A Comparative Survey of Three AI Techniques (NN, PSO, and GA) in Financial Domain

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Abstract—In the real world, the behaviors of financial applications are unstable and they change from time to time. Accordingly, dealing with such issues as nonlinear and time variant problems has been a serious problem in recent years. These types of problems along with inefficiency of the traditional models led to an increasing interest in artificial intelligence approaches. In this study, we briefly review three popular artificial intelligence methods, i.e., Artificial Neural Networks, Genetic Algorithms, and Particle Swarm Optimization, and compare their applications in financial domain. By considering the broad domain of financial applications, we classify financial market into three domains, including financial forecasting, credit evaluation, and portfolio management. For each technique, we have attempted to take the most recent and popular studies into account. The results are promising and represent that in handling financial problems, the performance and accuracy of the above mentioned artificial intelligence techniques are considerably higher, compared to the traditional statistical techniques, particularly in nonlinear models. Nevertheless, this superiority is not true in all cases.

Keywords—Artificial neural networks, Genetic Algorithms, particle Swarm Optimization, Credit evaluation, Portfolio management, Financial prediction and planning

I. INTRODUCTION

The importance and the considerable impact of financial organization on capital accumulation and economic development are taken for granted since the last century. During this period of time, researches have tried to simplify financial activities via predicting financial trends, simulating the behavior of financial circumstances, assessment of goals, management of asset portfolio, bankruptcy prediction, and stock market forecasting, etc [1-9]. In this regard, different methods have been used. Broadly speaking, these method can be classified into parametric statistical methods (including k-nearest neighbor and decision trees), and soft computing methods (e.g., artificial intelligent techniques and rough sets). Artificial intelligent techniques, especially Artificial Neural Networks (Artificial NNs), have been broadly used in financial domain.

In this paper, the study background of three popular artificial intelligent techniques, i.e., Artificial NNs, Genetic Algorithms (GAs), and Particle Swarm Optimization (PSO), in financial domain has been investigated. Artificial NNs were chosen because of such features as their ability in updating the data, their numerical nature, and their independence of any sort of assumptions for data distribution as inputs. Firstly, the numerical nature of Artificial NNs surpasses nominal nature in symbolic manipulation methods due to the fact that these methods before accepting numeric data as input data, require to convert numeric data into nominal values; hence, such problems as information losing and incorrect data intervals may be arisen. However, in Artificial NNs numeric data can directly be processed as input data. Second, although in statistical methods such as discriminant analysis and regression distribution assumptions are needed around input data, Artificial NNs don’t require any sort of assumption for data distribution, and consequently, they can be applied on a broader range of problems in comparison with statistical methods. Third, it is possible to add new data to a trained Artificial NN so as to improve the former training results. In opposition, the majority of statistical techniques are considered batch-oriented, because in order to produce new results, they require both new and old data presented as a single batch to the model. Eventually, Artificial NNs constitute estimators that are model free. This characteristic provides the ability of eliciting interaction effect among various variables without accurate formulating model by the users. Essentially, in an Artificial NN the more hidden layers lead to modeling the more complicated interaction effect [10]. For the sake of simplicity, with regard to financial markets, we selected three most significant domains, i.e., portfolio management, financial forecasting and planning, and credit evaluation. We attempted to investigate most significant researches carried out in above financial domains. The primary concentration of this study is to examine and compare these three techniques with traditional methods and other intelligent methods.

A. Portfolio Management

Portfolio management in finance is more than a mathematical problem of optimizing performance under risk constraints. A critical factor in practical portfolio problems is severe uncertainty – ignorance – due to model uncertainty. A portfolio consists of a set of segments, each of which is
predefined as a particular asset category, such as stocks, bonds, commodities, etc. Solving the selection problem means determining the best proportion each segment should be of the total investment. The portfolio selection problem is the subject of a vast body of work. The process can be divided into two phases. The first is asset allocation, in which investor philosophy, including risk position, is used to choose the best percentage of the portfolio to place in each segment. The second rebalancing, responds to changes in asset values by adjusting the percentages so that the portfolio continues to accurately reflect the investment philosophy [11].

In the regard of portfolio management we explore proposed techniques for optimal portfolio selection, equity selection, asset portfolio selection, etc.

B. Financial Forecasting and planning

Making accurate predictions for financial market prices is not a trivial task as several influencing factors have to be considered, especially many sudden factors which are difficult to be known in advance have a decided influence on the fluctuation of short-term prices. Forecasting has a long history and the importance of this old subject is reflected by the diversity of its applications in different disciplines ranging from business to engineering. The ability to accurately predict the future is fundamental to many decision processes in planning, scheduling, purchasing, strategy formulation, policy making, and supply chain operations. As such, forecasting is an area where a lot of efforts have been invested in the past. Yet, it is still an important and active field of human activity at the present time and will continue to be in the future [12]. A survey of research needs for forecasting has been provided by Armstrong [13]. For the sake of simplicity in financial forecasting domain we explore bankruptcy prediction, financial forecasting, stock and exchange rate prediction.

C. Financial forecasting and planning

In the domain of credit evaluation we explore research studies in credit scoring and ranking, credit risk analysis, bond rating, etc. The aim of credit scoring is essentially to classify loan applicants into two classes, i.e., good payers (i.e., those who are likely to keep up with their repayments) and bad payers (i.e., those who are likely to default on their loans). Credit scoring problems are basically in the scope of classification agenda that is a commonly encountered decision making task in businesses, and it is a typical classification problem to categorize an object into one of predefined groups or classes based on a number of observed attributes related to that object [14, 15]. Credit ratings are alphabetical indicators of credit risk provided by international rating agencies such as Standard and Poor’s Corporation, Moody’s Investors Service, and Fitch Ratings.

II. ARTIFICIAL NEURAL NETWORKS AND FINANCIAL DOMAIN

Artificial NNs are considered a significant class of quantitative modeling tools. These tools have been effectively used to obviate a diversity of tough problems in many domains such as business, industry, and science [16]. Especially, they are useful for discovering the relationship among a collection of patterns or variables in the data. The process of modeling task in Artificial NNs is greatly adaptable and the model is created highly based on the patterns or features the network has learned in the learning progress from data.

A. Feed-forward Artificial Neural Networks

Practically speaking, the multilayer feed-forward Artificial NNs, which are also termed as multilayer perceptrons (MLP), are most commonly used and studied NNs. Wong, Bodnovich, and Selvi have reported that around 95% of Artificial NNs applications in business domain uses this model [17]. Feed-forward NNs are best suited to model relationships among a collection of input variables and one or more output variables. Namely, they are suitable for functional mapping problems when we are interested to find how some input variables influence the output variable(s) [18].

A MLP is a NN comprises some simple computational units that are extremely interconnected, named neurons or nodes, and organized in terms of layers. Neurons process information via handling the inputs and producing processed outputs. The obtained knowledge from the processing task of neurons can be stored using the arcs that link these neurons. The knowledge is stored as weights where represent how strength is the relationship among various neurons. Figure 1 demonstrates a sample architecture for a three layer feed-forward Artificial NN.

The information is processed by neurons in two steps. The first step combines inputs (x_i) and creates a weighted sum from inputs and connecting link weights (w_i). In the second step, by applying a transfer function, the obtained weighted sum is converted to an output. Mathematically speaking, the neuron carries out the following calculations:

$$\text{Out}_n = f\left(\sum_i w_i x_i\right)$$

where Out_n is considered the output of this specific neuron and f is considered the transfer function. Albeit there exist many options for the transfer function, the sigmoid (logistic) function is the most common option, particularly for the nodes in hidden layer. It is because of the fact that this function is not complicated, has some good features (including nonlinear, monotonically increasing, and bounded), and is more similar to actual neurons [19].
\[ f(x) = (1 + \exp(-x))^{-1} \]

We can show a 3-layer NN in the form of a nonlinear model as follows:
\[ y = f_h(w_h f_i(w_i x)) \]

where \( f_i \) and \( f_h \) are transfer functions for nodes in hidden and output layers, in turn; \( w_i \) and \( w_h \) are two matrices containing arc weights from the input layer to the hidden layer and from the hidden layer to the output layer, respectively; \( x \) is a vector including \( d \) attribute variables and \( y \) is the output vector from this NN which is M-dimensional.

B. The applications of Artificial Neural Networks in financial domain

Generally speaking, Artificial NNs constitute information processing techniques that utilize generalization and learning features and are highly adjustable. Particularly, thanks to their adjustability, they introduce efficient responses for subjective features and are highly adjustable. Particularly, thanks to their processing techniques that utilize generalization and learning power, they have been used as a common tool for decision making in financial domain [22] and other problems related to industrial and real time applications in last decade. Particularly, during the recent years, due to the remarkable useful features of Artificial NNs, they have been used as a common tool for decision making in financial domain [10]. In this aspect, different researches have been carried out to investigate and categorize the applications of Artificial NNs in finance domain [5, 6, 23]. For instances, based on a categorization presented by [23], by using Artificial NN technology the following financial applications can be remarkably bettered: financial simulation, investor behavior prediction, management of asset portfolio, financial evaluating, determination of optimum capital structure, and public offerings pricing.

C. Credit assessment

Credit scoring is a method which is used to assess the credit worthiness of persons or corporates. It was introduced for the first time in 1950s. In general, credit scoring related problems are considered as a regular classification problem, so that the categorization of objects is done based on a collection of predefined groups or they should be classified based on a group of attributes related to each object. Thus far, for credit scoring diverse approaches have been put forward, such as logistic regression, and linear discrimination analysis [24, 25]. However, by considering the fast development of credit market, nowadays the industry seeks for more precise credit scoring models. This motivation was resulted in exploring the application of Artificial NNs in the field. One way to apply Artificial NNs in this financial domain is to utilize the customers’ banking information as the input vector and considering the real decisions of credit analyst as a goal output vector. The final aim of the system can be defined as to simulate the behavior of expert person when he/she allocates credit and determines credit limitations. By doing so, we would have a system that is capable to handles the variety of input data without restarting information [2]. There are some instances in utilization of Artificial NN to this area. For instance, to solve the credit scoring problem, Jensen applied back-propagation NN to the problem. Input neurons were associated to the applicant features which contain credit and demographic information of people. In order to demonstrate the loan results, the groups background history, offender, and paid off, were employed as the output neurons of the network. Albeit the sample data set was used by Jensen includes only 125 loan applicants, he makes a claim that while the correctness of his proposed NN is from 76% to 80%, the traditional credit scoring approach led to 74% of success rate [26]. Trinkle has explored the ability of Artificial NNs in comparison with other legacy statistic approaches in credit scoring domain. He considered two assumptions: first, if the classification power in an Artificial NN goes beyond that of traditional models, and second, if various weight interpretation methods led to final models with different classification power [27]. In 2008, two Artificial NNs were developed by Angelini et al. [28]. One of them was based on a regular feed-forward model and the other one had specific purpose architecture. The performance of the system was assessed using real world data, acquired from small corporations in Italia. They proved that if data analysis and preprocessing are done carefully, and suitable training is carried out, then Artificial NNs will demonstrate a powerful performance in estimating and learning the default direction of a borrower.

### Table I. A Brief Exploration of Comparing Artificial NN with Traditional Approaches

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<thead>
<tr>
<th>Domain</th>
<th>Author(s)</th>
<th>Approaches compared</th>
<th>Conclusion</th>
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</thead>
<tbody>
<tr>
<td>Credit scoring</td>
<td>[29]</td>
<td>Back-Propagation NN compared with MDA</td>
<td>Artificial NN has a better performance</td>
</tr>
<tr>
<td>Credit scoring</td>
<td>[30]</td>
<td>PNN and MLP compared with DA and LR</td>
<td>PPN and MLP have a better performance</td>
</tr>
<tr>
<td>credit measurement</td>
<td>[31]</td>
<td>Back-Propagation NN with OPM</td>
<td>Artificial NN has a better performance</td>
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<tr>
<td>Bond scoring</td>
<td>[32]</td>
<td>Back-Propagation NN compared with LR</td>
<td>Artificial NN has a better performance</td>
</tr>
<tr>
<td>Credit scoring</td>
<td>[35]</td>
<td>BPNN compared with MDA, LR, and LS-SVMs</td>
<td>LS-SVMs and BPNN have a better performance</td>
</tr>
</tbody>
</table>

In the comparison regard, some researches exist that examine Artificial NNs and attempt to compare their NN based models with other traditional methods. For example, the study done by [29] compares back-propagation Artificial NN with multiple discriminant analysis (MDA). They inferred that Artificial NNs has a much better performance in comparison with MDA. Abdou et al. [30] in their study tried to compare two neural architectures, Probabilistic Neural Network (PNN) and Multilayer Perceptron (MLP), for credit scoring with logistic regression (LR) and Discriminant Analysis (DA). They concluded that in comparison with other models, MLP and PNN have a better operation. Likewise, in another study [31] Artificial NN was used for credit measurement. Eventually, their results showed that in comparison with ordered probit models, the performance of Artificial NN is much higher. In
addition, researches by [32-35] illustrated that Artificial NN has a better performance in comparison with other methods. In table 1 a brief report of these comparisons has been presented.

D. Management of Portfolio

Today, the ability to determine the optimum assets allocation for a wide range of investments (such as stocks, real estates, cash, and so on), which is suitable for organizations based on time limitations and risk considerations is a critical phenomenon. Moreover, investors are properly aware of the fact that it is rational to broadly diversify their investments. With regard to the amorphous nature of the decisions in portfolio management processes, the hesitancy of the economic climate and the variety of information included, it can be considered as a decent domain for Artificial NN implementation [36]. In this area, a multilayer perceptron back-propagation Artificial NN was designed by [37] which were capable of forecasting the rate of prepayment mortgage by applying correlation learning algorithm. An analog Artificial NN was proposed by [38] to optimize portfolio under constraints. At the same time, he also designed a feed–forward NN for the problem of short-term entities forecasting which is considered to be a dilemma in nonlinear multichannel time series prediction. In order to economic analysis of risky projects for acquisition, an Artificial NN was utilized in [39]. According to the outcomes of this NN, compared to traditional models, the financial managers were able to easily and safely select financial projects in. In this paper all the comparison studies exploring portfolio management illustrate that compared to traditional approaches, Artificial NN has a better performance, this outcome is true particularly for back-propagation NNs, for example, an error correction NN was proposed by Zimmermann et al. for portfolio management that utilized a portfolio optimization algorithm named Black/Litterman. In this paper, to implement portfolio optimization two points are taken into account: (1) the allocations are adjusted to investor’s limitations and (2) it is possible to control the portfolio risk. In order to test this method, authors constructed multinational diversified portfolio among 21 various financial markets of the G7 countries. They concluded that their method exceeds traditional benchmark portfolios such as Markowitz’s mean–variance framework. Finally, in another study in 2009 in the field of portfolio optimization [1], mean-variance method has been compared to back-propagation NN. They concluded that back-propagation NN has a better performance. Such comparisons can be found in such other papers as [2] and [3]. In table 2 the result of these comparisons has been presented, briefly.

E. Financial forecasting and planning

Complicated and nonlinear nature of financial markets along with other subtleties related to them is difficult to understand for humans. Hence, Artificial NNs have been used extremely in this domain. Artificial NNs can be applied in such issues as predicting exchange markets, bank’s liquidity, and many other financial applications.

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<th>Domain</th>
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<tbody>
<tr>
<td>Mortgages choice decision</td>
<td>[2]</td>
<td>NN compared with probit</td>
<td>Artificial NN has a better performance</td>
</tr>
<tr>
<td>Portfolio optimization</td>
<td>[3]</td>
<td>B&amp;H strategy</td>
<td>Artificial NN has a better performance</td>
</tr>
<tr>
<td>Portfolio optimization</td>
<td>[1]</td>
<td>Back-Propagation NN with mean-variance model</td>
<td>Artificial NN has a better performance</td>
</tr>
</tbody>
</table>

Many studies have been done in this area, for example, in [4] a single layer feed-forward NN proposed in order to predict nonlinear regularities in price movements. Their concentration was on the case study of IBM stock daily returns. The training phase of this NN was done using the data of 1000 days and it tested using the data of 500 days. The outcome of this study is so optimistic. In [71] to predict the performance of credit card accounts two NNs designed. One of these NNs imitates the decisions of the current risk evaluation system, and another one tries to forecast credit card accounts performance by using the historical data. The authors pointed out that their model is able to detect potential problems at early stages of the credit card account life cycle. In another study [72], artificial intelligence techniques were used to assessing post-bankruptcy resolutions by considering the sample data containing 59 Taiwanese firms in financial crisis. They used Artificial NNs with five-variable models. They concluded that all of these five Artificial NN-based models benefit a remarkable degree of accuracy. In this regard, Celik and Karatepe [73] also used Artificial NNs in financial forecasting. They explored the application and performance of Artificial NNs in assessing and predicting crises in bank industry. The results showed that Artificial NNs are able to effectively evaluate and predict crises in banking industry. In the comparison regard, many studies have been done. In general, compared to traditional approaches (i.e., MDA, LR, Random Walk model, and so on), in most cases the results are upon the side of Artificial NNs. In [74], authors compare three traditional methods (i.e., buy-and-hold strategy, random walk model, and linear regression) with Artificial NNs. They concluded that the performance of designed NNs is improved by using the recent constant relevant variables. In another study [75], authors proposed an Artificial NN to forecast the exchange rate of Indian Rupee against US dollar in a weekly manner. They also assessed the prediction ability of Artificial NN with both random walk and autoregressive approaches. By considering such criteria as MAE, S IGN, CORR, RMSE, DA, and MAPE, they concluded that Artificial NN considerably has a better performance compared to those methods. In this category, there are some other studies that verify better performance of Artificial NNs in comparison with other conventional approaches. A brief result of these comparisons has been presented in table 3.

III. GENETIC ALGORITHM AND FINANCIAL MARKET

A genetic algorithm behaves similarly to its biological counterparts. The search mechanisms begin as a population of
individual organisms that evolve to optimize the way in which it fills their environment. These individuals are represented by sequences of information called chromosomes.

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</tr>
</thead>
<tbody>
<tr>
<td>selecting Financial variables</td>
<td>[40]</td>
<td>ANN models that uses constant relevant variables compared to LR, B&amp;H strategy, and random walk</td>
<td>Artificial NN has a better performance</td>
</tr>
<tr>
<td>Exchange rates prediction</td>
<td>[10]</td>
<td>ANN compared to linear autoregressive and random walk models</td>
<td>PPN and MLP have a better performance</td>
</tr>
<tr>
<td>post-bankruptcy resolutions</td>
<td>[9]</td>
<td>5 various models of ANN</td>
<td>Artificial NN has a better performance</td>
</tr>
<tr>
<td>Bankruptcy forecasting</td>
<td>[8]</td>
<td>ANN with MDA</td>
<td>Artificial NN has a better performance</td>
</tr>
<tr>
<td>Classification of financial data</td>
<td>[41]</td>
<td>ANN with LDA and LR</td>
<td>Artificial NN has a better performance</td>
</tr>
<tr>
<td>Asset value prediction</td>
<td>[7]</td>
<td>BPNN with regression models</td>
<td>Artificial NN has a better performance</td>
</tr>
<tr>
<td>Consumer price index forecasting</td>
<td>[6]</td>
<td>ANN with random walk model</td>
<td>Artificial NN has a better performance</td>
</tr>
</tbody>
</table>

A genetic algorithm first established a randomly generated population of chromosomes. Then, it creates successive generations by manipulating them through various genetic operators such as reproduction, crossover, and mutation much like that of biological genetics. Reproduction occurs when a new generation of chromosomes is created from a previous generation by replicating each chromosome in proportion to their fitness value. The crossover occurs when two chromosomes exchange pieces of themselves according to their fitness value. Mutation occurs when a random portion of a chromosome changes where the fitness value is poor [41].

A. Using Genetic Algorithms to Predict Financial Performance

Forecasting stock return of a stock index or individual stock is an important financial subject. It involves an assumption that fundamental information publicly available in the past has some predictive relationships to the future stock returns or indices. GA is a promising approach due to its effectiveness in searching very large spaces and the ability to perform global search for best forecasting model. Yanxia Jiang, et al. [42] apply genetic algorithms to predicting future performances of individual stocks in China.

Besides GAs, popular inductive learning methods include neural networks and decision trees. GAs are general-purpose, parallel search techniques for solving complex problems. GAs have traditionally been used in optimization, but with a few enhancements, can perform classification and prediction as well.

Mahfoud and Mani [43] address the general problem of predicting future performances of individual stocks. They compare a genetic-algorithm-based system to an established neural network system on roughly 5000 stock-prediction experiments. According to their experiments, both systems significantly outperform the B&H strategy. Trigueros [44] uses GAs to select sets of financial statement variables which contain information relevant to changes in earnings and finds that the predictive accuracy of his model. Shapcott employs GAs for investment portfolio selection.

IV. PARTICLE SWARM OPTIMIZATION

This section is intended to introduce the significance works has been done around financial market using Particle Swarm Optimization Algorithm (PSOA) and tries to explain the algorithm in simple words. Things change very fast in this field and many new variants put forth, hence, it is not possible to cover all the various applications of this algorithm in the restrict pages of this paper. Thus this paper can be seen as a brief survey of the particle swarm optimization.

A. Particle Swarm Optimization Algorithm for Option Pricing

Option pricing is one of the challenging problems of computational finance. The issue is to compute the price $F(t)$ at time $t$ of a call or put option of various styles on stock (or other underlying asset of the option) with dependence on various variables and parameters such as $S$, the current stock price; $T$, the expiration time of the option contract; $r$, the risk free interest rate; $\sigma$, the volatility of stock prices; and $K$, the strike price of the option. Hari Prasain, et al. [45] show that PSO could be effectively used for the option pricing problem. With complex models to capture the real market conditions it becomes difficult to find closed form solutions. This has led the researchers to consider other numerical approaches including heuristic methods for solving the option pricing problem.

V. CONCLUSION AND SUGGESTIONS

The need to solve highly nonlinear, time variant problems has been growing rapidly since many of current applications in the real world have nonlinear and uncertain behavior which changes with time. Conventional and traditional mathematical model-based approaches can considerably address linear, time invariant problems and model-based techniques can also solve more complex nonlinear time variant problems, but only in a limited way. These problems along with other problem of traditional models caused growing interest in artificial intelligent techniques such as fuzzy logic, NNs, genetic algorithms, and evolutionary algorithm. In this paper comparative research review of three famous artificial intelligence techniques, i.e., ANNs, GA and PSO in financial market have been done. A financial market also has been categorized on three domains: credit evaluation, portfolio management and financial prediction and planning. For each technique most famous and especially recent researches have been discussed in comparative aspect. However, due to a variety of research design and evaluation criteria, it is difficult to compare the results of different studies.
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