

DYNAMICALLY-GENERATED ELECTRONIC DATABASE FOR PORTFOLIO SELECTION

Cross-reference with Related Field

5 [0001] The present application is related to Malaysia Patent Application No. PI2017701611 filed 8 May 2017; the disclosure of which is incorporated by reference in its entirety.

Field of the Invention

10 [0002] The present invention relates generally to improvements in electronic processing systems, particularly, electronic databases used for determining selections from real-time-updated electronic exchanges. The novel electronic database structure is dynamically generated for selection of financial instruments with user specified inputs.

Background

15 [0003] Current techniques for achieving financial goals by automatically creating an optimal financial instruments portfolio are limited. Databases may be based solely on various market factors with no mechanism for customization based on various user selection preferences or user needs. Automatic portfolio selection is typically limited to exchange-
20 traded funds (ETFs) in which the financial instruments selected match those of a particular exchange, linking the portfolio performance solely to the performance of that index without a clear link to how to achieve the financial goals.

[0004] Alternatively, investors may purchase mutual funds in which a large portfolio management entity selects financial instruments for inclusion based on the portfolio
25 management entity's knowledge and research. These funds do not allow customization of the underlying securities based on individual investor preference such as a desire to support green technology or avoiding financial instruments originating in certain countries. Users are also not able to combine investment funds in a way that directly enables them to achieve their goals optimally.

30 [0005] Individual investors typically do not possess all the information to create an optimal portfolio and to rebalance it consistently in the future. Due to the fact that financial instruments are purchased on a real-time-updated exchange, it is technically impossible for human being to evaluate all of the factors needed to optimize and manage a financial instrument portfolio in real time. As used herein, the term "financial instrument" includes

stocks, bonds, contracts related to the purchase of stocks or bonds, packages of capital, currency, funds, or any assets that can be traded by means of a representation on an electronic exchange.

[0006] Due to the ever changing user's financial requirements and the technical problem of being unable to process all the information needed to create and maintain a customized portfolio in real time, there is a need in the art to dynamically create an electronic database that evaluates various variables in real time to enable selection from a real-time electronic exchange based on attributes identified by the dynamically-created electronic database.

Summary of the Invention

[0007] The present invention relates to a system, including an electronic database, and a method for executing a selection from a dynamically-generated electronic database. The database includes a plurality of selection parameters created according to statistical models for weighting desirability of financial instruments combined with user entered selection preferences for financial instruments. Each financial instrument is electronically associated with a dynamic electronic label indicating whether the financial instrument is restricted for selection at least in part based upon user entered selection preferences. The selection parameters are electronically converted by a selector engine to electronic output; the selector engine electronic output can be validated based on previously determined outcome parameters associated with past outcomes for the financial instruments in the electronic output of the selector engine.

[0008] A computer processor is configured for executing external selections from a real-time updating external electronic exchange database based on the electronic output of the selector engine, the computer processor including electronic selection limiters to prevent execution of external selections based on electronic flags computed from electronic checks relating to the amount and type of external selections.

Brief Description of the Drawings

[0009] Embodiments of the invention are described in more details hereinafter with reference to the drawings, in which:

[0010] FIG. 1 schematically depicts an electronic processing system including dynamically-created electronic data storage in accordance to one embodiment of the present invention;

[0011] FIG. 2 schematically depicts various details of the electronic processing system as shown in FIG. 1;

[0012] FIG. 3 schematically depicts an external data filter in the electronic processing system as shown in FIG. 1;

5 [0013] FIG. 4 schematically depicts a portfolio construction engine in the electronic processing system as shown in FIG. 1;

[0014] FIG. 5 schematically depicts a flow chart of the process in the execution platform in the electronic processing system as shown in FIG. 1;

10 [0015] FIG. 6 schematically depicts a flow chart of the 'backtest' operation process in the portfolio modeler in the electronic processing system as shown in FIG. 1;

[0016] FIG. 7 schematically depicts a logical architecture of a feedforward neural network having a parallel architecture;

15 [0017] FIG. 8 schematically depicts a logical architecture of a feedforward nonlinear autoregressive recurrent neural network (NARX) having a serial-parallel architecture in accordance to one embodiment of the present invention;

[0018] FIG. 9 schematically depicts a logical architecture of a long short term memory model (LSTM) block in accordance to one embodiment of the present invention; and

[0019] FIG. 10 schematically depicts a logical architecture of the LSTM layer in accordance to one embodiment of the present invention.

20

Detailed Description

25 [0020] In the following description, methods, apparatus, and systems for making financial instrument selection and creating a dynamic electronic database upon which to base financial instrument selection are set forth as preferred examples. It will be apparent to those skilled in the art that modifications, including additions and/or substitutions may be made without departing from the scope and spirit of the invention. Specific details may be omitted so as not to obscure the invention; however, the disclosure is written to enable one skilled in the art to practice the teachings herein without undue experimentation.

30 [0021] The electronic embodiments disclosed herein may be implemented using general purpose or specialized computing devices, computer processors, or electronic circuitries including but not limited to application specific integrated circuits (ASIC), field programmable gate arrays (FPGA), and other programmable logic devices configured or programmed according to the teachings of the present disclosure. Computer instructions or software codes running in the general purpose or specialized computing devices, computer

processors, or programmable logic devices can readily be prepared by practitioners skilled in the software or electronic art based on the teachings of the present disclosure.

[0022] All or portions of the electronic embodiments may be executed in one or more general purpose or specialized computing devices including server computers, personal computers, laptop computers, mobile computing devices such as ‘smartphones’ and ‘tablet computer’, one or more general purpose or specialized processors and electronic circuitries.

[0023] The electronic embodiments include one or more user interfaces and at least one computer storage media having computer instructions or software codes stored therein which can be used to program computers or microprocessors to perform any of the processes of the present invention. The user interfaces may be using webpages, apps, chatbots, and/or other means of communication and interaction with the user. The storage media can include, but are not limited to, floppy disks, optical discs, Blu-ray Disc, DVD, CD-ROMs, and magneto-optical disks, ROMs, RAMs, flash memory devices, or any type of media or devices suitable for storing instructions, codes, and/or data.

[0024] As used herein, the expression “dynamically-created database” relates to a collection of information that is organized so that it can be easily accessed and managed and is updated by various calculated results of various computer programs and while factoring in customizable preference data. The term “database” is used broadly and may include computer program storage regions for storing executing computer programs that act upon the database to dynamically create and store data therein. Thus the database may reside in various regions of memory that include both information and computer instructions for acting upon information.

[0025] Turning to the drawings in details, FIG. 1 schematically depicts an overview of a system for executing a selection from a dynamically-generated electronic database. In one embodiment, the selection of financial instruments and various parametric values in the portfolio construction 1000 is primarily executed by a selector engine 500 based on a plurality selection parameters 100 and statistical models for weighting desirability of the financial instruments to be included in one or more investment portfolios. Throughout the rest of this document, the term, investment portfolio, means a collection of one or more financial instrument with its respective holding size or amount, position, and future action(s) to be carried out. One input to the selection parameters 100 is user selection preferences 200. Another input to the selection parameters 100 is the data received from a financial instrument sub-database 300 having data on various financial instruments. The financial instrument sub-database 300 is dynamically updated with information from an external exchange database.

Each financial instrument is electronically associated with a dynamic electronic label 400 indicating whether the financial instrument is restricted for selection. In this regard, the dynamic electronic label 400 may include a setting that toggles between approved and restricted.

5 [0026] An external data electronic filter 800 may further provide input to the selection parameters 100. The external data electronic filter 800 eliminates noise from external data through electronic text processing, standardization, and electronic pre-computation. A statistical volatility engine 900 may further provide input to the selection parameters 100 by providing data regarding financial instrument volatility. The selection parameters 100 can be
10 set to off-limits to certain financial instruments with an undesirable level of volatility.

[0027] The selection parameters 100 are processed by a selector engine 500 to generate an output 600, which may optionally be validated based on simulated performance of the financial instruments using past outcomes ('backtest') as determined by portfolio modeler 700. The selector engine output 600, which may include data representing one or
15 more trades (trade basket), is then communicated to an execution platform 2000 for executing the trades with interaction and data exchanges with an external real-time updating electronic exchange database 3000.

[0028] In one embodiment, the system further comprises an investment sharing and democratization module 1100 that contributes to the selection parameters 100. The
20 investment sharing and democratization module 1100 accesses the invention portfolio data of peer users/investors of the system, and provides a user interface that allows each user/investor, who chooses to be "originator", to specify whether to share her investment portfolio with others or safeguard (keep confidential) a portion or whole of her investment portfolio, and to allow users/investors whether to become "followers" and follow one or more other
25 users/investors' investment portfolios as the target investment portfolios. The user interface also allows each follower user/investor to specify a variable degree of imitation of own investment portfolio to the specified target investment portfolios of the originator users/investors. The variable degree of imitation can range from identical tracking or cloning of a target investment portfolio without the follower user/investor's intervention to, as
30 example without limitation, tracking of selected individual financial instrument(s), financial instrument(s) of specific type(s), and weighted variants of the target investment portfolio. The module also captures if an investment portfolio is referred to a follower user/investor by another party ("referrer"). The originator user/investor and referrer user/investor of the investment portfolio are rewarded monetarily or in other ways.

[0029] In one embodiment, the system further comprises a deep learning decision engine 1200. The deep learning decision engine 1200 operates to augment the financial instrument selection in creating the investment portfolio. For example, the deep learning decision engine 1200 can be trained to improve decision making for factor weights in investment selection by overweighting one factor versus another in the selector parameters 100. This leads to a different portfolio being optimized from the selector engine 500 – one that has better predictive power of future returns by the investment factors. The deep learning decision engine 1200 employs one or more of deep learning methods including: a nonlinear autoregressive recurrent neural network (NARX) with exogenous inputs model; and a long short term memory (LSTM) neural network.

[0030] FIG. 2 focuses on the interaction of various aspects of FIG. 1 and indicates which subsequent figures include further details concerning these aspects of the invention. As seen in FIG. 2, further details of the external data filter 800 is presented in FIG. 3; the portfolio construction 1000 in FIG. 4; the process flow of the execution platform 2000 in FIG. 5; the ‘backtest’ operation process flow of the portfolio modeler platform in FIG. 6; the deep learning decision engine in FIGs. 7, 8, 9, and 10.

[0031] Concerning user selection preferences 200, the present invention can dynamically accept and update user preferences regarding acquisition or divestment of financial instruments, capturing an individual investor’s needs, preferences, and investment principles such that an individually bespoke and dynamically balanced portfolio is developed. Examples of user/investor preferences include individual principles (e.g. invest in only clean technology), objectives (e.g. for retirement, property purchase, etc.), risk-reward tolerance (e.g. aggressive growth vs. preservation of capital), capital vs. income needs (e.g. does the investor rely on dividends for income?), savings and spending pattern (e.g. how much to save and spending which can be varied in the future as the user’s life progresses), transaction costs incurred (e.g. bid-ask spread paid, broker and exchange fees), portfolio monitoring thresholds (e.g. level of take-profits and cut-loss), rebalancing mode and frequency (e.g. automatic vs. manual and the number of days between rebalancing). As the user preferences may be dynamically changed, the resulting database, investment strategy and portfolio are also dynamically changed.

[0032] Turning to FIG. 3, external data electronic filter 800 is presented. Various sources of external data are optionally input to the selection parameters 100. As seen in FIG. 3, the various sources of external data such as financial data 310, analysts’ reports 320, accounting data 330, news data 340, corporate data 350, and trading data 360 are interspersed

with “noise” such as insignificant investment factors, advertisements or false news reports. Using electronic filtering 370 including text processing, standardization, and electronic pre-computation, cleansed data 380 is produced for input to selection parameters 100 (FIG. 1). The electronic filtering 370 also cleans the external data in regards to certain extraordinary corporate events such as dividend payouts and stock splits.

[0033] FIG. 4 presents features of the portfolio construction engine 1000. As seen in FIG. 4, the selection parameters 100 receives input from the financial instrument sub-database 300, the external data filter 800, the statistical volatility engine 900, the portfolio modeler 700, the investment sharing and democratisation module 1100, the deep learning decision engine 1200, factor decomposition and weighting recommendation engine 1400, and the user selection preferences 200. Operating in connection with these input are factor data 110, risk management 120, and transactions cost minimization 130 in the selector engine 500. Factor data 110 may include analysts’ reports and valuations; behavioural finance may also be considered such as investors’ reaction (overreaction, overconfidence) to earnings announcements as measured in market movement; momentum and reversion may also be tracked. Other valuation measures are determined in the data section such as price to earnings ratio, dividend yield, market to book, and price/cash. Alternative data such as environment, social and governance index, social media and news sentiment is also incorporated where available. Various computer programs may be run in the factor data section 110 to do preliminary calculations regarding terminal/present value, annuity value, discount rate and financial instrument selection, including standardization of various financial measurements into a common currency such as US dollars or Euros.

[0034] Risk management section 120 takes input from user preferences regarding risk (e.g., aggressive growth vs. risk-averse preservation of capital) and combines it with an analysis of market risk, trading risk, position risk, and other risk factors. Risk management also may include information generated from statistical volatility engine 900 including CAPM beta, betas with respect to other factors (oil, USD etc.), industry-adjusted betas. Risk management 120 may optionally compute minimum and maximum size positions for contemplated financial instruments or the asset classes.

[0035] Cost minimization section 130 factors in costs associated with dealing with the financial instruments in determining whether various financial instruments should be selected. Section 130 may communicate with external real-time updating electronic exchange database 3000 in obtaining or calculating fees. Such fees may include the bid-ask spread, exchange charges, broker fees, fund management fees and stock borrow fees, among others.

[0036] The above three sections, data 110, risk management 120, and transaction cost minimization 130 are factored in to the optimizer 140 to maximize portfolio value. Section 140 optimizes a financial instrument distribution in order to maximize the value to the portfolio. Suppose that there are n different financial instruments. Regardless of the underlying distribution of financial instruments returns, a collection of n financial instruments returns $y_1, \dots, y_n$ has a mean of financial instruments returns:

$$m = \frac{1}{n} \sum_{n=1}^n y_n$$

And (sample) covariance of financial instruments returns:

$$C = \frac{1}{n-1} \sum_{n=1}^n (y_n - m)(y_n - m)^T$$

where C denotes the covariance matrix of rates of financial instruments return. The risk of each financial instrument i has the expected value of u_i . The optimizer will find out what fraction x_i to invest in each financial instrument i in order to maximize value, subject to various risk requirements.

[0037] The classical mean-variance model consists of maximizing portfolio value, as measured by

$$\frac{1}{2} x^T C x$$

subject to a set of constraints. The expected risk should be no more than the maximum risk r that an investor desires,

$$\sum_{i=1}^n u_i x_i \leq r_i$$

The sum of the investments in financial instruments fractions x_i should sum to one,

$$\sum_{i=1}^n x_i = 1$$

And, being fractions, x_i should be between zero and one.

$$0 \leq x_i \leq 1, i = 1 \dots n.$$

[0038] After the optimizer section 140, the selection preferences section determines whether there should be hedged positions in section 150. As used herein, the term “hedge” relates to investment in a second financial instrument to reduce the risk of adverse price movements in a first financial instrument. Typically, these are related financial instruments such as a futures contract in an underlying security in a portfolio or a short-sale of the security.

In determining the effect of a hedged position, section 150 evaluates the bid-ask spread, broker fees for contracts, index futures, and/or the costs of equity borrowing.

[0039] Selection parameters 100 also takes as input from the financial instrument sub-database 300 with constraints imposed by electronic labels 400. The financial instruments sub-database may be organized by geography, industry, themes, and/or financial instrument characteristics. The electronic labels indicate whether a stock is available for portfolio construction in the optimizer according to user preferences and other factors determined from selection parameters 100. The labels are dynamically updated as new information becomes available. Selector engine 500 further receives all of the selection parameters determined in selection parameters 100 in order to compute a trade basket of financial instruments that can be executed by the execution platform 2000 to generate a dynamically-balanced portfolio 2300.

[0040] The selector engine may run various computer programs in order to determine the final trade basket. These programs may load a pre-execution portfolio and then control for trading restrictions such as stocks not to be bought/sold/traded/shorted/ stocks to be liquidated. Additional risks check for compliance, sanity, and ‘fat finger’ trades may be performed by selector engine 500. The selector engine 500 may also optionally standardize various financial measurements into a common currency such as US dollars or Euros. The selector engine 500 may also utilize a standardized value of data 110 as set forth below:

Standardized Value

$$= \text{Confidence Weight (\%)} \\ * \frac{[\text{Ranking of value} - (\text{Sum of number of stocks with value}) * 0.5]}{\text{Sum of number of stocks with value}}$$

[0041] After all of the various computations are made in the selector engine 500, a final trade basket is sent to selector engine output 600. The output may be sorted by regular trades and those trades for which hedging will be performed. The regular trades include financial instruments for an optimal “long” portfolio (that is, financial instruments intended to be owned), an optimal long equities/short equities portfolio. For hedged instruments there is an optimal long equities/short futures portfolio. The selector engine output 600 may be sent to the execution platform 2000, which will communicate with the external real-time updating electronic exchange database 3000 for execution of the trades. In one embodiment, the external real-time updating electronic exchange database 3000 is a stock exchange trading platform.

[0042] FIG. 5 depicts details of the operation of the execution platform 2000. The optimal investment portfolio, optimal long equities portfolio, optimal long equities/short equities portfolio, or hedged optimal long equities/short equities portfolio received from the selector engine output 600 is first compared with the current portfolio executed. The differences are extracted and form the new trades to be executed. The new trades are finally checked against a group of parameters including lot size, minimum tradeable amount, accidental 'fat finger' trades, trade amount exceeding 'backtest'-predicted trade amount range, and externally imposed trading restrictions. The checked trades are properly data-formatted and packaged into trade orders to be sent to a broker or directly the external real-time updating electronic exchange database 3000 via an automated orders routing and placing sub-system 2500 (as shown in FIG. 1), which automatically routes and places the trade orders to brokers of a stock exchange and captures the trade order status. A trade order in non-base currency can be optionally paired with an equivalent foreign exchange order that is executed conditional upon the successful execution of the trade order. The automated orders routing and placing sub-system 2500 may be an external system. The checked trades and order status are also displayed to the user.

[0043] FIG. 6 depicts details of the 'backtest' operation of the portfolio modeler 700. The portfolio modeler 700 works to simulate the performance of an investment portfolio under various user input preferences and to determine the value and performance of that portfolio. Input from the portfolio modeler may be used as part of the input to the selection parameters 100 in assisting the financial instrument selection. One of the features of portfolio modeler 700 is that it determines the past performance of any collection of financial instruments using the same set of parameters so that a user may determine if a particular investment strategy has yielded positive returns for any specified previous period of time. Using this information, a user can determine if a particular portfolio has "out-performed" the market in the past. The portfolio modeler may employ artificial intelligence to select and model a set of financial instruments based on various user input factors. Such factors include age, initial capital to be invested, long-term and short-term investment goals, risk preferences, opinions on economic issues such as inflation, and personal principles regarding selection of particular financial instruments. The portfolio modeler may include a user interface that elicits the above information using interactive questions to which a user may input answers.

[0044] The input of user input preferences to the portfolio modeler 700 can be conducted by interactive user questioning. The user's answers to the questions. Based on the answers, the portfolio modeler 700 selects and tests the performance of a group of

financial instruments, provides appropriate advice, taking his/her financial choices into account, on the allocation of the user's capital into the recommended amount per investment strategy and/or group of financial instruments. As seen in FIG. 6, an iterative process determines the portfolio value and rebalances the portfolio from a specified prior date until the present date, displaying the final performance results. The user can also iteratively enter different set of answers to the questions, thereby generating different test scenarios. In this manner, a user may iteratively test various inputs and investment preference strategies until a desired combination is determined. This information may be shared with the selection parameters 100; the user may also capture this information by updating the user preferences 200 to reflect the output of the portfolio modeler 700.

[0045] The 'backtest' operation of the portfolio modeler 700 is substantially similar to the trade execution performed by the execution platform 2000. In both, the information 'universe' is filtered with data cleansed and standardized, followed by the generation of the optimal portfolios. Instead of comparing the optimal portfolio with the currently executing portfolio and create a trade basket to be executed, the backtest operation goes into a loop. In the backtest operation, information as of that particular date is used whereas in trade execution performed by the execution platform 2000 the latest information is used. The set of parameters, equations, and optimizer are the same and kept constant in both. As such the backtest operation creates a realistic situation of what it would have been in the past.

[0046] The NARX network is configured to learn and to predict a one-time series given as inputs the past values of the same time series, the feedback input, and another time series. The NARX model can be characterized by:

$$y(t) = f(y(t-1), y(t-2), \dots, y(t-n_y), u(t-1), u(t-2), \dots, u(t-n_u));$$

where the next value of a dependent output, $y(t)$, is regressed on previous values of the output and previous values of an independent exogenous input, $u(t)$. The NARX network is a feedforward neural network approximating the function f . The output, $y(t)$, is estimated in a nonlinear dynamic system that the NARX network is being trained to model. The final output, $y(t)$, is then taken as an estimated output of the combination of selection parameter weights that enters the selector engine 500 as input. The exogenous input, $u(t)$ can be other micro financial variables and/or macro financial market data. Examples of micro financial variables include technical signals (e.g. relative strength index), analysts forecasts (e.g. recommendations), company performance (e.g. earnings growth); and examples of macro financial market data include foreign currency exchange and the U.S. Dollar index. The output of the NARX network is fed back to the input of the feedforward neural network as part of a

standard NARX architecture (the parallel architecture as shown in FIG. 7). Since the true output, $y(t)$, is available during the training of the NARX network, the true output, $y(t)$, instead of the estimated output, $y^e(t)$, is used in the feedback as shown in series-parallel architecture depicted in FIG. 8. The advantages of the series-parallel architecture are that the input to the NARX network is more accurate, the resulting NARX network has a purely feedforward architecture, and static backpropagation can be used for training in the series-parallel architecture (as shown in FIG. 8). In one preferred embodiment, the series-parallel architecture is used in the training of the NARX network and the parallel architecture is used for multi-step-ahead prediction. During training, the number of neurons in the hidden layer is set, and the weight and bias values are set according to the Levenberg-Marquardt optimization (details are disclosed in Hagan, M.T. and M. Menhaj, "Training feed-forward networks with the Marquardt algorithm," *IEEE Transactions on Neural Networks*, Vol. 5, No. 6, 1999, pp. 989–993, 1994; and in https://en.wikipedia.org/wiki/Levenberg-Marquardt_algorithm). In one embodiment, an NARX is employed in the estimation of factor weights (in selection parameters 100) for momentums. In this case, part of the dataset is adopted for training the NARX model on $y(t)$ where $y(t)$ is the ideal factor weights for momentums that maximize the investment portfolio value. During training, $y(t)$ is estimated based on the ideal actual factor weights of the past, $y(t-n)$; and other contemporaneous variables such as volume of trade and rate of price change. Using the trained model, the NARX would forecast $y(t)$ that would maximize portfolio value in the selector engine 500.

[0047] The LSTM is a type of recurrent neural network (RNN). Training an RNN is usually done by backpropagation through time. The sequence-to-sequence LSTM network is trained for time series forecasting where the actual values are the training sequences with the values shifted by one time-step. That is, at each time step of the input sequence, the LSTM network learns to predict the value of the next time-step. FIG. 9 depicts the architecture of an LSTM block. Similar to that of a traditional RNN, an LSTM block typically has a cell candidate 802, input gate 803, output gate 804, a forget gate 801, and a hidden state 805. LSTM network is less sensitive to having gaps in the time series data. So, if a time series is incomplete, the LSTM network is better at the analysis of sequential data than traditional RNNs. The weights and biases to the input gate 803 control the extent to which a new value flows into the cell. Similarly, the weights and biases to the forget gate 801 and output gate 804 control the extent to which a value remains in the cell and the extent to which the value in the cell is used to compute the output activation of the LSTM block respectively.

[0048] Referring to FIG. 10. In accordance to one embodiment of the LSTM, a time series factor weight estimation is applied to an LSTM layer, wherein a time series x with C features (channels) of s number of time steps is flown through the LSTM layer. The states of the LSTM layer comprise a hidden state (also known as output state), h_t , and a cell state c_t .
 5 The first LSTM block uses the initial state of the LSTM layer and a first time-step of the sequence to compute a first output and an updated cell state. At time step t , the block uses the current states of the LSTM layer (c_{t-1} , h_{t-1}) and the next time step of the sequence to compute the updated hidden state h_t and the updated cell state c_t . The hidden state at time step t , h_t , contains the output of the LSTM layer for this time step.

[0049] The cell state c_t contains information learned from the previous time steps. At each time step, the layer adds information to or removes information from the cell state c_t . The LSTM layer controls these information additions and removals using the forget gates 801, the cell candidates 802, the input gates 803, and the output gates 804. These components control the cell state and hidden state of the LSTM layer through the flow of data at time step
 10 t . The learnable weights of these components comprise input weights W , recurrent weights R , and a bias b such that:

$$W = \begin{bmatrix} W_i \\ W_f \\ W_g \\ W_o \end{bmatrix}; R = \begin{bmatrix} R_i \\ R_f \\ R_g \\ R_o \end{bmatrix}; \text{ and } b = \begin{bmatrix} b_i \\ b_f \\ b_g \\ b_o \end{bmatrix};$$

where i denotes the input gate; f denotes the forget gate; g denotes the cell candidate; and o denotes the output gate.

20 The cell state at time step t , c_t , is given by:

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t;$$

where $\odot$ denotes the elementwise multiplication of vectors.

The hidden state at time step t , h_t , is given by:

$$h_t = o_t \odot \sigma_c(c_t);$$

25 where σ_c denotes the state activation function and it is computed using the hyperbolic tangent (tanh) function.

The components of the LSTM layer can then be described:

Component	Function	Equation
Input gate i	Control the level of cell state update	$i_t = \sigma_g(W_i x_t + R_i h_{t-1} + b_i)$
Forget gate f	Control the level of cell state reset (forget)	$f_t = \sigma_g(W_f x_t + R_f h_{t-1} + b_f)$
Cell candidate g	Add information to the cell state	$g_t = \sigma_c(W_g x_t + R_g h_{t-1} + b_g)$
Output gate o	Control the level of cell state added to the hidden state	$o_t = \sigma_g(W_o x_t + R_o h_{t-1} + b_o)$

where σ_g denotes the gate activation function, computed using the sigmoid function given by:

$$\sigma_g = (1 + e^{-x})^{-1};$$

Additional details are available from Hochreiter, S., and J. Schmidhuber. "Long short-term memory." *Neural computation*, Vol. 9, No. 8, pp.1735–1780, 1997. As an example, the number of analysts' forecast revisions can be forecasted by using a LSTM network where the data is a time series of analyst forecast revision. The procedure includes splitting the data for training and testing, standardizing the data to have zero mean and unit variance, then specifying the number of revisions to be the training sequences with values shifted by one time-step. That is, at each time step of the input sequence, the LSTM network learns to predict the value of the next time-step. The predictors are the training sequences without the final time-step. In this example, the LSTM is specified to have 200 hidden units.

[0050] Turning to FIG. 1 again. In one embodiment, the portfolio modeler 700 is augmented by a portfolio stress test engine 1300. The portfolio stress test engine 1300 works to introduce one or more market stress scenarios in the performance simulation of an investment portfolio and/or a 'backtest' by the portfolio modeler 700. The market stress scenarios can be modeled after historical market data recorded during one or more past market stress time periods. Portfolio stress test is performed by quantifying the 'backtest' portfolio performance over the periods of market stress. The past market stress time periods used can be user-defined or defaulted by the system. As the impetus to each market stress scenarios are unique on their own, these market stress scenarios cannot be captured by traditional risk metrics such as standard deviation of value at risk and would rely on 'backtest' results using historical data.

[0051] In another embodiment, the system further comprises a factor decomposition and weighting recommendation engine 1400. The factor decomposition and weighting recommendation engine 1400 uses actual historical price data of financial instruments to

compute an optimal weighting to each of the selection parameters 100 being processed by the selector engine 500 in generating investment portfolios. This allows the user to appraise the actual performance of the investment portfolios. The weighting recommendation engine 1400 estimates the factor weightings that maximizes the Sharpe ratio based on the following:

$$5 \quad \text{Max} \left(\frac{\mu^T x - r_f}{\sqrt{x^T C x}}, s. t. \sum x_i = 1, 0 \leq x_i \leq 1 \right);$$

where x_i is the weighting of the instruments in the portfolio, μ is the mean returns, C is the covariance matrix of the financial instruments return, and r_f is the risk-free rate. The numerator of ratio captures the excess portfolio return over the risk-free rate based on a set of weightings; whereas the denominator measures the risk / standard deviation taken on to achieve the return. In combination, the ratio is a reward to risk measure and a higher value implies a more desirable outcome.

[0052] In yet another embodiment, the system further comprises a market visualization and big data analytics engine 1500 that provides input to the selection parameters 100 in the portfolio construction 1000. The market visualization and big data analytics engine 1500 provides the function of supplementing traditional investment appraisal data (e.g. fundamental market data and corporate financial data) with alternative non-financial data. The market visualization and big data analytics engine 1500 is configured to continuously scan and retrieves non-financial data from traditional news sources and social media sites. The non-financial data is processed for sentiment analysis by a machine learning and natural language processing (NLP) module, which can be external to the system or an incorporated component in the market visualization and big data analytics engine 1500. The market visualization and big data analytics engine 1500 segregates non-financial data into separate information pieces and provides the sentiment analytical parametric results on each information piece. The parametric results include:

Sentiment Analysis Result Parameter	Description
Industry and country averages	Assessing one's position in comparison with peers'
News flow	Gauging how widely distributed is the information
News readership	Evaluating how likely the information would have a positive or negative impact

[0053] The market visualization and big data analytics engine 1500 may further comprise a heatmap user interface that provides a high-level view display at a single glance

of a variable. This allows a user to quickly digest the information and then drill into a specific area. Drilling deeper into that specific area identifies to the user the associated financial instruments. Possible variables that allow top-down drill are: country, industry, company fundamental data (e.g. P/E, dividend yield), equity price performance, sentiment, etc.

[0054] The execution platform 2000 includes a selection limiter 2100 that sets limits in a trade based on electronic flags 2200 computed from electronic checks relating to the amount and type of the trades. Selected financial instruments are input to a dynamically-balanced portfolio 2300 which is updated according to user specifications at any given frequency.

[0055] In one embodiment, the system further comprises a portfolio monitoring engine 2400 that interacts with the execution platform 2000. The portfolio monitoring engine 2400 processes the trade data being handled by the execution platform 2000 in executing the trades. The portfolio monitoring engine 2400 enables users to maximise payoff whilst limiting the downside. To achieve this, the portfolio monitoring engine 2400 provides the facility (e.g. via a user interface) for a user to pre-programme her desired stop losses and take profits levels. To maximise profits, the system holds on continuously to a long position of a specific financial instrument until its market price is moved above the user-defined take profits level price by which an order will automatically be placed so that the user can take advantage of sudden or unexpected changes in financial instrument prices. To limit the downside, the user specifies a limit on the maximum possible losses, without setting a limit on the maximum possible gain. The engine continuously recalculates the stop losses sell-trigger price and limit sell price at some points below the market price based on the user-defined amount of maximum possible losses. As the market price rises, both the stop losses sell-trigger price and the limit sell price rise proportionally, but if the stock price falls, the stop losses sell-trigger price remains unchanged, and when the stop losses sell-trigger price is reached, a limit sell order is submitted at the last calculated stop losses limit sell price. The engine is further enhanced by a mechanism to prevent accidental shorting of an instrument in highly volatile market when stop losses order (at a lower price) and take profits order (at a higher price) are placed simultaneously. For example, to avoid accidentally short-selling, when a stop loss order is executed, the corresponding take profit order is cancelled. If a stop loss order is partially executed, the remaining order in the corresponding take profit is reduced proportionately by the amount that was executed. If a cut loss order is cancelled before execution, the corresponding take profits order is cancelled. The reverse is true in the case of take profit order being executed partially, completely or cancelled.

[0056] In another embodiment, the system further comprises a portfolio yield enhancement engine 2600 that interacts with the execution platform 2000. The portfolio yield enhancement engine 2600 processes the trade data being handled by the execution platform 2000 in executing the trades. The portfolio yield enhancement engine 2600 is designed to specifically handle certain buy-and-hold ('long position') financial instruments or equities in a portfolio that regularly generates cashflows such as dividends and interests. The portfolio yield enhancement engine 2600 works to enhance these cashflows by writing covered call options against the underlying financial instruments' long positions, that is the underlying financial instruments are to be sold if and when a user-defined pre-determined price (higher than the present price) is reached in a future point of time before the expiration of the call option. The additional cashflow generated by the portfolio yield enhancement engine 2600 is the option premium paid for by the call option buyer.

[0057] The foregoing description of the present invention has been provided for the purposes of illustration and description. It is not intended to be exhaustive or to limit the invention to the precise forms disclosed. Many modifications and variations will be apparent to the practitioner skilled in the art.

[0058] The embodiments were chosen and described in order to best explain the principles of the invention and its practical application, thereby enabling others skilled in the art to understand the invention for various embodiments and with various modifications that are suited to the particular use contemplated.

Claims:

What is claimed is:

- 5 1. A system for executing a selection from a dynamically-generated electronic database comprising:
- a selector engine comprising at least one computer processor configured for:
- creating selection parameters according to a statistical model for weighting desirability of one or more financial instruments combined with entered user
- 10 selection preferences/objectives for financial instruments,
- creating one or more investment portfolios of financial instruments based on the selection parameters, and
- converting the investment portfolios data to output data representing trade instructions of financial instruments;
- 15 a deep learning decision engine comprising one or more neural networks configured to provide input to the selector engine; and
- an execution platform comprising at least one computer processor configured for executing the trade instructions.
- 20 2. The system of claim 1, wherein the deep learning decision engine input to the selector engine comprises one or more estimated weights to investment factors; and one or more diversification of investment portfolio by selecting alternative financial instruments that have little relationship with current financial instruments in the investment portfolio but are most similar in one or more characteristics.
- 25 3. The system of claim 1, wherein the deep learning decision engine neural networks comprising at least a nonlinear autoregressive recurrent neural network (NARX) with exogenous input.
- 30 4. The system of claim 1, wherein the deep learning decision engine neural networks comprising at least a long short term memory (LSTM) neural network.

5. The system of claim 1, further comprising:

a portfolio modeler having at least one computer processor configured for executing a performance simulation of an investment portfolio; and

a portfolio stress test engine having at least one computer processor configured for introducing one or more market stress scenarios in the performance simulation of an investment portfolio by the portfolio modeler.

6. The system of claim 1, further comprising a portfolio monitoring engine for:

continuously monitoring market prices of one or more financial instruments in the one or more investment portfolios;

generating a take profit trade order signaling a sale of a financial instrument having market price reaching at or above a defined take profits level price;

continuously calculating a stop losses sell-trigger price and a stop losses limit sell price of a financial instrument, wherein the stop losses sell-trigger price and the stop losses limit sell price move in proportion with a rising market price of the financial instrument, and wherein the stop losses sell-trigger price and the stop losses limit sell price remain unchanged with a falling market price of the financial instrument; and

generating a stop losses trade order signaling a sale of a financial instrument having market price reaching at or below stop losses sell-trigger price;

wherein the portfolio monitoring engine prevents accidentally short-selling a financial instrument due to volatile market when both take profits level price and stop losses limit sell price are set;

wherein when either the take profit trade order or stop losses trade order on a financial instrument is fully executed, any remaining pending trade order on the financial instrument is canceled;

wherein when either the take profit trade order or stop losses trade order on a financial instrument is partially executed, any remaining pending trade order on the financial instrument is reduced proportionately by the partially executed amount; and

wherein when either the take profit trade order or stop losses trade order on a financial instrument is canceled before execution, any remaining pending trade order on the financial instrument is canceled.

7. A system for executing a selection from a dynamically-generated electronic database comprising:

a selector engine comprising at least one computer processor configured for:

creating selection parameters according to a statistical model for weighting desirability of one or more financial instruments combined with entered user selection preferences/objectives for financial instruments,

creating one or more investment portfolios of financial instruments based on the selection parameters, and

converting the investment portfolios data to output data representing trade instructions of financial instruments;

an investment sharing and democratization module configured for:

accessing one or more invention portfolio data of other users of the system to generate a specified target investment portfolio adjustable by a degree of imitation of the one or more invention portfolio data of the other users, and

generating from the specified target investment strategy an additional input to the selector engine; and

an execution platform comprising at least one computer processor configured for executing the trade instructions.

8. The system claim 7, wherein the investment sharing and democratization module is further configured for:

allowing referral of one or more invention portfolio data of other users of the system to generate a specified target investment portfolio;

computing a reward for the referral;

computing a reward for the generation of the specified target investment portfolio.

9. The system of claim 7, further comprising:

a portfolio modeler having at least one computer processor configured for executing a performance simulation of an investment portfolio; and

a portfolio stress test engine having at least one computer processor configured for introducing one or more market stress scenarios in the performance simulation of an investment portfolio by the portfolio modeler.

10. The system of claim 7, further comprising a portfolio monitoring engine for:
continuously monitoring market prices of one or more financial instruments in the
one or more investment portfolios;

generating a take profit trade order signaling a sale of a financial instrument having
5 market price reaching at or above a defined take profits level price;

continuously calculating a stop losses a sell-trigger price and a stop losses limit sell
price of a financial instrument, wherein the stop losses sell-trigger price and the stop losses
limit sell price move in proportion with a rising market price of the financial instrument, and
wherein the stop losses sell-trigger price and the stop losses limit sell price remain
10 unchanged with a falling market price of the financial instrument; and

generating a stop losses trade order signaling a sale of a financial instrument having
market price reaching at or below stop losses sell-trigger price;

wherein the portfolio monitoring engine prevents accidentally short-selling a
financial instrument due to volatile market when both take profits level price and stop losses
15 limit sell price are set;

wherein when either the take profit trade order or stop losses trade order on a
financial instrument is fully executed, any remaining pending trade order on the financial
instrument is canceled;

wherein when either the take profit trade order or stop losses trade order on a
20 financial instrument is partially executed, any remaining pending trade order on the
financial instrument is reduced proportionately by the partially executed amount; and

wherein when either the take profit trade order or stop losses trade order on a
financial instrument is canceled before execution, any remaining pending trade order on the
financial instrument is canceled.