Multi Agent System for Forex Trading

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***Abstract*— Foreign exchange market (Forex) is a global marketplace which trades in currencies. This market is more distributed, decentralized, disturbed, and disorganized over the servers on the Internet than the stock market. Due to its very nature, individual investors or experienced traders find it difficult to access, collect, filter, and analyze information to draw meaningful decisions on Forex. Many existing Forex trading solutions use only one of quantitative facts or qualitative facts to reduce the complexity in data analysis. Having evident the potential of Multi Agent Systems (MAS) technology to model complex systems, we have come up with a MAS solution, ForexMA, which builds the mutual influence of quantitative and qualitative facts into decision making. ForexMA is designed with multiple Agents which access, collect, filter, and analyze the qualitative and quantitative information from multiple sources. ForexMA has been tested against its predictions and actual known results and found that performance of ForexMA is above the performance of decision made by human expert traders. More importantly, ForexMA can work on high frequency time frames and generate solutions in few seconds, whereas human expert traders work on low frequency timeframe and take few hours to generate a solution.**

Keywords—Stock Market, Forex Trading, Artificial Intelligence, Multi Agent Systems

I. INTRODUCTION

Forex is the global Foreign Exchange Market where trading is done in currencies of different countries with 5.1 trillion US dollars turnover daily [1]. It is the largest and most liquid asset market in the world. Forex assets are influenced by many factors including news of global political and economic situations, and traders' patterns of price fluctuations. In this sense, any successful trader must access the above information and do an analysis to make an effective decision. However, this analysis is a tedious task due to the inherent complexity of the Forex environment, where the information is distributed, decentralized, disturbed, distorted, and does not provide equal access to all traders. It should be noted that trading in the Forex environment is more complex than Stock Market trading where the trading assets are shares of companies which may not be diversely influenced by other forces [2], [3]. Apart from level of complexity, dynamics of both Forex and Stock Markets suffer from accessibility to the relevant information and analysis of such information.

In view of that numerous researches have been conducted to offer computer-based solutions for Forex trading and Stock Market trading. However, most of these solutions use statistical techniques and computer-based information systems technologies such as MIS. In the recent past, Artificial Intelligence techniques have also been used to model trading in markets. Among others, Multi Agent Systems (MAS) Technology has shown promising results in modelling complex systems such as Forex environments. Next, we discuss selected MAS solutions for trading in Forex and Stock trading.

Davis, Lou and Liu [4] have developed a framework for Multi Agent Systems for stock trading. This solution has been built with agents for gathering and integrating information from diverse sources and enabling decision making. Multi Agent for Forex Trading has been developed by Rui Pedro Barbosa and Orlando Belo [5] and defined six agents to work on six different assets. In general, higher the number of agents in the MAS better the performance. Vivien Delage and Christian Brandlhuber [6] have developed a MAS for understanding the behavior of Forex Market. This research has offered a facility for simulating the Forex market, which allows do experiments Forex trading experiments under different conditions. Xiaorong Chen and Shozo Tokinaga [7] have also developed a Multi Agent based artificial stock market to understand stock market behaviors. Their findings indicate consideration of multiple facts with price changes in assets in the Forex Stock Market.

MAS solution by R. Barbosa and O. Belo [8] automates the analysis of candle patterns, which is a tedious task. Here the candles are data stand for quantitative facts in forex market, and their analysis is an expert task.

Abdullah, Rahaman, and Rahman [9] developed a MAS solution for modelling stock market predictions based on qualitative data. Natural Language processing [10] techniques in Artificial Intelligence have also been used to analyze qualitative news data in social media.

Lee [11] has developed a Forex Advisor hybrid system with MAS and radial basis-function recurrent network (HRBFN). Being a hybrid system, this solution enables the analysis of both qualitative and quantitative facts in the Forex trading. Smart Agent solution which was developed by Alrefaie, Hamouda, and Ramadan [12] used Neuro-Fuzzy Inference, Genetic Programing with Agent technology for their Forex solution.

By Considering the above facts, the power of MAS technology is undisputed to model Forex and Stock trading markets. More importantly, MAS as an AI technology can bring other technologies such as Artificial Neural Networks, Genetic Algorithms, Fuzzy Logic, Natural Language Processing together for empowering Agent's capacity to reach smart solutions. However, due to inherent complex nature of the Forex trading, predicting Forex market dynamics with a higher level of accuracy remains as a research challenge.

As such, this paper presents our research in developing a MAS solution for Forex trading. This approach is different from other solutions as we define Agents to work with qualitative and quantitative data as two distinct sources of information, and agents operating on two different sources deliberate to achieve the final conclusions. As such, we build mutual influence of qualitative and quantitative into our MAS solution. Note that many Forex/Stock solutions have used Artificial Intelligence techniques to model only one qualitative (news) or quantitative (price information) aspects of Forex/Stock trading.

The rest of the paper is organized as follows. Section 2 presents the design of MAS solution, ForexMA. Section 3 is on implementation of ForexMA. Section 4 describes the evaluation of ForexMA. Finally, Section 5 concludes the research with a note on further work.

II. MAS SOLUTION FOR FOREX TRADING – FOREXMA

In general, depending on how we define agents and their interaction, a MAS solution for a given problem can be modelled in multiple ways. This is analogous to why two different traders could give different recommendations based on the same source of information. Strictly speaking, ForexMA is designed to mimic to the role of an expert trader in the Forex trading.

interaction among sources through the MAS technology. It should be noted that MAS technology offers facility for incorporating new sources of information, increasing/decreasing the number of active agents when needs arise. Therefore, MAS solutions can be developed as evolvable software.

A. Architecture of ForexMA

Top level architecture of ForexMA is given in Figure 1. Note that Quantitative facts and Qualitative facts are the inputs for the solution and decided action would be the decision generated by the MAS. The MAS comprises three agents, namely, Facts Analyzing Agent, Decision Agent, and Performance Analyzing Agent.

Given two kinds of facts, when Facts Analyzing Agents (FA) finds patterns in the facts, then the patterns are passed to the Decision Agent (DA). Consequently, DAs generate possible decisions with their risk levels. Having deliberated on the possible decisions, an action is passed to what we called Forex trading system, which is the interface for brokers or traders to interact with the solution.

Note that, at once a decision generated by the MAS may not be acceptable to a trader, which results in sending a feedback to Performance Analyzing Agent (PA). Up on the feedback, PA, FA and DA deliberate again and generate a new decision. This shows an amazing feature of MAS technology where a small change in one Agent

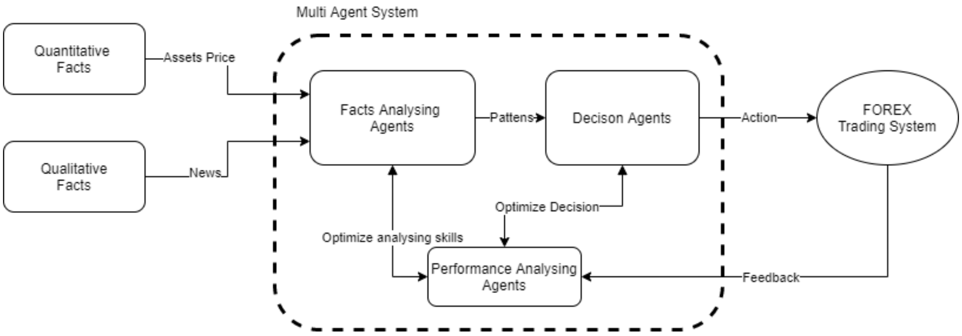

Fig. 6 High Level Architectural Design of proposed Multi Agent System

For ForexMA, we recognize two kinds of facts in Forex trading as Qualitative facts and Quantitative facts, which determine influence from news related information and trading patterns to decision making. Note that sources such as news, opinions, and discussions are treated as qualitative facts. On the other hand, Forex market assets price levels are considered under quantitative facts, which appear as numeric values. More importantly, we implement the mutual influence between qualitative and quantitative facts, without disregarding effect of change in one kind of facts on the other kind of facts.

To deal with qualitative facts and quantitative facts, we have developed several software agents as discussed below. Note that in the backend, these agents may use various statistical techniques and AI techniques such as Artificial Neural Networks to collect, analyze and interpret the information of the Forex market. A discussion on these back-end technologies are beyond the scope of this paper, instead we are interested in modeling

could lead to emergence of a new solution. More importantly, mutual influence of qualitative and quantitative aspects of the Forex environment could make a significant change in the decision. Just like in a group discussion by humans, in MAS, better solutions are generated in subsequent cycles of deliberations. Let us discuss roles of FA, DA, and FA separately.

B. Facts Analyzing Agents

Three types of agents, namely, quantitative pattern analyzing agent, qualitative pattern analyzing agent, pattern analyzing coordinator agent have been developed to implement FA. These agents and their interactions are shown in Figure 2.

Figure 2 shows quantitative pattern agent and qualitative pattern agent receiving two types of facts and identification of quantitative and qualitative patterns. These patterns are sent to pattern analyzing agents to determine the pattern and to release the selected pattern. Note that two types of patterns should be analyzed separately and then need to identify the false patterns by creating a discussion between both agents. If both agents give the same suggestion, there is no further discussion but if they are different the Pattern Analyzing Coordinator Agent must participate in deliberation. Those quantitative pattern analyzing agents and qualitative pattern analyzing agents are designed to use Artificial Neural Networks to achieve their pattern analyzing power.

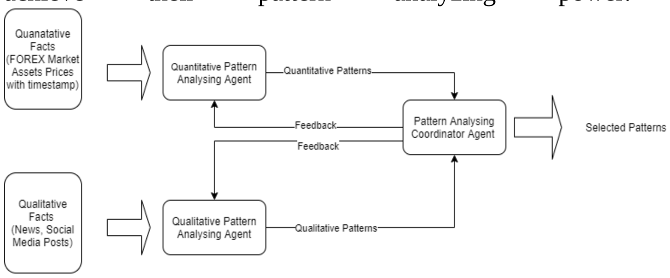

Fig. 7 Types of Facts Analyzing Agent

C. Decision Agent & Performance Analyzing Agent

Since DA and PA cannot operate independently, they are discussed together. To perform a trade in the Forex trading environment, the trading-instructions must be provided. In our system DA provides the necessary trading-instructions. Based on these instructions, DA deliberates with PA to generate Actions relevant to the pattern.

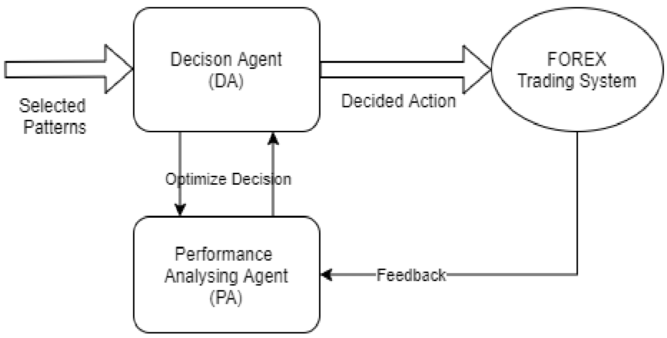

Fig. 3 Interaction between DA and PA

When DA receives patterns from FA, DA generates a decision by analyzing the patterns. Then it sends the decision to PA to get confidence value based on similar decisions in the past. After receiving the confidence from PA, DA evaluates its decision based on confidence value. If the DA is satisfied with the decision it generates an action (trading-instruction) and sends it to the Forex trading system. If it is not satisfied with the decision it rejects the decision and waits for the next pattern. If it is partially satisfied with the decision it restarts the analyzing process to optimize the decision.

The optimization of a decision is done by generating another decision based on the same pattern set. Then DA & PA perform the same analysis process explained earlier. This iterative optimization process leads to generating more accurate decisions.

III. THE IMPLEMENTATION OF THE FOREXMA

This section briefly describes the implementation of the design of MAS solution stated above. ForexMA has been implemented as a MAS solution on python and Redis based agent platform. Redis creates a pub-sub channel for ForexMA agents to have a Real Time distributed message passing system. Because of that agents can be run in different locations based on their requirements of hardware. Like Qualitative FA need GPU support.

A. Implementation of Agents

ForexMA is designed to achieve its end goal by performing three types of agents and those agents are specialized for different types of tasks. However, implementing these agents are not different from each other's core features. Figure 4 is showing the way of implementation of Agent in ForexMA.

The implementation of Agent mainly focuses on improving the communication power of each agent according to their tasks in the designed section. Therefore, each agent has their own communication channel, for example, DA has its own communication channel which is named as Decision-Agent. Once that channel receives a message from another agent Message Receiver start call message driven methods. After that agent can perform any action based on that message.

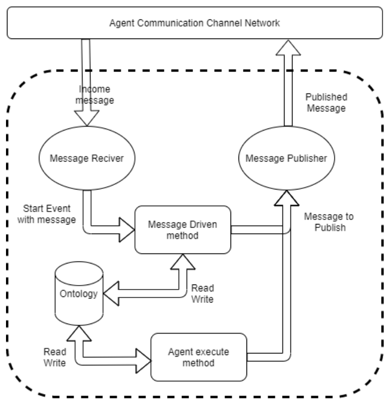

Fig. 8 General Implementation of Agents

Sometimes agents need to perform tasks at the beginning of the agent start to work. For that purpose, there is a method called execute to such a task.

Here is an example of agent skeleton code.

```
class QualitativeAnalyticalAgent:
 name = "QualitativeAnalyticalAgent"

   # Execute with start of agent
        async def start(self):
                   pass
    #Execute on start of agent
    async def accept_message(self,
         agent, message):
                   pass
   #Execute before stop of agent
      async def stop(self, *args,
            **kwargs):
                   pass
   #Execute after start function
    async def execute(self, *args,
            **kwargs):
```

```
await self.publish("AgentTwo",
        {
    "message": "Qualitative
Analytical Agent Found a Pattern"
        })
```

B. Implementation of FA

The design of the ForexMA supports two types of data such as qualitative facts and quantitative facts. To achieve that goal, We need to implement two types of agents such as Qualitative Facts Analyzing Agent and Quantitative Facts Analyzing Agent. Both agents are work same but two different kinds of data types consider as the inputs. Quantitative FA uses a rule based Expert System to identify the price action patterns from received price data. In contrast, Qualitative FA uses Artificial Neural Network to perform the analyzing the sentimental value of given qualitative facts such as news, social media posts. Figure 5 shows implementation of FA. Accordingly, FA use message driven execution method to perform facts analysis.

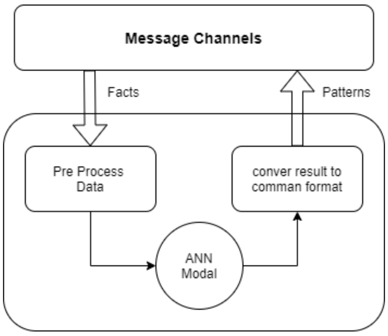

Fig. 9 FA implementation

C. Implementation of DA

After the patterns received from Fact Analyzing Agent, DA need to inference those patterns. Because of that, the implementation of DA needs to integrate with Rule Based Expert System (ES). To the implementation of ES should have to use an external python library which is called 'Experta'. Figure 6 shows the implementation of the DA.

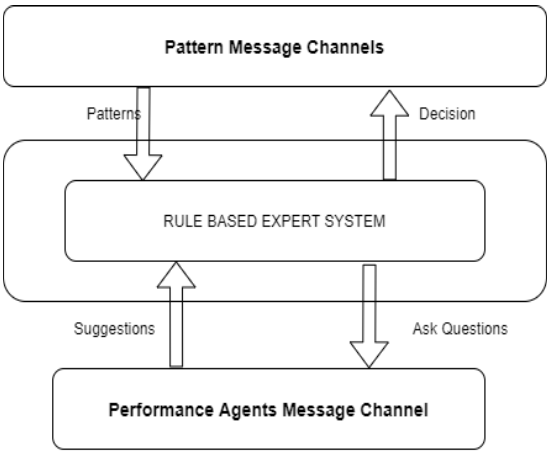

Fig. 10 Implementation for decision agent

According to Figure 6, DA's message channel is getting messages from both PA and FA. The flow of the status is managed by DA's ontology which is implemented using SQLight.

D. Implementation of PA

PA plays a key role in our MAS solution by receiving feedback from Forex Trading System and using that feedback, PA keeps a record about all other agent's performance based on their actions against the received feedbacks trading instructions. For analyzing and optimization purposes, PA has been implemented as an expert system. Also, that implementation support communicating with DA for having a performance analysis of DA's decisions.

E. Implementation of agent's communication

Each Agent has its own communication channel. The implementation of the channel communication, we used the subscriber design pattern. Figure 7 shows the implementation of DA's message channel, which is the same for all other agents.

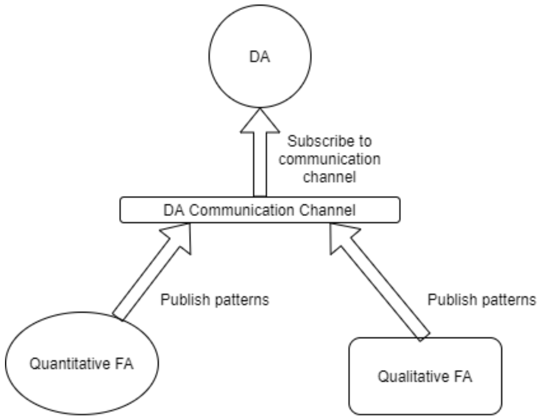

Fig. 11 Implementation of Agents communication Channel

According to Figure 7, DA has its own message channel which is called DA Communication Channel. DA subscribes to that channel and any other agents can publish messages to that channel using the following line of python code.

```
self.publish("DecisionAgent", {"data":
        {} })
```

Once a message is arrived at the DA's Message Channel, the following method is called by the agent platform.

```
async def accept_message(self, agent,
        message):
            ...
```

Parameters of these methods, agent stands for sender Agent's Name and message brings the sender's data to the receiving agents. Using those two details Agents can perform its tasks.

F. Agents Message passing flow

According to the implementation of message channels, each agent has its own message passing channel as shown in Figure 8.

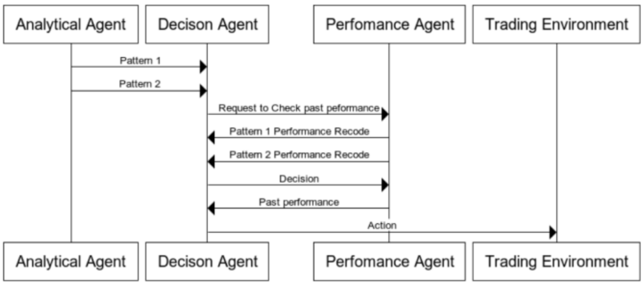

Fig. 12 Agents Message passing flow

Figure 8 shows an example of message flow between FA, DA, PA, and Forex Trading systems. Note that, there is no predefined order of passing messages by agents, yet any agent can pass a message when a message is ready.

IV. EVALUATION OF FOREXMA

To discuss evaluation of ForexMA, the first reader should have an idea of how Forex trading works. Forex markets allow traders to gain profit by investing their money in multiple trading types such as day trading, swing trading and position trading. Regarding an asset, traders need to identify the trend before making any decision. A trend shows the direction in which the selected asset is heading. For a given trend, traders need to identify its measurable fact such as variation of the price. ForexMA is designed to generate actions with direction of trend and expected amount of price variation.

Forex market assets price frequently change because of the market trend. Traders try to understand the market trend by analyzing qualitative facts such as news, social media posts. Once they identify the trend, they can calculate the expected price variation due to the trend. Note that frequency of price change happens more than twice a second. Because of the high frequency of price variation, we must consider the price change for a time window.

For a given time window, we are interested only in a few key price values. They are, value at the opening of the time window (OPEN), value at the end of the time window (CLOSE), highest value in the time window (HIGH) and lowest value in the time window (LOW).

As per above discussion, the evaluation of performance of ForexMA should validate the combined prediction power of *trend identification* and *price variation*. Therefore, reward functions have been used to calculate a combined reward value.

A. Inputs of the ForexMA

ForexMA needs quantitative facts and qualitative facts as inputs. We have used price variations, as quantitative facts of EUR-USD between the 2019-11-27 and 2020-10-15. For the same time duration, we have also used textual data such as news, social media posts which are related to EUR-USD, as qualitative data.

Table 1 shows a sample of quantitative data collected in 5 minutes intervals for three days. Here the volume of data is about 65000 records. Note that when human expert traders analyze the Forex market, normally by collecting data only every 4-8 hours, this results in reducing the accuracy of prediction. As such making a time frame as 5 minutes has a big contribution to improve accuracy of making decisions.

Table 1 Quantitative Input for ForexMA

Timestamp	Open	High	Low	Close
2020.10.08 14:00	1.65	1.658	1.649	1.647
2020.10.08 14:05	1.647	1.652	1.642	1.643
2020.10.08 14:10	1.643	1.67	1.643	1.66
2020.10.08 14:15	1.66	1.67	1.658	1.662

Table 2 Qualitative Inputs for ForexMA

Timestamp	Text
2020.10.08 12:00	Paris hospitals postpone non-essential operations – as it happened
2020.10.08 14:48	Five Greek islands added to England's quarantine-free list
2020.10.08 15:23	Covid drug given to Trump developed using cells derived from…
2020.10.08 18:16	New Zealand National party leader yearns for the star treatment

In addition to quantitative inputs, ForexMA receives qualitative inputs pertaining to news. We have used data crawlers to collect news from news websites and used their title to generate ForexMA outputs. ForexMA used those title and identifies the sentimental value of them and that is helping to generate the output action. Qualitative data does not have a unique period, Once update the original news source crawlers will collect the data and feed them to the ForexMA. Table 2 shows few samples of qualitative data.

B. Output of ForexMA

Input Figures to ForexMA (Table 1, Table 2) cannot be comprehended by the trader to make decisions, but the trader is interested in the output of ForexMA. Table 3 shows the outputs of the ForexMA as Predicted Action (PA), Predicted Price Variation (PPV) and End Timestamp. Note that these figures can occur at any time. There is no relationship between Timestamps in Table 1 and Table 3. It should be noted that figures in Table 3 have been generated by ForexMA, after deliberation between quantitative and qualitative facts shown in Table 1 and Table 2 by the agents in the MAS solution. These PA and PPV are used by Forex traders for decision making.

Table 3 Output of ForexMA

Timestamp	End Timestamp	PA	PPV
2020.10.08 15:00	2020.10.08 15:10	BUY	20
2020.10.08 15:15	2020.10.08 15:25	SELL	5
2020.10.08 15:30	2020.10.08 15:40	BUY	115
2020.10.08 15:55	2020.10.08 15:55	BUY	90

C. Performance test for ForexMA

For the evaluation process, we need to compare performance from known data and output created by ForexMA. For this purpose, many literatures have used the formula [13] to compute two parameters, namely, Actual Action (AA) and Actual Price Variation (APV). These AA and APV are computed for known data and ForexMA generated solutions. Figure 9 shows the algorithm for calculating AA and APV.

```
Algorithm parameters: ETP, STP
Algorithm outputs: AA, APV

  Initialize V, AA, APV
  Calculate V = ETP − STP
  If V > 0:
    Asign AA =' SELL'
  else:
    Asign AA =' BUY'
  end if
    Assign APV = |V|
  return AA, APV
```

Fig. 13 Actual Action and Actual Price Variation Calculation Algorithm

Where,
ETP – Assets Price at the give end point (End Timestamp)
STP – Assets Price at the given start point (Start Timestamp)
AA – Actual Action which supposed to come with output of ForexMA
APV – Actual Price Variation which supposed to come with output of ForexMA

Each output of ForexMA must compare with the actual status of the market. For that purpose, we used the above described scenario to calculate AA and APV. Table 4 shows samples rows of actual action and actual price variation.

Table 4 Calculated Actual Outputs

Timestamp	AA	APV
2020.10.08 15:00	SELL	12
2020.10.08 15:15	SELL	15
2020.10.08 15:30	BUY	75
2020.10.08 15:55	BUY	150

We calculate reward for each action. If AA is not equal to PA we give reward as 0, and if AA is equal to PV we calculate the reward [14] using formula (1).

$$\text{Reward} = 1- |\ APV - PPV\ | \ / \ |\ (APV - PPV)/2|. \qquad (1)$$

Where,
APV - Actual Price Variation
PPV - Predicted Price Variation

Once we calculate each action's reward value, we use the formula (2) to calculate the performance of the sample. Note that performance is a percentage value and highest is the best.

$$\text{Performance} = (\text{Sum of all Rewards} \ / \ \text{Number of actions}) \times 100\ . \qquad (2)$$

D. Evaluation of Test Results

We have used 4 different known datasets considering USD-JPY, GBP-USD, AUD-USD and EUR-USD of Forex trading and calculated performance as per formulae (1). Each of these data sets consists of 65000 records. Table 5 shows performance of ForexMA related to each decision.

According to Table 5, the average performance of ForexMA is 57.11%. This is higher than the performance of expert traders, which is average to 55% [15], [16]. It should also be noted that ForexMA can generate the solution with the above accuracy in a few seconds. However, in general, human traders takes few hours for generating a decision.

Table 5 Performance analysis details for each sample

Sample	Time duration	Asset	Performance %
1	2019.06.08 2020.05.11	USD-JPY	58.23%
2	2019.06.15 2020.05.18	GBP-USD	55.85%
3	2019.06.15 2020.05.18	AUD-USD	52.63%
4	2019.09.22 2020.08.25	EUR-USD	63.38%
5	2019.09.22 2020.08.25	AUD-USD	52.63%
6	2019.09.22 2020.08.25	GBP-USD	56.15%
7	2019.11.27 2020.10.15	USD-JPY	59.03%
8	2019.11.27 2020.10.15	AUD-USD	52.63%
9	2019.11.27 2020.10.15	GBP-USD	56.35%
10	2019.11.27 2020.10.15	EUR-USD	64.18%

V. Conclusion and Further Work

Forex is the largest and most liquidated asset market in the world by reason of the involvement of multiple factors. This paper narrates design, implementation, and evaluation of MAS solution, ForexMA, for Forex trading. ForexMA takes into consideration qualitative and qualitative facts to make decisions about Forex trading. The overall system developed on Python and Redis based MAS platform. This agent solution is designed to explore the power of several AI technologies, including Artificial Neural Network and Expert System. ForexMA is significantly different from other solutions for Forex trading, where they consider only one of the qualitative or quantitative facts related to Forex trading. Our ForexMA implements the mutual influences of qualitative and quantitative measures of Forex trading.

According to results of evaluation, ForexMA has shown 57% performance. This value is above the average performance of expert human traders, which is 55%. It should also be noted that ForexMA generates a decision in few seconds, while the human traders take few hours for the same but with lesser accuracy in performance. Furthermore, ForexMA can work on high frequency time frames such as 1-minute, 5-minute durations to archive higher accuracy. However most human traders do not perform well in such data frames. They generally work on 4-hour to 8-hour time durations, in which case accuracy of predictions goes down.

Further work of this research has been identified as improving agents with more rules used by expert traders when they make decisions. We should also ensure that

ForexMA access the reliable data sources to get quality data for analysis. When ForexMA deals with qualitative data such as news and information coming from social media, this matter is of utmost importance. We also intend to expand ForexMA with a mobile interface.

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