PARTICLE SWARM OPTIMIZATION (PSO) WITH STOCHASTIC DATA

by

Raam Bharathwaaj Chennai Jagannathan

Submitted in partial fulfilment of the requirements
for the degree of Master of Applied Science

at

Dalhousie University
Halifax, Nova Scotia
December 2014

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Abstract:

In photonics, numerous phenomena display stochastic behavior for example phase noise in LASERS or speckle in imaging. The study on stochastic data remains as a strong subject of interest. Evolutionary computational techniques serve as a vehicle for understanding and analyzing such chaotic environments. In this work Particle Swarm Optimization (PSO) algorithm, a popular evolutionary computational technique is extended to handle one such stochastic data.

PSO is a popular optimization technique inspired from observing the natural optimization processes involving flocking of birds or swarming of insects especially bees. The idea of achieving a near target using individual and collective intelligence is the main feature behind the development of this optimization technique. The technique uses evolutionary process to search and achieve a near optimal solution.

Through this research study we have made an attempt to comprehend the application of PSO Algorithm to chaotic environment where stochastic data play an integral role in affecting the PSO performance. This has not been attempted yet since the PSO has been applied mostly to deterministic problems. Numerical experiments were performed to analyze and predict the behavior of the stochastic datasets. In this research study, PSO algorithm is used along with a combination of Technical Indicators to investigate the stochastic patterns exhibited in foreign exchange (forex) market. Main Contribution of the research is to explore the possibilities of using PSO as a bridge to understand and comprehend chaotic environments for fuelling further research and additionally applying PSO as an independent tool for designing and developing better future photonic devices that presently suffer from effects of stochastic behavior. A foreign exchange market data serve as a test-bed for the PSO studies.

List of Abbreviations & Symbols Used

ABBREVIATIONS:

PSO	Particle Swarm Optimization
AI	Artificial Intelligence
GA	Genetic Algorithms
GP	Genetic Programming
EP	Evolutionary Programming
RSI	Relative Strength Index
MI	Momentum Indicator
PROC	Price Rate of Change
EMA	Exponential Moving Average
S&R	Support & Resistance
EMH	Efficient Market Hypothesis
AMH	Adaptive Market Hypothesis

SYMBOLS:

V_t	Optimized Velocity Parameter from the PSO Equation
V_{t-1}	Previous Velocity Parameter of the Particle
X_t	Optimized Position Parameter from the PSO Equation
X_{t-1}	Previous Position Parameter of the Particle
W	Inertia weight Parameter from the Velocity Equation
c1, c2	Social Constants from the PSO Equation
n1, n2	Stochastic Parameters in the Velocity Equation

P_{t-1}, P_{Best} Best position of the Particle

G_{t-1}, G_{Best} Best position among all the Particles

Acknowledgements

I wish to express my gratitude to my research supervisor Dr. Michael Cada, Professor, Department of Electrical and Computer Engineering, Dalhousie University, for his guidance and continuous help throughout my research work. I greatly appreciate the Personal guidance and immense motivation provided by Dr Michael Cada during the times of personal difficulties and casualties experienced by me during my graduate studies.

I would also like to acknowledge Dr El-Masry and Dr William Phillips for serving on my supervisory committee and for their respective suggestions on my thesis.

Moving forward I take this opportunity to thanks my friend especially Lakshmi Venkatesan and my mother who were source of constant motivation and support for me during my tough times. Without these motivating persons and their loving support this thesis would not have been possible. More importantly, I would like to dedicate this work in loving memory of my beloved father R.Jagannathan and my beloved aunty P.A.Chellammal

CHAPTER 1: INTRODUCTION

Non-Deterministic phenomena are an integral part of photonics. In photonics, fundamental processes such as light emission, absorption, reflection etc. are highly dynamic in nature. Subsequently most of the optical devices are dependent on these fundamental properties for their functionality. The performances of the optical devices are evaluated based on the quality of reproduction of these fundamental processes. Poor and non-reproduction of these fundamental functionalities can adversely affect the performance of the optical devices. Non-Deterministic phenomena such as spontaneous emission, Speckle in LASER's, polarization effects, Phase Noise, nonlinearities etc. severely downgrade the optical processes in optical devices [47].

Analyzing and processing non-deterministic phenomena has been a hotspot for several researches because of the enormous scope for performance improvements, design variations and as well as for several commercial applications. These phenomena have their origin in stochastic behavior and the reason behind their occurrence and the effect of such phenomena on the optical systems are highly random in nature. In order to understand these stochastic behaviors, diverse information about its existence and its sustainability are required. Several efforts are being made to investigate possible sources and solutions to this phenomenon and possibly analyze this phenomenon using numerical techniques [48].

In this research we propose working with Particle Swarm Optimization (PSO), a popular numerical technique, to understand stochastic behaviors. Particle Swarm Optimization (PSO) has become an emerging technology with an increasing number of real-world applications including operational research [4]. However their enormous advantages and limitations have created more skeptical empirical evidence around their extrapolating power among the researchers. This skepticism is further fuelled by the fact that the algorithm's parameters and inputs are selected based more on trial & error and the researcher's market knowledge rather than on formal statistical procedure.

The main motivation of this research is to propose PSO Algorithm as a vehicle or bridge to understand and comprehend complex stochastic patterns such as LASER's. In this research we consider one such stochastic environment i.e Foreign Exchange Market or Forex Market as medium and a test-bed to investigate the optimization capabilities of PSO Algorithm.

Forex market has long served as the empirical vehicle for analyzing and testing several optimization techniques. There has always been a constant study on investigating the PSO Algorithm and its application to forex market. In a benchmark study done by M. Jiang, Y. P. Luo and S. Y. Yang, it was strongly emphasized that the random stochasticity exhibited by the PSO Algorithm provides better chances for achieving near optimal solution [52]. Another detailed study done by Hime Aguiar e Olivera Jr & team, points to PSO Algorithm as the strong candidate for solving complex global optimization tasks over conventional numerical techniques [53]. Additionally Yin, Peng Yang through their research strongly suggested that PSO Algorithm outperforms several numerical techniques in understanding deterministic problems such as I-beam etc and a good resource for understanding non-deterministic issues [55]. Evaluating and optimizing non-deterministic environments such as Forex market, which exhibit stochastic behaviour, has always been a constant struggle and subject of interest for several researches. In a recent study by Nayak S.C, Misra B.B, Behera S.S, it was found that co-operative algorithms such as PSO etc. have superior performance in analyzing complex non-linear environments such as forex market [54]. Jui-Fang Chang & Pei-Hu Hseigh proposed a novel way to understand forex market by utilizing PSO Algorithm and providing it with additional knowledge of the environment behaviour using Neural Networks. Through their research, they were able to make a point that analyzing forex market was complimented by the use this additional knowledge [56]. This concept of providing complimentary knowledge to PSO Algorithm was further supported by the study done by Yeuhei Chen, Lezhi Peng and Ajith Abraham, where forex market analysis through PSO Algorithm was fuelled by supplementary knowledge provided to it [57]. Bingxiang Liu, Hua Wang, Xiang Cheng provide further justification, with their research study, proposed that PSO Algorithm was able to understand the forex market to a certain extent with the help of the supplementary information provided to it [58].

With the above-mentioned evidence foreign exchange market was chosen as a perfect test bed candidate because of the nonlinearities and high complexities in understanding the nature of each currency. Moreover each currency is valued against another currency based on diverse set of factors that may not be the same for all currency pairs. More specifically we propose a profitable trading strategy by harnessing the power of Technical Indicators into the PSO algorithm in a novel way. The proposed architecture is unique by the way in which the number of technical indicators used and how they are incorporated into the PSO Algorithm, which is not been found in the literature. Our proposed architecture can be subjected to any volume of data, any currencies and for any time period.

In our benchmark study we use a series of highly popular and widely used Technical Indicators such as Relative Strength Index (RSI), Momentum Indicator (MI), Price Rate of Change (PROC), Exponential Moving Average (EMA) and Support & Resistance (S&R) along with PSO Algorithm plus a novel strategy to simulate profitable trading scenarios for six highly traded currency pairs such as EUR/USD, USD/CAD, GBP/USD, USD/CHF, USD/JPY, AUD/USD. The trading is simulated for daily closing price of the currency pairs so that we give enough time and volume of data for the algorithm to identify and optimize hidden trends and pattern in the market.

We introduce a leveraging trading strategy where importance is given to both buying and selling points in assuming a closed transaction and examine if the application can increase the trading efficiency of our model. This technique is implemented as a part of fitness function in the algorithm along with the transaction costs to give the algorithm more stability and efficiency when considering the profit/loss recurred. This consideration is crucial with respect to financial applications where statistical accuracy need not be always in harmony with financial profitability of the trading strategy.

With the help of this novel strategy we were able to generate profitable trading scenarios successfully and its adaptability and flexibility seems to add up to its success. These results serve as a foundation in extending the possibilities of exploring PSO as medium for understanding random chaotic behaviors and results serve as an empirical evidence to support it.

1.1 STOCHASTIC PROCESSES IN PHOTONICS:

Enormous deal of interest has been generated and subsequent researches undertaken in designing and developing optical devices. Extensive research and development are being conducted worldwide in order to develop ultra fast optical devices. Many of these researches are focused on developing compensation techniques for identifying and minimizing the stochastic degrading optical process such as spontaneous emissions, Phase noise and LASER Speckle. Conventional numerical optimization techniques used for simulating optical processes have limitations and difficulties in simulating mechanisms responsible for the system's behavior [48]. Some major stochastic optical processes are discussed as follows.

1.1.1 SPONTANEOUS EMISSION:

Spontaneous emission is defined as a process when an atom emits a photon during its transition from a higher energy level to lower level without the influence of any external field or light after a certain period of time, which is uncertain. The emitted photon propagates in a random direction. This process is defined as spontaneous emission [49].

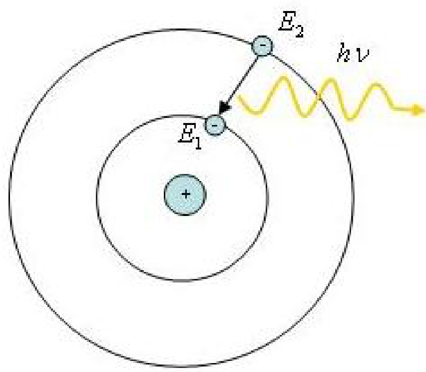


Fig 1.1.1 Spontaneous Emission

Rate of at which the spontaneous emission occurs is highly stochastic in nature and depends on the electrical dipole moment associated with the transition between the two states. It is a vector, which includes a phase direction associated with the two states. Phase direction gives the polarization of the transition, which determines the nature of interaction between the system and an electromagnetic wave. But in spontaneous emission the polarization direction is random. More analysis on this parameter can throw some light on possible ways to control and reduce this type of emission.

1.1.2 PHASE/SHOT NOISE:

Quantum noise is the result of fluctuations arising due to atomic properties of a physical quantity. Majority of Optical communication systems use amplitude modulation. So quantum noise can also be referred as shot noise. In the field of

Photonics especially LASERs, noise is a combination of uncertainties occurring in both amplitude and phase. Hence it is also known as phase noise.

In optics, quantum noise exists due to several factors such as non-linearities occurring in fibers, Raman Scattering, effects of amplifiers and filters.

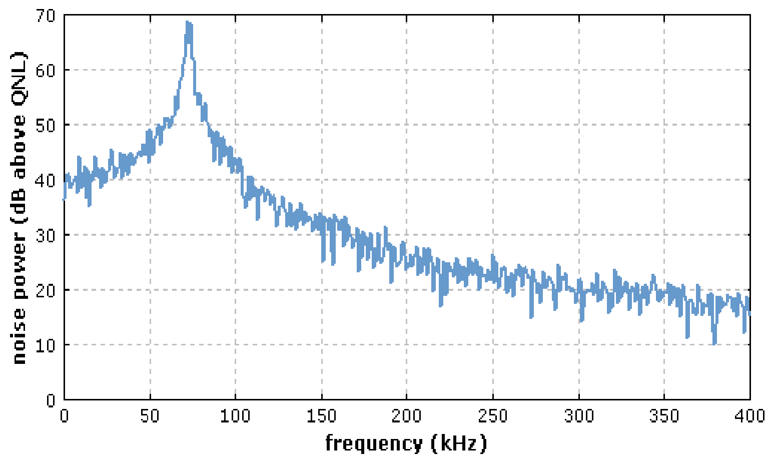


Fig 1.1.2 Intensity Noise Spectrum of Solid State Laser

The above graph describes the Power Spectral Density of Shot Noise associated with solid state LASER. Historically shot noise were analyzed using Nonlinear Schrödinger Model, Heisenberg equations etc. It was recommended that a numerical solution to represent the noise effects was difficult to establish due to the uncertainty nature of photons involved [50]. Due to the stochastic nature involved in the generation of noise, a numerical technique having parameters of a similar nature could help understand such noise and help development of optimization techniques for reducing such phenomena in optics.

1.1.3 SPECKLE IN LASERS:

Laser speckle noise occurs owing to the strong interference that originates in the high coherency of laser light and the surface topography of the screen. This adversely affects the quality of images produced from LASER, medical ultrasound images etc. The occurrence of speckle is highly volatile and dynamic, hence it is known as dynamic speckle.

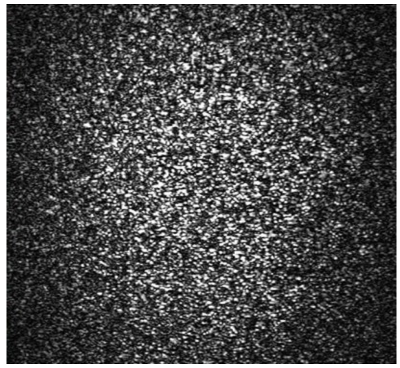


Fig 1.1.3 Speckle Pattern in LASER

Generation of Speckle is highly sensitive to surface movement. Local changes to the surface generate the random intensity distribution, which generate complex stochastic patterns, which is termed as Speckle [51].

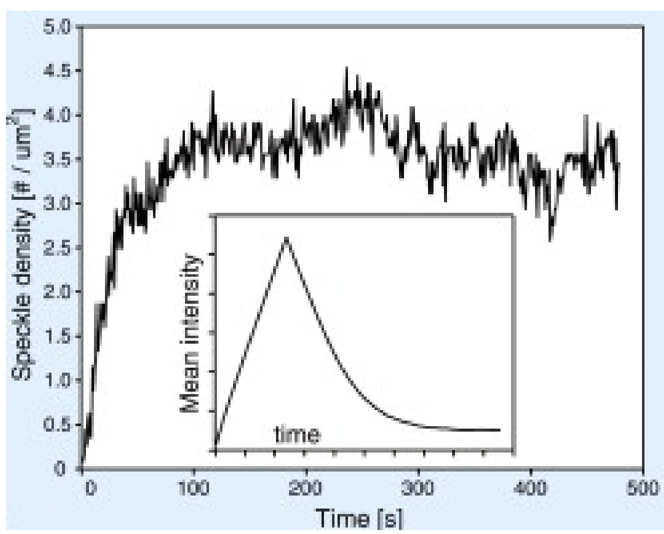


Fig 1.1.4 Speckle Density Distribution

The above figure explains the stochastic nature of Speckle. A numerical technique with similar properties can help understand and control the occurrences of speckle and improve the quality of imaging and also help study a given surface properties.

1.2 RESEARCH GOAL & MOTIVATION:

Main motivation for this research study is to create an opportunity to understand the origin and occurrences of non-deterministic phenomena in Optics. In-order to understand and evaluate stochastic behavior, various tests is required on the random parameters incorporated in the environment. Numerical techniques can be used as a vehicle for understanding the stochastic behaviors. This implementation will provide an in-sight in better understanding the occurrences of the non-linear principles.

1.3 RESEARCH CONTRIBUTION:

First major contribution of this work involves in introducing Particle Swarm Optimization (PSO) Algorithm as a bridge or a link to understand and analyze the chaotic behavior exhibited by stochastic environments such as laser and other optical phenomenon. Second main Contribution of this research involves in proposing PSO as an independent algorithm for designing and developing a profitable forex trading strategy. Proposed model considers the profit/loss associated with both buying and selling currency pairs including the transaction costs associated while making a closed trade. So it gives more realistic sense of actual live trading.

1.4 ORGANIZATION OF THE REPORT:

The rest of the research is organized as follows. In section 2 we present some relevant recent applications of technical trading and influence of PSO in foreign exchange market trading and section 3 describes the inception of Artificial Intelligence (AI) Algorithms, its fundamentals and followed by the effect of introducing social behavior into optimization is discussed in section 4. PSO Algorithm is discussed in detail on section 5. Detailed introduction to foreign exchange market and technical indicators are provided in section 6. A detailed overview of the proposed model and its benchmark qualities are explained in section 7. Section 8 gives the empirical results of the model considered and investigates the possibility of improving their performance. Finally section 9 provides concluding remarks along with the scope of future work in extending this model.

CHAPTER 2: LITERATURE REVIEW

Technical trading Models based on artificial intelligence are not relatively new as there have already been several studies in this area. Charles Dow first introduced the concept of technical trading at the end of 19^{th} century. Since its inception, there has been enormous research on developing profitable rules for successful trading.

2.1 TECHNICAL TRADING RULES:

Popular Technical Indicators such as Moving Average (MA) [27], Relative Strength Index (RSI) [28] has long served the purpose of technical trading and is still used by traders. Apart from the inception of these indicators, several studies have been purely focused on credibility of trading rules generated by these indicators. In 1992, Brock, Lakonishok and LeBaron (BLL, hereafter) [27] tested two of the most popular and the simplest trading rules - Moving Average and Trading Range Breakout - on the Dow Jones Industrial Average (DJIA) from 1897 to 1986. The results showed that the Moving Average and Trading Range Breakout were able to generate valuable 'buy' and 'sell' signals and significantly outperformed a bench- mark buy-and-hold strategy. One strong research conducted by researchers at the federal bank of St.Loius on intraday technical trading on forex market suggested that even though they weren't able to achieve significant excess returns but they were able discover stable patterns in market data with the help of technical trading [29]. Moving forward traders started using complex trading systems relying on multiple trading rules rather than a single trading rule in order to analyze risks and stabilize profits. Hsu and Kuan's work indicated the higher profitability of complex trading strategies than simple trading rules [32]. This supported Pring's opinion that no single trading rule can ever be expected to forecast all price trends and it is important to combine these simple rules together to get a complex trading strategy [33].

Certain trading rules performed exceptionally well for in sample data and occasional significant returns for out-of sample data. The presence of irregularities in technical trading rules was recorded first by Blake LeBaron through his benchmark research study [30]. It was strongly argued that there was no rational explanation behind the generation of profit or loss from the trading rules. There is a hidden factor between holding, intervening and profiting from a trade, which needs to be explored in order to understand behavior of technical rules. Another benchmark study explored the instability of technical trading rules in generating profitable scenarios when used independently [31]. It was strongly recommended that technical trading when used independently suffered serious instabilities leading non-profitable trading. This research strongly advocated the need for collaboration in Technical trading.

2.2 ARTIFICIAL INTELLIGENCE IN TECHNICAL TRADING:

Ever since gaining commanding reputation, Artificial Intelligence (AI) based Evolutionary Computation techniques are widely used to find optimized trading rules for greater profits and stability analysis. Evolutionary computation refers to a group of individual algorithms that uses the concept of artificial intelligence or machine learning to arrive at a specific solution in a multi solution search space. Most attractive feature of evolutionary computation is their superior ability to explore a given search space and identifying various non-static dependencies in such environments, which has invited their use in the field of technical trading. Allen and Karjalainen [34] proposed a Genetic Programming (GP) method to find an optimal complex trading strategy for the Standard & Poor’s composite index (S&P 500). In their study, simple trading rules’ indicators generated from past price data were the building blocks of complex trading strategy. These building blocks were then optimized by GP was to find a random combination that generates the highest return. Subramanian et al. [35] proposed a linear combination of simple trading rules. Each simple rule was assigned a weight and the strategy's signal was determined by the sum of simple rules' weighted signals. The best set of weight vector was optimized by GA.

These studies have shown that EA techniques can outperform traditional mathematical modeling. With growing interest in artificial intelligence, researchers' interest started slowly moving towards advanced intelligence systems, such as Particle Swarm Optimization (PSO), which has better computational efficiency and better performance than GA [36]. One of the promising research conducted by Knok N.M., attempted to optimize the trading rules generated by Moving Average and maximize the trading profit, this paper proposed the use of the particle swarm optimization algorithm to determine the appropriate long/short durations when calculating the averages. The best combination of long/short durations is determined by comparing the profits that can be made among alternative durations [37]. Briza and Naval [38] used a multi-objective PSO to create stock trading system, which aimed to provide a better tradeoff between profit and risk. Another study proposed by Papacostantis and Engelbrecht [38] combined two technical indicators (Bollinger Bands & Relative Strength Index) with PSO to generate profitable trading signals.

From an in-depth perspective it is more impelling that the EA Algorithms have gained substantial reputation in technical trading because they were able to achieve profitable scenarios. Adding up to the fact is that these algorithms do not test the individual's independent capabilities towards technical trading. From the literature, it becomes more evident that the amount of work done in testing these algorithms independent capabilities towards trading is very limited. As well as choosing and combining indicators of different nature to generate a profitable trading scenario has not yet been explored.

Based upon the above evidence, this research study focuses on one of the popular technique (i.e.) Particle Swarm Optimization (PSO) and its ability to optimize technical rules independently. Main motivation for this research comes in the form a substantial study done earlier in our research group. It was shown that PSO can also be used as an independent algorithm for forecasting exchange rate values. Experiments were performed using two different methodologies for PSO and accuracies up to 55% were achieved. The main goal of this research study is to propose a novel technical trading model using PSO Algorithm independently to generate profitable scenarios.

CHAPTER 3: INCEPTION OF ARTIFICIAL INTELLIGENCE (AI) ALGORITHMS

Ever since human race started to evolve, Intelligence became the crucial factor in deciding the sustainability of the species. Intelligence is basically defined as the interaction among the individuals and application of the knowledge acquired through it. Intelligence is an elusive quality which forms the fundamental trait of any living species [40]. The most dominant species in this planet are the Homo sapiens. Interesting fact is that we are dominant because of the success of our intelligence. The far most reason behind this success is that we humans are the most social of all the species and we have adapted to nearly every environment on this planet. We live together in families, cities, nations behaving and thinking according to the rules and norms of our communities. Even when left alone we think about other people and what's happening around us .We think all these using an important factor called Language which forms the medium of interpersonal communication.

3.1 INTELLIGENCE & ADAPTATION:

There has always been a significant relationship between Intelligence and Adaptation but some people argue that there is no such evidence between the former and latter. Intelligence in other words is ability of any living thing to adapt to any given environment. Adaptation is not a simple task and it doesn't happen shortly. It takes its own time to settle in with the new parameters of the given environment. One important parameter which greatly influences adaptation is the social interaction. Social Interaction greatly involves in exchange of ideas and thoughts which in turns influences one's ways of thinking and thereby helps in improving the survival strategy. Therefore an expanded opportunity for social interaction enhances Intelligence [41]. Since then it was also seen as the first level in developing systems intelligence

3.2 BIRTH OF ARTIFICIAL INTELLIGENCE:

After the invention of the first mechanical analytical machine by Babbage, there has been a critical debate on the similarities between the human minds and computers. A computer can accept, process and retrieve any symbolic information, all that mind can do. Since then there has always been claims that if minds can be intelligent, so can the computers be. This eventually gave birth to an important concept called Artificial Intelligence (AI) [40].

Early research on artificial intelligence began with some interesting solutions to large problems. Any given problem will have multiple solutions some of which might be non efficient, few of which may be not tangible and finally only a very few would be the best. Mark of AI programs was that how it could successfully get to the right feasible solution. So early AI scientists developed a number of methods to sort out the best possible solutions, called Heuristics, to speed up the process. The process involved in developing a common logical method which can be used for complex multiple problems. Fundamental assumption made in early Artificial Intelligence was that interaction is something happening inside an individual's mind. Early AI programs were designed based on the vision of a single person, processing information inside one's mind (i.e.) the way in which we experience our own thinking, as if we hear private voices and have a private vision in our mind.

Although AI programs were able to solve complex problems, perform multiple calculations and had tremendous memory storage, but they failed at simple things. Early intelligent systems weren't good enough in solving real time problems and weren't good enough for real time business problems. For many problems it seemed like something was missing even though many new variables were added to the decision process. These intelligent systems didn't work the same way when they were hot or cold, in the presence of light or in dark and didn't respond the same way when two things went wrong at the same time. These problems marked the importance of social interaction in order to develop a smart intelligent system .So conclusion drawn in by the AI researches was that, in order to develop a smart system, individuals have to be modeled in a social structure interacting with each other [41].

3.3 EVOLUTION OF COMPUTATIONAL THEORY & MODELING:

Evolutionary computation deals mainly with solving computational problems using ideas from nature's evolution. Evolution and Mind are the two biggest stochastic systems of nature which does not follow any described rules or regulations. They still remain as a big challenge since the history of computation. Analyzing and modeling the information processing technique of mind and modeling the adaptive technique of nature's evolution, paved the way for the Artificial Intelligence movement.

Biological evolution has been the source of motivation for addressing the various complex computational problems. According to the definition, Evolution is a method of searching for an optimized solution among an enormous number of possibilities. Biological definition states that Evolution is a method of adapting to changing environment. The best example for evolution is the nature itself where only the fittest of any species resulting from various mutation, recombination and other factors, tend to survive and will propagate its genes to future generations.

Many difficult computational problems require searching through huge space of possibilities for solutions to come up with a configuration that gives the desired results. Such problems require intelligent systems that continue to perform well in the changing environment. Problems with complex solutions are very difficult for human programmers to crack. Early AI researchers framed a set of basic rules that formed the foundation for any AI program. But nowadays many researchers started to believe that the best route to any Artificial Intelligence program and other complex computational problems is through a fashion in which humans write only the basic rules and provide a means for system to adapt. Complex behaviors will emerge from the parallel application and interaction of these rules. Best example is the neural networks.

Evolutionary computation field has been classified into four areas. They are

a) Genetic Algorithms (GA)

b) Evolutionary Programming (EP)

c) Evolution Strategies

d) Genetic Programming (GP)

These four areas are collectively known as Evolutionary Algorithms.

CHAPTER 4: OPTIMIZATION THROUGH SOCIAL BEHAVIOUR

Evolution in general is defined as the search for optima in different difficult landscapes. The various factors that empower evolution in various scenarios are mutation, genetic recombination and self-organization. The important functions of mutation and recombination are to introduce random variations to the population and whereby selection ensures that better solutions persist over time. Many human observers over time have argued that creativity requires some kind of genetic operations such as mutation etc in some way to produce new solutions. Introduction of random variations always results in some sort of new solutions. Trial and error learning is one way to create new varieties of problem solutions. The generations of these random behaviors are common throughout the animal kingdom. Zig zagging of a chased rabbit, movements of amoeba and movements of threatened fish are good examples of random behaviors. All these indicate the ability to generate random unpredictable behaviors which are adaptive for animals.

Random activity is a key tool for animal kingdom in various aspects such as predator avoidance, foraging for food, in finding mate, place to build nest or to find a safe hideout. *Konrad Lorenz* (1973) an animal behavior observer, in one of his chapters entitled "Oscillation and Fluctuation as cognitive Functions" discusses the importance of random variations in an organism's movements. He gives a good example of marine snail. The snail has a long breathing tube and it uses this tube to detect the scent of something to eat, as it moves randomly on the ocean floor [24]. The snail is sensitive to differences in the strength of a scent picked up the two extremes of the tube. These differences are naturally high when the snail is at right angles to the goal, so that food is one side or the other. Once the snail picks up the scent of a food source, instead of turning right angles to source, it makes a reversal that resembles an escape response and continuous crawling along so that the scent will reach the receptor on the other side .the result is a zig- zag motion through which it reaches the nearest food source. Lorenz typically compares the fluctuating movement of snail with human public opinion where he justifies that "public idea of what's true and real in a human environment is based upon highly complicated system of human interactions ". Lorenz ultimate emphasis was always on his view of cognition as a function of collective adaptive search. Many species benefit from sociality in different ways. Interaction among the species is very much important under several instances such as during mating. Strongest bonds are always formed between the mother and the off spring. Sometimes lifetime monogamous pair bonds are formed between the mates. The benefits it brings up are improved off spring rearing and ability of the pair to defend its nest as well as its territory. This gregarious life also permits the ability to share food and to provide warning as well as collaborative defense under attack. Among the groups of prey, social interaction reduces the probability of any individual targeted for attack as well as helps in improving foraging efficiency rather than an individual looking for food. At the same time for predators, there is additional advantage in cooperative strategic hunting especially when the labor is divided among the group.

A study conducted by *Dr Doug Hoskins*, a behavior analyst has shown that even the behaviors of the simplest organism in the animal kingdom can be shown as optimization function. According to Hoskins, an E.coli bacterium shows what perhaps the simplest intelligent behavior imaginable is. These single-cell organisms are capable of two kinds of motion namely 'run' & 'tumble' [24]. Running is implemented by a forward motion by rotating the flagella counterclockwise. Tumbling occurs when the flagella is rotated clockwise. The cell tumbles frequently in the presence of an adverse chemical change. The overall change in direction is enough to increase the survival of the bacteria and enabling it to escape from the toxins. When the bacterium encounters an adverse chemical environment, it reverses its direction randomly until it reaches a stable chemical environment. So the bacterium's behavior includes a simple run and tumble that is highly adaptive to the changes around it. Hoskins has significantly used this simple bacterium adaptation to model human interaction.

Apart from the animal kingdom, Social insects have gained enormous benefits through the social interaction which has improved their survival strategy to a great level. It can also be strongly said that insect world have taken the major advantage through sociality.

4.1 ACCOMPLISHMENTS OF SOCIAL INSECTS:

Most inspirational information noted from the studies on insects is their optimization potential from their simplest behaviors. It may be seen that an insect has only few hundred brain cells but insect organizations or colonies are capable of some great architectural marvels, excellent communication systems or terrific resistance to threats from outside world. First systematic study on behavior of ants was conducted by *E.O. Wilson* in 1953 [42]. Wilson source of inspiration came from Lorentz's understanding of imprinting phenomenon in animals. According to Lorentz's 'some kinds of baby birds adopt the first thing they see when they hatch as their parent and follow it everywhere it goes'. He defines this imprinting is a form of instinctive behavior and calls it as "*Fixed Action Pattern*". So from description of fixed action pattern, Wilson theorized that the accomplishments of ant colonies can be understood in terms of the fixed action pattern. Wilson discovered that the mode of communication between ants happen through *pheromones*, chemicals that posses a kind of odor that can be detected by other ants. Wilson showed that these ants emit specific pheromones and he even identified the glands emitting it [42]. Through his extensive studies, he showed that fixed action responses to each of various pheromones. He found that pheromones comprise a medium for communication among the ants, allowing fixed action collaboration, result of which is a group behavior that is adaptive.

According to Wilson, the problem of construction of mass behavior from behavior of single ant was the major problem since the behavior of a single ant is almost random and highly stochastic.

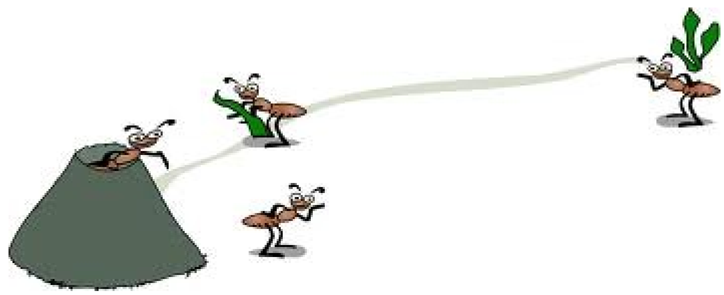


Fig 4.1.1 Foraging Behavior of Ants

There is always some level of communication among the ants, that is enough to keep them wandering off completely at random and also maintaining minimal communication with each other so that they are not left alone but are cooperating with teammates. Following set of diagrams explains the foraging behavior of ants in detail.

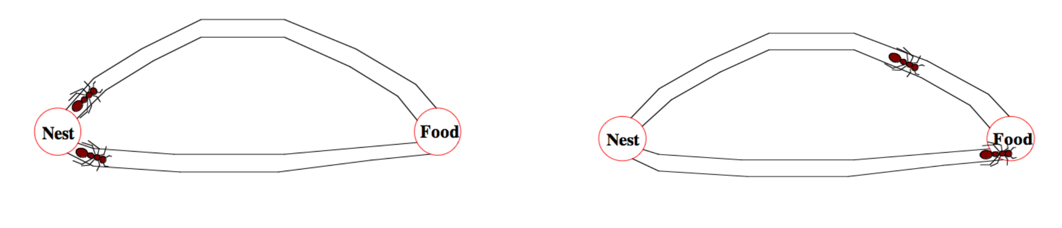


Fig 4.1.2 Two Ants on their way to food & Ant in the shortest path reaches first

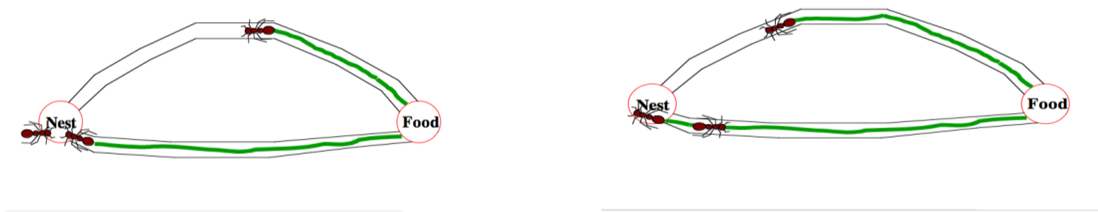


Fig 4.1.3 Ant in the shortest path reaches back first & Next Ant takes the shorter route

Fig 4.1.4 Following ants take the same path & All Ants use the shortest path exclusively

Another classic example of social behavior in insects are termites. Termites are able to build elaborate domed structures that begin as pillars, in the course these pillars are tilted towards one another until their tops touch and form a beautiful arch. Connection between these arch results in typical dome structure. Termites follow two simple steps in the process of building this beautiful architecture:

a) Move in the direction of strongest pheromone concentration

b) Deposit your carry where the smell is strong.

Searching for a strong pheromone field, termites will have started a number of small pillars. These pillars signify places where a greater number of termites have passed recently and obviously pheromone concentration is high there. Since pheromone concentration dissipates in time, in order to accumulate, number of termites must exceed some threshold so that they leave pheromones at a rate higher than the evaporation. This prevents the formation of great number of pillars. Formation of these pillars is the result of autocatalysis [43]. Autocatalysis is a significant aspect of many complex systems. As the termite pillars ascend and termites become increasingly involved in depositing their load, pheromone concentration is high near the pillars. A termite approaching the area will move towards the pillar with highest pheromone concentration. As the termite approaches the pillar, it is likely to climb up the side of the pillar that faces the other one, tends to deposit on the inner face of the pillar that builds up with more substance on the facing side. Ultimately higher it goes the more it leans towards the other resulting in an arch.

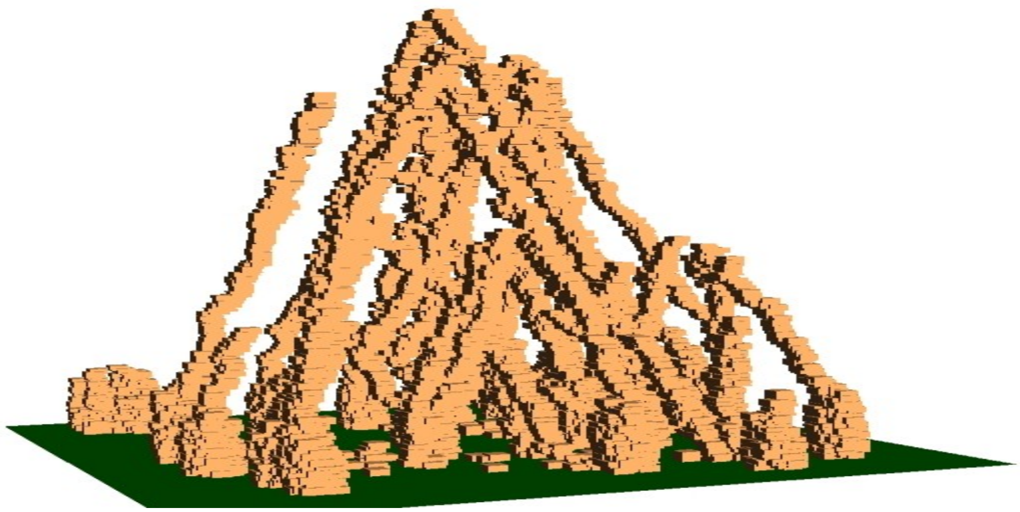


Fig 4.1.5 Construction of pillars by Termites

Termite builders are one kind of perfect example for self-organizing systems. There is no central control, the work force and the intention is distributed evenly throughout the organization and the members themselves are unaware of the plan they are carrying out. All that they do is follow simple rules and marvelous structures emerge from those simple rules from lower level activities.

4.2 STAYING TOGETHER BUT NOT COLLIDING:

Ants & other social insects move in random manner but there are other social animals that move about in more orderly ways. For instance many species of fishes swim in schools that seem to take on an emergent life of their own. In 1954

Zoologist named *Breder* formulated a mathematical model to describe the behavior of schooling of fishes. According to Bredar probability that the school of fishes remain together is a function of number of fishes in the school, distance between the fishes. He introduced a term called *"potential"* for each individual fish, which varies with size of school [44]. Breder showed that the attraction of a school for a solitary fish was described by the formula:

$$C= k N^t$$

Equation 4.2.1 Breder's Equation for Attraction

Where k and t are constants and N is the number of fishes in the school. According to one of his examples, when k=0.355 and t=0.818. The effect of having an exponent t, less than 1is that the attractiveness of the group increases but this increase becomes less when the group size increases i.e. larger school is more attractive than a smaller school but the impact adding one to smaller is more than that of an addition to a larger group. His assertion was that the effect of adding one to group of four is much greater in terms of social attractiveness.

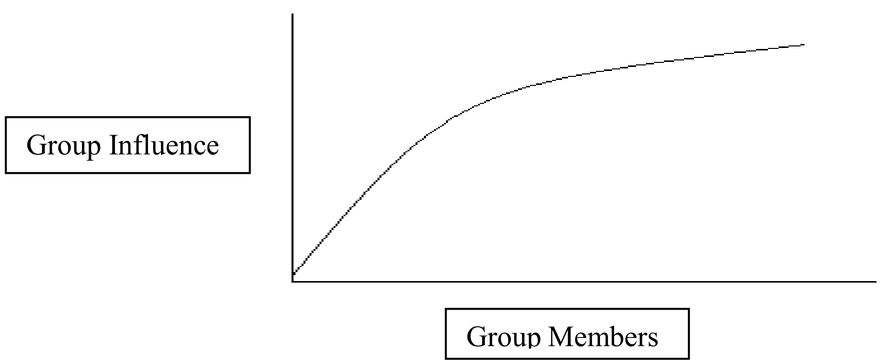


Fig 4.2.1 Effect of increase in members

Since 1930, the literature of social psychology shows the humans to be herding creatures declining the concept of individual. Whenever people interact with one another, they become more similar as they lead and follow each other, teach and learn from one another and also imitate and influence one another. Interesting fact is that we humans move synchronously through mountains, landscapes, water etc like the fishes or the birds but human physical behavior are not flock like or school like but the result of human thoughts happening in high dimensional cognitive space. Thinking differs from behavior of the birds or fishes in two major ways.

1) Thinking takes place in a space many dimensions (i.e.) high dimensional analog of language and neural nets.

2) When two minds converge at the sample point in the cognitive space, we call it as an agreement and not collision.

Amidst this discussion, Craig Reynolds published a very influential simulation of bird flocking in 1987. He used the term “BOIDS” to represent the simulated birds in his simulation [45]. According to Reynolds flocking of birds were driven by simple rules:

a) **Collision Avoidance**: Pull Away before they crash into one another

b) **Velocity Matching**: Try to go about the same speed as their neighbors in the flock

c) **Flock Centering**: Try to move towards the center of flock as they move along.

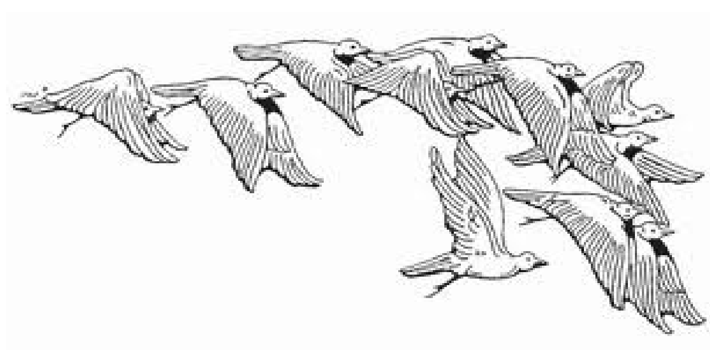
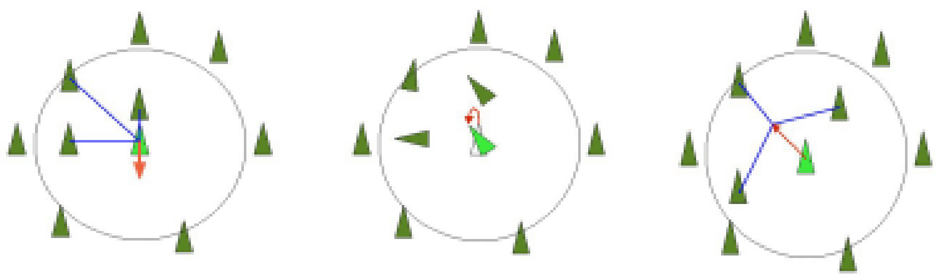


Fig 4.2.1 Flocking of Birds

Reynolds in his paper titled 'Flocks, herds and schools: A distributed behavior model' compared his model to a *Particle system.* Particle Systems are a kind of graphical images developed on the computer comprising of large number of individual agents or objects, each having its own behavior [45]. According to *Reynolds* the BOID behavior was less complicated than behavior of real birds.



Collision Avoidance Velocity Matching Flock Centering

Fig 4.2.2 Basic Frame structure of Reynolds BOID Model [45]

By implementing just these three simple rules Reynolds was able to show very realistic flocking behavior, with cluster of boids whirling through the simulated search space splitting around obstacles and rejoining again. The study on the behavior of flocking of birds served as the source of inspiration for development of Swarm Intelligence and further extensive studies on it. First experimental model on swarm intelligence was developed by *R Eberhart* and *J Kennedy*. In their very first experiments, population of birds flew in orderly flocking patterns towards a '*roost*' [5]. They defined the roost as center of attraction of the entire flock. This model is an extension of Reynolds flocking model, which follows three simple rules as well. They are

a) Each agent was attracted towards the location of roost.

b) Each agent remembered where it was closest to the roost.

c) Each agent shared information with its neighbors about its closest location to the roost.

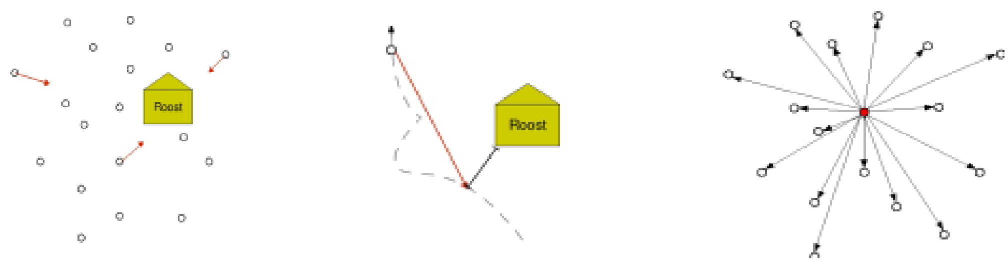


Fig 4.2.3 First experimental model on Swarm Intelligence

Through this fundamental model the researchers were able to extend their ideas as to how birds flying hundreds of feet away could see something as tiny as seed on the ground and were to find it. A flock of birds might fly over a neighborhood watching for signs of eatables, and they find the sources by observing the other birds eating or circling on a target or seeing a neighbor descending towards the ground after seeing something and at same time cautiously approach a source after they are sure that it’s a safe place. In flocking simulations the important thing to simulate is the co-ordinate movement of the organisms whether flocks or herds or schools. Main motive for analyzing such a topic include the desire to understand biological aspects of social behavior and wish to create interesting graphical effects. Further successful investigations on this principle made swarm intelligence as an important tool for various optimizations problems.

CHAPTER 5: PARTICLE SWARM OPTIMIZATION (PSO)

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed in 1995 by Dr. Eberhart, an electrical engineering professor at Purdue University and Dr. Kennedy, a social psychologist with the US Department of Labor, inspired by social behavior of bird flocking or fish schooling. This concept was inspired from their study on Dr Reynolds and Dr Heppener's work on modeling the behavior of animals and birds. The idea of achieving an objective using an individual and its interaction among the group is the main theme behind its development into an optimization technique. This technique uses an evolutionary process to search and determine a near optimal solution. Most interesting feature of this algorithm, the interaction of individual particles in given search space, is the reason behind its huge success and attraction for further research. Even though the algorithm has performed well for certain applications through social interaction, mathematical working structure of the algorithm is still under scrutiny.

One way of understanding PSO is through its fundamental logic that led to its development. Consider an instance where a group of bees move about in some search space in nature. Their goal is to find a location with highest density of flowers. Each bee remembers the locations where it found more flowers and by interacting with other bees, it knows the locations where other bees found an abundance of flowers. Based on this information the bee would probably take a path between its own knowledge of best location and the information about where the other bees found a high density of flowers. This decision would depend on whether personal knowledge or social influence dominated in the case. Along its path, bee may find a higher concentration of flowers than it had found earlier. It is then drawn to this location as well as to the location found by whole swarm. Initially one bee would have flown through the place with more flowers than any others. In no time the whole swarm would be inclined towards that particular location added upon to its personal discovery. In this fashion bee explore the search space i.e. the natural environment flying over concentrated location, exchanging information with its neighbors and altering their path in accordance with the location where density of flowers are maximum. Added to this, bees frequently compare the space where they are flying with its previously found region of maximum concentration. Eventually this makes bee's flight to land up in a particular place which relatively has the highest concentration of flowers.

If a location with higher flower concentration was not found, then bees would return back to that particular place with maximum density of flowers found from its previous experience. In a attempt to model this simple behavior, Dr Eberhart and Dr Kennedy using their respective fields of expertise devised a model to simulate this behavior by changing the terminology i.e. 'Bees' to 'particle in space' and 'flowers' to 'optimal solution'. The term 'particles' denotes the possible solution which could fly across in a given search space and land upon an optimal solution. Parameters such as velocity and direction were used to locate a particle in the search space; this would be the same which is used to locate a bee moving in a swarm.

Fundamental structure governing the PSO is its velocity and position equations, which are as follows:

$$V_t = V_{t-1} + c_1 r_1 (P_{t-1} - X_{t-1}) + c_2 r_2 (G_{t-1} - X_{t-1}) \quad \text{(Eqn 5.1)}$$

$$X_t = X_{t-1} + V_t$$

Here V_t and X_t represent the current calculated velocity and position parameters of the particle. V_{t-1} and X_{t-1} are the previous velocity and position of the particle and w is the inertia weight. The value of w is limited between 0.4 &

0.9, this is base3d on its ability to act as a constriction coefficient to dictate whether a particle would explore new value or follow other particles. Constants C_1 and C_2 are social constants. Generalized value of 1.4 is considered for various applications. This value is derived after several trial and error experiments. P_{t-1} represents the previous best position of the particle and G_{t-1} is the previous best position of the entire swarm.

General working of PSO can also be explained with the help of a flow chart:

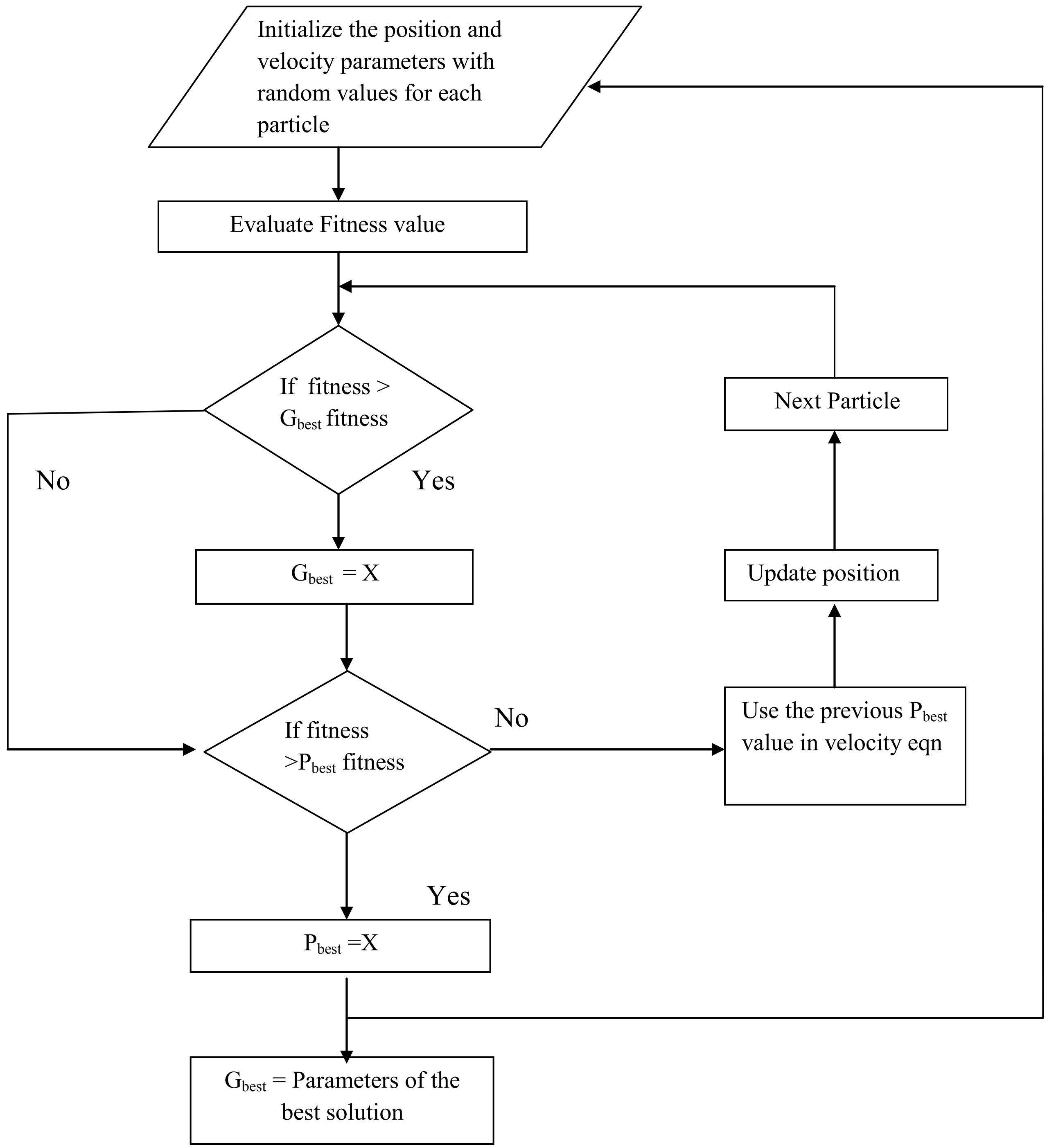


Fig 5.1 Fundamental PSO Flowchart

The algorithm consists of the following steps:

a) Each particle is initialized by assigning random position and velocity values.

b) Fitness value for each particle is calculated. This fitness value is calculated depending upon the nature of the problem by inserting the position parameter into the fundamental equation of the problem. Higher or lower fitness values represent its closest distance from the optimal solution.

c) The fitness value is compared with the best fitness value that is calculated within the swarm. Best fitness value is finalized depending upon the nature and objective of the problem i.e. if maximizing the function is the objective then position parameter which gives the highest functional value when fitted into the functional equation, is considered as the best fitness function and vice versa if minimizing is the solution. The term G_{best} represents the position parameter, which yields the best fitness value in the entire swarm.

d) If fitness value of a particle found to be greater than global best fitness value, this results in new global best fitness value and hence the global best value is replaced by present value. If it is found to be lower than global best, then particle's previous fitness values are checked. If the value is higher, then a new personal best P_{best} value is found and updated using that position parameter value.

e) If the particle's fitness value is found to be lower than previous fitness value, then previous personal best fitness value is considered for position parameter which is then used in velocity equation. This completes the function for one particle and all particles follow the same loop process.

f) End condition can be considered the situation when all particle starts to land on same solution which in other words can be said that the algorithm is not able to optimize further.

Optimal solution is processed based on the fitness value of the particle. The optimal solution is the reference assigned by the user based on an assumption or by calculating an estimate.

5.1 MODIFIED PARTICLE SWARM OPTIMIZER:

Though Particle swarm optimizer has emerged as a successful optimization technique, it is still at its infancy with respect to various aspects and solving various types of problems. To expand its search ability a new modification has been done on the existing PSO algorithm. Consider the fundamental PSO back bone equation 5.1, right side of which contains three parts: first part is the previous velocity of the particle; the second and the third parts are the ones contributing to the change in velocity of the particle. Without second and third terms particles will keep moving with the current speed till it reaches the boundary. Particles will not find a solution unless it has acceptable solutions along its course of path. Now considering only second and third parts of the equation 5.a, we can see that flying particle's velocities are determined by its current position and previous best positions alone. Added to it is that the velocities are memory less. Therefore we can imagine that search process for PSO without the first part is a process where search space statistically reduces throughout the generations. Most likely it resembles a local search algorithm. Upon imagining or visualizing this scenario, we can see that without the first part all the particles tends to move towards the same position there by making the search area shrink after every generation. Only when the global optimum is within the initial search space, there is a chance for PSO to find the solution. We can conclude that the final solution is heavily dependent on initial conditions that are a characteristic of local search ability without the first part. So they are more likely to have global search ability along with the first term. From this we can clearly say that there is a tradeoff between local search and global search ability. Based on the problems balances between the local global search varies. Considering this inertia weight **'*w*'** was introduced into the fundamental backbone equation of PSO (Eqn 5.1). Inertia plays the role of balancing the global and local search. It can be a positive constant or even a positive linear or nonlinear function of time.

$$V_t = w * V_{t-1} + c_1 r_1 (P_{t-1} - X_{t-1}) + c_2 r_2 (G_{t-1} - X_{t-1}) \qquad \text{(Eqn 5.1.1)}$$

$$X_t = X_{t-1} + V_t$$

CHAPTER 6: FOREIGN EXCHANGE MARKET & TECHNICAL INDICATORS

The foreign exchange market (forex for short) involves the purchase and sale of national & international currencies. It is one of the most exciting, fast –paced stochastic market around. Currencies form a medium of communication between countries and are exchanged and valued against each other in order to conduct foreign trade and businesses. This need to exchange currencies lays the foundation for the existence of forex market, making it the largest and the most volatile financial market in the world with revenues extending U.S $4 trillion per year [14].

One unique feature of this international market is that there is no central headquarters or marketplace for exchanging currencies. But trades are conducted electronically or over-the counter (OTC), which means that the transactions occur via computer networks or registered counters that operate around the world eliminating the need of a central location. The market operates 24 hours a day, five and half days a week [15]. In other words, forex market is extremely active during any time of the day with price quotes changing radically. Until the emergence of internet, trading in forex market has been dominated by large financial institutions, banks, corporations and other wealthy individuals. Internet has opened the doors for average investors to buy and sell currencies at their will. Even though forex market provides plenty of opportunities for investors, in order to be successful the trader has to understand the science behind currency movements and the factors affecting it. The goal of the following sections is to provide a brief foundation to forex market.

6.1 CURRENCY EXCHANGING STANDARDS:

In order to successfully trade in forex market, one has to understand the currency quoting standards and its intricacies. In forex market, currencies are always quoted in pairs defined as currency pairs in order to reflect the relationship of one currency to another. If we are trying to determine the exchange rate between U.S dollar (USD) and Japanese yen (JPY), the quote would be represented as follows:

USD/JPY = 119.50

This is collectively referred as currency pair. The currency left to the slash is known as base currency, which in our case is the US dollar and it is always equivalent to one unit. Japanese yen in our case is the quote currency, the value of which represents the equivalent of one unit base currency (USD). In plain words, one can buy US$1 by paying 119.50 Japanese yen. Currency pairs can be quoted in two ways, directly or indirectly. A direct quote involves trading domestic currency as base currency and an indirect quote involves trading domestic currency as quoted currency. For example considering Canadian market where Canadian dollar is the domestic currency and U.S dollar as foreign currency, a direct quote would be defined as CAD/USD while an indirect quote would be USD/CAD. In other words a direct quote of 0.85 in Canadian market (CAD/USD) would mean that you can purchase CAD$1 for U.S$ 0.85. The indirect quote for this would be inverse (1/0.85) which is 1.18 USD/CAD and it means that U.S $1 would be equivalent to CAD$1.18.

Looking from the perspective of the forex market globally, most currencies are traded against the U.S dollar where U.S dollar is the base currency in the currency pairs. However not all currencies have U.S dollar as the base. For example Britain’s Pound Sterling, Australian dollar, European Union’s Euro and New Zealand dollar, are all quoted as base currency against U.S dollar. Currency pairs can also be quoted without U.S dollar as one of its components; such as currency pairs are defined as cross currencies. Most popular and common cross currency pairs are EUR/GBP, EUR/CHF and EUR/JPY. Introduction of cross currencies have expanded the trading horizons and possibilities in forex market but the trading activity for cross currencies are not as proactive as pairs involving U.S dollar which are formally called as “Majors”.

6.2 CURRENCY PAIR TRADING:

Trading in forex market is fairly simple i.e. exchange a currency or another currency but profiting from the trade is the intellectual task which is always a constant struggle. When trading a currency pair, there are four important parameters that decide your profit/loss for the trade. The first two important parameters are the bid price (buy) [16] and the ask price (sell) [16]. Ask price (sell) refers to the amount of quoted currency required to be paid in order to buy one unit of base currency. In other words, how much would forex market sell one unit of base currency for in accordance to the quoted currency. Similarly bid price (buy) reflects amount of quoted currency obtained when selling one unit of base currency or how much forex market would pay for quoted currency in accordance to base currency. Bid and Ask prices are defined in the following example.

USD/CAD = 1.2033/40, Bid = 1.2033, Ask = 1.2040

In the above case, the amount or quote before the slash is defined as the bid price and the two digits after the slash represents the ask price (generally the last two digits of full price are quoted). Bid price will be always smaller than the ask price.

If we consider buying this currency pair, then we intend to buy the base currency so we need to look at the ask price to see how much CAD dollars would the market charge for U.S dollars which means we can buy one U.S dollar with 1.2040 CAD dollars.

However if we decide to sell the currency pair i.e. sell the base currency in exchange for the quoted currency, we need to look at the bid price to see how much the market would buy U.S $1 base currency for an equivalent price to 1.2033 CAD dollars, which is the quoted currency. Currency which is quoted first is always the one through which transaction is conducted and is also the base currency. We can buy and sell the base currency. But depending on what currency we would like to trade our base currency with, we always refer to the corresponding currency pair's exchange rate to determine the price and then associate the corresponding profit/loss.

The final two parameters, which also determine the status of our trade, are the Spread and the Pips. The difference between the bid price and the ask price is defined as a Spread [16]. Consider the following quote:

USD/CAD =1.2033/40

The spread according to the above quote is 7 pips or points. Though the spread may seem insignificant, in reality even the smallest price movements may result in significant profit/loss. A pip is defined as the smallest price movements in the currency pair value or currency quote [16]. For all the major currencies except for Japanese Yen, one pip would be equivalent to 0.0001. With Japanese Yen, a pip would be 0.01 as currency is quoted to only 2 decimal places. In a forex quote of USD/CAD, the pip would be equal to 0.0001 CAD dollars. The value of a pip typically depends on a lot size. The smallest lot available is a micro lot which is a bundle of 1,000 units of currency (often times referred to as 1k). This means the smallest trade size you can make is in multiples of 1k. You can trade 1k, 2k, 3k, or 138k just so long as it is in multiples of 1k. Each 1k is referred to as a lot. Most popular currencies trade within a spread of range of 100 to 150 pips a day.

The following table explains all the currency quote definitions and trading parameters in a nutshell.

Consider the currency quote USD/CAD =1.2033/40

Base Currency	Currency to the left (USD)	
Quote Currency	Currency to the right (CAD)	
Bid Price	1.2033	Price at which one buys the base currency.
Ask Price	1.2040	Price at which one sells the base currency.
Pip	One point move, it is 0.0001 that would be from 1.2033 to 1.2034	Smallest possible movement a price can make.
Spread	In this case is 7 pips, (1.2040-1.2033)	Difference between bid and ask price.

Table 6.2.1 Currency Quote definitions & Parameters

6.3 TECHNICAL TRADING IN FOREX MARKET:

Traders use technical trading to establish tailor made rules for buying and selling currencies with intension of maximizing profit and minimizing the loss. It is based on the analysis that patterns displayed in market prices are assumed to recur in the future. This serves as a motivation behind the technical trading to identify those patterns at early stages and helps maintain our investment goal until the trend reverts [17]. According to the Adaptive Market hypothesis (AMH) proposed by Lo and MacKinlay, which stresses the point that market prices are predictable to some extent [18], believed that the prices may follow trends so the past history of the market can be used to extrapolate future market conditions. Based on the considerable evidence provided by AMH and growing popularity, technical trading has become an important aspect in fundamental trading analysis, which involves in effective use of technical indicators to quantify market data, by considering past and current market conditions.

Technical indicators can be defined as the translators of the forex market raw data. They serve as a vehicle for traders and investors to analyze the past and predict future price trends and patterns. They look at price information and translate it into simple, easy-to-read signals that help us to determine when to buy and when to sell a currency pair. Technical indicators are based on mathematical equations that produce a value, which can also be plotted on a chart for further analysis. Indicators can provide a firm foundation while taking speculative decisions by taking advantage of the historical precedent. So we don't need to personally observe the market for several years to learn its behavioral patterns and take decisions. This saves precious time.

With the advantages of technical indicators being said, there are hundreds of them available in the market today, custom made to meet individual's targets and goals. In this research study, we utilize the potential of 5 most popularly and widely used technical indicators. Each of the five chosen indicators falls under different classification categories. This gives the research more leverage to utilize the unique advantages of each type of indicator in determining a trading strategy. The indicators under consideration are listed as follows:

1. RSI (Relative Strength Index)
2. MI (Momentum Indicator)
3. EMA (Exponential Moving Average)
4. PROC (Price Rate of Change)

5. Support & Resistance

1. Relative Strength Index (RSI):

Introduced by J. Welles Wilder, in 1978, the Relative Strength Index (RSI) is a momentum oscillator that is used to identify the speed and change of price movements [19]. RSI oscillates between zero and 100. Traditionally, and according to Wilder, RSI is considered to generate a sell signal when above 70 and a buy signal when below 30. In general, RSI can also be used to identify the general trend.

This technical momentum indicator compares the magnitude of recent gains to recent losses in order to distinguish the buy and sell conditions on the market. It is calculated using the following formula:

Relative Strength (over 'n' period): Average gain in pips / Average loss in pips

RSI (over 'n' period): 100 - [100 / (1+RS)] (Eqn 6.3.1)

Here 'n' period represents duration of the forex market data, which may range from minutes to months depending upon the forex data considered. The average gain and average loss over a 14 period can be explained as follows:

- First Average Gain = Sum of pips gains over the past 14 periods / 14.
- First Average Loss = Sum of pips lost over the past 14 periods / 14

The second, and subsequent, calculations are based on the prior averages and the current gain loss:

- Average Gain = [(previous Average Gain) x 13 + current Gain] / 14.
- Average Loss = [(previous Average Loss) x 13 + current Loss] / 14.

Taking the prior value plus the current value is a smoothing technique to minimize fluctuations. Accuracy of the RSI increases subject to increase in the data points.

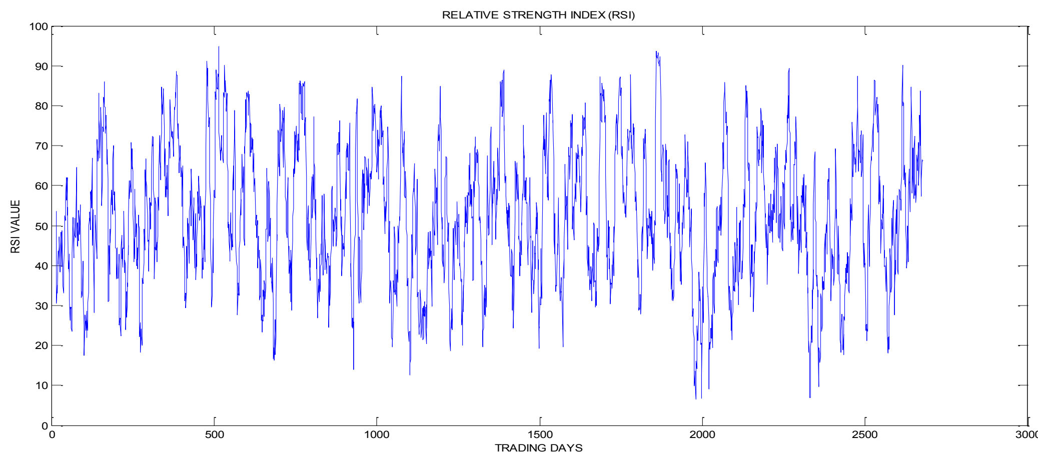


Fig 6.3.1 14 Day RSI over 2800 Days

2. **Momentum Indicator (MI):**

One of the popularly used indicators, which seek to predict future market trends, based on recent price and volume data. It compares the current price of the currency pair to the price a selected number of periods ago. This number represents the rate of change of the currency pair's price over that given time period. It is calculated as follows:

MO (over 'n' period): Present price / Price 'n' period ago (Eqn 6.3.2)

Here 'n' period represents duration of the forex market data, which may range from minutes to months depending upon the forex data considered. Momentum Indicator is generally used as a leading indicator as it quick to respond to fluctuations. As a market peaks, the Momentum indicator will climb sharply and then fall off diverging from the continued upward or sideways movement of the price. Similarly, at a market bottom, Momentum will drop sharply and then begin to climb well ahead of prices. Both of these situations result in divergences between the indicator and prices. The peaks generated by MI are used to capture the market trend, which in turn helps to determine the conditions to buy and sell currency pairs.

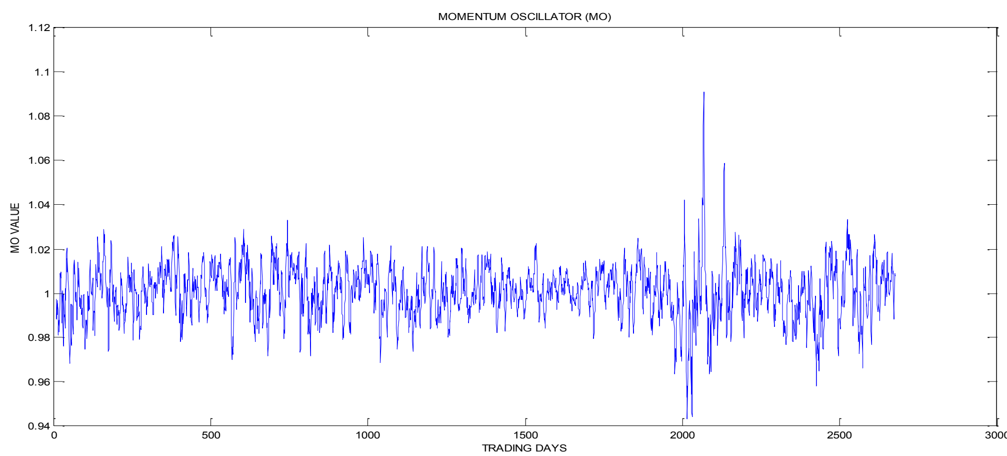


Fig 6.3.2 9 Day MI over 2800 Days

3. **Exponential Moving Average (EMA):**

EMA is an extension of the simple moving average (SMA) that gives more weight to the latest data. Moving averages smooth the price data to form a trend following indicator. They do not predict price direction, but rather define the current direction with a lag. SMA lag because they are based on past prices. Despite this lag, SMA helps smooth price action and filter the noise.

SMA is formed by computing the average price of the currency pair over a specific number of periods. Most moving averages are based on closing prices. A 5-day simple moving average is the five-day sum of closing prices divided by five.

As its name implies, a moving average is an average that moves. Old data is dropped as new data comes available. This causes the average to move along the time scale. Below is an example of a 5-day moving average evolving over three days.

Daily Closing Prices: 11,12,13,14,15,16,17

First day of 5-day SMA: (11 + 12 + 13 + 14 + 15) / 5 = 13

Second day of 5-day SMA: (12 + 13 + 14 + 15 + 16) / 5 = 14

Third day of 5-day SMA: (13 + 14 + 15 + 16 + 17) / 5 = 15

Exponential moving averages reduce the lag by applying more weight to recent prices. The weighting applied to the most recent price depends on the number of periods in the moving average. There are three steps to calculating an exponential moving average. First, calculate the simple moving average. An exponential moving average (EMA) has to start somewhere so a simple moving average is used as the previous period's EMA in the first calculation. Second, calculate the weighting multiplier. Third, calculate the exponential moving average. The formula below is for a 10-day EMA.

SMA (over 'n' period): sum of all Closing Price (C.P) over 'n' period / n

EMA (over 'n' period): [C.P - (SMA)] * multiplier + SMA (Eqn 6.3.3)

Multiplier: 2/('n' period +1)

Exponential moving averages have less lag and are therefore more sensitive to recent prices - and recent price changes. A 10-day exponential moving average will hug prices quite closely and turn shortly after prices turn. Short moving averages are like speed boats - nimble and quick to change. In contrast, a 100-day moving average contains lots of past data that slows it down. Longer moving averages are like ocean tankers - lethargic and slow to change.

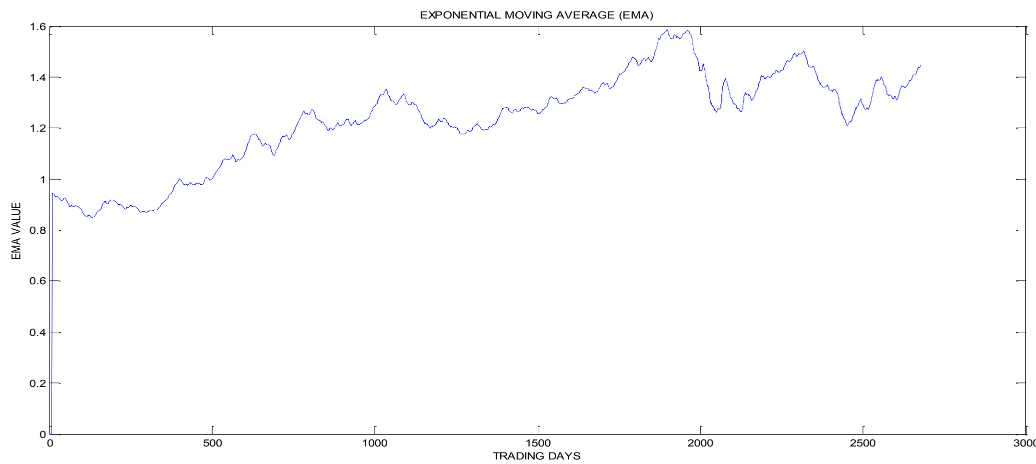


Fig 6.3.3 10 Day EMA over 2800 Days

4. **Price Rate of Change (PROC):**

The Price Rate-of-Change (PROC) indicator, which is a pure momentum oscillator measures the percent change in price from one period to the next. The PROC calculation compares the current price with the price "n" periods ago. The plot forms an oscillator that fluctuates above and below the zero line as the Rate-of-Change moves from positive to negative.

The PROC indicator is momentum in its purest form. It measures the percentage increase or decrease in price over a given period of time. Think of its as the rise (price change) over the run (time). In general, prices are rising as long as the Rate-of-Change remains positive. Conversely, prices are falling when the Rate-of-Change is negative. ROC expands into positive territory as an advance accelerates. ROC dives deeper into negative territory as a decline accelerates. There is no upward boundary on the Rate-of-Change. The sky is the limit for an advance. There is, however, a downside limit. Securities can only decline 100%, which would be to zero. Even with these lopsided boundaries, Rate-of-Change produces identifiable extremes that signal buy and sell conditions. The Rate-of-Change oscillator should be used in conjunction with other aspects of technical analysis. Calculation of PROC is defined as follows:

PROC = [(Present Closing Price – Closing Price ‘n’ periods ago) / (Closing Price ‘n’ periods ago)] * 100 (Eqn 6.3.4)

Momentum oscillators are ideally suited for sideways price action with regular fluctuations. This makes it easier to identify extremes and forecast turning points. Security prices can also fluctuate when trending. For example, an uptrend consists of a series of higher highs and higher lows as prices zigzag higher. Pullbacks often occur at regular intervals based on the percentage move, time elapsed or both. A downtrend consists of lower lows and lower highs as prices zigzag lower. Counter trend advances retrace a portion of the prior decline and usually peak below the prior high. Peaks can occur at regular intervals based on the percentage move, time elapsed or both. The Rate-of-Change can be used to identify periods when the percentage change nears a level that foreshadowed a turning point in the past.

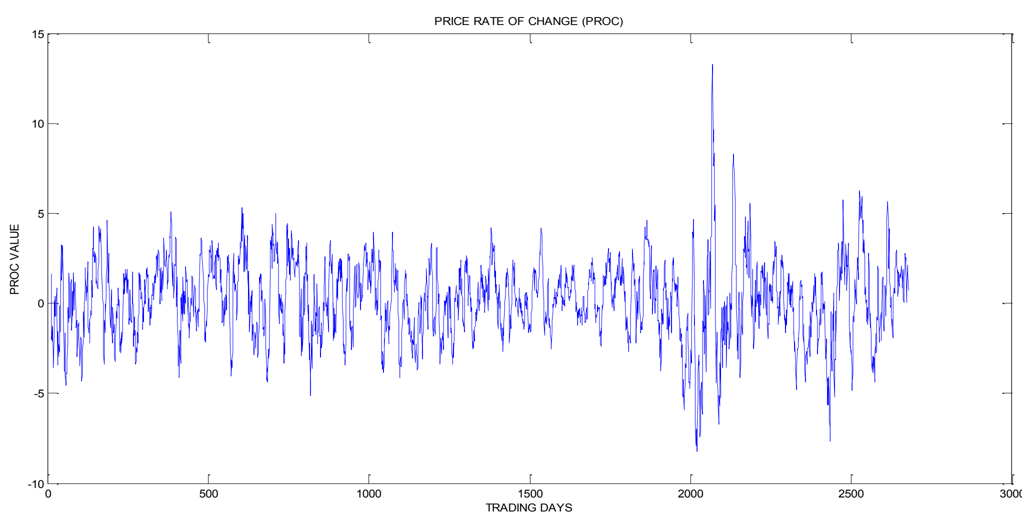


Fig 6.3.4 12 Day PROC over 2800 Days

5. **Support & Resistance (S&R):**

Support & Resistance serves as a fundamental tool for technical analyses, which are used as reference for generating Buy and Sell signals. Generally they are be defined as the maximum and minimum values reached by the currency pair over a certain period of time. More specifically, Resistance Levels are typically defined as a ceiling, preventing the market price level from moving prices upward. If we can reach an appropriate resistance level, it can help us generate profitable sell signals. On the other hand, Support Levels are defined as a floor, preventing the market price level slipping further downwards. Similarly if we can reach a proper support level, it can help us generate convincing buy signals.

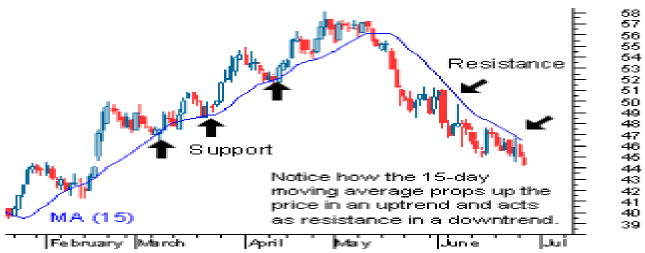


Fig 6.3.5 Support & Resistance [39]

CHAPTER 7: PROPOSED PSO BASED TECHNICAL TRADING MODEL:

Trading currency pairs has long served as an important factor in determining a country's economy as it determines the profitability and risks involved in international business trading. An effective trading system can fetch an individual remarkable profit by generating profitable scenarios. Trading currencies may appear to be a simple process but profiting from it is not an easy job. According to Efficient Market Hypothesis (EMH), it was strongly argued that predicting market condition is impossible as market prices are already incorporated with relevant information [21]. It was strongly emphasized that market prices are as random as flipping a coin. In contrary Lo and Mackinley proposed the Adaptive Market hypothesis (AMH), which stresses the point that market prices are predictable to some extent [20]. They believed that the prices might follow trends so the past history of the market can be used to extrapolate future market conditions. Based on considerable evidence from AMH and several other supporting contributions [22][23], technical analysis has prominently established itself as an important aspect of foreign exchange trading.

Forex market being highly dynamic in nature, exhibits stochastic and random behavior. Primary Optimization problem in hand for our research is to maximize the profit/ minimize the loss involving a set of transactions over a specific period of investment. Artificial Intelligence based Evolutionary computational techniques have long served as a vehicle for understanding and analyzing such chaotic environments for generating near optimal solutions i.e. profitable trading scenarios. In our benchmark research study, we propose a novel model using Particle Swarm Optimization (PSO) and Technical Indicators for generating profitable trading scenarios. The following diagram explains the proposed model in a nutshell:

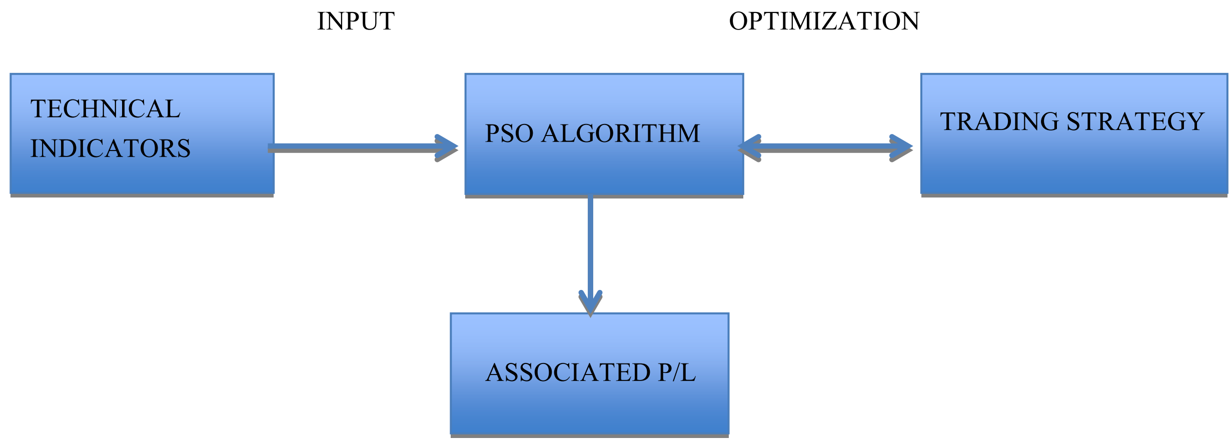


Fig 5.1 Proposed Design Architecture

The infrastructure for this design is to feed a set of 5 standard technical indicators as input and let the PSO algorithm explore the search space and determine a near optimal solution, which would be a profitable trading scenario. The model is novel in the way it incorporates the technical indicators into the PSO Algorithm along with the combination of technical indicators chosen for generating a trading scenario, which has not been found in the literature.

7.1 DESCRIPTION OF THE PSO VARIABLES CONSIDERED:

The description of the PSO Algorithm's parameters is inspired from the analogy of bees/particles in a swarm. Detailed Description of all the parameters considered is listed below:

a. **PARTICLES**: Each individual in the group or swarm is referred to as a particle i.e. a bee in analogy. All the particles in the swarm act independently as well as collectively to accelerate towards individual's best location as well as towards overall best location, while constantly having a memory or trace of its own current location. In our approach, each particle represents an array of 5 technical indicators under consideration that needs to be optimized.

$$\text{particles}=[\text{RSI, MI, PROC, S\&R, EMA}]_i$$

Where i=1,2,3…N, N= number of particles

Each particle is the identical to each other but different by its unique position.

b. **POSITION (X_t, X_{t-1}):** A particle's position is defined as the bee's place in a field, in analogy. This can be a co-ordinate on a x-y plane. This convention can be extended into any N-dimensional space depending upon the problem at hand. The N-dimensional space is the solution space of the problem being optimized, where any co-ordinate on the search space represents a solution to the problem. Reducing the optimization problem to a set of values that represent a position in the search space is the primary step in utilizing the PSO Algorithm. In our approach, each particle is assigned a set of random time durations a position for the particle. That is a set of random time frame lengths for each indicator is assigned as a position for the particle, e.g.,

$$\text{position}= [23, 41, 18, 31, 12]$$

where each value in the array corresponds to a random time duration associated with a particular technical indicator. In the above example, considering daily closing market data, 1st dimension represents a 23 day Relative Strength Index (RSI). 2nd dimension represents a 41 day Momentum Indicator (MI), 3rd dimension represents an 18 day Price Rate of Change (PROC), 4th dimension represents a 31 day Support and Resistance and finally the 5th dimension represents a 12 day Exponential Moving Average (EMA).

c. **VELOCITY:** Velocity represents the direction towards which the bees, in analogy, would fly. This parameter has a special purpose in the PSO Algorithm, because it determines the sense of direction of the particle. P_{Best}, G_{Best}, c1, c2 and the random parameters affect it. In our approach, velocity is referred to as the amount of change in the random time frame length for each of the indicators. The summation of the velocity component along with previous position gives a predicted value of position, which could be better or worse, determined by the fitness function, e.g.,

Old position= [23, 41, 18, 31, 12]

Velocity determined by standard PSO equation (Refer Eq. 5.1) = [10,5,12, 7, 11]

New position= old position + velocity= [33, 46, 30, 38, 23]

d. FITNESS FUNCTION: A quantification factor that is essential to evaluate the accuracy of a particle's position is defined as a fitness function. The fitness function must take the particle's position in the solution space and return a value representing the proximity of that position to the global best position. In analogy, the fitness function would represent density of flowers. Higher the density of flowers, better the location. Ultimately the fitness function serves as a bridge between the PSO algorithm and the optimization problem at hand. The fitness function considered in our approach is the profit/loss associated with a closed transaction.

In the forex market a profit or a loss can be incurred while both buying and selling currency pairs. So a closed transaction can be defined as both buying and selling the same currency pair or selling and buying the same currency pair. Closed transactions for both the cases are defined below:

A two-step closed transaction:

1. [Selling price*(number of buying times)]-[sum of all the buying price's]
2. [Buying price*(number of selling times)]-[sum of all the selling price's]

Total Profit/loss: Sum of all closed transactions (Maximum number of pips gained or minimum number of pips lost over the closed transactions)

e. **PERSONAL BEST POSITION (P_{Best}):** In analogy, each bee remembers the location personally where it had the highest concentration of flowers. The location with the best fitness value personally discovered by a bee is defined as the Personal Best. At each point of time, the bee or the particle would compare the fitness function of its current location to that of P_{Best}. If the current location has a better value for the fitness function, then P_{Best} would be replaced by its current location. The P_{Best} in our approach is defined as the set of time durations for an individual particle that had the best performance for the fitness function i.e. best profit or minimum loss associated with each iteration or at the end of all iterations.

f. **GLOBAL BEST POSITION (G_{Best}):** Each bee has some way of knowing the highest concentration of flowers discovered by the entire swarm or group. The location where the highest fitness value is encountered in the entire swarm is defined as the Global Best. In contrary to P_{Best}, there can be only one G_{Best} location towards which each individual bee would be attracted. At every point of time, a particle would compare its current location against G_{Best}, if a location with a higher fitness were to be discovered then G_{Best} would automatically be replaced by current position of the corresponding particle. The G_{Best} in our approach is defined as the set of time durations for an individual particle that had the best performance for the fitness function i.e. best profit or minimum loss associated among all the particles or the entire swarm.

g. **INERTIA WEIGHT (w):** The goal behind inclusion of inertia weight to the original PSO Algorithm was to facilitate an optimal balance between global explorations while exploiting the local maxima. According to [24], it was strongly suggested that inertia weight should be linearly varied from 0.9 to 0.4 gradually over the course of the run. It is also suggested to choose a reasonable number of iterations, so that the PSO Algorithm doesn't get stagnant while weighting for inertia to decrease, in case of large number of durations. Similarly if the iterations are very low, the algorithm may not have enough scope to search for an optimal solution globally.

h. **RANDOM NUMBERS (n_1, n_2):** Random number parameters return a value between 0.0 and 1.0, when called in the iteration. Main reason for using random number is to introduce a stochastic nature in the optimization process when simulating the unpredictable nature of natural swarm behavior. Generation of the random number can be utilized from the rand function in Matlab™.

i. **SOCIAL CONSTANTS (c_1, c_2):** These scaling factors i.e. Cognitive & Social factors are used to determine the trade off between how a particle is influenced by the memory of its own best location and by the best location in the entire swarm. Increasing c_1 encourages exploration of search space as each particle move towards its P_{Best}. On the other hand, increasing c_2 facilitates global exploration. Based on several trial and error experiments [25], it was suggested to have a value of 0.7 and 0.8 for c_1 and c_2. Same values were considered in our approach as well.

7.2 MODEL IMPLEMENTATION PROCEDURE:

The following steps explain the process flow of the proposed model.

1. The parameters defined in the Eq.5.1.1 were initialized first with standard values suggested in [24] [25]. These values were typically used to solve optimization problem using Particle Swarm Optimization. Inertia weight was started 0.9 and linearly decreased from 0.9 to 0.4 over the course of the iteration to facilitate both global and local search [24]. The cognitive and social parameters were set to 0.7 & 0.8. Random parameters were initialized using rand function in Matlab™.

2. To start, 100 particles were initialized. Each particle was assigned an array of five random time durations, each corresponding to a particular technical indicator under consideration. Initial Velocity V_{t-1} was considered zero. Each particle's present position was considered their P_{Best} and G_{Best} was set to zero before beginning the simulation.

3. A loop was run for 100 iterations during which optimization was continuously done for each iteration, which generated new position and velocity values based on the Eq. 5.1.1. These values were consistently checked for the fitness function and P_{Best}, G_{Best} were updated according to the value returned by the fitness function for each particle. In our approach, Fitness function is defined as the profit/loss incurred from a closed transaction. In order to start and complete a closed transaction a buy or sell signal must be generated. In order to generate a buy or sell signal, tailor made trade rules were defined and implemented. Following conditions define the rules for buying and selling a currency pair.

- ✓ If the closing price crosses down the EMA curve: generate a sell signal
- ✓ If the RSI cross down the level 70%: generate a sell signal
- ✓ If the closing price crosses down the Resistance level: generate a sell signal
- ✓ If the momentum is smaller than one: generate a sell signal
- ✓ If the PROC negative: generate a sell signal

- ✓ If the closing price is higher than the EMA curve, and not overbought: generate a buy signal (only make a transaction when 30<RSI<70)
- ✓ If the closing price crosses up the Support level generate a buy signal
- ✓ If the momentum is larger than one, not overbought and not oversold: generate a buy signal
- ✓ If the PROC is positive, not overbought and not oversold: generate a buy signal

Note: These rules are customizable and user defined. It can be altered any time.

4. The stop condition is user defined and depends on the problem. In general, the potential stop condition could be an expected optimized value within a range, fixed iterations or problem specific conditions [3][26]. In our experiment, we consider a stopping condition to be a specific number of iterations. Simulations were performed by varying the number of iterations and number of particles, in order to attain a relevant optimized data for both scenarios.

5. The value that satisfied the fitness function from the overall values obtained during each iteration was selected as an optimized value. The same procedure was followed to calculate the position parameters for all particles. One such process of optimization for each of the particle is considered as one iteration.

Summary and the associated results are discussed in the following section.

CHAPTER 8: RESULTS & SUMMARY

Simulation results obtained upon implementing the proposed trading model to the stochastic environment i.e. forex market using Particle Swarm Optimization (PSO) is presented and the obtained results are analyzed carefully. Forex data was collected for all the 6 currency pairs under consideration from 2001 to 2011 [46]. The simulation was carried out with the primary goal of maximizing the profit or minimizing the loss associated over a trading period.

Historical data from the year 2001-2011 consisting of daily closing prices for all the 6 major currency pairs were collected. The collected historical data was split into two parts. First part was considered for training the model and the second part for testing the model.

The forex data associated with the training period was considered from 2001-2007 and the data associated with testing period was considered from 2007-2011. Main reason for splitting the historical data is to provide the PSO Algorithm with a sense of past. According to Efficient Market Hypothesis (EMH), PSO would be able to identify the hidden patterns, or trends, which could be utilized in improving the performance of testing or out of sample data.

For every currency pair, PSO Algorithm was trained for two criteria's

a. Varying the iterations
b. Varying the number of particles

These two factors were carefully selected over other parameters because they give us more scope for understanding the nature of the PSO Algorithm. Since there is no mathematical justification behind the functionality of the algorithm, considered two parameters can serve as a test bed for analyzing and improving the PSO 's optimization capabilities. So the proposed model's performance for each currency pair was evaluated in a two-step process.

1. In the first step, the model was subjected to a varied iteration count. The best-performed iteration, which resulted in a maximum profit was

considered as the reference for the second step.

2. In the second step, the reference iteration count, which resulted in a maximum profit, was chosen and kept constant while the number of particles was varied. Finally the best set including the iteration count and number of particles, which resulted in the highest profit during the training period, was chosen as final best performing source and were subjected to the out of sample or testing data.

8.1 RESULTS DISCUSSION [TRAINING PERIOD]:

The values for all the parameters associated with the PSO Algorithm were chosen in accordance with the literature. The position parameter is the random time duration for each technical indicator under consideration; the velocity would be the amount of change in the time duration for the successive iterations. Inertia was chosen to be 0.9 while social and cognitive parameters were set to 0.7 and 0.8 respectively.

Transaction costs of 6 pips were considered to incorporate actual market conditions. In order to have uniformity in profit analysis the closing price data of the three currency pairs namely USD/CAD, USD/JPY and USD/CHF were converted into equivalent US Pips; that data was used for training and testing. Simulation results for a varied number of iterations and a varied particle count for each currency pair over the training period [2001-2007] is presented below:

8.1.1 SIMULATION RESULT FOR AUD/USD FOR TRAINING PERIOD [2001-2007]:

ITERATIONS	PARTICLES	PROFIT (IN PIPS)	TRANSACTION COUNT	PROFIT AFTER TRANSACTION COSTS	OPTIMIZED TIME DURATIONS
20	100	- 1055	269	-2669	[7,12,10,13,7]
40	100	3193	213	1915	[6,2,8,17,2]
60	100	- 3346	256	- 4882	[3,2,2,6,29]
80	100	8818	156	7882	[8,14,10,13,5]
100	100	1478	303	-340	[8,13,10,15,21]

Table 8.1.1 Iteration count (vs) Profit/Loss for AUD/USD over Training Period [2001-2007]

PARTICLES	ITERATIONS	PROFIT (IN PIPS)	TRANSACTION COUNT	PROFIT AFTER TRANSACTION COSTS	OPTIMIZED TIME DURATIONS
80	80	3900	335	1890	[10,14,10,5,14]
100	80	8818	156	7882	[8,14,10,13,5]
120	80	3910	234	2506	[8,11,36,31,24]
140	80	- 944	215	- 2234	[6,2,8,50,49]
160	80	3008	212	1736	[6,2,8,21,23]

Table 8.1.2 Particle count (vs) Profit/Loss for AUD/USD over Training Period [2001-2007]

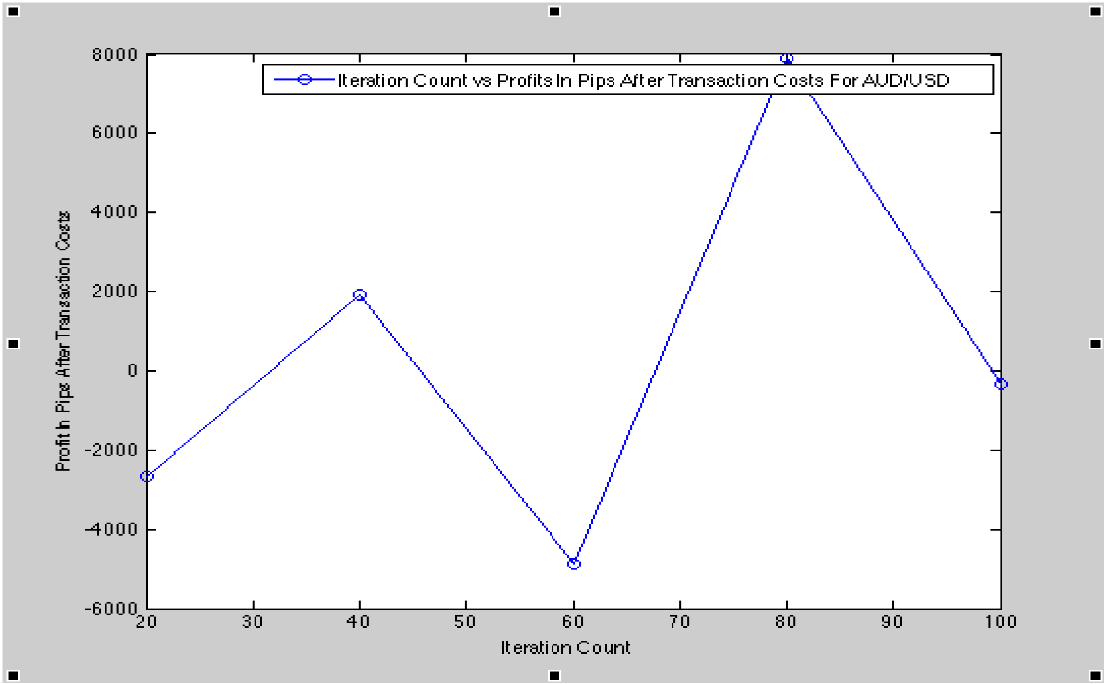


Fig 8.1.1 Iteration count (vs) Profit/Loss for AUD/USD over Training Period [2001-2007]

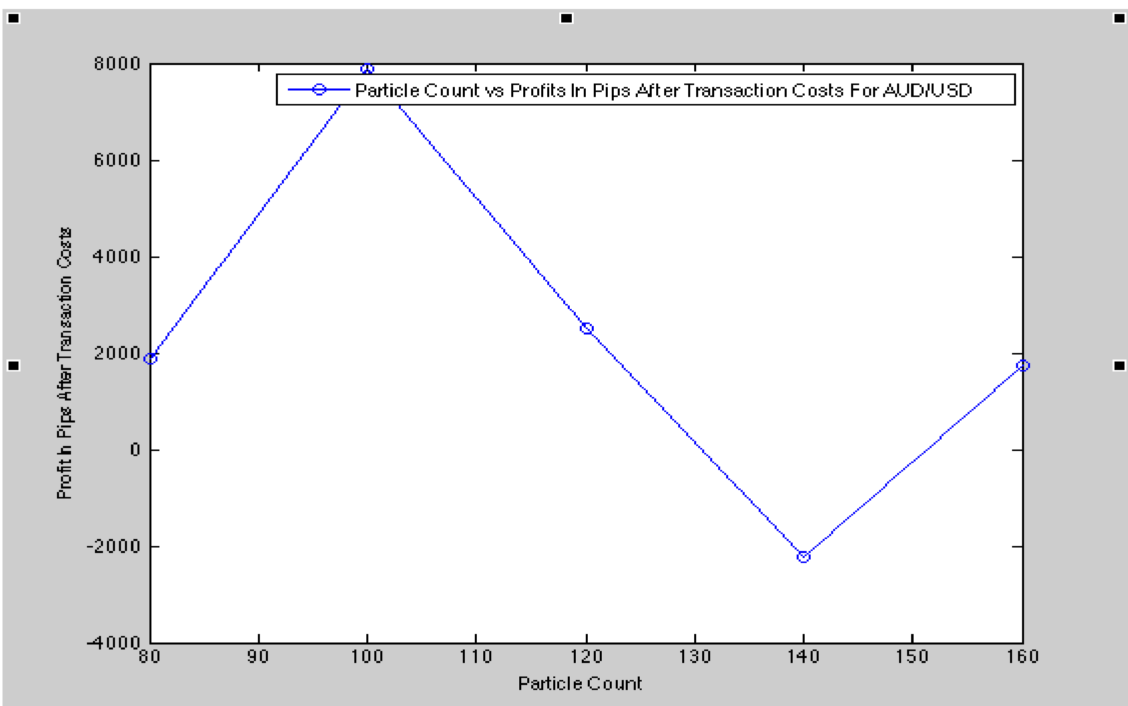


Fig 8.1.2 Particle count (vs) Profit/Loss for AUD/USD over Training Period [2001-2007]

The best time duration associated with AUD/USD is [8,14,10,13,5] which resulted in maximum profit of 8350 pips after considering the transaction costs.

8.1.2 SIMULATION RESULT FOR EUR/USD FOR TRAINING PERIOD [2001-2007]:

ITERATIONS	PARTICLES	PROFIT (IN PIPS)	TRANSACTION COUNT	PROFIT AFTER TRANSACTION COSTS	OPTIMIZED TIME DURATIONS
20	100	27,497	368	25,289	[16,37,36,7,17]
40	100	35,690	138	32,862	[33,39,36,22,26]
60	100	29,527	454	26,803	[28,26,36,27,33]
80	100	36,922	539	33,688	[36,39,36,28,27]
100	100	32,262	474	29,418	[36,36,36,25,2]

Table 8.1.3 Iteration count (vs) Profit/Loss for EUR/USD over Training Period [2001-2007]

PARTICLES	ITERATIONS	PROFIT (IN PIPS)	TRANSACTION COUNT	PROFIT AFTER TRANSACTIO N COSTS	OPTIMIZED TIME DURATIONS
80	80	35,587	513	32,509	[10,14,10,5,14]
100	80	36,922	539	33,688	[36,39,36,28,27]
120	80	33,513	487	30,591	[36,29,36,29,9]
140	80	35,716	539	32,482	[36,37,36,29,29]
160	80	35,353	151	32,447	[37,37,36,31,11]

Table 8.1.4 Particle count (vs) Profit/Loss for EUR/USD over Training Period [2001-2007]

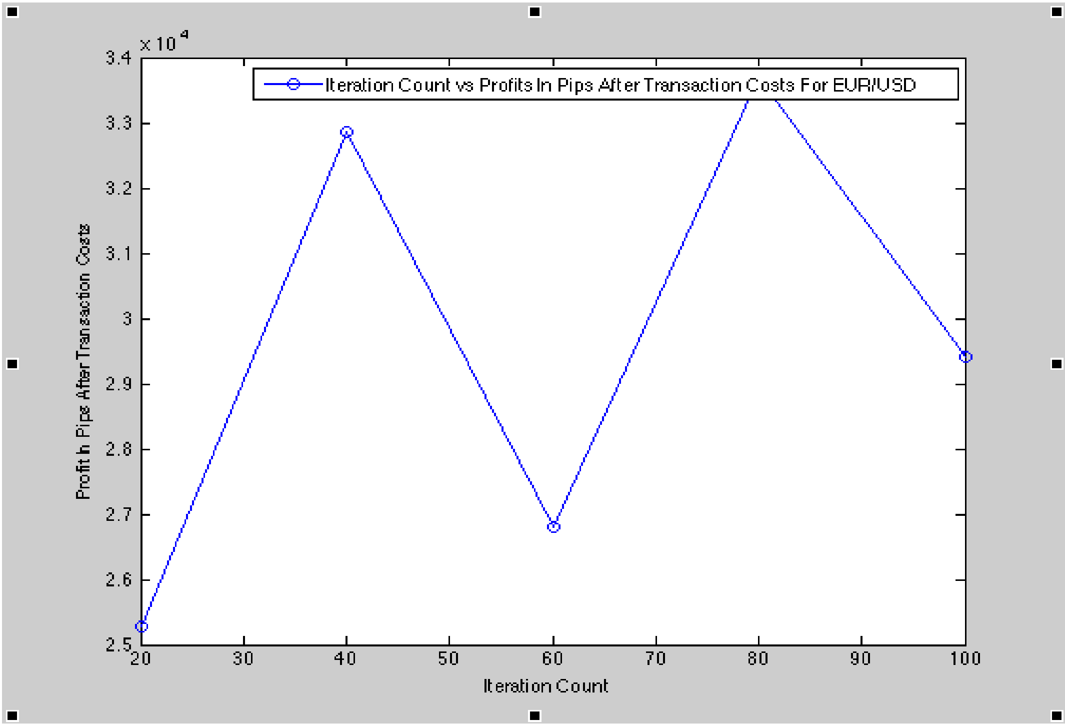


Fig 8.1.3 Iteration Count (vs) Profit/Loss for EUR/USD over Training Period [2001-2007]

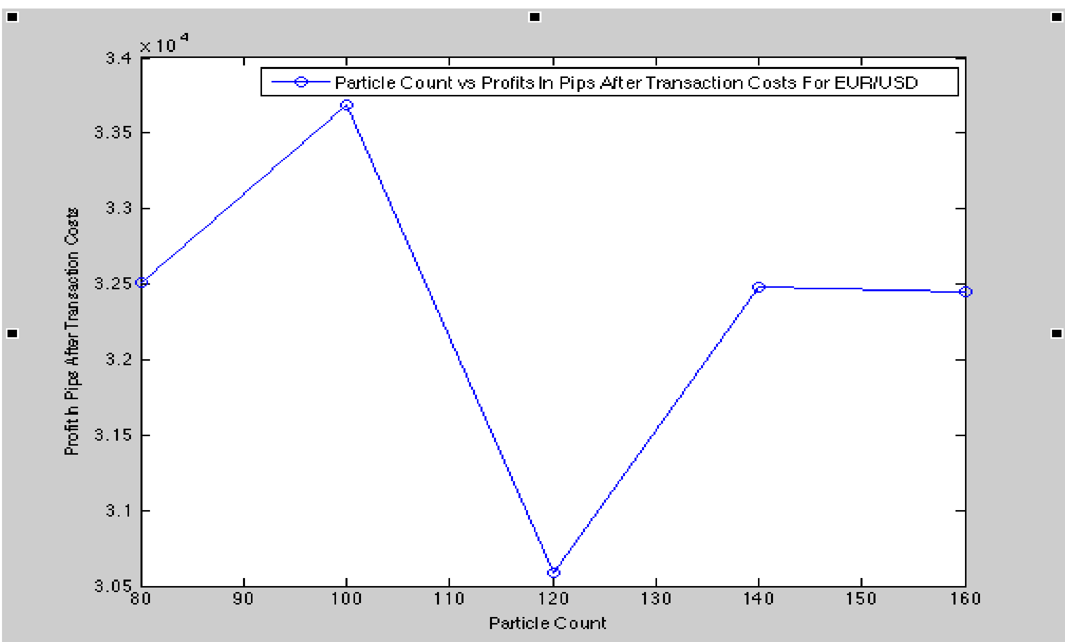


Fig 8.1.4 Particle Count vs Profit/Loss for EUR/USD over Training Period [2001-2007]

The best time duration associated with EUR/USD is [36,39,36,28,27] which resulted in maximum profit of 35,305 pips after considering the transaction costs.

8.1.3 SIMULATION RESULT FOR GBP/USD FOR TRAINING PERIOD [2001-2007]:

ITERATIONS	PARTICLES	PROFIT (IN PIPS)	TRANSACTION COUNT	PROFIT AFTER TRANSACTION COSTS	OPTIMIZED TIME DURATIONS
20	100	- 8879	510	- 11,939	[49,2,5,2,2]
40	100	333	621	- 3393	[40,4,5,50,50]
60	100	-10,065	313	- 11,943	[6,3,410,50]
80	100	12,655	60	12,295	[2,4,3,47,2]
100	100	-761	539	- 3995	[40,2,5,30,48]

Table 8.1.5 Iteration count (vs) Profit/Loss for GBP/USD over Training Period [2001-2007]

PARTICLES	ITERATIONS	PROFIT (IN PIPS)	TRANSACTION COUNT	PROFIT AFTER TRANSACTION COSTS	OPTIMIZED TIME DURATIONS
80	80	-14,547	597	- 18,129	[50,4,2,44,5]
100	80	12,655	60	12,295	[2,4,3,47,2]
120	80	-3265	539	- 6499	[37,2,5,46,2]
140	80	12,059	61	11,693	[2,4,3,50,50]
160	80	-5973	562	- 9345	[37,2,4,50,2]

Table 8.1.6 Particle count vs Profit/Loss for GBP/USD over Training Period [2001-2007]

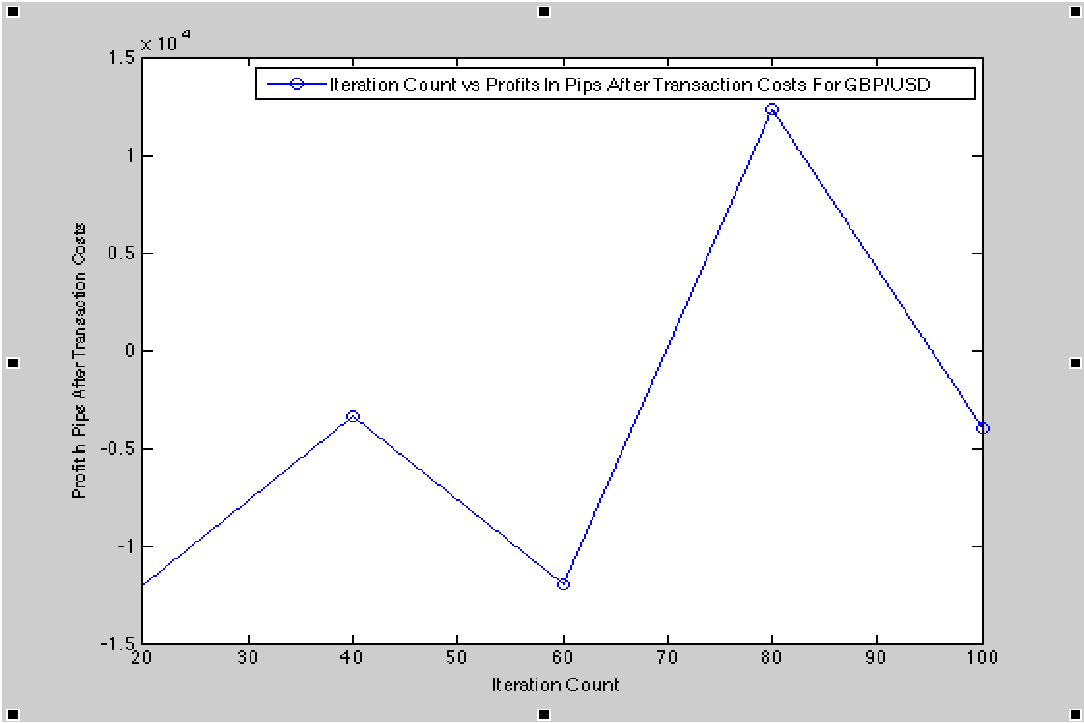


Fig 8.1.5 Iteration Count (vs) Profit/Loss for GBP/USD over Training Period [2001-2007]

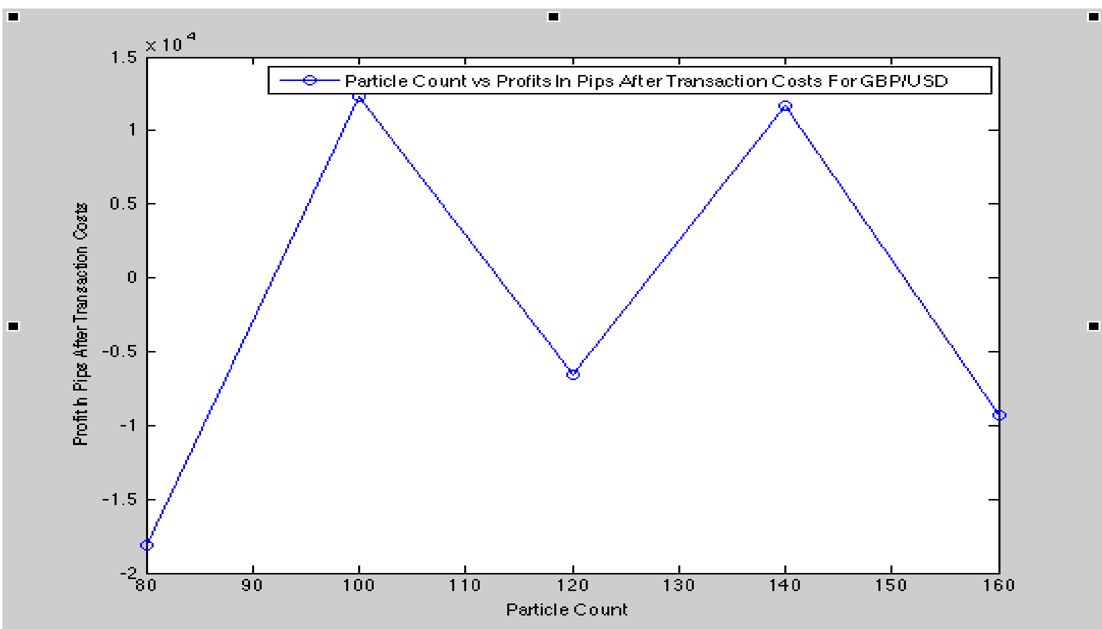


Fig 8.1.6 Particle Count (vs) Profit/Loss for GBP/USD over Training Period [2001-2007]

The best time duration associated with GBP/USD is [2,4,3,47,2] which resulted in maximum profit of 12,475 pips after considering the transaction costs.

8.1.4 SIMULATION RESULT FOR USD/CHF (IN US PIP) FOR TRAINING PERIOD [2001-2007]:

ITERATIONS	PARTICLES	PROFIT (IN PIPS)	TRANSACTION COUNT	PROFIT AFTER TRANSACTION COSTS	OPTIMIZED TIME DURATIONS
20	100	- 6907	602	- 10,519	[41,2,2,50,2]
40	100	1008	469	- 1806	[50,2,7,36,3]
60	100	- 6430	381	- 8716	[11,43,29,8,44]
80	100	11,221	184	10,117	[5,2,7,2,49]
100	100	11,015	190	9875	[5,2,7,2,22]

Table 8.1.7 Iteration count (vs) Profit/Loss for USD/CHF over Training Period [2001-2007]

PARTICLES	ITERATIONS	PROFIT (IN PIPS)	TRANSACTION COUNT	PROFIT AFTER TRANSACTION COSTS	OPTIMIZED TIME DURATIONS
80	80	- 357	474	- 3201	[50,2,7,50,2]
100	80	11,221	184	10,117	[5,2,7,2,49]
120	80	- 14	469	- 2828	[50,2,7,49,41]
140	80	- 31	472	- 2863	[50,2,7,50,50]
160	80	- 9058	539	- 12,292	[42,38,25,42,16]

Table 8.1.8 Particle count (vs) Profit/Loss for USD/CHF over Training Period [2001-2007]

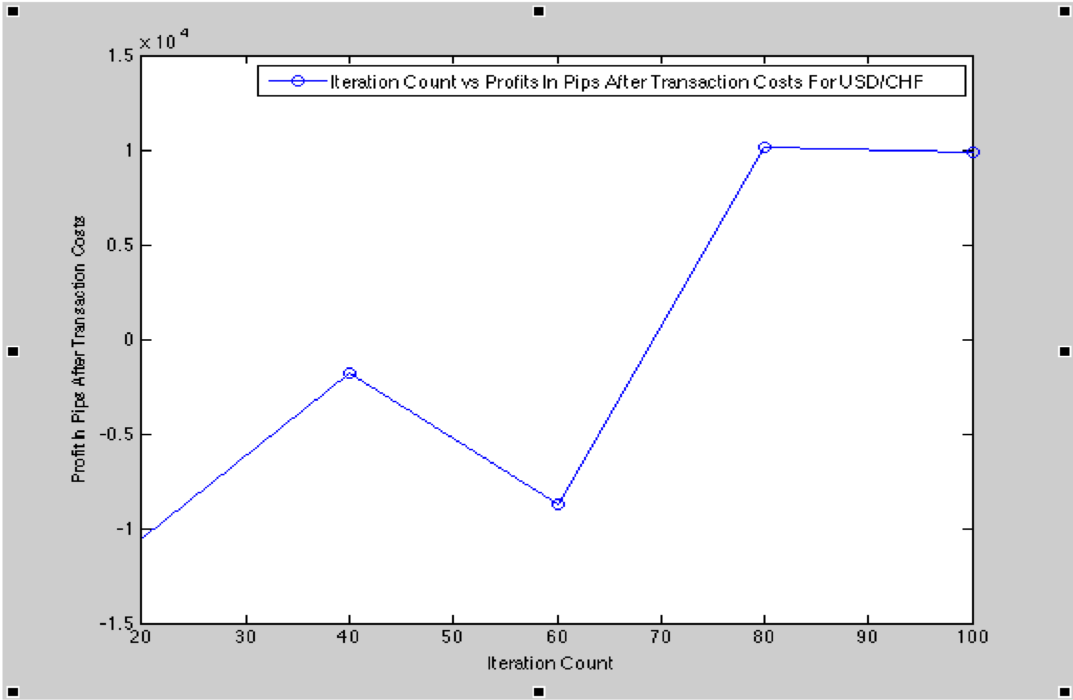


Fig 8.1.7 Iteration Count (vs) Profit/Loss for USD/CHF over Training Period [2001-2007]

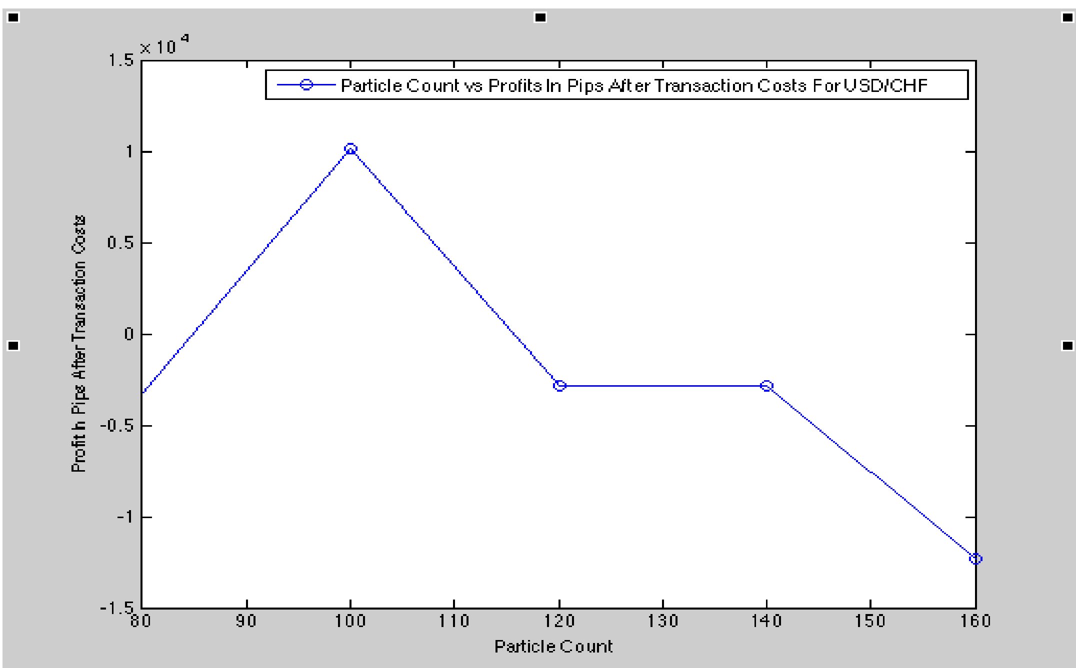


Fig 8.1.8 Particle Count (vs) Profit/Loss for USD/CHF over Training Period [2001-2007]

The best time duration associated with USD/CHF is [5,2,7,2,49] which resulted in maximum profit of 10,669 US pips after considering the transaction costs.

8.1.5 SIMULATION RESULT FOR USD/JPY (IN US PIP) FOR TRAINING PERIOD [2001-2007]:

ITERATIONS	PARTICLES	PROFIT (IN PIPS)	TRANSACTION COUNT	PROFIT AFTER TRANSACTION COSTS	OPTIMIZED TIME DURATIONS
20	100	415	250	- 1085	[41,2,2,50,2]
40	100	370	214	- 914	[50,2,7,36,3]
60	100	364	207	- 878	[11,43,29,8,44]
80	100	561	85	51	[2,7,4,2,2]
100	100	426	243	- 1032	[5,2,7,2,22]

Table 8.1.9 Iteration count (vs) Profit/Loss for USD/JPY over Training Period [2001-2007]

PARTICLES	ITERATIONS	PROFIT (IN PIPS)	TRANSACTION COUNT	PROFIT AFTER TRANSACTION COSTS	OPTIMIZED TIME DURATIONS
80	80	275	474	- 2569	[50,2,7,50,2]
100	80	561	85	51	[2,7,4,2,2]
120	80	553	121	- 173	[4,7,29,12,17]
140	80	536	138	- 292	[5,7,29,45,8]
160	80	366	218	- 942	[10,2,14,36,11]

Table 8.1.10 Particle count (vs) Profit/Loss for USD/JPY over Training Period [2001-2007]

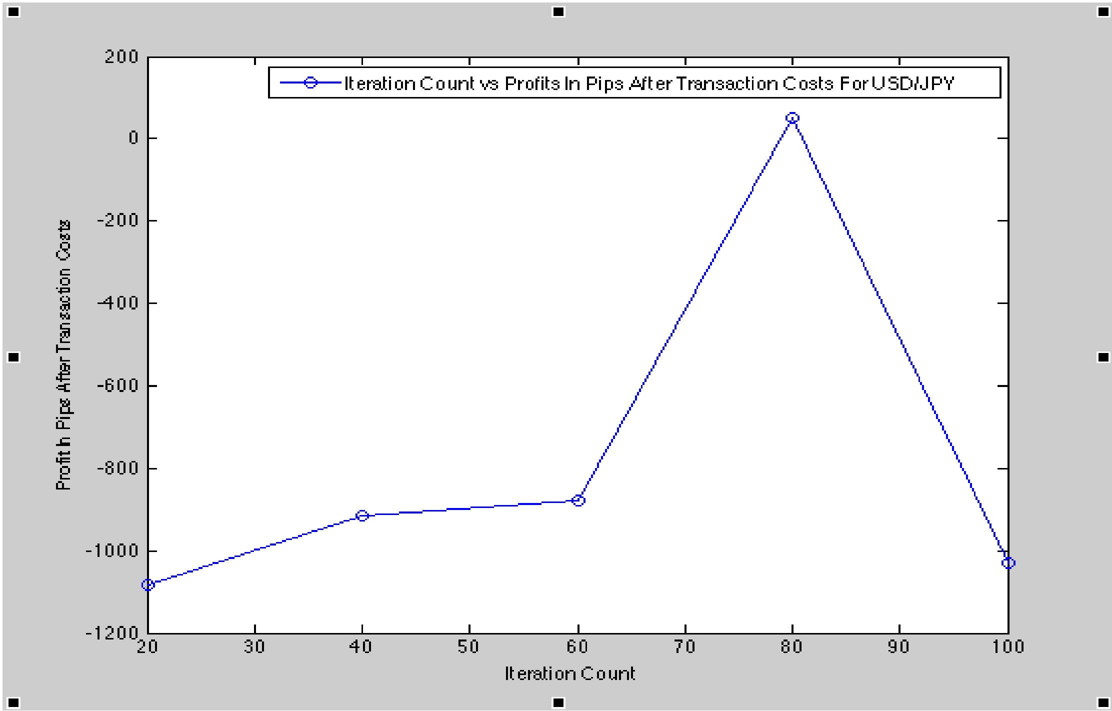


Fig 8.1.9 Iteration Count (vs) Profit/Loss for USD/JPY over Training Period [2001-2007]

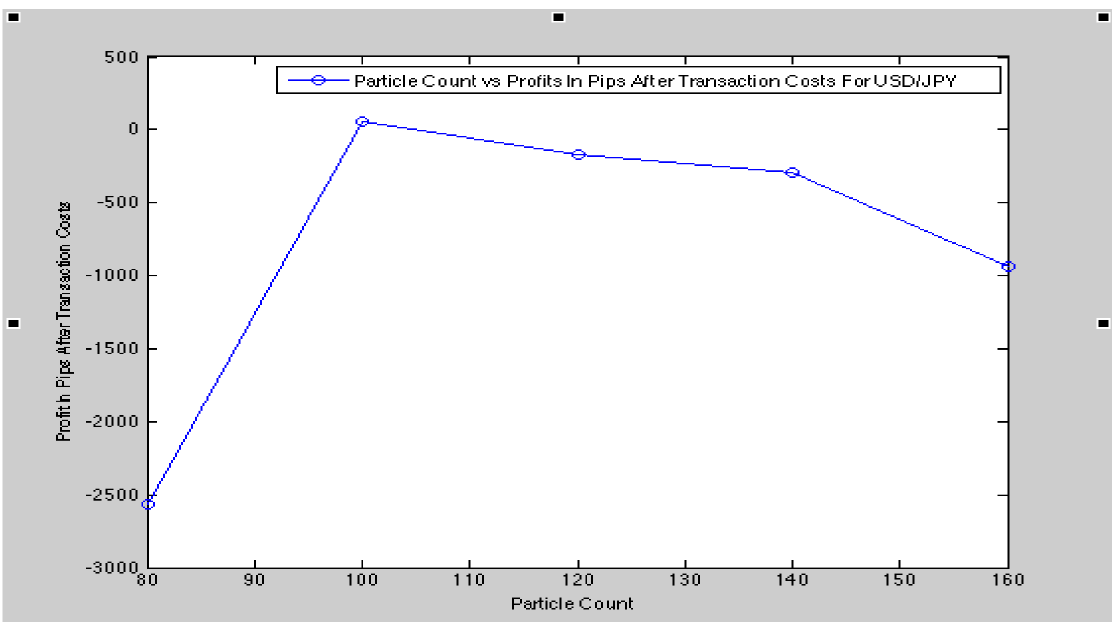


Fig 8.1.10 Particle Count (vs) Profit/Loss for USD/JPY over Training Period [2001-2007]

The best time duration associated with USD/JPY is [2,7,4,2,2] which resulted in maximum profit of 306 US pips after considering the transaction costs.

8.1.6 SIMULATION RESULT FOR USD/CAD (IN US PIP) FOR TRAINING PERIOD [2001-2007]:

ITERATIONS	PARTICLES	PROFIT (IN PIPS)	TRANSACTION COUNT	PROFIT AFTER TRANSACTION COSTS	OPTIMIZED TIME DURATIONS
20	100	- 5095	385	- 7405	[10,5,4,2,2]
40	100	- 4114	371	- 6340	[7,2,2,50,7]
60	100	- 4143	221	- 5469	[7,2,2,50,39]
80	100	- 1245	176	- 2301	[4,8,3,25,18]
100	100	- 4052	392	- 6404	[8,2,3,50,50]

Table 8.1.11 Iteration count (vs) Profit/Loss for USD/CAD over Training Period [2001-2007]

PARTICLES	ITERATIONS	PROFIT (IN PIPS)	TRANSACTION COUNT	PROFIT AFTER TRANSACTION COSTS	OPTIMIZED TIME DURATIONS
80	80	- 5893	656	- 9829	[42,2,2,47,50]
100	80	- 1245	176	- 2301	[4,8,3,25,18]
120	80	- 4379	413	- 6857	[8,2,2,7,13]
140	80	- 5881	658	- 9829	[42,2,3,31,2]
160	80	- 4223	383	- 6521	[7,2,2,22,17]

Table 8.1.12 Iteration count (vs) Profit/Loss for USD/CAD over Training Period [2001-2007]

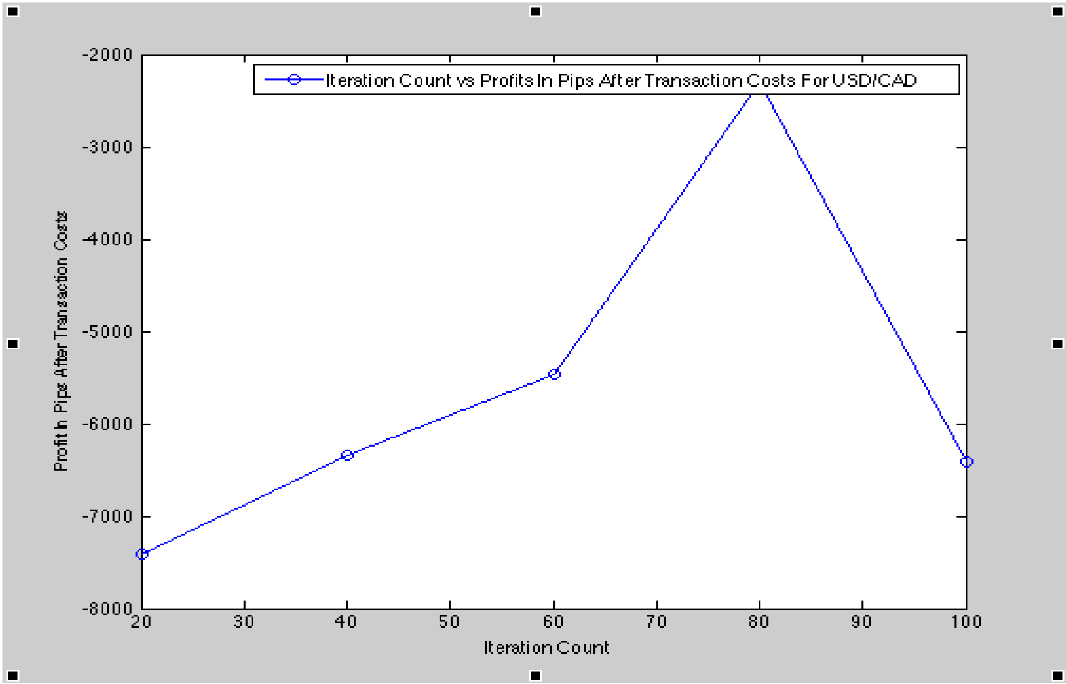


Fig 8.1.11 Iteration Count (vs) Profit/Loss for EUR/USD over Training Period [2001-2007]

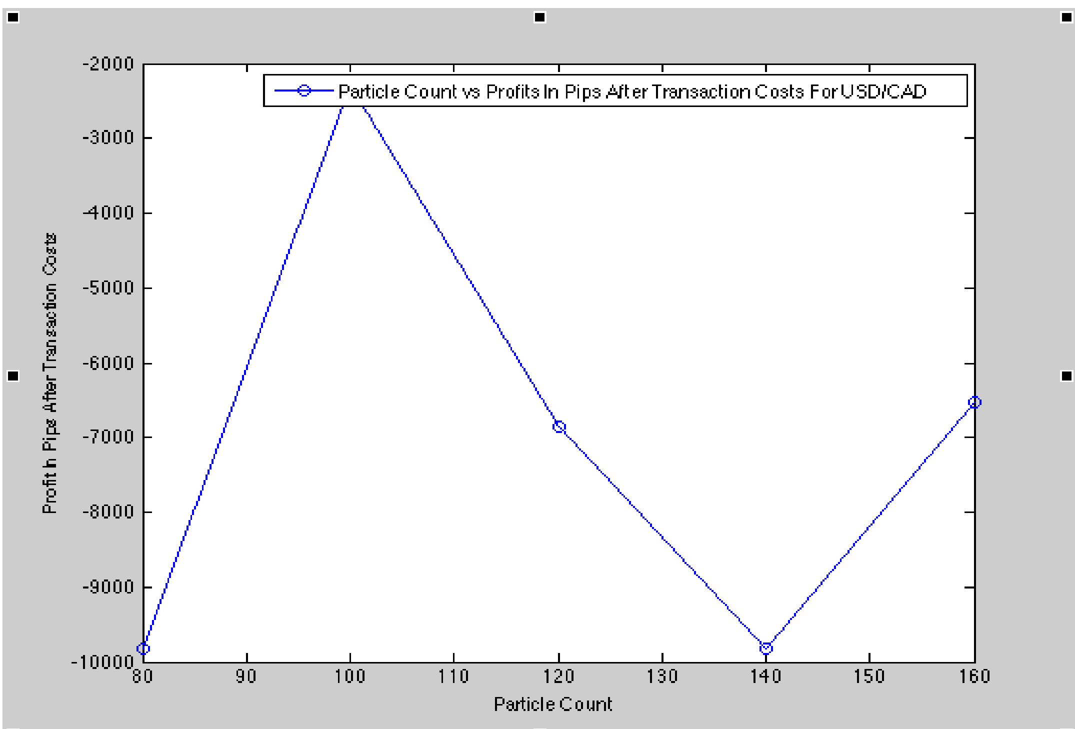


Fig 8.1.12 Particle Count vs Profit/Loss for USD/CAD over Training Period [2001-2007]

The best time duration associated with USD/CAD is [4,8,3,25,18] which resulted in minimum loss of 1773 pips after considering the transaction costs.

8.2 RESULTS DISCUSSION [TESTING PERIOD]:

Testing period or out of sample period was split into 3 parts ranging from 1 year [2007-2008], 2 years [2007-2009] and 4 years [2007-2011] to experiment the model's capability to produce profitable scenarios from shorter investment period to longer investment period. The reference time durations for each technical indicator, which is resulted in maximum profit over the training period, was selected and subjected to unknown out of sample data to explore the possibilities of generating profitable scenarios. The same transaction cost of 6 pips was considered over the testing period as well.

Testing period results are presented below:

8.2.1 SIMULATION RESULT FOR AUD/USD FOR TESTING PERIOD:

TESTING PERIOD (IN YRS)	OPTIMIZED TIME DURATIONS	PROFIT (IN PIPS)	TRANSACTION COUNT	PROFIT AFTER TRANSACTION COSTS
2007-2008	[8,14,10,13,5]	- 640	25	- 790
2007-2009	[8,14,10,13,5]	9922	56	9586
2007-2011	[8,14,10,13,5]	- 7259	109	- 7913

Table 8.2.1 Testing Period Results for AUD/USD

8.2.2 SIMULATION RESULT FOR EUR/USD FOR TESTING PERIOD:

TESTING PERIOD (IN YRS)	OPTIMIZED TIME DURATIONS	PROFIT (IN PIPS)	TRANSACTION COUNT	PROFIT AFTER TRANSACTION COSTS
2007-2008	[36,39,36,28,27]	- 11,319	34	- 11,523
2007-2009	[36,39,36,28,27]	57,166	52	56,854
2007-2011	[36,39,36,28,27]	49,059	109	48,405

Table 8.2.2 Testing Period Results for EUR/USD

8.2.3 SIMULATION RESULT FOR GBP/USD FOR TESTING PERIOD:

TESTING PERIOD (IN YRS)	OPTIMIZED TIME DURATIONS	PROFIT (IN PIPS)	TRANSACTION COUNT	PROFIT AFTER TRANSACTION COSTS
2007-2008	[2,4,3,47,2]	20,117	12	20,045
2007-2009	[2,4,3,47,2]	32,242	24	32,098
2007-2011	[2,4,3,47,2]	67,472	49	67,178

Table 8.2.3 Testing Period Results for GBP/USD

8.2.4 SIMULATION RESULT FOR USD/CHF (IN US PIP) FOR TESTING PERIOD:

TESTING PERIOD (IN YRS)	OPTIMIZED TIME DURATIONS	PROFIT (IN PIPS)	TRANSACTION COUNT	PROFIT AFTER TRANSACTION COSTS
2007-2008	[5,2,7,2,49]	- 3193	28	- 3361
2007-2009	[5,2,7,2,49]	- 825	57	- 1167
2007-2011	[5,2,7,2,49]	- 1821	115	- 2511

Table 8.2.4 Testing Period Results for USD/CHF (IN US PIP)

8.2.5 SIMULATION RESULT FOR USD/JPY (IN US PIP) FOR TESTING PERIOD:

TESTING PERIOD (IN YRS)	OPTIMIZED TIME DURATIONS	PROFIT (IN PIPS)	TRANSACTION COUNT	PROFIT AFTER TRANSACTION COSTS
2007-2008	[2,7,4,2,2]	- 77	14	- 161
2007-2009	[2,7,4,2,2]	- 299	35	- 509
2007-2011	[2,7,4,2,2]	- 326	68	- 734

Table 8.2.5 Testing Period Results for USD/JPY (IN US PIP)

8.2.6 SIMULATION RESULT FOR USD/CAD (IN US PIP) FOR TESTING PERIOD:

TESTING PERIOD (IN YRS)	OPTIMIZED TIME DURATIONS	PROFIT (IN PIPS)	TRANSACTION COUNT	PROFIT AFTER TRANSACTION COSTS
2007-2008	[4,8,3,25,18]	- 7519	20	- 7639
2007-2009	[4,8,3,25,18]	5522	41	5276
2007-2011	[4,8,3,25,18]	- 5683	81	- 6169

Table 8.2.6 Testing Period Results for USD/CAD (IN US PIP)

8.3 SUMMARY:

OVERALL BEST TRAINING RESULTS:

CURRENCY PAIR	TRAINING PERIOD	PROFIT (In pips)	TRANSACTI ON COUNT	PROFIT AFTER TRANSACTION COST (In pips)	OPTIMIZED TIME DURATIONS
AUD/USD	2001-2007	8818	156	7882	[8,14,10,13,5]
EUR/USD	2001-2007	36,922	539	33,688	[36,39,36,28,27]
GBP/USD	2001-2007	12,655	60	12,295	[2,4,3,47,2]
USD/CHF	2001-2007	11,221	184	10,117	[5,2,7,2,49]
USD/JPY	2001-2007	561	85	51	[2,7,4,2,2]
USD/CAD	2001-2007	- 1245	176	- 2301	[4,8,3,25,18]

Table 8.3.1 Overall Training Period Results

8.3.1 DAILY PROFIT/LOSS ASSOCIATED WITH AUD/USD OVER THE TRAINING PERIOD BETWEEN 2001-2007:

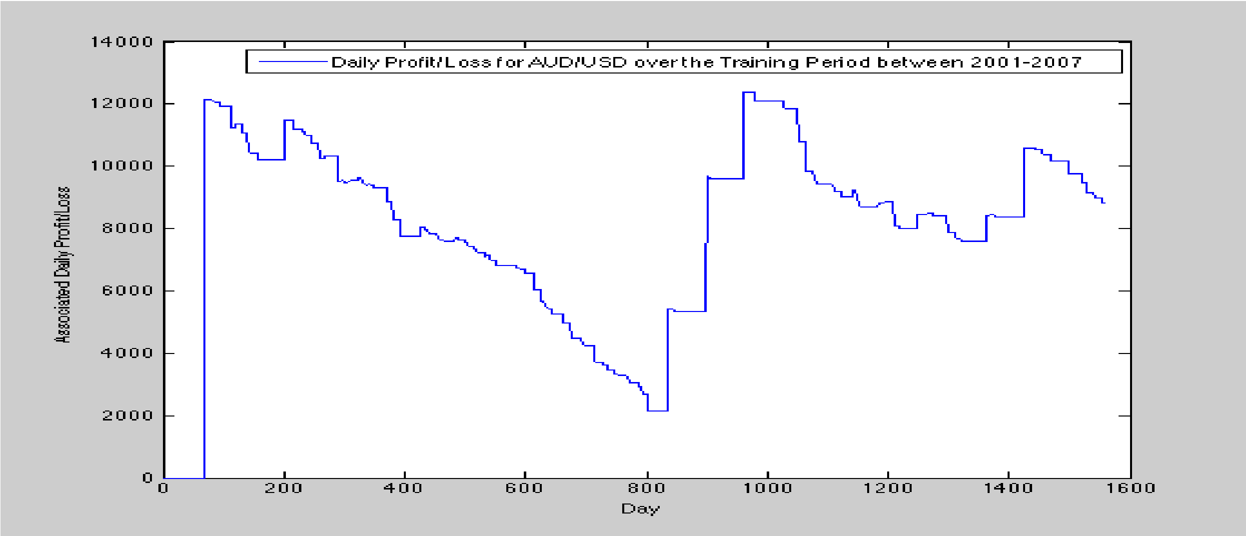


Fig 8.3.1 Daily Profit/Loss for AUD/USD over Training Period between 2001-2007

8.3.2 DAILY PROFIT/LOSS ASSOCIATED WITH EUR/USD OVER THE TRAINING PERIOD BETWEEN 2001-2007:

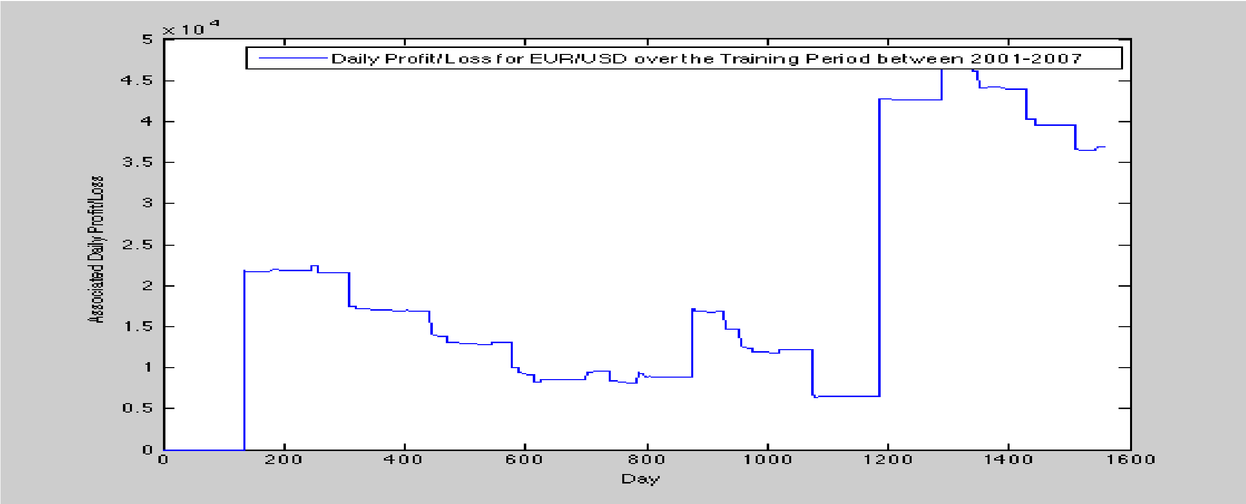


Fig 8.3.2 Daily Profit/Loss for EUR/USD over Training Period between 2001-2007

8.3.3 DAILY PROFIT/LOSS ASSOCIATED WITH GBP/USD OVER THE TRAINING PERIOD BETWEEN 2001-2007:

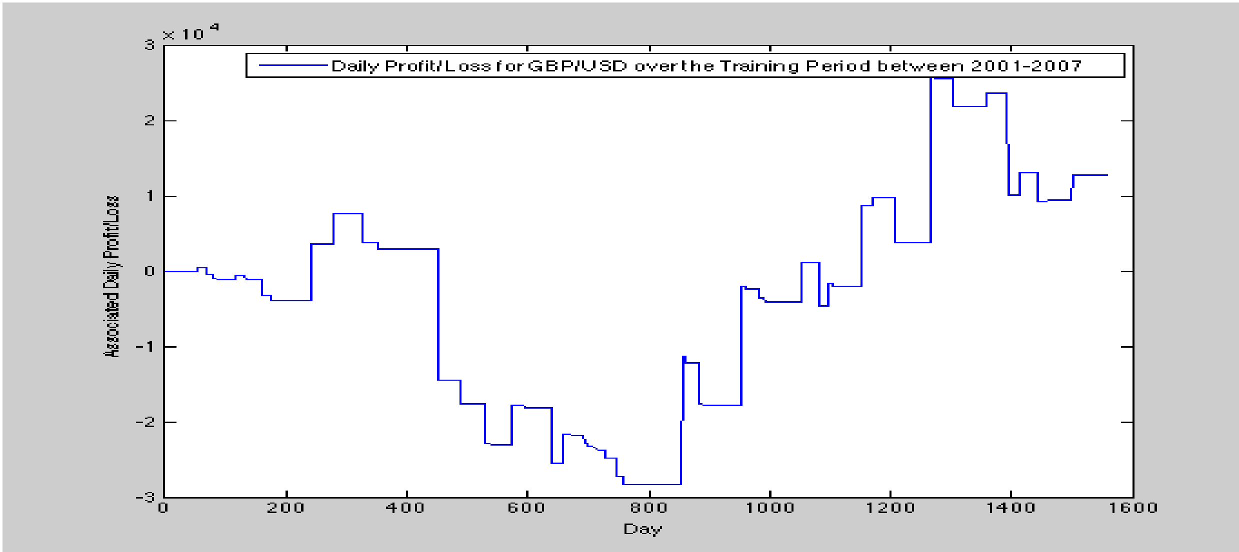


Fig 8.3.3 Daily Profit/Loss for GBP/USD over Training Period between 2001-2007

8.3.4 DAILY PROFIT/LOSS ASSOCIATED WITH USD/CHF OVER THE TRAINING PERIOD BETWEEN 2001-2007:

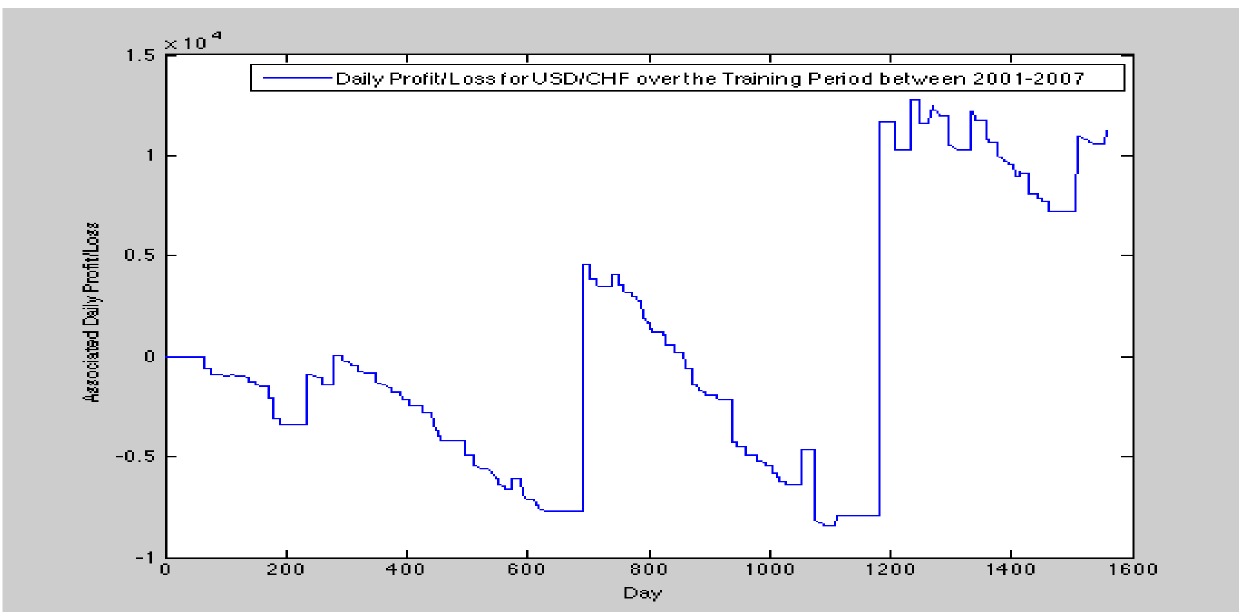


Fig 8.3.4 Daily Profit/Loss for USD/CHF over Training Period between 2001-2007

8.3.5 DAILY PROFIT/LOSS ASSOCIATED WITH USD/JPY OVER THE TRAINING PERIOD BETWEEN 2001-2007:

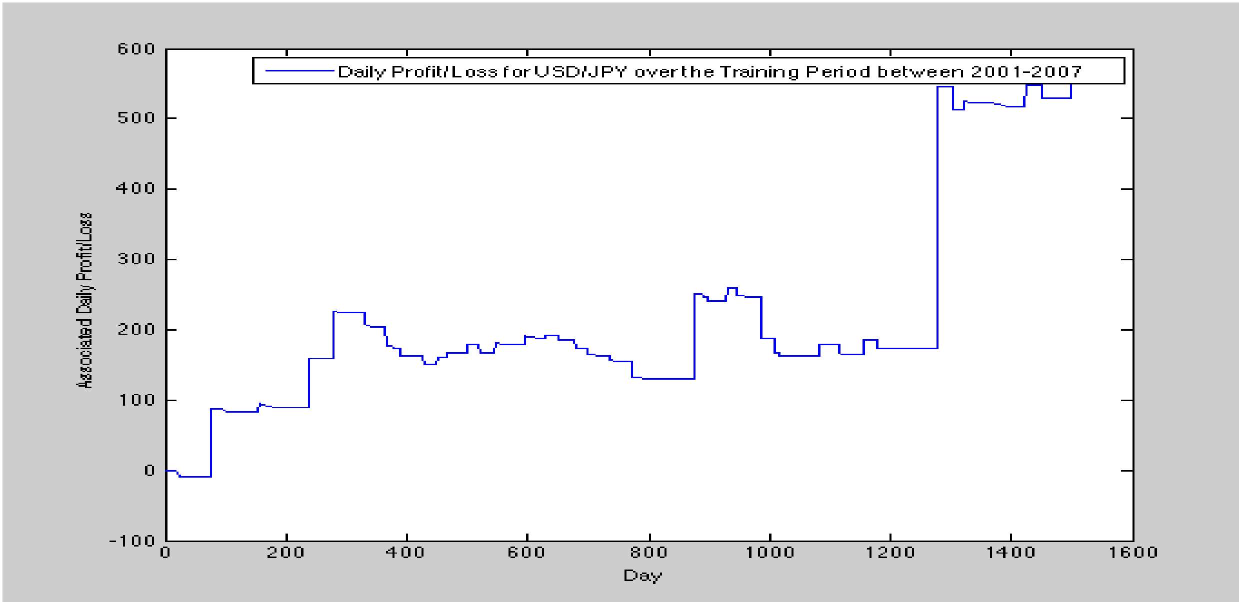


Fig 8.3.5 Daily Profit/Loss for USD/JPY over Training Period between 2001-2007

8.3.6 DAILY PROFIT/LOSS ASSOCIATED WITH USD/CAD OVER THE TRAINING PERIOD BETWEEN 2001-2007:

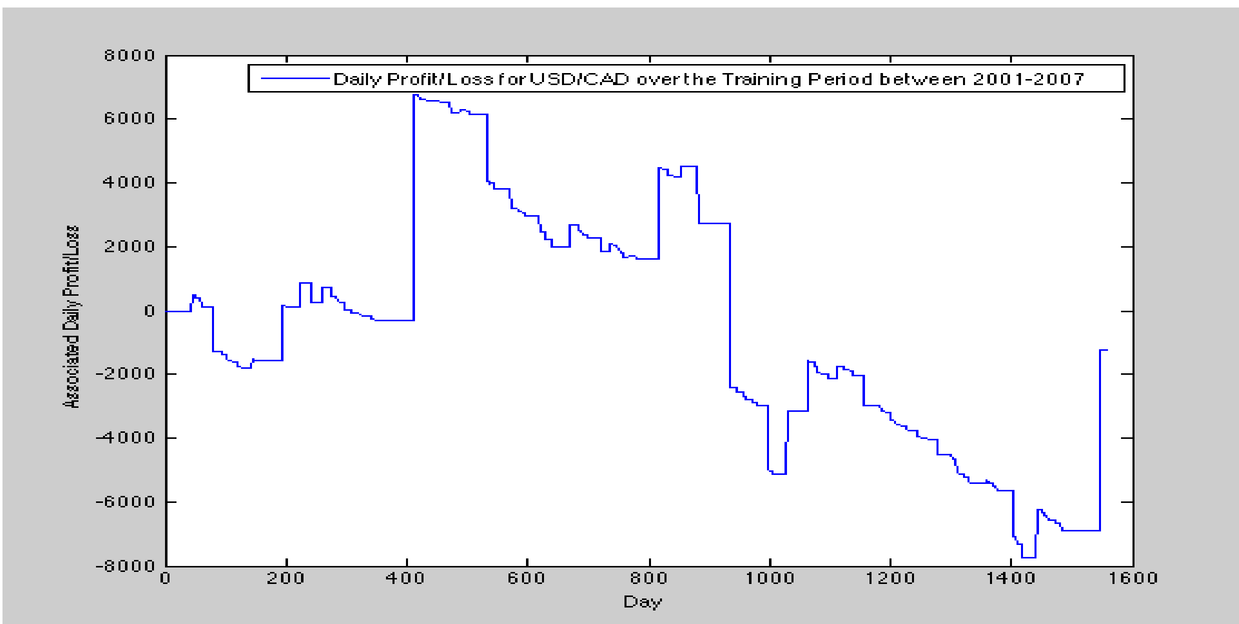


Fig 8.3.6 Daily Profit/Loss for USD/CAD over Training Period between 2001-2007

OVERALL TESTING RESULTS FOR THE PERIOD 2007-2008:

CURRECY PAIR	TESTING PERIOD	PROFIT (In pips)	TRANSACTION COUNT	PROFIT AFTER TRANSACTION COST (In pips)	OPTIMIZED TIME DURATIONS
AUD/USD	2007-2008	- 640	25	- 790	[8,14,10,13,5]
EUR/USD	2007-2008	- 11,319	34	- 11,523	[36,39,36,28,27]
GBP/USD	2007-2008	20,117	12	20,045	[2,4,3,47,2]
USD/CHF	2007-2008	- 3193	28	- 3361	[5,2,7,2,49]
USD/JPY	2007-2008	- 77	14	-161	[2,7,4,2,2]
USD/CAD	2007-2008	- 7519	20	- 7639	[4,8,3,25,18]

Table 8.3.2 Testing Results For Period 2007-2008

OVERALL TESTING RESULTS FOR THE PERIOD 2007-2009:

CURRECY PAIR	TESTING PERIOD	PROFIT (In pips)	TRANSACTION COUNT	PROFIT AFTER TRANSACTION COST (In pips)	OPTIMIZED TIME DURATIONS
AUD/USD	2007-2009	9922	56	9586	[8,14,10,13,5]
EUR/USD	2007-2009	57,166	52	56,854	[36,39,36,28,27]
GBP/USD	2007-2009	32,242	24	32,098	[2,4,3,47,2]
USD/CHF	2007-2009	- 825	57	- 1167	[5,2,7,2,49]

USD/JPY	2007-2009	- 299	35	-509	[2,7,4,2,2]
USD/CAD	2007-2009	5522	41	5276	[4,8,3,25,18]

Table 8.3.3 Testing Results For Period 2007-2009

OVERALL TESTING RESULTS FOR THE PERIOD 2007-2011:

CURRECY PAIR	TESTING PERIOD	PROFIT (In pips)	TRANSAC TION COUNT	PROFIT AFTER TRANSACTION COST (In pips)	OPTIMIZED TIME DURATIONS
AUD/USD	2007-2011	- 7259	109	-7915	[8,14,10,13,5]
EUR/USD	2007-2011	49,059	109	48,405	[36,39,36,28,27]
GBP/USD	2007-2011	67,472	49	67,178	[2,4,3,47,2]
USD/CHF	2007-2011	- 1821	115	-2511	[5,2,7,2,49]
USD/JPY	2007-2011	- 326	68	-734	[2,7,4,2,2]
USD/CAD	2007-2011	- 5683	81	- 6169	[4,8,3,25,18]

Table 8.3.4 Testing Results For Period 2007-2011

OVERALL BEST TESTING RESULTS:

CURRECY PAIR	TESTING PERIOD	PROFIT (In pips)	TRANSAC TION COUNT	PROFIT AFTER TRANSACTION COST (In pips)	OPTIMIZED TIME DURATIONS
AUD/USD	2007-2009	9922	56	9586	[8,14,10,13,5]
EUR/USD	2007-2009	57,166	52	56,854	[36,39,36,28,27]
GBP/USD	2007-2011	67,472	49	67,178	[2,4,3,47,2]
USD/CHF	2007-2009	- 825	57	- 1167	[5,2,7,2,49]
USD/JPY	2007-2008	- 77	14	-161	[2,7,4,2,2]
USD/CAD	2007-2009	5522	41	5276	[4,8,3,25,18]

Table 8.3.5 Overall Testing Period Best Results

8.3.7 DAILY PROFIT/LOSS ASSOCIATED WITH AUD/USD OVER THE TESTING PERIOD BETWEEN 2007-2009:

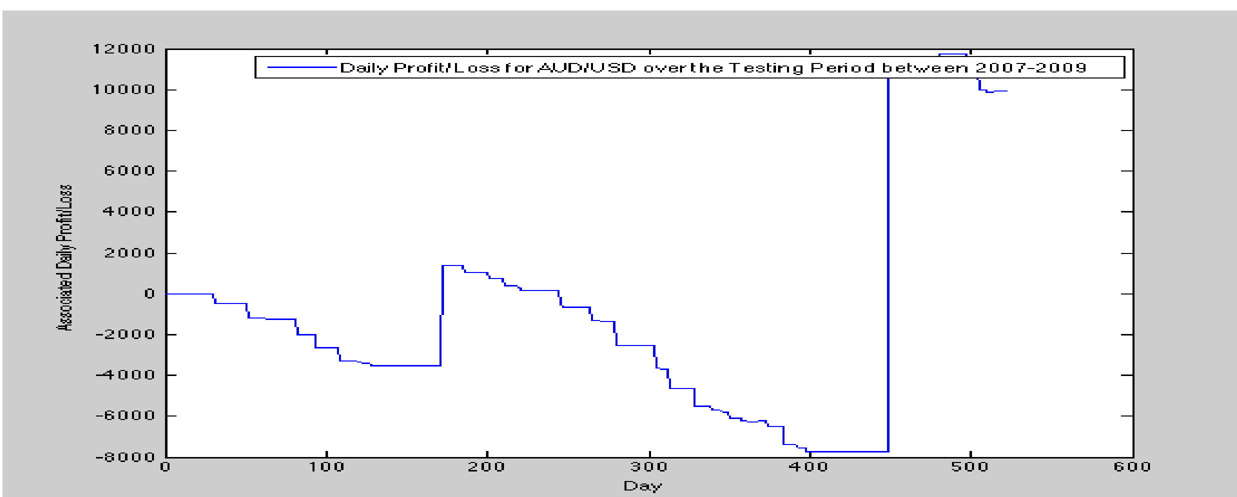


Fig 8.3.7 Daily Profit/Loss for AUD/USD over Testing Period between 2007-2009

8.3.8 DAILY PROFIT/LOSS ASSOCIATED WITH EUR/USD OVER THE TESTING PERIOD BETWEEN 2007-2009:

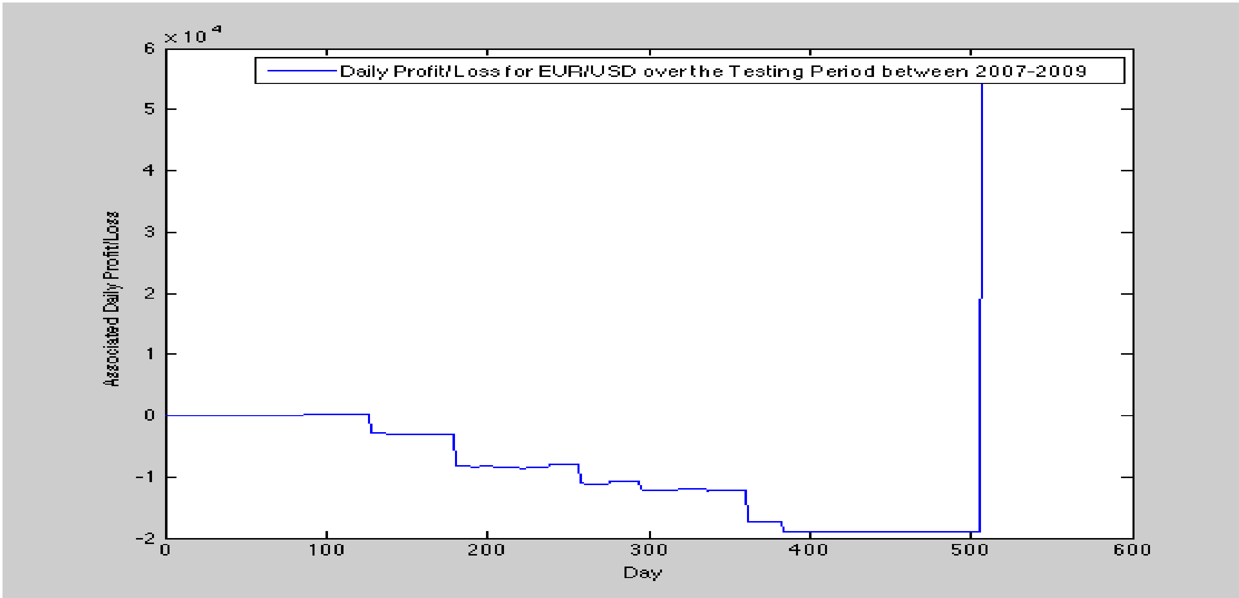


Fig 8.3.8 Daily Profit/Loss for EUR/USD over Testing Period between 2007-2009

8.3.9 DAILY PROFIT/LOSS ASSOCIATED WITH GBP/USD OVER THE TESTING PERIOD BETWEEN 2007-2011:

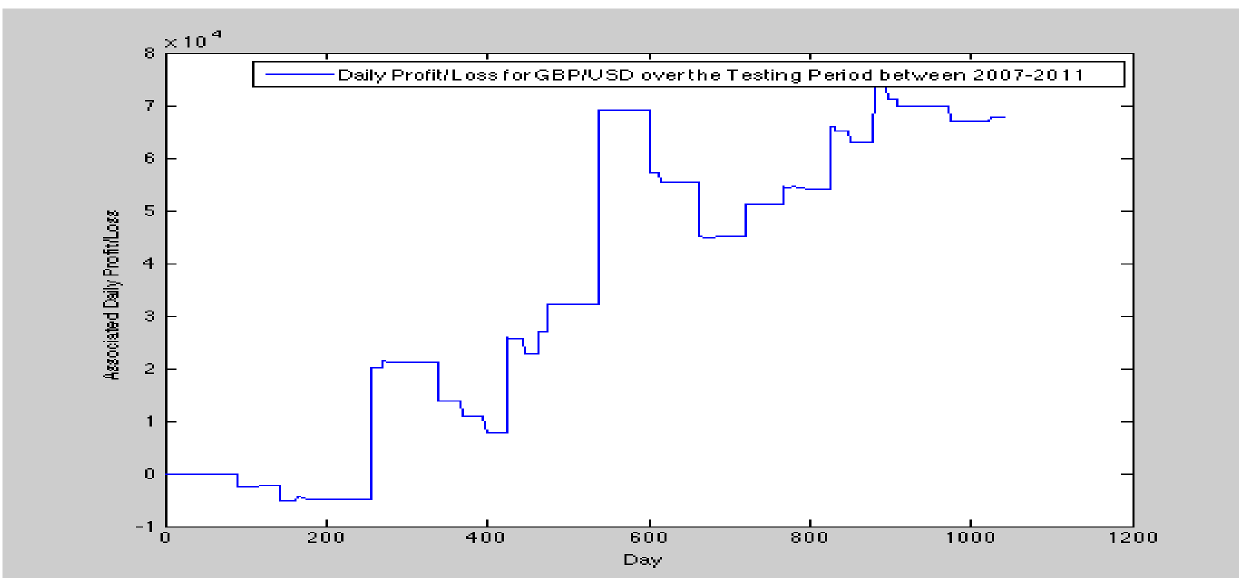


Fig 8.3.9 Daily Profit/Loss for GBP/USD over Testing Period between 2007-2011

8.3.10 DAILY PROFIT/LOSS ASSOCIATED WITH USD/CHF OVER THE TESTING PERIOD BETWEEN 2007-2009:

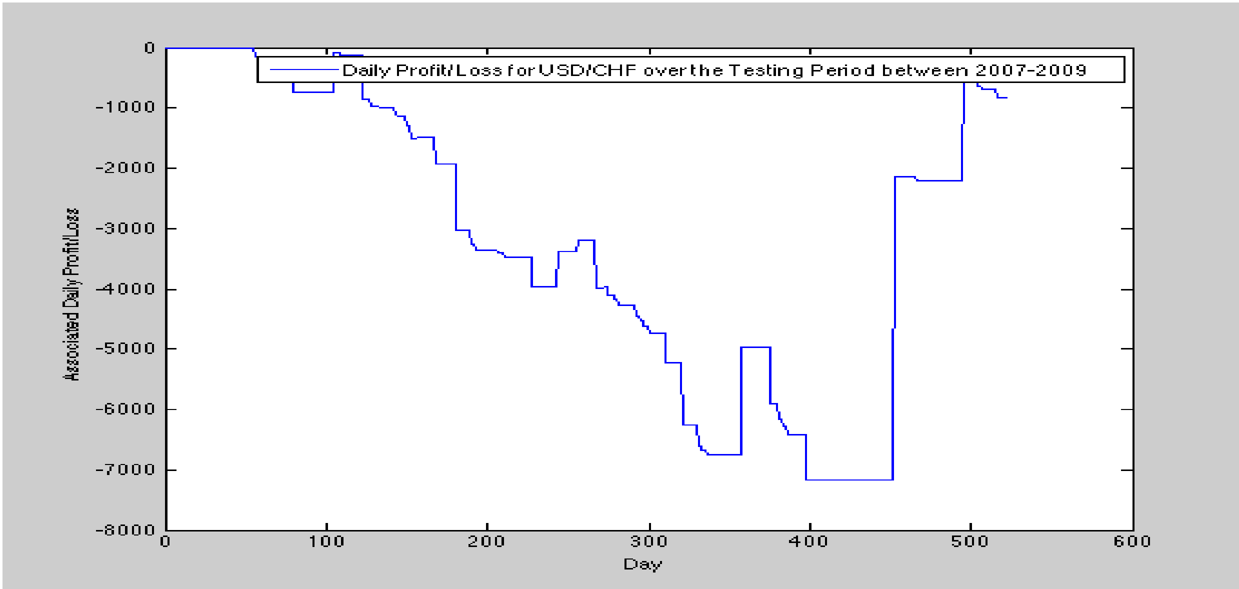


Fig 8.3.10 Daily Profit/Loss for USD/CHF over Testing Period between 2007-2009

8.3.11 DAILY PROFIT/LOSS ASSOCIATED WITH USD/JPY OVER THE TESTING PERIOD BETWEEN 2007-2008:

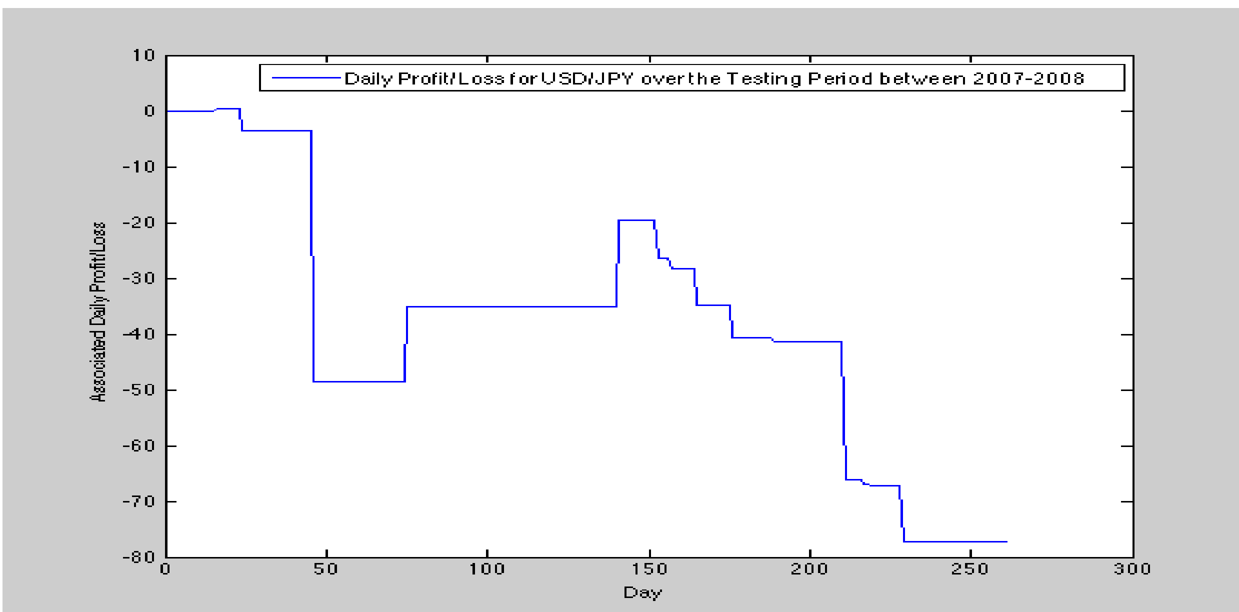


Fig 8.3.11 Daily Profit/Loss for USD/JPY over Testing Period between 2007-2008

8.3.12 DAILY PROFIT/LOSS ASSOCIATED WITH USD/CAD OVER THE TESTING PERIOD BETWEEN 2007-2009:

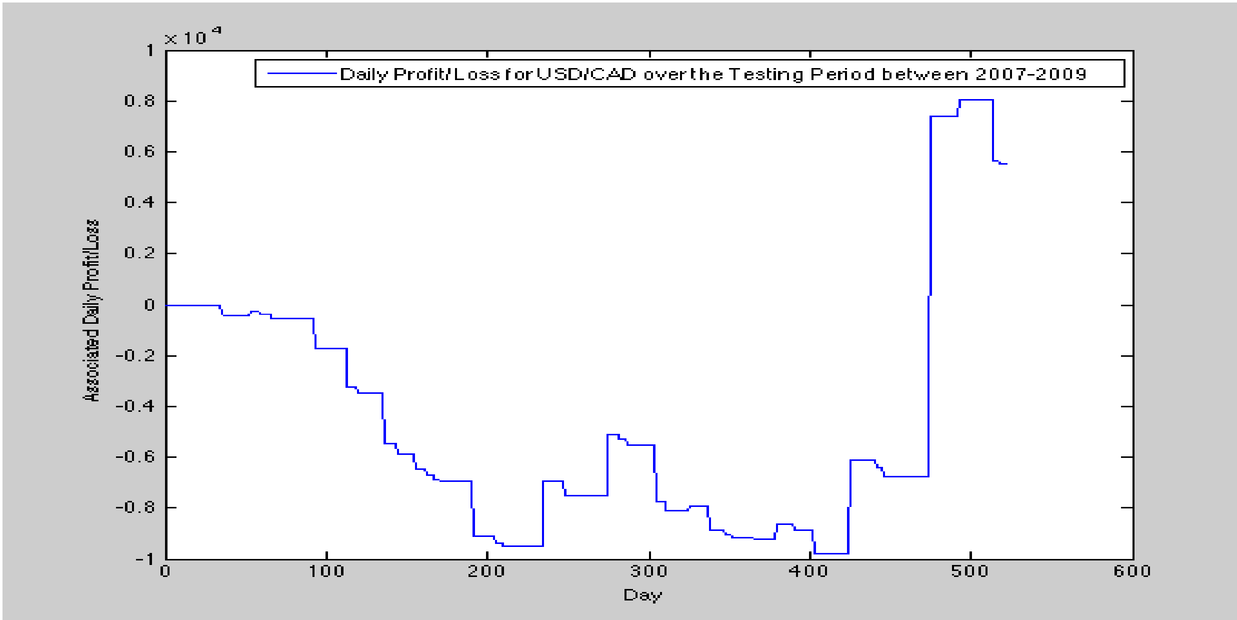


Fig 8.3.12 Daily Profit/Loss for USD/CAD over Testing Period between 2007-2009

The performance of the Particle Swarm Optimization was analyzed in conjunction with Technical Indicators by training the algorithm repeatedly over a volume of stochastic data corresponding to six years [2001-2007] and testing it over 3 different investment periods of unknown out-of-sample data corresponding to 4 years [2007-2011]. Experiments were performed for two different criteria, i.e. by varying the number of particles and the number of iterations of the PSO Algorithm with the goal of the fitness function generating a maximum profit or a minimized loss over an investment period.

The PSO Algorithm showed traits of possible understanding of the stochastic data when it was provided with some sort of memory of the historical stochastic data. This was achieved with a help of Technical indicators, which generated an analysis of the stochastic data sets over different periods of consideration between 1-50 days of the closing price data. Through this research study, we propose a novel trading model using Particle Swarm Optimization (PSO) and Technical Indicators for generating profitable trading scenarios, trained it extensively over a span of 6 years and tested it over 3 different investment periods ranging between 2007-2011. Transaction costs of 6 pips were included to simulate real time trading conditions. Over the training period we were able to generate profitable trading conditions for 5 out of the 6 currency pairs namely AUD/USD, EUR/USD, GBP/USD, USD/CHF, USD/JPY while USD/CAD was associated with a minimized loss (see table 8.3.1). And in the testing period we extrapolated the knowledge gained from the training period and were able to generate profitable conditions for 4 out the 6 currency pairs under consideration namely AUD/USD, EUR/USD, GBP/USD and surprisingly USD/CAD which resulted in loss in training period (see table 8.3.5). But USD/CHF and USD/JPY resulted in a loss over the testing period. With the help of this research study and its associated results, PSO can help in analyzing and comprehending the stochastic data if it can be provided with some sort of memory of the stochastic data sequences with which it can extrapolate the stochastic behavior. However the disadvantage is the lack of a strong mathematical explanation for inconsistencies in generation of optimized data.

CHAPTER 9: CONCLUSION & FUTURE WORK

Stochastic environment has always been a subject of a challenge for researchers to analyze and comprehend because of its sporadic nature. It has always been a constant struggle to validate its nature. Many numerical syntheses are being worked on in an attempt to define, analyze these environments so that the solution can be incorporated into several engineering problems. Through this research study, an attempt has been made to study the possibilities of using Particle Swarm Optimization (PSO) algorithm as a vehicle to understand and analyze one such stochastic environment i.e. Foreign Exchange Market or Forex Market. The PSO Algorithm was modified and its implementation was tested in the forex market, which is stochastic in nature.

The proposed PSO Strategy has shown a considerably successful performance in analyzing the known volume of data and extrapolating the knowledge gained to unknown volume of data in the stochastic test environment. This application of the PSO Algorithm to the test environment has shown positive traits of understanding the stochastic nature exhibited by the test environment i.e. forex market, upon providing some sort of memory related to the stochastic behavior, which was supplemented by the use of technical indicators. In general technical indicators are readily available mathematical expressions that can be applied to any data sets. Its functionality is streamlined irrespective of the applied environment. It would be interesting to observe and analyze the results obtained upon application of the PSO Algorithm along with Technical Indicators, in the actual optical domain to study and understand the stochastic parameters that are an integral part of non-deterministic phenomena such as spontaneous emission, phase noise, LASER speckle etc.

The existence of these stochastic processes on one hand severely affects the performance of the Photonic devices but on the other hand has its own applications. For e.g. speckle noise in LASER is used for analyzing the properties of the surface it is shined upon. The research model proposed through this research has shown a positive sign in picking up the hints left by the stochastic processes and the obtained results from this model has shown that it can lead to better understanding the existence of these processes and minimize it. While the obtained results have also shown that this model can also be used towards improving the performance of these processes, which can contribute towards refining and expanding its photonic applications. Also there is a popular belief that stochastic processes are memory less noises. This research study has also contributed towards establishing a considerable connection between the PSO Algorithm and stochastic test-bed environment i.e. forex market complimented by the use of technical indicators in a novel way. The application of the proposed model to the actual stochastic processes in photonics would be a significant and remarkable future work.

Additionally from this research study, we were able to propose a successful trading technique using the PSO Algorithm in the forex market. The obtained results can be further enhanced by bringing in economical and political factors such as GDP Growth, Consumer Price Index (CPI), Price Point Parity (PPP), Export and Import Volume etc. The effective use of these parameters in the PSO Algorithm can further improve the results and can lay a solid foundation in understanding the statistical relationship between the forex market and stochastic phenomena exhibited in optics. Further more the algorithm needs to be modified in order to extend its capabilities for analyzing a very high frequency data such as hourly or minute data. Also an additional work is required for modifying the proposed PSO Algorithm in order for it to be effectively used for prediction. The above-mentioned points would serve as a fitting effort for the future work.

REFERENCES:

1. Angeline, P. J. Evolutionary optimization versus particle swarm optimization: philosophy and performance differences *Evolutionary Programming VII: Proceedings of the Seventh Annual Conference on Evolutionary Programming* 1998a.

2. Angeline, P. J. Using selection to improve particle swarm optimization: *Proceedings of IEEE Congress on Evolutionary Computation 1998,* Anchorage, Alaska, USA, 1998b.

3. Eberhart, R. C. and Kennedy, J. A new optimizer using particle swarm theory. *Proceedings of the Sixth International Symposium on Micromachine and Human Science.* pp. 39-43. IEEE service center, Piscataway, NJ, Nagoya, Japan, 1995.

4. Eberhart, R. C. and Shi, Y. Particle swarm optimization: developments, applications and resources. *Proceedings of IEEE Congress on Evolutionary Computation 2001.* IEEE service center, Piscataway, NJ, Seoul, Korea., 2001a.

5. Eberhart, R. C. and Kennedy, J. Particle Swarm Optimization. *Proceedings of IEEE Congress on Neural Networks (Perth, Australia) 1995.* Vol. IV, pp. 1942-1948 IEEE service center, Piscataway, NJ.

6. Eberhart, R. C. and Shi, Y and Hu, X. Recent Advances in Particle Swarm. *Proceedings of IEEE Congress on Evolutionary Computation*

2004. IEEE service center, Portland, Oregon, USA.

7. Poli, R. An Analysis of Publications on Particle Swarm Optimization Applications. *Journal Of Artificial Evolution and Applications* 2008. Vol 2008. Article ID 685175. New York, USA.

8. Shi, Y. and Eberhart, R. C. A modified particle swarm optimizer. *Proceedings of IEEE Congress on Evolutionary Computation 1998.* pp. 69-73. IEEE press, Piscataway, NJ.

9. http://en.wikipedia.org/wiki/Emotional_intelligence

10.http://skyview.vansd.org/lschmidt/Projects/TheNineTypesofIntelligence.html

11. http://www.personalityresearch.org/papers/skottke.html

12. http://paper.ijcsns.org/07_book/200610/200610B03.pdf

13. http://rstb.royalsocietypublishing.org/content/361/1465/5.full

14. http://www.nobrainertrades.com/wp-content/uploads/2012/01/Foreign%20Exchange%20Market%20Dynamics,%20Participants%20and%20Transaction%20Methods.pdf

15. Roger D. Huang and Ronald W. Masulis. FX spreads and Dealer Competition across the 24 hour trading day. *Proceedings of first Annual Conference on High Frequency Data. March 30 1998.* Oslo, Norway.

16. http://www.winning-stock-trading-fundamentals.com/PDF/forex-terminology.pdf

17. Ramazan Gencay. Optimization of technical trading strategies and the profitability in security markets. *University of Windsor, Department of Economics,* December 19 1997, Windsor, ON Canada

18. Lo, A.W., Mackinlay, A.C., 2002. A Non-Random Walk Down Wall Street (5th ed.). *Princeton University Press*. pp. 4–47. ISBN 0691092567

19. J. Welles Wilder Jr., New Concepts in Technical Trading Systems 1978, pp. 89. *Dickinson School Law*, Greensboro, N.C.

20. Lo, A.W., Mackinlay, A.C., A Non-Random Walk Down Wall Street (5th ed.). *Princeton University Press*. 2002. pp. 4–47. ISBN 0691092567

21. Eugene Fama, Efficient Capital Markets: A Review of Theory and Empirical Work. *Journal of Finance*. 1970. 25:2, p.p. 383-417.

22. Jae H. Kim, Kian-Ping Lim, Abul Shamsuddin, Stock Return predictability and Adaptive Market Hypothesis: Evidence from

century-long US Data. *School of Economics and Finance*. 2009 . La Trobe University, Victoria, Australia

23. Christopher J. Neely, Paul A.Weller, Joshua M.Ulrich. The Adaptive Markets Hypothesis: Evidence from the Foreign Exchange Market. *Research Division, Federal Reserve Bank of St.Louis*. Working paper 2006-046B. August 2006. St.Louis, MO.

24. J. Kennedy, R. C. Eberhart and Y. Shi, *Swarm Intelligence*. The Morgan Kaufmann Publishers, 2001, pp. 419, pp.94, pp.96.

25. Shi, Y., Eberhart, R.C., Empirical Study of Particle Swarm Optimization, Evolutionary Computation, 1999. CEC 99. *Proceedings of the 1999 Congress on Evolutionary Computation*, vol.3, no., pp.-1950 Vol.3,1999

26. M. Clerc. 2002, The particle swarm- explosion, stability and convergence in a multidimensional complex space. *IEEE Transactions on Evolutionary Computation*, 6 (1), pp. 58-73

27. W. Brock, J. Lakonishok, and B. LeBaron. Simple technical trading rules and the stochastic properties of stock returns. *Journal of Finance*, pages 1731–1764, 1992.

28. J.W. Wilder. *New concepts in technical trading systems*. Trend Research Greensboro, North Carolina, 1978.

29. Christopher J. Neely, Paul A.Weller. Intraday Technical Trading in the Foreign Exchange Market. *Research Division, Federal Reserve Bank of St.Louis*. Working paper 1999-016B. January 2001. St.Louis, MO.

30. Blake LeBaron. Technical Trading Rule Profitability and Foreign Exchange Intervention. *Graduate School of International Economics and Finance, Brandeis University.* Waltham, MA. July 1994

31. Cialenco, I., Protopapadakis, A., Do Technical Trading Profits remain in Foreign Exchange Market – Evidence from 1 currencies. *Illinois Institute of Technology, Department of Applied Mathematics.* Chicago, IL. August 2006.

32. P.H. Hsu and C.M. Kuan. Reexamining the profitability of technical analysis with data snooping checks. *Journal of Financial Econometrics*, 3(4):606–628, 2005.

33. M.J. Pring. *Technical analysis explained: The successful investor's guide to spotting investment trends and turning points.* McGraw-Hill. 1991.

34. F. Allen and R. Karjalainen. Using genetic algorithms to find technical trading rules. *Journal of Financial Economics*, 51:245–271. 1999.

35. H. Subramanian, S. Ramamoorthy, P. Stone, and B.J. Kuipers. Designing safe, profitable automated stock trading agents using evolutionary algorithms. *In Proceedings of the 8th annual conference on Genetic and evolutionary computation*, pages 1777–1784. ACM, 2006.

36. J. Lee, S. Lee, S. Chang, and B.H. Ahn. A comparison of ga and pso for excess return evaluation in stock markets. *Artificial Intelligence and Knowledge Engineering Applications: A Bioinspired Approach*, pages 45–55, 2005.

37. Knok N.M., Moving Average-Based Stock Trading Rules from Particle Swarm Optimization. *International Conference on Artificial Intelligence and Computational Intelligence,* 2009, AICI ‘09. Pages 149-153. November 2009.

38. A.C. Briza and P.C. Naval Jr. Stock trading system based on the multi-objective particle swarm optimization of technical indicators on end-of-day market data. *Applied Soft Computing*, 11(1):1191–1201, 2011.

39.http://www.investopedia.com/articles/technical/061801.asp#axzz2Kosi1AIU

40. Turing, Alan. 1950. Computing Machinery and Intelligence. *Mind 49*, 433 – 460.

41. B. Edmonds. The Social Embedding of Intelligence. *Centre for Policy Modeling, Manchester Metropolitan University.*

42. E.O. Wilson, On Flander’s Hypothesis of Caste Determination in Ants. *Biological Laboratories. Harvard University.* 1953.

43. Turner S.J , Termites as models of swarm intelligence. *Springer Publications,* ISSN 1935-3812, Volume 5, Number 1.

44. C. M. Breder, Equations ascriptive of fish school and other animal aggregations. *Ecology* 35, 361-370

45. Reynolds C.W, Flocks, Herds and Schools: A Distributed Behavioral Model. *ACM SIGGRAPH'87 Conference Proceedings on Computer Graphics.* Anaheim, California. July 1987.

46. FXHistory – Historical currency exchange rates [online]

47. G. Keiser, "Optical sources," in *Optical Fiber Communications*, 3rd edition. McGraw-Hills International Editions, Electrical Engineering Series, 2000, pp.141-199.

48. J. Bravo-Abad. (2007, Modeling nonlinear optical phenomena in nanophotonics. *Lightwave Technology, Journal of 25(9)*, pp.2539-2546.

49. R.W. Boyd, *Nonlinear Optics*. San Deigo, CA: Academic, 1992.

50. P.D Drummond and J.F Corney. (2001, Quantum noise in optical fibers. I. stochastic equations. *Optical Society of America* 18(2)), pp. 139-152

51. Hector J. Rabal, Roberto A. Braga Jr, Dynamic Laser Speckle and Applications. CRC Press, November 2008.

52. M.Jiang, Y.P.Luo and S.Y.Yang (2007), Particle Swarm Optimization-Stochastic Trajectory Analysis and Paramter Selection, Swarm Intelligence, *Focus on Ant and Particle Swarm Optimization*, Felix T.S.Chan and Manoj Kumar Tiwari (Ed.)

53. Hime Aguire e Olivera Junior, Lester Ingber, Antonio Petraglia, Mariane Rembold Petraglia, Maria Augusta Soares Machado, *Stochastic Global Optimzation and Its Applications with Fuzzy Adaptive Simuated Annealing,* pp. 25, 2012

54 Nayak S.C, Misra B.B, Behera H.S, Cooperative Optimization for efficient financial time series forecasting: *IEEE International Conference on Computing For Sustainable Global Development*, pp 14-129, March 2014

55. Yin, Peng Yang, *Modelling, Analysis and Applications in Metahueristic Computing: Advancements & Trends*, pp 122, IGI Global, 2012

56. Jui-Fang Chang, Pei-Yu Hsieh, *International Journal Of Innovative Computing,* Particle Swarm Optimization using Back Propagation Network Forecasting Exchange Rates, pp 6837-6847, August 2010

57. Yuehui Chen, Lizhi Peng, Ajith Abraham, *Exchange Rate Forecasting using Flexible Neural Trees*, School of Information Science and Engineering, Jinan University, China

58. Bingxiang Liu, Hua Wang, Xiang Cheng, Exchange Rate Forecasting Method Based on Particle Swarm Optimization and Probablistic Neural Network Model, pp 288-292, 2011