4) [78].

$$minimize \;\; \text{both } \hat{\sigma}_p^2 \text{ and } -R_p \text{ simultaneously} \tag{4}$$

where, $\hat{\sigma}_p^2$ indicated total portfolio risk; R_p indicated the predicted portfolio return.

3.2 Modelling

Various metaheuristic algorithms can be suitable for problem modelling. Such models can be integrated with stock market information to target portfolio management-based problems.

A PSO-based heuristic method was proposed to solve the extended Markowitz portfolio selection model in [79]; it included bounds on holdings, cardinality, minimum transaction lots, and sector capitalization constraint sets. A combined approach of binary PSO (BiPSO) and improved PSO (IPSO) was proposed to select securities from the available ones in order to satisfy cardinality constraints and to attain investment amounts for the selected securities. Here, each particle's fitness value was calculated by Eq. (5) if it belonged to a feasible region and by Eq. (6), otherwise [79].

$$F_{fit} = f(\overrightarrow{x^*}) \tag{5}$$

where, $\overrightarrow{x^*}$ indicated point-wise multiplication of vectors representing the invested amount ($\vec{x}$) and M selected securities ($\vec{z}$).

$$F_{fit} = max\left[\left(B - \sum_{d=1}^{N} x_d z_d c_d\right), \left(BR - \sum_{d=1}^{N} x_d z_d c_d \overline{R}_d\right), \left|\sum_{d=1}^{N} z_d - M\right|, \Delta_s^-\right] + BigN \tag{6}$$

where, B denoted total budget; c_d defined minimum transaction lot for asset d and x_d defined number of purchased c_d's; z_d indicated the decision variable for cardinality constraint; R_d specified the expected portfolio return value; Δ_s^- defined the deviation of particle position from the constraint; N denoted the available securities whereas $BigN$ represented a large number.

One of the financial instruments is options; based on the strike price for buying or selling the security before its expiration date, the option contract must be used. They can be divided into call options for buying and put options for selling the asset at a stated price within a specific timeframe [80]. One of the reasons for trading options can be reduction of the risk exposure of portfolios. Hence, a normalized PSO (NPSO) model was proposed for portfolio management in [81]; the preferable stock prices and feasible time period to buy or sell the underlying asset(s), i.e., the exercise time, were determined to optimize a portfolio.

Modelling an optimal portfolio may get difficult with an increase in the number of available assets. To address a large-scale asset allocation problem, multi-objective dynamic multi-swarm PSO (DMS-MO-PSO) was proposed in [82]. While each particle learned from its historical as well as local best information in DMS-PSO [83], the local best was selected from the non-dominated solutions obtained during the search process in DMS-MO-PSO. To maintain the portfolio diversity, particles' self-learning was ceased to speed up the convergence process.

A comprehensive learning PSO (CLPSO) was proposed to update a particle's velocity based on the previous best information of all other particles [84]. It was showed to outperform many PSO variants for the multi-modal problems. Based on CLPSO, a dimension-decreasing PSO (DDPSO) was proposed in [85] where the particle dimensions after a certain number of iterations were cut. Such a concept could be useful for the portfolio optimization task where an investor might choose to invest in a specific number of assets out of the available ones. DDPSO could deal with multi-constrained portfolio optimization problems.

In PSO population, degree of a particle derives the number of neighbouring particles maintained; structures of such population topology has shown to have a direct impact on the performance [86, 87]. A random topology can be generated with a fixed number of neighbours for each particle under random population topology based on the degree (RT-D) strategy, whereas random topology with a given average degree can be created and maintained during PSO evolution in random population topology based on the average degree (RT-AD) strategy. Dynamic RT (DRT) strategies, on the other hand, indicate generation of random topologies with a specific degree after every number of generations; here, the degree may be fixed, i.e., DRT-D, or average degree, i.e., DRT-AD. Hence, PSO variant with inertia weight (WPSO) was extended as RTWPSO-AD, RTWPSO-D, DRTWPSO-AD, and DRTWPSO-D approaches in [88]. These methods were applied to cardinality-constrained portfolio optimization using M-V model (CCMV) as given by Eq. (7) [88]; the experimental results enhanced the performance.

$$f_p = \lambda \left[\sum_{i=1}^{N} \sum_{j=1}^{N} z_i x_i z_j x_j \sigma_{ij} \right] - (1-\lambda) \left[\sum_{i=1}^{N} z_i x_i \mu_i \right] \tag{7}$$

where, λ indicated risk aversion parameter; N denoted number of different assets; for asset i, z_i defined the decision variable whereas x_i specified the proportion; σ_{ij} defined the covariance between returns of assets i and j and μ_i indicated the mean return.

Similarly, a DRT-based generalized portfolio selection model was proposed in [89] by considering DRT-AD, DRT-D, DRT based on linear increasing AD and D, i.e., DRT-LIAD and DRT-LID, respectively. The proposed strategies were modelled using PSO with constriction factor (CPSO) for CCMV as DRTCPSO-AD, DRTCPSO-D, DRTCPSO-LIAD, and DRTCPSO-LID where the linear increasing-based approaches outperformed solving portfolio selection problem. The fitness function was evaluated using Eq. (7) [89].

While the constraints can be applied in generating a portfolio, constraint handling can be a challenging task in order to find feasible solutions. Some of the existing constraint handling methods include penalty function and augmented Lagrangian methods; they converted the constrained portfolio optimization problem into an unconstrained problem where the algorithm had to search over (n-dimensional) fitness landscape, i.e., the complete search space. Hence, to overcome large dimensionality search problem, particle repair method and preserving feasibility method were proposed in [90] based on bare-bones PSO (BBPSO) approach. The particle repair method translated infeasible solutions into feasible ones, which outperformed traditional constraint handling methods in various dimension. Subsequently, preserving feasibility method augmented the update operator of BBPSO as given by Eq. (8) [90] such that after being initialized within a feasible region, the particles never left the region; its performance degraded with an increase in the problem dimensionality.

$$\begin{aligned} \textit{minimize} \;\; \phi(x_i, t)_L = {} & f(x_i) \\ & + \frac{1}{2}\mu_E(t) C_E(x_i)^2 - \lambda_E(t) C_E(x_i) \\ & + \frac{1}{2}\mu_B(t) C_B(x_i)^2 - \lambda_B(t) C_B(x_i) \end{aligned} \tag{8}$$

where, x_i denoted each particle i in swarm X; $\lambda_E(t)$ and $\lambda_B(t)$ indicated time-dependent coefficients that were initialized to 0.5 whereas $\mu_E(t)$ and $\mu_B(t)$ specified time-dependent constraint penalty coefficients, initialized to 2.0; functions equality constraint $C_E(x_i)$ and boundary constraint $C_B(x_i)$ were given by Eq. (9) and (10), respectively.

$$C_E(x_i) = 1.0 - \sum_{j=1}^{n} x_{ij} \tag{9}$$

$$C_B(x_i) = \sum_{j=1}^{n} b(x_{ij}) \tag{10}$$

where, $b(x_{ij})$ was given by Eq. (11).

$$b(x_{ij}) = \begin{cases} |x_{ij}|, & \text{if } x_{ij} < 0.0 \\ 0, & otherwise \end{cases} \tag{11}$$

In the real-life scenario, a financial expert has information regarding the sector capitalization, price/annual earning, management calibre, dividend rate, etc.; an in-depth analysis could aid the guide's opinion about inclusion or exclusion of an asset within a portfolio. Hence, an extended Markowitz M-V model was proposed by introducing expert opinion constraint for real-life portfolio selection in [91]. Authors incorporated bounds on holdings, cardinality, minimum transaction lots, and expert opinion constraints; PSO approach was used to solve the portfolio selection problem. This model was classified as a quadratic mixed integer programming model; comparison with GA indicated an improved portfolio optimization using PSO for different test-cases.

One of the comparative studies between cardinality-constrained efficient frontier (CCEF) and unconstrained efficient frontier (UEF) models was carried out using cat swarm optimization (CSO), bat algorithm (BA), and PSO in [92]. For portfolio optimization, such efficient frontier could be considered as an example of Pareto optimal set [93]. The results have discussed the significance of risk associated with the returns. Apart from the existing approaches, authors in [94] considered distributional asymmetry and parameter uncertainty aspects for performance improvement in a portfolio optimization problem. For this reason, the higher moments such as skewness and kurtosis were integrated to describe the risk behaviour of an asset. An MOPSO was adopted for a portfolio-based uncertain multi-objective problem to generate robust efficient solutions.

Based on the fuzzy set theory, Sharpe ratio and VaR ratio were used to build a multi-objective portfolio selection model in [95]. VaR ratio reflected the risk premium per unit of the systematic risk; here, the risk premium indicated the return in excess of the risk-free rate of return an investment was expected to yield. In other words, it determined the extra amount gained by investing in a risky asset as compared to the amount that the same investment could have received by investing in a risk-free asset. Thus, VaR ratio had an index with dimensional knowledge. The portfolio selection was carried out using fuzzy simulation-based MOPSO (FMOPSO); the global best was conducted by an improved dominance times-based approach for each iteration [95]. The proposed approach could determine portfolio composition based on the conflict between Sharpe ratio and VaR ratio.

The multi-objective optimization problems may involve parallel optimization of multiple objectives which may conflict with each other; instead of having a single solution, such approaches generate a set of solutions that compromise objectives. MOPSO is one of the dominance-based algorithms which was tested against decomposition-based multi-objective evolutionary algorithms (MOEA/D) to solve constrained portfolio optimization [96].

A variation to PSO, namely, dynamic search space PSO (DSSPSO), was proposed with the concept of population entropy to enhance the speed of searching as well as convergence accuracy [97]. A portfolio selection model was developed using DSSPSO in [98]; authors identified that it was also suitable to find securities portfolio with certain low-risk interests. Such a dynamic approach showed efficient optimization for the constrained portfolio selection problem. To make an investment decision for a risk-constrained portfolio, the unbalanced returns of assets were considered in [99]; the general portfolio model and combined constraints of market value and upper bound were analyzed using PSO. Also, the investment decision model with irrational consumer behaviours was transformed into a linear planning-based model problem. Authors proposed to use automatic factor scaling for adaptive learning of the PSO parameters and evaluated the prediction performance.

In order to handle the risk associated with various sources in the investment process, risk parity was integrated within cardinality-constrained portfolio optimization problem in [100]. Authors addressed the mixed integer programming problem using an improved hybrid constraint-handling MOPSO (HMOPSO) to deal with cardinality, quantity, and risk parity constraints at the same time [101]. Based on the feasibility ratio r_f, an objective function was defined as Eq. (12).

$$F_j(x_s) = \begin{cases} \phi(x_s,\tau), & \text{if } r_f = 0 \\ \sqrt{f_j(x_s)^2 + \phi(x_s,\tau)^2} & \\ \quad + (1-r_f)\phi(x_s,\tau) & \\ \quad + r_f f_j(x_s), & \text{if } r_f \neq 0 \text{ and } x_s \notin \chi \\ f_j(x_s), & \text{if } r_f \neq 0 \text{ and } x_s \in \chi \end{cases} \tag{12}$$

where, $\phi(x_s, \tau)$ denoted the overall constraint violation for candidate portfolio x_s; $\tau \geq 0$ denoted a tolerance parameter to retain the infeasibile solutions nearby the feasible region;

χ indicated the Pareto set of portfolios; $j = 1, 2$ were used to provide normalization formula for functions f_1 and f_2.

A particle's position and velocity are important properties in PSO; velocity can be helpful in identifying a particle's local position learns based on the local as well as global solutions. For cardinality constrained binary optimization problem of a portfolio, mapping smaller number of solutions to higher-dimensional solution space might lead to early stagnation, i.e., sparse velocity PSO (SV-PSO); therefore, using an untransformed solution to define BiPSO velocity direction was proposed in [102] as continuous velocity PSO (CV-PSO). With the varying number of assets available for a fixed stock size, CV-PSO provided reliable results as compared to SV-PSO [102].

3.3 Hybrid

Though PSO and its variants are capable of deriving optimal portfolios, some of their limitations such as local search or premature convergence may be addressed using other nature-inspired algorithms. Such hybrid methods can be suitable for generating robust solutions.

In order to select efficient funds and allocate optimal assets for portfolio optimization, GA and PSO were integrated [103]. Mutation and elitist strategy were adopted, respectively for avoiding local optima and for faster evolution in PSO. Another approach considered PSO to optimize an unrestricted risky portfolio and determined optimal parameter values using GA [104]. Based on the expected value, semivariance, and CVaR parameters, a hybrid portfolio optimization model was proposed in [105]. Authors considered transaction costs experienced for the buying as well as selling assets in the proposed multi-stage portfolio optimization. The parameters of GA and PSO-based hybrid approach were selected using a Taguchi experimental design method; it was intended to reduce the impact of uncontrollable factors whereas to identify the suitable levels of controllable factors based on robustness [106].

In order to ensure optimal asset allocation for minimum risk and maximum returns, a hybrid approach combining clonal selection and PSO was proposed in [107] and followed the fitness function given by Eq. (13).

$$maximize \;\; \alpha_1(w^T m) - \alpha_2\left(a + \frac{1}{t(1-b)}\sum_{k=1}^{t} u_k\right) \tag{13}$$

where, w^T denoted the asset weights; m defined the mean of daily yield for each stock; α_1 and α_2 indicated the investor preferences; the degree of belief for an objective function and CVaR were given by a and b, respectively; u_k represented the portfolio loss in k^{th} day of t trading days. A class of immune algorithms (IAs), i.e., clonal selection algorithm was inspired by biological cloning and hypermutation concepts; for portfolio optimization based on clonal selection (POCS), antibody represented a portfolio with parameters such as return for each stock, expected return, expected risk, and fitness function. POCS integrated with PSO (POCSPS) outperformed individual approaches with an increased fitness for a medium population size [107].

For large portfolios, a hybrid PSO approach was proposed in [108] where the global best position of particle swarm acted as the initial point to sequential quadratic programming (SQP) algorithm; it could utilize the faster convergence ability of SQP based on the optimal starting point derived using PSO. Hence, the proposed method could handle the diversification for cardinality constrained portfolio optimization; Eq. (14) defined the fitness function considered in [108].

$$f(\overline{W}, \mu_i, \sigma_{ij}, \lambda) = \lambda \sum_i \sum_j W_i W_j \sigma_{ij} - (1-\lambda) \sum_i W_i \mu_i \tag{14}$$

where, $\overline{W}$ represented the portfolio weights; W_i denoted the portfolio weight to be assigned to asset i; μ_i defined the expected return whereas σ_{ij} defined covariance between the returns of assets i and j; λ indicated a risk aversion parameter.

Though PSO has been widely applied to the portfolio optimization problem, it may encounter being trapped into local optima. Hence, beetle antennae search (BAS) was integrated with PSO as the beetle swarm optimization (BSO) approach for constructing an investment portfolio model [109]; BSO was proposed to provide the judgement ability to each particle. While PSO is capable of efficient global search, its premature convergence may become one of the drawbacks; based on the potential local search ability of an external optimization (EO), a combined eo-PSO approach was introduced to solve cardinality and bonding constraints-based portfolio optimization problem in [110]. Also, a chaotic mutation operation was considered for exploration and the fitness was calculated using Eq. (14).

A two-stage hybrid PSO was proposed by including budget and restriction on short sale constraints for portfolio selection and optimization tasks [111]. Authors considered mean return, variance of return, and return as the profit, risk, and selection criteria, respectively. It was named as the financial tool-box PSO (FTB-PSO) where portfolio construction, mean and standard deviation (SD) calculations, and the task of plotting assets as particles were carried out using FTB of MATLAB. Here, Sharpe ratio was considered as a fitness function, as defined by Eq. (15) [111].

$$Sharpe\ ratio = \frac{R_p - R_f}{Standard\ Deviation(p)} \tag{15}$$

where, R_p defined mean return of the portfolio p whereas R_f defined the risk-free rate of return for the assets.

A portfolio optimization approach has been experimented with methods based on swarm intelligence [112]. Using the resultant return, variance-measured risk, Sharpe ratio, and per iteration time, various algorithms such as cuckoo search (CS), harmony search (HS), elephant herd optimization (EHO) algorithm, bat echolocation algorithm (BEA) along with PSO have been evaluated. Comparison analysis showed stable results with high Sharpe ratio while using CS and HS whereas EHO and BEA could significantly optimize the portfolio.

On the other hand, recurrent reinforcement learning (RRL) and PSO were combined with Calmar ratio for asset allocation as well as constraint optimization in [113]. Here, Calmar ratio was considered as the fitness function for asset selection and weight allocation as given by Eq. (16); it served as an objective function for RRL whereas as the fitness function for PSO-based methods.

$$C_T = \frac{\gamma^T}{E(MDD)} \tag{16}$$

where, T denoted the time horizon; γ indicated mean of returns; $E(MDD)$ defined the expected maximum drawdown. Authors proposed to create portfolio trading systems to generate short and long signals while handling the portfolio constraints. These included PSO, IPSO, drift PSO (DPSO), and many optimization liaisons PSO (MOLPSO) with RRL portfolio. Also, the transaction cost was handled using the market condition stop-loss retraining mechanism for an adaptive RRL-PSO portfolio rebalancing decision system [113].

The degree of membership could deal with imprecise concepts using fuzzy logic; thus, it could be used to partly assign data to multiple clusters. A fuzzy clustering-based PSO (FPSO) was ensembled with granular computing (GC) technique for portfolio optimization in [114]. Authors considered dividing stocks into granules and further divided them into small clusters in order to maximize portfolio returns using diversification and evaluated such solutions using fitness function for fuzzy relationship X given by Eq. (17).

$$f(X) = \frac{K}{J_m} \tag{17}$$

where, K denoted a constant whereas J_m defined fuzzy C-means objective function as Eq. (18).

$$J_m = \sum_{j=1}^{c} \sum_{i=1}^{n} \mu_{ij}^m d_{ij} \tag{18}$$

where, μ_{ij} denoted the membership value of object i to cluster j; n and c denoted the matrix size of velocity, i.e., number of rows and number of columns, respectively; d_{ij} defined the Euclidean distance. The six information granules were formed based on the capitalization properties of the clustering stock members [114]; efficient portfolio management could be achieved using the proposed approach.

A summary of the existing approaches for PSO-based portfolio optimization and parameter specifications is given in Table 3. The reviewed articles have been summarized based on their targets, features considered and methods followed. We have also provided the dataset specifications including the duration for which specific dataset was considered for the experimentation along with PSO parameter values. We have briefly summarized the results obtained using specific approach.

4 Stock Price Prediction

In order to trade various stocks, their prices are evaluated and predicted for future stock valuation. The short-term price prediction may indicate intraday price, within an hour or an interday price, such as one-day-ahead price prediction; on the other hand, the long-term price prediction regards to weekly, monthly, or yearly basis. Various price prediction techniques can be integrated with PSO for improved forecasting accuracy. Hence, we have considered parameter optimization, as well as hybrid techniques, followed using PSO for stock price prediction.

4.1 Parameter Optimization

In order to analyze the non-linear time-series data of stock prices, various machine learning approaches such as ANN, SVM, clustering [33, 115, 116] have been considered; similarly, deep learning networks have been applied as well [117]. The prediction accuracy of such algorithms is likely to be influenced by the weights of the framework. Hence, different swarm and evolutionary approaches have been incorporated for parameter optimization of the existing methods.

The inherent non-linearity of the stock price data can be addressed by SVM kernel functions. Based on SVM, an SVR-based third-day stock close price prediction was carried out in [118]. Authors proposed to use Gaussian radial basis function (RBF) (σ) for SVR kernel and considered PSO to optimize σ, penalty coefficient (C), and insensitive loss coefficient (ε); the particles were given random initial values for $\{C, \sigma, \varepsilon\}$ combination as current positions and their speed and positions were updated to reduce the error rate of SVR.

A three-level NNs-based ensemble model was proposed in [119] for improving financial returns by considering that an ensemble model could improve the performance as compared to several base models. It combined Elman

Table 3 Summary of PSO-based portfolio optimization approaches

Paper	Aim	Features	Method	Data Specifications		PSO Parameters				Result
				Dataset	Duration	m	ω	c_1, c_2	V_{min}, V_{max}	
[77]	Portfolio selection for index fund	Time-scale	MODWT for features decomposition; PSO for weight optimization	Hang Seng 33, DAX 100, FTSE 100, S&P 100, Nikkei 225, S&P 500, Russell 2000, Russell 3000	03/1992 to 09/1997 (weekly)	20	0.8	2, 2	−0.2, 0.2	Improved index tracking problem than Canakgoz's approach
[78]	Constrained portfolio optimization	Mode, median, MA of 10 weeks	HFLANN for expected returns prediction; SR-MOPSO for optimization	Hang Seng, DAX 100, FTSE 100, S&P 100, Nikkei 225	03/1992 to 09/1997 (weekly)	100	0.5	2.05, 2.05	0.06, 0.5	Comparable PBMV solutions as the Markowitz M-V model
[79]	Cardinality constrained portfolio selection	Not specified	BiPSO, IPSO	9, 30, 150 stocks	Not specified	30	0.7298	1.496, 1.496	Not specified	PSO outperformed GA
[81]	Portfolio management	Volatility, expiration time	NPSO for option pricing	European Call, Put; American Call, Put options	Not specified	40 – 50	Not specified	Not specified	Not specified	Improved optimization
[82]	Large-scale asset allocation for portfolio	Close price	DMS-MO-PSO	Chinese stock market	100 days from 04/01/2012	30	Not specified	Not specified	Not specified	Improved performance than NSGA-II, MOPSO, MODE
[85]	Multi-constrained portfolio optimization	Not specified	DDPSO, CLPSO	Eight test cases	Not specified	Not specified	Not specified	Not specified	Not specified	Improved portfolio optimization
[88]	CCMV portfolio optimization	Not specified	RTWPSO-AD, RTWPSO-D, DRTWPSO-AD, DRTWPSO-D	Hang Seng, DAX 100, FTSE 100, S&P 100, Nikkei 225	03/1992 to 09/1997 (weekly)	100	Not specified	Not specified	Not specified	Improved performance than WPSO; best optimization strategy using DRTWPSO-D
[89]	Generalized portfolio selection for CCMV	Not specified	DRTCPSO-AD, DRTCPSO-D, DRTCPSO-LIAD, DRTCPSO-LID	Hang Seng, DAX 100, FTSE 100, S&P 100, Nikkei 225	03/1992 to 09/1997 (weekly)	30	Not specified	2.1, 2	0.1	Improved performance with DRTCPSO-LIAD and DRTCPSO-LID

Table 3 (continued)

Paper	Aim	Features	Method	Data Specifications		PSO Parameters				Result
				Dataset	Duration	m	ω	c_1, c_2	V_{min}, V_{max}	
[90]	Constrained portfolio optimization	Not specified	BBPSO	Not specified	Not specified	30	Not specified	Not specified	Not specified	Particle repair method outperformed traditional constraint handling methods; preserving feasibility method degraded performance
[91]	Constrained portfolio selection	Not specified	PSO	Hang Seng, DAX 100	Not specified	Not specified	Not specified	Not specified	Not specified	PSO outperformed GA; PSO resulted in higher mean execution time
[92]	CCEF, UEF	Not specified	PSO	Hang Seng, DAX 100, FTSE 100, S&P 100, Nikkei	Not specified	Not specified	Not specified	Not specified	Not specified	Comparison between PSO, CSO, BA
[94]	Multi-objective portfolio models with higher moments	Not specified	MOPSO	Chinese stock market	01/01/2006 to 31/12/2010 (daily)	Not specified	Not specified	Not specified	Not specified	MOPSO outperformed SPEA2 and NSGA-II
[95]	Multi-objective portfolio selection with VaR ratio	30 decision variables	FMOPSO	NYSE, SSE	01/01/2012 to 30/04/2012	Not specified	Not specified	Not specified	Not specified	Reduced investment risk; slight profit depression
[96]	Constrained portfolio optimization	Not specified	MOEA/D	Tehran stock exchange	03/04/2010 to 20/12/2016	100	0.4	1, 3	Not specified	Decomposition-based method performed better than dominance-based methods
[98]	Portfolio selection	Close price	DSSPSO	Chinese stock market	01/2016 to 12/2016	20	Not specified	Not specified	Not specified	Efficient constrained portfolio selection
[99]	Portfolio prediction model	Not specified	PSO	15 stock funds from Sina Finance	10/04/2014 to 10/04/2016	Not specified	0.7298	1.4962, 1.4962	Not specified	Reduced investment risks, improved returns-based portfolio scheme

Table 3 (continued)

Paper	Aim	Features	Method	Data Specifications		PSO Parameters				Result
				Dataset	Duration	m	ω	c_1, c_2	V_{min}, V_{max}	
[100]	Equity portfolio management	Not specified	HMOPSO	DowJones, FF49Industries, NASDAQ100	02/1990 to 04/2016, 07/1969 to 07/2015, 11/2004 to 04/2016 (weekly)	200	0.4	1.494, 1.494	0.002, 0.2	Improved performance for risk parity control
[102]	Cardinality constrained portfolio optimization	Mean, covariance matrix	CV-PSO, SV-PSO	Nikkei 225	03/1992 to 09/1997	1000	0.4	1.5, 1.5 and 2, 2	Not specified	CV-PSO generated reliable results compared to SV-PSO

network, generalized regression NN (GRNN), and wavelet NN (WNN) using SVM NN in a non-linear manner. The proposed meta-learning modelling integrated different training set and different learning approach methods and the base models were optimized with IPSO; it consisted of adaptive inertia weights and the dynamic arccosine function acceleration parameters. While weights and bias of NNs were optimized with decimal PSO (DePSO), the architecture was optimized with BiPSO to predict one-day-ahead stock price.

Considering the existing ensemble models, it was pointed out that a linear weighted approach might not be suitable for non-linear time-series data such as stock prices. In [120], authors proposed to predict stock e-exchange price using Elman network, GRNN, and WNN with SVM NN similar to that in [119] where model parameters were optimized using IPSO using DePSO and BiPSO. Here, two-point crossover and mutation operations of GA were incorporated in IPSO. The proposed approach, ANNs-PSO-GA [120], delivered significant improvement in predicting stock indices with high volatility and noise.

While global search capabilities of PSO have been adapted for solving various financial problems, other approaches having the ability to search within local areas may be exploited and/or combined with PSO so as to boost the overall performance. The local search advantages of back-propagation (BP) NN (BPNN) were integrated with adaptive PSO as HBP-PSO for predicting stock price in [121]. PSO was utilized to train connection weights and thresholds of BP; here, the mean value of errors between the predicted and the actual output was used as a fitness function. Based on the global search of PSO, BPNN was applied then onwards to ensure that it did not get trapped into local optima. The proposed approach overcame the standard BP model; the forecasting outcomes were useful for stock price trend prediction as well.

A TSK fuzzy model-based structure identification method was incorporated for stock price prediction in [122]. The primary task of relevant input selection was carried out with mutual information using variable ranking (VR) as well as sequential forward input selection (SFIS) methods; the fuzzy if-then rules were generated using fuzzy c-means (FCM) clustering followed by fixing parameter search space boundaries. Authors proposed to optimize the premise and consequent parameters by using cooperative random learning PSO (CRPSO). As compared to the VR-based approach, SFIS showed improved performance in case of considering mutual dependencies among input variables. Hence, the proposed model with five rules [122] enhanced one-day-ahead stock price forecasting.

Another SVM-based stock price forecasting method was proposed in [123] where SVM parameter weights were optimized using PSO. Authors also considered ANN and Naïve Bayes classifier (NBC) for the same; as compared to

ANN, NBC, and LS-SVM, the proposed SVM-PSO model achieved the highest accuracy for short-term stock price prediction. Similarly, SVM, LS-SVM, and partial least squares (PLS) were employed for stock price prediction application in [124]. The derived LS-SVM used equality constraints in SVM and hence, transformed the quadratic programming problem into linear equation groups; the reduced calculation complexity could be helpful in reducing the number of parameters that needed to be optimized in LS-SVM. The ability of PLS to solve problems with variable dependencies was considered as well. Results indicated that cross-validation (CV) LS-SVM and PSO-optimized LS-SVM could improve the prediction accuracy whereas PLS could achieve similar accuracy as that of SVM. It can be understood that SVM may be applied to small-scale stock data whereas LS-SVM may be suitable in resolving high-dimensional complex stock data prediction. Subsequently, PSO-optimized SVR forecasting models were proposed for stock price prediction in [125] and [126].

Among various modifications and advances of PSO, simplified swarm optimization (SSO) [127] was proposed to randomly update rules and discard the concept of velocity in PSO. SSO has demonstrated more effectiveness as well as higher stability as compared to the traditional PSO in order to identify optimization solutions [128]. However, a lack of variety in the solutions may lead to a slower convergence rate. In one of the conditions of SSO, a random new position is selected without having been related to the previous position; this may emphasize stochastic search behaviour of SSO. Hence, a combined approach, PSOSSO, was developed for stock price prediction in [129]. It integrated the velocity factor of PSO within SSO as an undated rule; fuzzy WNN (FWNN) prediction model was optimized using PSOSSO.

In order to maintain the search space diversity, the physical principle of center of mass was integrated with PSO as PSOCoM to support cognitive behaviour of the particles [130]. For stock index prediction, authors considered an adaptive linear combiner with parallel inputs as the features calculated from technical indicators. With respect to the mean-squared error (MSE) objective function, the performance of PSOCoM was compared with PSO, BFO, adaptive BFO (ABFO), and GA for long-term and short-term predictions.

For the purpose of intraday stock price prediction, a multiresolution technique, variational mode decomposition (VMD) was integrated with BPNN whereas its initial weights were obtained using PSO in [131]. The primary benefits of applying VMD for financial time-series was to derive similar frequencies for improved characterization of the noisy intraday stock price data and it could be effective towards denoising [132]. Authors set the number of extracted modes to ten which showed to be determining enhanced prediction accuracy with the proposed VMD-BPNN-PSO approach when evaluated with prediction error-based fitness function [131].

Various ANN approaches were compared for stock index prediction in [133] which included multi-layer perceptron (MLP), RBF, and an optimized RBF NN. From the stock data, a set of centers of an RBF NN was optimized using PSO. The updated set of centers were utilized in the proposed, optimized RBF approach; evaluation of the weekly stock data of various companies indicated improved results achieved from the proposed method as compared to MLP and RBF. On the other hand, a BPNN-based model was proposed with PSO and GD for predicting the next-day stock close price in [134]. The fast convergence ability of PSO towards the global optimum whereas local optima handling tendency of BPNN were integrated for stock price prediction.

A hybrid ANN model was adapted for stock price forecasting along with CS, improved CS (ICS), ICSGA, GA, and PSO metaheuristics in [135]. The comparative analysis disclosed the highest performance improved attained using PSO. Other approaches include ANN model optimized with PSO for predicting the next-day high price [136]. Similarly, WNN was proposed for stock price prediction where the suitable initial network configurations were determined using PSO [137]; the experimental results found that this method could accomodate drastic change within stock prices. To deal with the possibility of over-fitting ANN weights, probabilistic network weights were determined using bayesian-regularized ANN (BR-ANN) in [138]. Authors proposed to address the uneven distribution of network weights and optimized them using PSO; the technical indicators were utilized with daily stock market prices to predict one-day future close price. Using a self-adaptive variant PSO for optimizing the weights and threshold of Elman network was proposed for short-term stock open price prediction in [139]; this approach considered only the historical open price data for training the network. Results indicated enhanced prediction accuracy as compared to Elman network as well as BPNN.

Based on the supply and demand forces, the equilibrium monetary value of a traded stock can determine the clearing price. A hybrid approach for hourly prediction of market clearing price of electricity was proposed in [140]; while PSO was used to optimize NN learning ability, GA was combined to enhance the NN structure optimization. Authors considered k-means clustering method for seasonality pattern detection. The proposed method improved prediction accuracy as compared to BA-based NN.

4.2 Hybrid

While PSO has been largely applied for parameters optimization to forecast stock prices, other approaches can also be integrated in an ensembled way to improve the prediction performance.

For stock index forecasting, FLANN was hybridized with improved wavelet mutation (WM) based PSO in [141]. The proposed IWM-PSO-FLANN model could expand mutation range by integrating PSO with the wavelet theory. The motivation behind application of WM was based on the observations that PSO could sharply converge in the initial phase whereas could saturate or even terminate during the later phase; by introducing WM in PSO, each particle could have an opportunity to mutate. Hence, for financial time-series data, IWM introduced expansion of mutation range during each generation [141]; expansion using Chebyshev and trigonometric functions determined improved index prediction accuracy of IWM-PSO-FLANN.

We have briefly summarized existing PSO-based stock price prediction approaches along with the parameter specifications in Table 4. Along with the prediction aim such as close price, open price, etc., we have specified the target in terms of intraday or interday prediction. We have provided the methods followed in respective articles and dataset specifications including duration and training, validation, and testing periods. We have also summarized PSO parameters and the results.

5 Stock Trend Forecasting

The stock price movement as compared to the previous price values can indicate the market situations. While the bull market indicates the up trend, bear market stands for the down trend. Using various technical indicators, the historical data can be exploited for the market trend prediction. Here, we have grouped PSO applications into parameter optimization and feature selection approaches for stock trend forecasting.

5.1 Parameter Optimization

Identification of appropriate time in order to take the buy or sell decision for specific stocks is a crucial task; utilization of various indicators for making an appropriate market trading choice can be helpful in gaining. Another way that may be considered by various investors is security lending; it can be understood as an act of loaning a security to other investors or firms.

Security lending can be helpful in short selling where an investor can borrow securities and sell them to other market participants; the borrowed securities are purchased back and returned to the lenders. Kickback is the amount of fees charged for each borrowed share. While some of the existing studies indicated that short selling can be useful in creating efficient price discovery, it was also mentioned to be adversely affecting the price movement fundamentals [142].

Based on the short selling trade actions, a competitive co-evolutionary PSO (CCPSO) model was integrated for training FFNN in [143]. These actions included buy, sell, and cut; while buy and sell represented purchasing an underlying security and short selling the security, respectively, cut action indicated selling the purchased security or buying back the security that was short sold. The proposed approach was useful in determining trend reversals. However, such short selling actions were restricted or banned in various financial markets; such constraints were also lifted in some cases over the years; the bid-ask spreads, as well as unaffected stock prices due to such bans, were studied in [144].

Due to the complications in predicting the stock trend that might lead to excessive trading, associated costs, and eliminated opportunities, a trading model was developed by integrating NNs, PSO, and denoising concepts in [145]. Authors developed an adaptive stock direction prediction system where the initial NN weights were obtained using PSO and fitness was evaluated using MSE. Because an excessive trading might lead to miss out potential opportunities, the everyday fluctuations of the market trend and hence, noises were filtered using the denoising process. This could also reduce the number of transactions by negotiating small fluctuations and following the larger trends.

While the historical data can reveal various inherent market patterns, consideration of sentiment analysis can be beneficial in deriving important trend information. The financial news can be one of the platforms to collect sentimental features; in [146], authors proposed to consider historical stock market data along with sentiment analysis for financial market prediction. The prediction model was built using SVM where its parameters were optimized using PSO; the preprocessing step of sentiment analysis could aid into feature dimensionality reduction and performance improvement.

Various factors influence the stock price movement; manual analysis with variations, volatility, or other technical indicator-based activities may not be able to forecast precisely. A multi-linear weighted regression-based NN approach was proposed for stock trend prediction in [147] and defined particle fitness as given by Eq. (19) for weighted particle i (x_i) and predicted weight combination (y_i). In order to make reliable predictions, this approach used local optima-based linear structures; here, local optima, arbitrarily closer to the value were given higher weights in the initial stage. Such local minima, as well as maxima, were utilized to predict stock trends.

$$\phi(i) = |x_i - y_i| x_i \tag{19}$$

Table 4 Summary of PSO-based stock price prediction approaches

Paper	Aim	Target	Method	Data Specifications			PSO Parameters				Result
				Dataset	Duration	Training : Validation : Testing	m	ω	c_1, c_2	V_{min}, V_{max}	
[118]	Close price	Third-day	SVR, PSO	Eastern Hotel stock price	01/09/2010 to 17/12/2010	60 : – : 10 (days)	Not specified	Not specified	2, 2	Not specified	Improved prediction accuracy
[119]	Stock price	One-day-ahead	Elman network, GRNN, WNN, SVM, IPSO	Shanghai composite index, Shenzhen component index	01/07/2004 to 30/06/2010, 01/01/2005 to 31/12/2010	972 : 244 : 244 (observations), 971 : 244 : 242 (observations)	Not specified	Not specified	Not specified	Not specified	Improved performance than single base model
[120]	E-exchange price	Day-ahead	ANNs-PSO-GA	Shanghai composite index, Shenzhen component index, Shanghai-Shenzhen 300	01/07/2004 to 30/06/2010, 01/01/2005 to 31/12/2010, 01/07/2004 to 01/07/2010	972 : 244 : 244 (observations), 971 : 244 : 242 (observations), 973 : 244 : 243 (observations)	30	1.0	1.14, 1.14	−0.6, 0.6	Improved prediction for high volatile data with noise
[121]	Stock price	Three-days-ahead	HBP-PSO	Zhong Guo Yi Yao (600056)	18/11/2009 to 15/03/2010 (75 groups)	60 : – : 15 (groups)	40	0.9	0.5, 0.5	Not specified	Effective stock price and trend prediction
[122]	Stock index	One-day-ahead	Fuzzy, CRPSO	Korea composite stock price index (KOSPI)	01/01/2011 to 31/12/2014	3 years (training)	30	0.9	1.5, 0.75	Not specified	Improved prediction results
[123]	Stock price	One-day-ahead	SVM, PSO	Apple, Google	01/2005 to 03/2014 (daily)	Not specified	20	Not specified	12.6, 1.5	Not specified	Enhanced prediction accuracy as compared to NBC, ANN, LS-SVM
[124]	Stock open price	One-day-ahead	LS-SVM, PSO	SSE	23/05/2011 to 30/04/2014	23/05/2011 – 08/07/2013 : – : 09/07/2013 – 30/04/2014	Not specified	Not specified	Not specified	Not specified	Higher prediction accuracy than SVM, PLS
[125]	Stock price	Next-day	PSO-SVR	Tata steel stocks (BSE)	24/07/2001 to 19/03/2018 (daily)	75% : – : 25%	Not specified	Not specified	Not specified	Not specified	0.7 MAPE
[126]	High-frequency stock price	Not specified	PSO, adaptive SVR	SSE	Listing date to 31/03/2017 (daily), 01/01/2017 to 31/03/2017 (30-minute), 01/02/2017 to 28/02/2017 (5-minute)	80% : – : 20%	40	0.7	0.01, 0.01	Not specified	Higher predictions compared to BPNN, SVR
[129]	Close price	One-day-ahead	FWNN, PSO, SSO	Hang Seng	02/10/2009 to 30/10/2015 (daily)	1226 : – : 245 (observations)	120	0.8	1.47, 1.47	Not specified	Improved particle search ability and prediction
[130]	Stock price	Not specified	PSOCoM	S&P 500, NASDAQ 100, DJIA	02/01/2005 to 31/12/2014 (daily)	100 : – : 100 (days), 200 : – : 100 (days), 500 : – : 100 (days) for short-term; 1000 : – : 750 (days), 1500 : – : 750 (days) for long-term	30	0.9 – 0.4	2, 2	0.5	Faster convergence than ABFO, BFO, GA, PSO

Table 4 (continued)

Paper	Aim	Target	Method	Data Specifications			PSO Parameters				Result
				Dataset	Duration	Training : Validation : Testing	m	ω	c_1, c_2	V_{min}, V_{max}	
[131]	Stock price	Intraday	VMD-PSO-BPNN	Apple, Dell, Hewlett-Packard, IBM, Microsoft, Oracle	28/02/2011 to 03/03/2011 (intraday)	80% : – : 20%	50	0.9 – 0.4	2, 2	Not specified	Higher accuracies than single PSO-BPNN
[133]	Stock close price	Not specified	RBF NN, PSO	Nifty (NSE), Sensex (BSE)	17/09/2007 to 01/09/2015 (weekly)	70% : – : 30%	Not specified	Not specified	Not specified	Not specified	Improved prediction accuracy
[134]	Close price	Next-day	PSO, BPNN	13 companies	Not specified	Not specified	Not specified	Not specified	Not specified	Not specified	98.25% accuracy
[135]	Stock price	Not specified	PSO, ANN	Not specified	Not specified	70% : 15% : 15%	40	0.9	2, 2	Not specified	PSO-based highest performance improvement compared to CS, ICS, GA, ICSGA
[136]	High price	Next-day	PSO, ANN	Yahoo, Microsoft	05/2006 to 05/2016	Not specified	Not specified	Not specified	Not specified	Not specified	1.0% MAPE
[137]	Stock price	10 days	PSO, WNN	Taiwan stock exchange 50	15/07/2010 to 16/12/2010; year 2014 for testing	10% : – : 90%	Not specified	1	2, 2	Not specified	73% success rate
[138]	Future close price	One-day-ahead	PSO, BR-ANN	Shanghai composite index	02/01/1996 to 30/05/2014	4000 : – : 456 (groups)	40	Not specified	2.8, 1.3	Not specified	17.057 MAE, 0.77 MAPE
[139]	Stock open price	Short-term	Elman network, self-adaptive variant PSO	340 data	Not specified	273 : – : 59 (columns)	30	Not specified	2, 2	−1, 1	Improved prediction than BPNN and Elman network
[140]	Market clearing price	Hourly	NN, PSO, GA, k-means clustering	Iran electricity market	2010 to 2013 (hourly)	720 records (testing)	Not specified	Not specified	Not specified	Not specified	Improved prediction than BA-based NN

5.2 Feature Selection

The financial market experiences fluctuations which can largely impact on stock market trend; different factors may influence the market behaviour as well. Hence, for an effective forecasting of the stock price trend, identification of the closely related and/or influential features may be one of the crucial tasks.

High-dimensional, non-linear stock data can be addressed by machine learning approaches such as SVM, however, selection of the input features can be a challenging task. A method of PSO-based optimal feature set selection was proposed in [148] to facilitate SVM, which was further applied for stock trend forecasting. Additionally, PSO was considered for deriving optimal RBF parameters γ and C; while γ influenced feature space partitioning, the tuning parameter, C, controlled the generalization ability of SVM. The proposed, PSOSVM approach removed unnecessary features and predicted more robust stock price movement than the conventional SVM approach.

In order to determine the stock index movement, a stacked denoising autoencoder model was proposed to learn a compact representation of the historical data of price and volume in [149]. The hyper-parameters of this model were optimized by integrating gravitational search algorithm (GSA) in PSO as hybrid GSA (HGSA). The stacked denoising autoencoder-based deep learning approach was utilized to study compact feature representations; by integrating HGSA with deep networks, authors proposed this theoretical methodology.

6 Other Stock Market Concepts

Apart from the portfolio, stock price and trend, there are various financial concepts which have been integrated with PSO for prediction enhancement.

6.1 Trading Prediction

In the financial markets, a large number of assets get traded on a regular basis. The trading approach can be determined based on individuals' objectives, goals, time-span, risk tolerance factors, and other transaction-oriented aspects. Various well-organized methods have been developed to assist investment and trading; such approaches are adopted, practised, and extended for various instruments such as equity [150], futures [151]. Hence, combination of the pre-defined trading rules can determine trading strategies.

6.1.1 Trading Rules

To succeed a financial market, traders may follow a group of tried-and-true rules. Such rules are likely to be derived from the past experiences and analyses that can suggest whether an individual should buy or sell specific stocks. The existing studies have also discussed profit gains based on such trading rules [152]. Hence, deriving optimal trading rules can be critical.

One of the trading strategy, namely weight reward strategy (WRS), combined MA and trading range breakout (TRB) technical indicators [153]; similarly, performance-based reward strategy (PRS) was proposed in [154] based on MA and TRB. Various parameter combinations were used to derive component trading rules which were initialized with starting weights; these weights were updated using the reward/penalty mechanism based on their performance. In order to maximize the annual net profit, an improved time variant PSO (TVPSO) algorithm was integrated in PRS.

By means of expanding the scope of PRS, authors proposed to incorporate MA, TRB, Bollinger bands (BB), relative strength index (RSI), stochastic oscillator (STO), moving average convergence/divergence (MACD), and on-balance volume average (OBVA) [155]. Similar to the earlier approach [154], starting weights were updated; the search space consisted of a large number of parameters including starting weights, time spans, thresholds, and reward factor. Hence, the extended PRS was optimized using parallel PSO on Hadoop [155].

For the European Union Allowance (EUA) futures market, MA trading rule was integrated in [156]. Because of the performance of adaptive moving averages (AMA) to describe the price features [157], authors proposed to optimize the weights of base AMA rules using PSO and GAs which could further optimize MA trading rules in the targetted market.

6.1.2 Trading Strategy

Investors may prefer to trade on short-term as well as long-term basis. Such trading require knowledge and analysis of associated factors and their implications for the purpose of increasing the expected profits; various trading strategies have been developed to accomodate the investment planning.

One of the important aspects of reducing investment risks is to adapt a hedging strategy; this can be useful in minimizing the effects of adverse situations. Such a strategy can be applied for assets having negative correlations. In [158], a hedging strategy was proposed for portfolio management by considering "long the outperformed stock portfolio and short the index future". Authors selected active portfolios and minimized the downside risk using PSO; evaluation of the defined strategy could achieve a relatively positive return.

Mutual funds (MFs) introduce diversity of investment as well as scatter the associated risks; MFs generally intend for short-term investments in order to beat the market and gain higher profits [159]. It can be carried out using fundamental and/or technical analysis. Several factors influence the fund performance; the internal variations and their impacts have also been evaluated [160]. A funds trading strategy was introduced by integrating turbulent PSO (TPSO) and mixed MA approaches in [161]. Authors determined the trend and hence, buy and sell signals using MA with differing lengths; here, the optimal number of MAs was dependent on the MF target. Hence, TPSO was considered to find a good buy point and a good sell point that were represented by gold cross point and death cross point, respectively.

Due to the continuous time-series data of stock market, PSO can be frequently applied with other continuous values. A piecewise aggregate approximation (PAA) based time-series representation was combined with PSO, i.e., PAA-PSO [162]. Authors proposed this approach to find inherent patterns and formulated an investment strategy to maximize the profits. The results were evaluated and compared with symbolic aggregate approximation (SAX) and GA-based investment strategy, i.e., a discrete value-based approach.

Options are important financial instruments that allow the buyer to buy or sell an underlying asset based on the type of contract. An options trading strategy was proposed in [163] using GA and PSO; while GA was used to identify the stock trend, PSO was applied to derive trading strategies for the specific trend. Authors optimized strike prices and expiration dates of the traded options and tested it on five exchange traded funds (ETFs).

A weighted signal-based trading strategy was proposed in [164] where trading signals, buy, sell, and hold, were optimized using modified PSO. The daily stock prices were experimented and evaluated for the investment returns. Considering the facts that the final financial balance function might have multiple peaks, a multimodality-based trading method was proposed in [165]. It considered PAA with multi-swarm of improved self-adaptive PSO (MS-IDPSO) with validation (V), i.e., PAA-MS-IDPSO-V; the patterns were determined and used with investment rules to maximize the profit.

6.2 Financial Market Prediction

Based on the second-order fuzzy-trend logical relationship groups and PSO, stock indices as well as exchange rates were predicted in [166, 167]. Other PSO-based applications included trend prediction with quantum-behaved PSO [168], exchange rate volatility [169] and time-series volatility [170], financial futures [171] as well as MA rules optimization [156], market liquidity optimization [172], trading point [173], and time-series segmentation [174]. Hence, PSO can be integrated with various financial aspects for enhancing the prediction performance and/or optimization.

6.2.1 Stock Returns

The global stock market (GSM) transactions have been a subject of interest to analyze inherent patterns and predict market returns; the correlations among markets of various countries and their economic factors can be exploited. A modified clustering approach was introduced in [175] to evaluate the financial market dependencies and hence, associations among their returns. The k-means clustering was integrated with PSO to find an optimal number of clusters using price as the stock market integration measure. The problem of unsynchronized time zones of different countries was resolved using weekly stock indices log difference. The proposed approach with cost function and Silhouette cohesion identified the optimal number of clusters that indicated the significance of geographical similarities and economic status in cluster formation.

Stock returns prediction is one of the crucial aspects to determine the expected investment outcome. There may be unusual profit generation because of the stocks or portfolios; such abnormal returns or excess returns perform differently from the anticipated return. An abnormal return may be positive or negative. An early work demonstrated that the direction of such returns might not be predictable but the amount of abnormality in security returns could be forecasted using news-based text classification [176]. To predict such returns through the inherent noise as well as volatility, generalization characteristics of interval-valued fuzzy cognitive map (IVFCM) was proposed in [177]; authors extracted financial indicators such as log of market capitalization (lnMC) and linguistic analysis from corporate-related documents. PSO was integrated to estimate casual relationships of IVFCM to predict one-day-ahead abnormal stock returns.

6.2.2 Initial Public Offering

The concept of initial public offering (IPO) is important in the financial market where IPO offers shares of a private corporation to the public under a new stock issuance. This can be useful for the company to raise capital from public investors. For the purpose of recognizing valid IPO pricing and determining profitable opportunities, PSO-based IPO pricing forecasting approach was proposed in [178]. Authors proposed to apply PSO with SVM to increase forecasting ability. They considered the ninth day offering prices to ensure dealing with realistic prices and limited volatility influences.

6.2.3 Cryptocurrency

Cryptocurrency is a virtual currency system with decentralized authority operations. Bitcoin was the first blockchain-based cryptocurrency and has been a subject of interest for many investors in the financial markets [179]. In order to predict the bitcoin price, an MLP NN-based non-linear autoregressive with exogenous input (NARX) model was developed in [180]. It consisted of inputs with open, close, high, and low prices along with MA technical indicator with different intervals. The model parameters such as the number of hidden units, input lag, and output lag were optimized using PSO to predict next-day bitcoin price.

7 Challenges and Future Directions

This survey primarily concerns PSO-based stock market prediction; financial concepts and traders' perspectives have shown that market analyses can be beneficial to predict future market behaviour. Stock features play a crucial role in determining market performance; such features may be derived using the historical data of stock prices. It has been encountered that a large number of stock exchanges and corresponding companies have been aimed to derive technical indicators, however, a rationale has not been found for the selection of a specific dataset. As given by Table 3 and 4, stock data duration, intervals, parameter specifications, methods, as well as features have largely varied in various approaches. Hence, a group of stock price datasets and respective performance results may not be comparable; hence, we have presented our analysis through summary tables. This may induce thorough study over a wide range of datasets, as well as the development of data selection criteria in order to emphasize the significance of one method over others.

Study of a financial market etiquette can be influenced by various macroeconomics as well as microeconomics factors [9, 10]. The highly fluctuating characteristics of a stock market have encouraged the application of computational intelligence for stock-based predictions. The limitations of parameter optimization, feature selection, or classification using machine learning as well as deep learning approaches have been addressed using swarm and evolutionary computation. We have focused our survey on PSO and its variants that have enhances the forecasting performance; the suitability of PSO for continuous data such as stock market has been exploited in various articles. Hence, this survey considers recent advances in portfolio optimization, stock price and trend prediction based on PSO-optimized methods. We believe that knowledge of financial aspects can be productive to develop a clear understanding of the field of work. In order to balance the economical aspects and computational applications to the stock market, we have also incorporated background information about the field. Though a large number of articles have majorly considered the technical analysis, it may be an appropriate choice to study and incorporate the fundamental concepts for improving the prediction. While a large number of applications have targetted portfolio, stock price and trend, a limited amount of attention has been received by PSO-based applications such as returns, futures, trading, cryptocurrencies. The impact of individuals' choice, beliefs, financial, social, as well as psychological states can be crucial aspects of financial market trading. Subsequently, country-specific perspectives such as government regulations, political events, and other external matters can also influence market trends. However, the identification of linkages among such market dynamics and consideration of their impact on stock market prediction is a challenging task.

PSO can be observed with the capability of dealing with continuous data. Its simplicity due to less number of parameters and rapid convergence ability within large search space have been exploited for the financial market problems; its parallel computation ability may be exploited to make PSO suitable for the target application. Though PSO has shown performance improvements, it may suffer premature convergence for complex problems, leading the solutions to be trapped within local optima. This issue may be encountered in scattered problems. Also, selection of initial parameter values may be a challenging task. PSO weakness of local search ability may be overcome with other approaches such as GA. Thus, integration of PSO with other swarm and evolutionary approaches may be useful to resolve its limitations. The objective function must be carefully selected to enhance the prediction approach. Though a large number of fitness functions were chosen based on risk and return factors for stock portfolios, consideration of other features and derivation of their trade-offs can be considered as a potential research direction. Also, various such factors can be integrated for stock price as well as stock trend prediction.

A generalized flow of stock market-based forecasting can be given as shown in Fig. 3. Based on the target application, the steps can be determined to develop a prediction model and enhance it using the PSO-based approach; here, the collected data is pre-processed for marking it suitable for the problem and necessary features are extracted from the same. The stock dataset may be divided into training and testing and submitted to the prediction model which is to be optimized using PSO; the generated predictions can be evaluated. It may be observed that various specifications may be integrated to enhance the stock market prediction. Though we have centred PSO-based stock market prediction, it may be adapted for other potential optimization methods and appropriate modifications may be carried out for predictions. Fig. 4 provides an overview of algorithms hybridized with PSO and its variants for stock market; the linkages of such methods and the features utilized for various stock market applications have been demonstrated. It has been observed that PSO variants can be integrated with a large number of algorithms and various stock features can be adapted to derive useful information about the stock movement. However, deriving an optimal combination of algorithms and features is challenging. It can be considered as a potential future direction for financial time-series data forecasting.

8 Concluding Remarks

A continuously increasing involvement of a large number of traders and investors in the financial market has been witnessed since the past decades. The stock market trading has been a subject of interest and hence, one of the major attractions for academicians and researchers. This article presents a comprehensive survey of various stock market concepts and PSO-based computational aspects.

Companies get registered on one or more stock exchanges to expand the business dimensions; with a motivation of gaining profits of the investment, individuals trade stocks of such listed companies. We have discussed the influences of various aspects, microeconomic and macroeconomic factors, individuals' behavioural features, as well as the financial market conditions on the buying and selling actions within stock markets; investment and speculation have also been exhibited as two important criteria in the stock market. Though individuals having expertise in this field can determine the potential assets that they may trade, it is emphasized that there has been a constant requirement of having a preliminary awareness of the probable market behaviour and the expected returns. We have discussed the fundamental analysis and technical analysis that can derive crucial factors of a stock market and forecast the future valuation; while the former analysis is based on analyzing targetted company profiles, products, and related factors, the latter is based on the historical data of a specific stock and the derived technical indicators. For maximizing the expected returns, various trading strategies have been developed with the help of such analyses; their usefulness in the existing literature studies have also been reviewed. Another way to maximize profit and minimize associated risks, i.e., a stock portfolio, has also been considered in this survey. The concept of diversification is presented wherein different stocks and/or securities are traded to ensure that the negative impacts of adverse events could be reduced; we have also discussed the challenges related to suitable portfolio selection and optimization. We have surveyed the influential features as well as the time-series data that help to derive inherent trends and to predict the stock price movement. In addition to this, the survey presents the use of forecasted data to decide trading signals such as buy, hold, or sell for a particular stock.

Various techniques have been developed for stock market prediction including machine learning, deep learning, sentiment analysis, as well as mining approaches. To improve prediction accuracies, swarm intelligence and evolutionary algorithms have also been incorporated. PSO is one of the nature-inspired swarm intelligence approaches that has been adapted for various continuous value optimization problems such as stock market prediction. Hence, in the presented survey, we have primarily focused on reviewing a wide range of stock market prediction concepts which have been

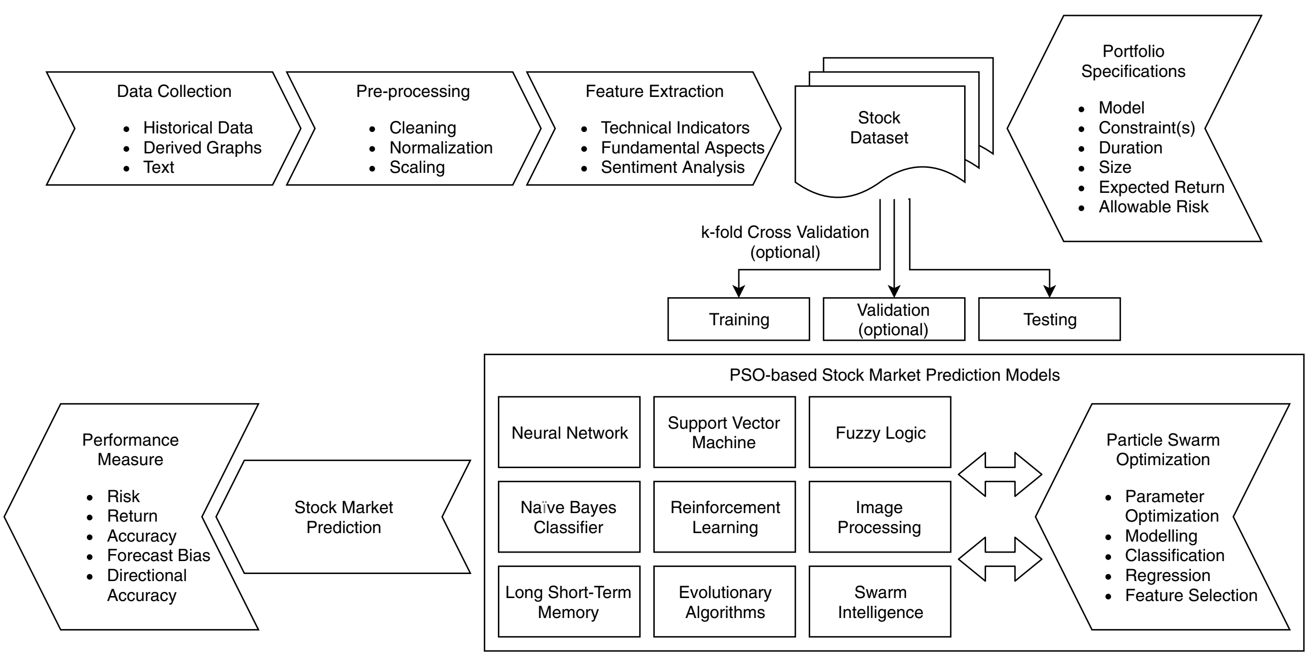

Fig. 3 A generalized step-by-step PSO-optimized stock market prediction

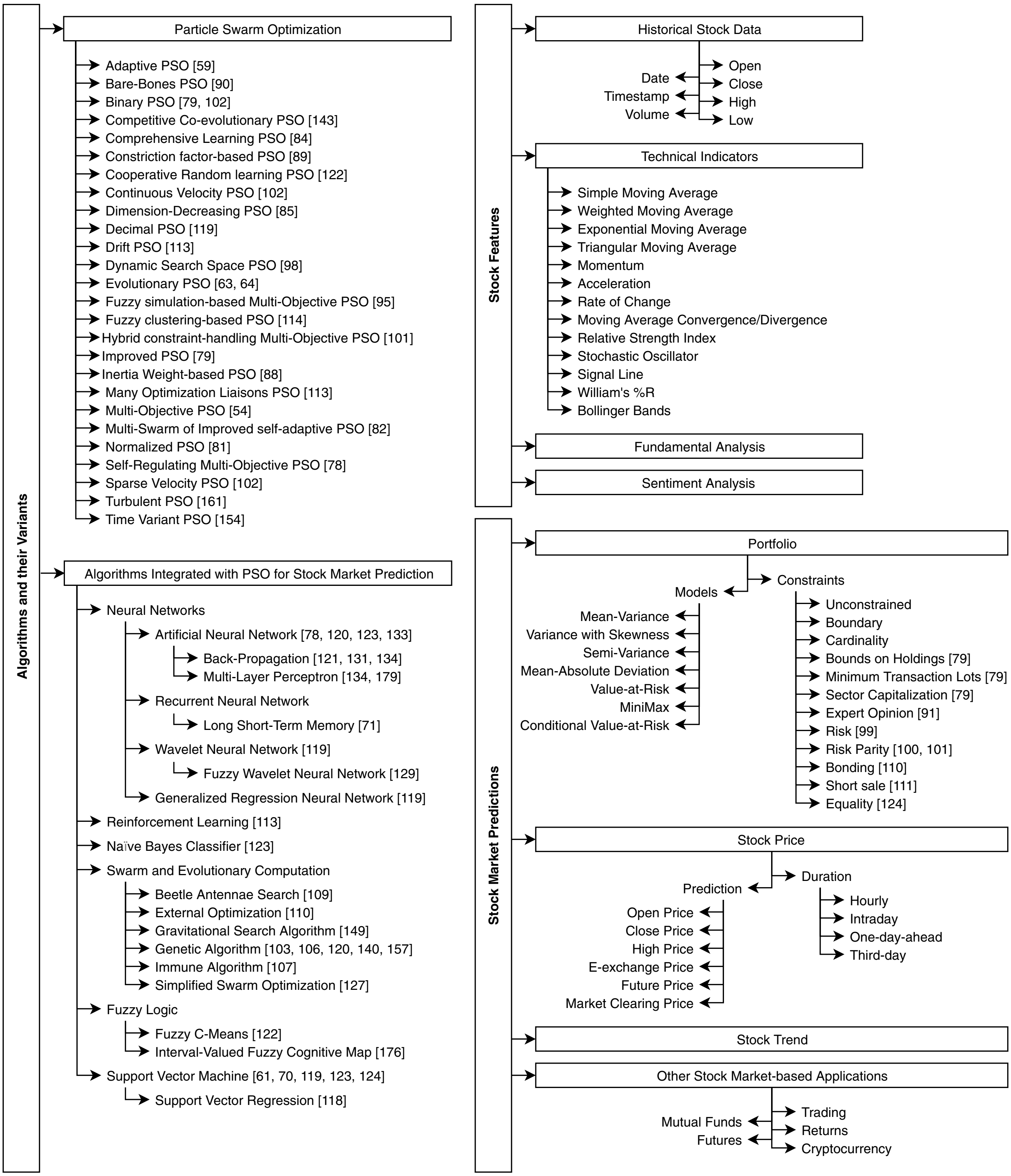

Fig. 4 An overview of PSO-optimized methods, stock features, and their potential stock market applications

addressed using PSO and its variants. We have conducted a detailed study of portfolio optimization, stock price and trend prediction, along with trading, returns, futures, and other financial market-based forecasting approaches. Though the historical stock data can be useful in deriving important features, understanding of the financial concepts, derivable technical indicators, and applicability of optimization techniques such as PSO may be effectively combined for enhancing the predictions. Therefore, we have included the useful financial market concepts associated with the existing approaches for balancing the survey. Our comparison with the existing surveys indicates that the presented survey article can be helpful to the readers in gaining financial market knowledge along with understanding the implications of PSO for the same. We have briefly reviewed other nature-inspired approaches that have been hybridized with PSO for financial market prediction and have demonstrated the superiority of PSO. The objective is to determine the compatibility constraints of using PSO for the stock market and to analyze their potential solutions; it can be observed that hybrid approaches, such as PSO and GA, may be helpful in designing robust prediction models. To support the presented survey, we have also provided a generalized step-by-step PSO-optimized stock market prediction along with a detailed presentation of PSO variants, the hybridized algorithms, stock features, and prediction applicabilities.

It has been perceived that a large number of existing research works consist of applying PSO to historical data and derived technical indicators; the integration of fundamental analysis, as well as sentiments based on various events, may help derive stronger predictions. The risk aversion features and associated psychological and socioeconomic perspectives can significantly impact on an individual's trading behaviour; consideration of such details may be a potential future direction. Such influential factors may be aggregated for deriving personalized recommendations for the portfolio as well as a trading strategy.

Compliance with ethical standards

Conflict of Interest The authors declare that they have no conflict of interest.

References

1. Matvos G, Seru A, Silva RC (2018) Financial market frictions and diversification. J Financ Econ 127(1):21
2. Pramanaswari ASI, Yasa GW (2018) Graham & Dodd theory in stock portfolio performance in LQ 45 index at Indonesia stock exchange. Int Res J Manag IT Soc Sci 5(6):52
3. Jordan BD, Miller TW, Dolvin SD (2015) Fundamentals of investments: valuation and management. McGraw-Hill Education, New York
4. Elbannan MA (2015) The capital asset pricing model: an overview of the theory. Int J Econ Finance 7(1):216
5. Elton EJ, Gruber MJ, Brown SJ, Goetzmann WN (2009) Modern portfolio theory and investment analysis. Wiley, London
6. Abbey BS, Doukas JA (2012) Is technical analysis profitable forindividual currency traders? J Portfolio Manag 39(1):142
7. Lau CKM, Demir E, Bilgin MH (2013) Experience-based corporate corruption and stock market volatility: evidence from emerging markets. Emerg Markets Rev 17:1
8. Durusu-Ciftci D, Ispir MS, Yetkiner H (2017) Financial development and economic growth: some theory and more evidence. J Policy Model 39(2):290
9. López RA (2005) Trade and growth: reconciling the macroeconomic and microeconomic evidence. J Econ Surv 19(4):623
10. Bahloul S, Mroua M, Naifar N (2017) The impact of macroeconomic and conventional stock market variables on Islamic index returns under regime switching. Borsa Istanbul Rev 17(1):62
11. Bettman JL, Sault SJ, Schultz EL (2009) Fundamental and technical analysis: substitutes or complements? Account Finance 49(1):21
12. Wafi AS, Hassan H, Mabrouk A (2015) Fundamental analysis models in financial markets-review study. Proc Econ Finance 30:939
13. Thakkar A, Chaudhari K (2020) CREST: cross-reference to exchange-based stock trend prediction using long short-term memory. Proc Comput Sci 167:616
14. Wafi AS, Hassan H, Mabrouk A (2015) Fundamental analysis vs technical analysis in the Egyptian stock exchange-empirical study. Int J Business Manag Study IJBMS 2(2):212
15. Gilbert CL (2010) Commodity speculation and commodity investment. Market Rev 1:26
16. Bogle JC (2012) The clash of the cultures: investment vs. speculation. Wiley, London
17. Cavalcante RC, Brasileiro RC, Souza VL, Nobrega JP, Oliveira AL (2016) Computational intelligence and financial markets: a survey and future directions. Expert Syst Appl 55:194
18. Mullainathan S, Spiess J (2017) Machine learning: an applied econometric approach. J Econ Perspect 31(2):87
19. Oliveira N, Cortez P, Areal N (2017) The impact of microblogging data for stock market prediction: using Twitter to predict returns, volatility, trading volume and survey sentiment indices. Expert Syst Appl 73:125
20. Xing FZ, Cambria E, Welsch RE (2018) Natural language based financial forecasting: a survey. Artif Intel Rev 50(1):49
21. Azar AT, Vaidyanathan S (2015) Computational intelligence applications in modeling and control. Springer, Berlin
22. Mavrovouniotis M, Li C, Yang S (2017) A survey of swarm intelligence for dynamic optimization: algorithms and applications. Swarm Evol Comput 33:1
23. Chakraborty A, Kar AK (2017) Swarm intelligence: a review of algorithms. In: *Nature-inspired computing and optimization* (Springer), pp. 475–494
24. Chaudhari K, Thakkar A (2019) Travelling salesman problem: an empirical comparison between ACO, PSO, ABC, FA and GA. In: Emerging research in computing, information, communication and applications. Springer, pp. 397–405
25. Slowik A, Kwasnicka H (2017) Nature inspired methods and their industry applications-Swarm intelligence algorithms. IEEE Trans Ind Inf 14(3):1004
26. Balamurugan R, Natarajan A, Premalatha K (2015) Stellar-mass black hole optimization for biclustering microarray gene expression data. Appl Artif Intel 29(4):353
27. Ertenlice O, Kalayci CB (2018) A survey of swarm intelligence for portfolio optimization: algorithms and applications. Swarm Evol Comput 39:36
28. Wang D, Tan D, Liu L (2018) Particle swarm optimization algorithm: an overview. Soft Comput 22(2):387
29. Wong WK, Manzur M, Chew BK (2003) How rewarding is technical analysis? Evidence from Singapore stock market. Appl Financ Econ 13(7):543

30. Neely CJ, Rapach DE, Tu J, Zhou G (2014) Forecasting the equity risk premium: the role of technical indicators. Manage Sci 60(7):1772
31. AnyChart (2019) Stock charts technical indicators mathematical description. https://docs.anychart.com/Stock_Charts/Technical_Indicators/Mathematical_Description. Accessed 05 Oct 2019
32. Sedighizadeh D, Masehian E (2009) Particle swarm optimization methods, taxonomy and applications. Int J Comput Theory Eng 1(5):486
33. Krollner B, Vanstone BJ, Finnie GR (2010) Financial time series forecasting with machine learning techniques: a survey. In: ESANN
34. Garcia-Gonzalo E, Fernández-Martínez JL (2012) A brief historical review of particle swarm optimization (PSO). J Bioinf Intel Control 1(1):3
35. Beiranvand V, Bakar AA, Othman Z (2012) A comparative survey of three AI techniques (NN, PSO, and GA) in financial domain. In: 2012 7th international conference on computing and convergence technology (ICCCT) (IEEE), pp 332–337
36. Zhang Y, Wang S, Ji G (2015) A comprehensive survey on particle swarm optimization algorithm and its applications. Math Probl Eng 2015:1–38
37. Kar AK (2016) Bio inspired computing: a review of algorithms and scope of applications. Expert Syst Appl 59:20
38. Das SR, Mishra D, Rout M (2017) A survey on impact of bio-inspired computation on stock market prediction. J Eng Sci Technol Rev 10(3):104
39. Bharne PK, Prabhune SS (2017) Survey on combined swarm intelligence and ANN for optimized daily stock market price. In: 2017 international conference on soft computing and its engineering applications (icSoftComp) (IEEE), pp 1–6
40. Kalayci CB, Ertenlice O, Akbay MA (2019) A comprehensive review of deterministic models and applications for mean-variance portfolio optimization. Expert Syst Appl 4:2019
41. Eberhart R, Kennedy J (1995) A new optimizer using particle swarm theory. In: MHS'95. Proceedings of the sixth international symposium on micro machine and human science (IEEE), pp 39–43
42. Van Den Bergh F, et al (2001) An analysis of particle swarm optimizers. Ph.D. thesis, University of Pretoria South Africa
43. Shi Y, Eberhart R (1998) A modified particle swarm optimizer. In: 1998 IEEE international conference on evolutionary computation proceedings. IEEE world congress on computational intelligence (Cat. No. 98TH8360) (IEEE), pp 69–73
44. Dali N, Bouamama S (2015) GPU-PSO: parallel particle swarm optimization approaches on graphical processing unit for constraint reasoning: case of Max-CSPs. Proc Comput Sci 60:1070
45. AlRashidi MR, El-Hawary ME (2008) A survey of particle swarm optimization applications in electric power systems. IEEE Trans Evol Comput 13(4):913
46. Kulkarni RV, Venayagamoorthy GK (2010) Particle swarm optimization in wireless-sensor networks: a brief survey. IEEE Trans Syst Man Cybernet Part C (Applications and Reviews) 41(2):262
47. Rana S, Jasola S, Kumar R (2011) A review on particle swarm optimization algorithms and their applications to data clustering. Artif Intell Rev 35(3):211
48. Sarkar S, Roy A, Purkayastha BS (2013) Application of particle swarm optimization in data clustering: a survey. Int J Comput Appl 65(25):38
49. Xie X, Wz Jiang, Nie H, Chi Jh (2016) Empirical study on how to set prices for cruise cabins based on improved quantum particle swarm optimization. Comput Inf Sci 9(2):82
50. Masdari M, Salehi F, Jalali M, Bidaki M (2017) A survey of PSO-based scheduling algorithms in cloud computing. J Netw Syst Manage 25(1):122
51. Li W, Huyan J, Xiao L, Tighe S, Pei L (2019) International roughness index prediction based on multigranularity fuzzy time series and particle swarm optimization. Expert Syst Appl X 2:100006
52. Okulewicz M (2017) 2-Dimensional rectangles-in-circles packing and stock cutting with particle swarm optimization. In: 2017 IEEE symposium series on computational intelligence (SSCI) (IEEE), pp 1–5
53. Abraham A, Rohini V (2019) A particle swarm optimization-backpropagation (PSO-BP) model for the prediction of earthquake in Japan. In: Emerging research in computing, information, communication and applications. Springer, pp 435–441
54. Briza AC, Naval PC Jr (2011) Stock trading system based on the multi-objective particle swarm optimization of technical indicators on end-of-day market data. Appl Soft Comput 11(1):1191
55. Botosan CA, Plumlee MA (2005) Assessing alternative proxies for the expected risk premium. Account Rev 80(1):21
56. Dye CY, Ouyang LY (2011) A particle swarm optimization for solving joint pricing and lot-sizing problem with fluctuating demand and trade credit financing. Comput Ind Eng 60(1):127
57. Dye CY (2012) A finite horizon deteriorating inventory model with two-phase pricing and time-varying demand and cost under trade credit financing using particle swarm optimization. Swarm Evol Comput 5:37
58. Hung JC (2011) Adaptive Fuzzy-GARCH model applied to forecasting the volatility of stock markets using particle swarm optimization. Inf Sci 181(20):4673
59. Liyan G, Zhanfu Z (2012) CARRX model based on LSSVR optimized by adaptive PSO. In: 2012 third international conference on digital manufacturing & automation (IEEE), pp 268–271
60. Kuo RJ, Chao CM, Chiu Y (2011) Application of particle swarm optimization to association rule mining. Appl Soft Comput 11(1):326
61. Qin X, Peng Q (2012) Stock turning point recognition using multiple model algorithm with multiple types of features. In: Proceedings of the 10th world congress on intelligent control and automation (IEEE), pp 4020–4025
62. Butler M, Kazakov D (2012) Testing implications of the adaptive market hypothesis via computational intelligence. In: 2012 IEEE conference on computational intelligence for financial engineering & economics (CIFEr) (IEEE), pp 1–8
63. Pinto T, Morais H, Sousa TM, Sousa T, Vale Z, Praca I, Faia R, Pires EJS (2015) Adaptive portfolio optimization for multiple electricity markets participation. IEEE Trans Neural Netw Learn Syst 27(8):1720
64. Faia R, Pinto T, Vale Z, Corchado JM (2018) Optimization of multiple electricity markets participation using evolutionary PSO. In: 2018 IEEE/PES transmission and distribution conference and exposition (T&D) (IEEE), pp 1–9
65. Faia R, Pinto T, Vale Z, Corchado JM (2017) Hybrid particle swarm optimization of electricity market participation portfolio. In: 2017 IEEE symposium series on computational intelligence (SSCI) (IEEE), pp 1–8
66. Faia R, Pinto T, Vale Z, Corchado JM (2018) Multi-objective portfolio optimization of electricity markets participation. In: 2018 power systems computation conference (PSCC) (IEEE), pp 1–6
67. Faia R, Pinto T, Vale Z, Corchado JM (2019) Hybrid approach based on particle swarm optimization for electricity markets participation. Energy Inf 2(1):1
68. Tekın P, Erol R (2017) A new hybrid model for dynamic pricing strategies of perishable products. In: 2017 seventh international

conference on innovative computing technology (INTECH) (IEEE), pp 85–89
69. Xiong T (2018) Forecasting soybean futures price using dynamic model averaging and particle swarm optimization. In: Proceedings of the genetic and evolutionary computation conference companion (ACM), pp 75–76
70. Zhang JL, Zhang YJ, Zhang L (2015) A novel hybrid method for crude oil price forecasting. Energy Econ 49:649
71. Hu Y, Sun X, Nie X, Li Y, Liu L (2019) An enhanced LSTM for trend following of time series. IEEE Access 7:34020
72. Paravisini D, Rappoport V, Ravina E (2016) Risk aversion and wealth: Evidence from person-to-person lending portfolios. Manage Sci 63(2):279
73. Agarwal V, Mullally KA, Tang Y, Yang B (2015) Risk aversion and wealth: evidence from person-to-person lending portfolios. J Finance 70(6):2733
74. Guiso L, Sapienza P, Zingales L (2018) Time varying risk aversion. J Financ Econ 128(3):403
75. Afik Z, Arad O, Galil K (2016) Using Merton model for default prediction: an empirical assessment of selected alternatives. J Empir Finance 35:43
76. Rua A, Nunes LC (2009) International comovement of stock market returns: a wavelet analysis. J Empir Finance 16(4):632
77. Li Z, Liu Y, Tan S, Liu B, Li J (2011) A novel time-scale feature based hybrid portfolio selection model for index fund. In: 2011 fourth international conference on business intelligence and financial engineering (IEEE), pp 63–67
78. Mishra SK, Panda G, Majhi B (2016) Prediction based mean-variance model for constrained portfolio assets selection using multiobjective evolutionary algorithms. Swarm Evol Comput 28:117
79. Golmakani HR, Fazel M (2011) Constrained portfolio selection using particle swarm optimization. Expert Syst Appl 38(7):8327
80. Garcia R, Ghysels E, Renault E (2010) The econometrics of option pricing. In: Handbook of financial econometrics: tools and techniques (Elsevier), pp 479–552
81. Sharma B, Thulasiram RK, Thulasiraman P (2012) Portfolio management using particle swarm optimization on GPU. In: 2012 IEEE 10th international symposium on parallel and distributed processing with applications (IEEE), pp 103–110
82. Liang JJ, Qu BY (2013) Large-scale portfolio optimization using multiobjective dynamic mutli-swarm particle swarm optimizer. In: 2013 IEEE symposium on swarm intelligence (SIS) (IEEE), pp 1–6
83. Liang JJ, Suganthan PN (2005) Dynamic multi-swarm particle swarm optimizer. In: Proceedings 2005 IEEE swarm intelligence symposium, 2005. SIS 2005. (IEEE), pp 124–129
84. Liang JJ, Qin AK, Suganthan PN, Baskar S (2006) Comprehensive learning particle swarm optimizer for global optimization of multimodal functions. IEEE Trans Evol Comput 10(3):281
85. Wang Jb, Chen WN, Zhang J, Lin Y (2015) A dimension-decreasing particle swarm optimization method for portfolio optimization. In: Proceedings of the companion publication of the 2015 annual conference on genetic and evolutionary computation (ACM), pp 1515–1516
86. Tsujimoto T, Shindo T, Kimura T, Jin'no K (2012) A relationship between network topology and search performance of PSO. In: 2012 IEEE congress on evolutionary computation (IEEE), pp 1–6
87. Ni Q, Deng J (2013) A new logistic dynamic particle swarm optimization algorithm based on random topology. Sci World J 2013:409167
88. Yin X, Ni Q, Zhai Y (2015) A novel particle swarm optimization for portfolio optimization based on random population topology strategies. In: International conference in swarm intelligence (Springer), pp 164–175
89. Ni Q, Yin X, Tian K, Zhai Y (2017) Particle swarm optimization with dynamic random population topology strategies for a generalized portfolio selection problem. Nat Comput 16(1):31
90. Reid SG, Malan KM (2015) Constraint handling methods for portfolio optimization using particle swarm optimization. In: 2015 IEEE symposium series on computational intelligence (IEEE), pp 1766–1773
91. Adebiyi A, Ayo C (2015) Improved constrained portfolio selection model using particle swarm optimization. Indian J Sci Technol 8(31):1
92. Kamili H, Riffi ME (2016) A comparative study on portfolio optimization problem. In: 2016 International conference on engineering & MIS (ICEMIS) (IEEE), pp 1–8
93. Fieldsend JE, Matatko J, Peng M (2004) Cardinality constrained portfolio optimisation. In: International conference on intelligent data engineering and automated learning (Springer), pp 788–793
94. Chen C, Ys Zhou (2018) Robust multiobjective portfolio with higher moments. Expert Syst Appl 100:165
95. Wang B, Li Y, Wang S, Watada J (2018) A multi-objective portfolio selection model with fuzzy Value-at-Risk ratio. IEEE Trans Fuzzy Syst 26(6):3673
96. Rajabi M, Khaloozadeh H (2018) Investigation and comparison of the performance of multi-objective evolutionary algorithms based on decomposition and dominance in portfolio optimization. In: Iranian conference on electrical engineering (ICEE) (IEEE), pp 923–929
97. Maopeng R, Qing W, Chaoyang D (2014) A dynamic search space particle swarm optimization algorithm based on population entropy. In: The 26th Chinese control and decision conference (2014 CCDC) (IEEE), pp 4292–4296
98. Feng C, Dong Y, Jiang Y, Ran M (2018) Dynamic search space particle swarm optimization approach for portfolio optimization. In: Proceedings of the 2018 international conference on control and computer vision (ACM), pp 127–131
99. Liu C, Yin Y (2018) Particle swarm optimised analysis of investment decision. Cogn Syst Res 52:685
100. Kaucic M (2019) Equity portfolio management with cardinality constraints and risk parity control using multi-objective particle swarm optimization. Comput Oper Res 109:300
101. Mishra SK, Panda G, Majhi R (2014) A comparative performance assessment of a set of multiobjective algorithms for constrained portfolio assets selection. Swarm Evol Comput 16:38
102. Boudt K, Wan C (2019) The effect of velocity sparsity on the performance of cardinality constrained particle swarm optimization. Optim Lett 2019:1–12
103. Kuo R, Hong C (2013) Integration of genetic algorithm and particle swarm optimization for investment portfolio optimization. Appl Math Inf Sci 7(6):2397
104. Cortés DG, Jofré AJC, San Martín L (2018) Artificial intelligence based method for portfolio selection. In: 2018 Congreso Internacional de Innovación y Tendencias en Ingeniería (CONIITI) (IEEE), pp 1–4
105. Najafi AA, Mushakhian S (2015) Multi-stage stochastic mean-semivariance-CVaR portfolio optimization under transaction costs. Appl Math Comput 256:445
106. Tsai JT, Ho WH, Liu TK, Chou JH (2007) Improved immune algorithm for global numerical optimization and job-shop scheduling problems. Appl Math Comput 194(2):406
107. Shalan SAB, Ykhlef M (2015) Solving multi-objective portfolio optimization problem for Saudi Arabia stock market using hybrid clonal selection and particle swarm optimization. Arab J Sci Eng 40(8):2407
108. Pai GV, Michel T (2017) Metaheuristic optimization of constrained large portfolios using hybrid particle swarm optimization. IJAMC 8(1):1

109. Chen T, Zhu Y, Teng J (2018) Beetle swarm optimisation for solving investment portfolio problems. J Eng 2018(16):1600
110. Chen C, Chen By (2018) Complex portfolio selection using improving particle swarm optimization approach. In: 2018 IEEE 20th international conference on high performance computing and communications; IEEE 16th international conference on smart city; IEEE 4th international conference on data science and systems (HPCC/SmartCity/DSS) (IEEE), pp 828–835
111. Zaheer KB, Aziz MIBA, Kashif AN, Raza SMM (2018) Two stage portfolio selection and optimization model with the hybrid particle swarm optimization. Matematika 34(1):125
112. Sethia AM (2018) Application of swarm intelligence to portfolio optimisation. In: 2018 international conference on computing, power and communication technologies (GUCON) (IEEE), pp 1029–1033
113. Almahdi S, Yang SY (2019) A constrained portfolio trading system using particle swarm algorithm and recurrent reinforcement learning. Expert Syst Appl 130:145
114. Burney SA, Jilani T, Tariq H, Asim Z, Amjad U, Mohammad SS (2019) A portfolio optimization algorithm using fuzzy granularity based clustering, BRAIN. Broad Res Artif Intell Neurosci 10(2):159
115. Soni S (2011) Applications of ANNs in stock market prediction: a survey. Int J Comput Sci Eng Technol 2(3):71
116. Sharma A, Bhuriya D, Singh U (2017) Survey of stock market prediction using machine learning approach. In: 2017 International conference of electronics, communication and aerospace technology (ICECA), vol. 2 (IEEE). pp 506–509
117. Chong E, Han C, Park FC (2017) Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies. Expert Syst Appl 83:187
118. Xie Gq (2011) The optimization of share price prediction model based on support vector machine. In: 2011 International conference on control, automation and systems engineering (CASE) (IEEE), pp 1–4
119. Xiao Y, Xiao M, Zhao F (2012) Improving financial returns using neural networks and adaptive particle swarm optimization. In: 2012 Fifth international conference on business intelligence and financial engineering (IEEE), pp 15–19
120. Xiao Y, Xiao J, Lu F, Wang S (2014) Ensemble ANNs-PSO-GA approach for day-ahead stock e-exchange prices forecasting. Int J Comput Intell Syst 7(2):272
121. Sun Y, Gao Y (2015) An improved hybrid algorithm based on PSO and BP for stock price forecasting. Open Cybern Syst J 9(1):2565
122. Yu J, Kim S (2015) Automatic structure identification of TSK fuzzy model for stock index forecasting. In: 2015 IEEE international conference on fuzzy systems (FUZZ-IEEE) (IEEE), pp 1–8
123. Sands TM, Tayal D, Morris ME, Monteiro ST (2015) Robust stock value prediction using support vector machines with particle swarm optimization. In: 2015 IEEE congress on evolutionary computation (CEC) (IEEE), pp 3327–3331
124. Yin S, Wu F, Luo H, Gao H (2015) Support vector regression based approach for key index forecasting with applications. In: 2015 IEEE 13th international conference on industrial informatics (INDIN) (IEEE), pp 591–596
125. Siddique M, Mohanty S, Panda D (2018) A hybrid forecasting model for prediction of stock value of tata steel using support vector regression and particle swarm optimization. Int J Pure Appl Math 119(14):1719
126. Guo Y, Han S, Shen C, Li Y, Yin X, Bai Y (2018) An adaptive SVR for high-frequency stock price forecasting. IEEE Access 6:11397
127. Yeh WC (2013) New parameter-free simplified swarm optimization for artificial neural network training and its application in the prediction of time series. IEEE Trans Neural Netw Learn Syst 24(4):661
128. Yeh WC, Huang CL (2015) Simplified swarm optimization to solve the K-harmonic means problem for mining data. In: Proceedings of the 18th Asia pacific symposium on intelligent and evolutionary systems, Vol 2 (Springer), pp 429–439
129. Pan J, Tang YY, Wang Y, Zheng X, Luo H, Yuan H, Wang PSP (2016) A hybrid swarm optimization for neural network training with application in stock price forecasting. In: 2016 IEEE international conference on systems, man, and cybernetics (SMC) (IEEE), pp 004450–004453
130. Jamous RA, Seidy EE, Bayoum BI (2016) A Novel efficient forecasting of stock market using particle swarm optimization with center of mass based technique. Int J Adv Comput Sci Appl 7(4):342
131. Lahmiri S (2016) Intraday stock price forecasting based on variational mode decomposition. J Comput Sci 12:23
132. Dragomiretskiy K, Zosso D (2013) Variational mode decomposition. IEEE Trans Signal Process 62(3):531
133. Mahanta R, Pandey TN, Jagadev AK, Dehuri S (2016) Optimized radial basis functional neural network for stock index prediction. In: 2016 International conference on electrical, electronics, and optimization techniques (ICEEOT) (IEEE), pp 1252–1257
134. Swami P, Vyas R (2016) Prediction of stock rates using PSO hybridized BPNN model. Int J 6(2):117
135. Ghasemiyeh R, Moghdani R, Sana SS (2017) A hybrid artificial neural network with metaheuristic algorithms for predicting stock price. Cybern Syst 48(4):365
136. Siddique M, DebdulalPanda SD, Mohapatra SK (2017) A hybrid forecasting model for stock value prediction using soft computing. Int J Pure Appl Math 117(19):357
137. Wang KC, Yang CI, Chang KF (2017) Stock prices forecasting based on wavelet neural networks with PSO. In: MATEC web of conferences, vol. 119 (EDP Sciences), p 01029
138. Yan D, Zhou Q, Wang J, Zhang N (2017) Bayesian regularisation neural network based on artificial intelligence optimisation. Int J Prod Res 55(8):2266
139. Zhang Z, Shen Y, Zhang G, Song Y, Zhu Y (2017) Short-term prediction for opening price of stock market based on self-adapting variant PSO-Elman neural network. In: 2017 8th IEEE international conference on software engineering and service science (ICSESS) (IEEE), pp 225–228
140. Ostadi B, Motamedi Sedeh O, Husseinzadeh Kashan A, Amin-Naseri MR (2018) An intelligent model to predict the day-ahead deregulated market clearing price: a hybrid NN, PSO and GA approach, Scientia Iranica
141. Lu T, Li Z (2017) Forecasting CSI 300 index using a hybrid functional link artificial neural network and particle swarm optimization with improved wavelet mutation. In: 2017 International conference on computer network, electronic and automation (ICCNEA) (IEEE), pp 241–246
142. Kaplan SN, Moskowitz TJ, Sensoy BA (2013) The effects of stock lending on security prices: an experiment. J Finance 68(5):1891
143. Papacostantis E, Engelbrecht AP (2011) Coevolutionary particle swarm optimization for evolving trend reversal indicators. In: 2011 IEEE symposium on computational intelligence for financial engineering and economics (CIFEr) (IEEE), pp 1–8
144. Beber A, Pagano M (2013) Short-selling bans around the world: evidence from the 2007–09 crisis. J Finance 68(1):343
145. Chiang WC, Enke D, Wu T, Wang R (2016) An adaptive stock index trading decision support system. Expert Syst Appl 59:195

146. Chiong R, Fan Z, Hu Z, Adam MT, Lutz B, Neumann D (2018) A sentiment analysis-based machine learning approach for financial market prediction via news disclosures. In: Proceedings of the genetic and evolutionary computation conference companion (ACM), pp 278–279
147. Albert AA, de Mingo López LF, Blas NG (2019) Multilinear weighted regression (MWE) with neural networks for trend prediction. Appl Soft Comput 58:105555
148. Zhen LZ, Choo YH, Muda AK, Abraham A (2013) Forecasting FTSE bursa malaysia klci trend with hybrid particle swarm optimization and support vector machine technique. In: 2013 World congress on nature and biologically inspired computing (IEEE), pp 169–174
149. Li J, Liu G, Yeung HWF, Yin J, Chung YY, Chen X (2017) A novel stacked denoising autoencoder with swarm intelligence optimization for stock index prediction. In: 2017 International joint conference on neural networks (IJCNN) (IEEE), pp 1956–1961
150. Chen H, Chen S, Chen Z, Li F (2017) Empirical investigation of an equity pairs trading strategy. Manage Sci 65(1):370
151. Hutchinson MC, O'Brien J (2018) Testing futures trading strategy assumptions
152. Aitken M, Cumming D, Zhan F (2015) Exchange trading rules, surveillance and suspected insider trading. J Corpor Finance 34:311
153. Wang F, Philip L, Cheung DW (2012) Complex stock trading strategy based on particle swarm optimization. In: 2012 IEEE conference on computational intelligence for financial engineering & economics (CIFEr) (IEEE), pp 1–6
154. Wang F, Philip L, Cheung DW (2014) Combining technical trading rules using particle swarm optimization. Expert Syst Appl 41(6):3016
155. Wang F, Philip L, Cheung DW (2014) Combining technical trading rules using parallel particle swarm optimization based on Hadoop. In: 2014 International joint conference on neural networks (IJCNN) (IEEE), pp 3987–3994
156. Liu X, An H, Wang L, Jia X (2017) An integrated approach to optimize moving average rules in the EUA futures market based on particle swarm optimization and genetic algorithms. Appl Energy 185:1778
157. Wang L, An H, Xia X, Liu X, Sun X, Huang X (2014) Generating moving average trading rules on the oil futures market with genetic algorithms. Math Probl Eng 2014:58
158. Jingshu L, Shuguang Z (2011) Empirical research on hedging strategy of Chinese index future market. In: MSIE 2011 (IEEE), pp 731–734
159. Berk JB, Van Binsbergen JH (2015) Measuring skill in the mutual fund industry. J Financ Econ 118(1):1
160. Barber BM, Huang X, Odean T (2016) Which factors matter to investors? Evidence from mutual fund flows. Rev Financi Stud 29(10):2600
161. Hsu LY, Horng SJ, He M, Fan P, Kao TW, Khan MK, Run RS, Lai JL, Chen RJ (2011) Mutual funds trading strategy based on particle swarm optimization. Expert Syst Appl 38(6):7582
162. Souza VL, Brasileiro RC, Oliveira AL (2015) A PAA-PSO technique for investment strategies in the financial market. In: IJCNN, pp 1–8
163. Ucar I, Ozbayoglu AM, Ucar M (2015) Developing a two level options trading strategy based on option pair optimization of spread strategies with evolutionary algorithms. In: 2015 IEEE congress on evolutionary computation (CEC) (IEEE), pp 2526–2531
164. Worasucheep C, Nuannimnoi S, Khamvichit R, Attagonwantana P (2017) An automatic stock trading system using particle swarm optimization. In: 2017 14th international conference on electrical engineering/electronics, computer, telecommunications and information technology (ECTI-CON)
165. Brasileiro RC, Souza VL, Oliveira AL (2017) Automatic trading method based on piecewise aggregate approximation and multi-swarm of improved self-adaptive particle swarm optimization with validation. Decis Support Syst 104:79
166. Chen SM, Manalu GMT, Pan JS, Liu HC (2013) Fuzzy forecasting based on two-factors second-order fuzzy-trend logical relationship groups and particle swarm optimization techniques. IEEE Trans Cybern 43(3):1102
167. Chen SM, Jian WS (2017) Fuzzy forecasting based on two-factors second-order fuzzy-trend logical relationship groups, similarity measures and PSO techniques. Inf Sci 391:65
168. Bagheri A, Peyhani HM, Akbari M (2014) Financial forecasting using ANFIS networks with quantum-behaved particle swarm optimization. Expert Syst Appl 41(14):6235
169. Hajizadeh E, Mahootchi M, Esfahanipour A, Kh MM (2015) A new NN-PSO hybrid model for forecasting Euro/Dollar exchange rate volatility. Neural Comput Appl 2015:1–9
170. Pradeepkumar D, Ravi V (2017) Forecasting financial time series volatility using particle swarm optimization trained quantile regression neural network. Appl Soft Comput 58:35
171. M'ng JCP, Mehralizadeh M, (2016) Forecasting East Asian indices futures via a novel hybrid of wavelet-PCA denoising and artificial neural network models. PloS one 11(6):e0156338
172. El Hami N, Bouchekourte M (2016) Optimising liquidity with modified particle swarm optimization application: case of casablanca stock exchange. In: 2016 4th IEEE international colloquium on information science and technology (CiSt) (IEEE), pp 725–729
173. Huang Q, Yang J, Feng X, Liew AWC, Li X (2019) Automated trading point forecasting based on bicluster mining and fuzzy inference. IEEE Trans Fuzzy Syst 6:755
174. Durán-Rosal AM, Gutiérrez PA, Carmona-Poyato Á, Hervás-Martínez C (2019) A hybrid dynamic exploitation barebones particle swarm optimisation algorithm for time series segmentation. Neurocomputing
175. Barak S (2017) Dependency evaluation of financial market returns for classifying and grouping stocks. In: 2017 3rd Iranian conference on intelligent systems and signal processing (ICSPIS) (IEEE), pp 193–198
176. Luss R, d'Aspremont A (2015) Predicting abnormal returns from news using text classification. Quant Finance 15(6):999
177. Hajek P, Prochazka O (2017) Learning interval-valued fuzzy cognitive maps with PSO algorithm for abnormal stock return prediction. In: International conference on theory and practice of natural computing (Springer), pp 113–125
178. Gandoman SH, Kiamehr N, Hemetfar M et al (2017) Forecasting initial public offering pricing using particle swarm optimization (PSO) algorithm and support vector machine (SVM) In Iran. Business Econ Res 7(1):336
179. Iansiti M, Lakhani KR (2017) The truth about blockchain. Harvard Business Rev 95(1):118
180. Indera N, Yassin I, Zabidi A, Rizman Z (2017) Non-linear autoregressive with exogeneous input (NARX) Bitcoin price prediction model using PSO-optimized parameters and moving average technical indicators. J Fund Appl Sci 9(3S):791