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Escola Tècnica Superior d'Enginyeria Informàtica  
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# Forecasting exchange rates using recurrent neural networks

DEGREE FINAL WORK

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# Resum

El FOREX és un mercat on s'invertixen grans quantitats de recursos amb l'objectiu de predir amb la major exactitud possible els canvis en els parells de divises. On a més l'aprenentatge automàtic està tenint un gran impacte i nombrosos estudis són desenvolupats per a oferir solucions que maximitzen el benefici obtingut.

El següent projecte aborda un d'aquests estudis, en el que es presenten els beneficis de les xarxes neuronals recurrents LSTM en la predicció de sèries temporals. Posteriorment es comprova la viabilitat del model sobre el parell de divises EURUSD. A continuació es presenta un model basat en unes vàries xarxes neuronals i es desenrotlla un sistema de comunicació asíncrona amb el mercat que permet l'execució automàtica de transaccions a partir dels resultats obtinguts en les prediccions realitzades.

**Paraules clau:** Predicció, xarxa neuronal, xarxa neuronal recurrent, LSTM, FOREX, EURUSD

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# Resumen

El FOREX es un mercado donde se invierten grandes cantidades de recursos con el objetivo de predecir con la mayor exactitud posible los cambios en los pares de divisas. Donde además el aprendizaje automático está teniendo un gran impacto y numerosos estudios son desarrollados para ofrecer soluciones que maximicen el beneficio obtenido.

El siguiente proyecto aborda uno de estos estudios, en el que se presentan los beneficios de las redes neuronales recurrentes LSTM en la predicción de series temporales. Posteriormente se comprueba la viabilidad de dicho modelo sobre el par de divisas EURUSD. A continuación se presenta un modelo basado en varias redes neuronales y se desarrolla un sistema de comunicación asíncrona con el mercado que permite la ejecución automática de transacciones a partir de los resultados obtenidos en las predicciones realizadas.

**Palabras clave:** Predicción, redes neuronales, redes neuronales recurrentes, LSTM, FOREX, EURUSD

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# Abstract

FOREX is a market in which large amounts of resources are invested in order to predict changes in currency pairs as accurately as possible. In this market, machine learning is also having a great impact and numerous studies are developed to offer solutions that maximize the benefit that can be obtained from it.

This project addresses one of these studies, which presents the benefits of LSTM recurrent neural networks in the prediction of time series. Subsequently, the viability of said model is tested on the EURUSD currency pair. Finally, a model based on various neural networks is presented and an asynchronous communication system with the market is developed. This system allows for the automatic execution of transactions based on the results obtained in the previously made predictions.

**Key words:** Forecasting, neural networks, recurrent neural networks, LSTM, FOREX, EURUSD

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# CHAPTER 1

## Introduction

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The following document describes the application of computer methods for the prediction of time series in detail, specifically focusing on the prediction of foreign exchange rates or **FOREX** and on the **EURUSD** currency in particular. In a broad approach and for the reader's initial understanding, this document can be divided in three phases.

The first phase is based on the article *A Guide For Time Series Prediction Using Recurrent Neural Networks (LSTMs)*[18], in which the data scientist Neelabh Pant presents a solution to the existing problem of high volatility of the currency of his home country India (Rupee - INR), comparing it with the currency of the country where carries his work out, the United States of America (Dollar - USD). Neelabh Pant uses his knowledge of neural networks to try to predict the changes that will occur in the currency pair USD / INR as accurately as possible. In order to achieve this he uses a neural network with the peculiarity that the nodes of said network are of the **LSTM** type. This peculiarity improves the accuracy of the results by applying neural networks in a time series. Therefore, the objective of the first phase is to put the aforementioned test into practice and try to replicate and corroborate with the obtained results.

In a second phase and with practical purposes, the document sets out to define how the solution would be applied, but this time to the currency pair corresponding to the Euro and the Dollar (**EURUSD**). After applying the model described in phase one, the model's weaknesses and strengths are analyzed to create a new model that allows for better results to be achieved in this specific domain.

Finally, in the third and last phase, the practical application is analyzed and adjusted to obtain plausible results. In order to attain this, a system that automatically analyses and obtains prediction results (in a defined time set) is presented, together with a series of functions that allow the subsequent creation of an algorithm for the implementation of an **Automated trading system (ATS)**. This enables the possibility of obtaining financial benefits.

## 1.1 Motivation

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### 1.1.1. Personal motivation

From a personal point of view, the goal of this project has been to fulfill curiosity and to fill a gap of knowledge that has not been covered during my university degree. Taking the growing popularity of artificial intelligence into account, it is inevitable to accept that neural networks are going to be part of our society. In my specific case, I am the type of person who believes that artificial intelligence is the next logical step in the evolution of

our society. I consider that the human ability of understanding and facing problems is highly limited by our physiological capacity and that, without a doubt, as studies show, that limit has been reached long ago. The problems that arise today, not only for their complexity but also because of the time set in which a solution must be found, exceed the limit of man's ability. Therefore, the key to solving this is to evolve from the current state, in which man is helped by technology, to the state where technology is helped by man. With this statement in mind, the idea of further investigating everything related to artificial intelligence is very attractive to me. For practical reasons, the fact that artificial intelligence is figured in this case in **FOREX** trading makes a lot of sense for the scope of the project: previously digitized data that is available on the internet for free and with time periods of between one second and thirty years, in addition to the existing information related to automated trading systems. These factors made this project an achievable goal.

### 1.1.2. Professional motivation

Regarding the professional domain, there are numerous sources of information that can provide extra knowledge about this theme to students close to finishing their undergraduate studies. With the help of the referred article, the knowledge gap related to the topic is easily reduced or at least the tools that can be used are defined and the steps to follow are made clear. This path focuses first of all on learning about the new and booming programming language Python[19]. Secondly, it focuses on a sector very well known for its great resources: the stock market sector; and thirdly on the previously mentioned neural network technology. All this means that these three factors can provide the student with an applicable knowledge in any of these three areas.

Finally, and albeit less important, the last motivation is the possibility of creating a fully autonomous and functional system that can generate profit after an initial monetary investment.

## 1.2 Delimitation of scope and assumptions

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The main objective of this project is to analyze, improve and implement the solution proposed in the article previously described by Neelabh Pant. This solution to the problem of currency exchange prediction using neural networks raises the variant of recurrent neural networks in which the nodes of said network are of the **LSTM** type.

The main objective is divided into the four following sub-objectives or secondary objectives:

1. Corroborate with the information presented in the article and verify that the data obtained by Neelabh Pant is between the correct limits.
2. Check the feasibility of the solution outlined above, but in this case to a different currency pair.
3. Analyze the weaknesses and develop possible improvements for subsequent practical application.
4. Implement the architecture in the practical application of an automated trading system.

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## 1.3 Expected impact

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From a user's point of view, the result of the project will provide a new generation automated trading system (autonomous use of artificial intelligence). This system will allow the user to obtain results with greater precision than many of the existing systems on the market with the additional advantage of removing the investment related to the prediction system, all with the simple connection to a broker and an initial investment capital. This way it also allows the user to remove psychological barriers already well known in manual trading.

Furthermore, the development of this project will provide one additional sample of the positive results achieved by using recurrent neural networks and **LSTM** nodes in forecasting time series.

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## 1.4 Methodology

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1. Corroborate the information presented in the article and verify that the data obtained by Neelabh Pant is between the correct limits. In this case, we will proceed to:
  - a) Detailed analysis of the code.
  - b) Set-up of the machine for code execution.
  - c) Code execution.
  - d) Comparison of the results presented in the article with those obtained in the execution of the previous point.
2. Check the feasibility of the solution outlined above, but in this case to a different currency pair.
  - a) Obtaining the data corresponding to the currency pair **EURUSD**.
  - b) Implementing the article code together with the data obtained in the previous point.
  - c) Code execution.
  - d) Analysis and comparison of the result obtained with the new data.
3. Analyze the weaknesses and develop possible improvements for their subsequent practical application.
  - a) Analysis of the results obtained and their possible viability.
  - b) Study of applicable improvements.
  - c) Application of improvements.
  - d) Analysis of results obtained with improvements.
4. Implement the architecture for the practical application of an automated trading system.
  - a) Implementation of a communication system between the application provided by the Broker and the logical side of the system.
  - b) Integration of the communication of the logical system with the communication tool described in the previous point.

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## 1.5 State of the arts

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### 1.5.1. Forecasting FOREX

Currency exchange prediction methods are mainly divided in two types: technical analysis and fundamentalist analysis. As Charles D. Kirkpatrick II, CMT Julie Dahlquist, Ph.D., CMT explains in the book *Technical Analysis: The Complete Resource for Financial Market Technicians*, “technical analysts study the action of the market itself rather than the goods in which the market deals”. The technical analyst believes that “the market is always correct”[7]. This means that the technical analysis is based on the fact that future changes in the market are predictable by studying past changes. This can be visualized in five trend keys described in *Technical Analysis of Stock Trends*[8].

- Stock prices are determined solely by the interaction of demand and supply.
- Stock prices tend to move in trends.
- Shifts in demand and supply cause reversals in trends.
- Shifts in demand and supply can be detected in charts.
- Chart patterns tend to repeat themselves.

On the other hand, fundamental analysis is based on the essential or fundamental value of an action or title. This means that considering a share with a current market price that differs from its fundamental value, this share or security will tend to vary in the direction of its fundamental price. Therefore the objective of fundamental analysis is to determine what is its essential value and therefore to define the trend of that action. This type of analysis was first identified in 1962 by Benjamin Graham [9] and continues to be a basic part of **FOREX** analysis.

A very successful example for the project that follows is presented by the professors of computer science JingTao Yao and Chew Lim Tan in 2000 in the paper *A case study on using neural networks to perform technical forecasting of FOREX* [1]. This paper presents an empirical test of the application of neural networks to predict exchange rates with various currency pairs. It is worth mentioning, however, that the **EURUSD** currency pair is not analyzed.

More recently, in early 2020, a paper by Michal Dobrovolny was published regarding the theme of *Forecasting of FOREX Price Trend Using Recurrent Neural Network - Long Short-term Memory* [2]. The research analyzes the results obtained using the dataset in the range of 10-58 days where precision results of **mean of absolute errors (MAE)** 0.003052 and the least **Mean squared errors (MSE)** 0.002390 are obtained.

### 1.5.2. Neural networks in time-series

The first reference to **LSTM** neural networks was proposed in 1997 by Sepp Hochreiter and Jürgen Schmidhuber in their book *Long Short-Term Memory*[10] and its modification with respect to standard perceptron nodes. This modification as described, aims to improve results in the use of time-series. Later in 1999 Jürgen Schmidhuber introduced a very significant improvement adding a *forget gate*[11] with the aim of allowing the **LSTM** node to reset its state. These two functionalities allow addressing the vanishing gradient problem which affects the propagation of the error during the node update which was previously identified by Sepp Hochreiter[12].

Currently, **LSTM** cells or nodes have not varied since the application of the *forget gate* and as was shown in 2015 under the paper *Long Short Term Memory Networks for Anomaly Detection in Time Series*[3], **LSTM** networks are one of the most common solutions. optimal until now developed for the prediction in time series.

### 1.5.3. Automated trading systems

**Automated trading system (ATS)** are a set of rules implemented on a system which is allowed to make buy and sell trades automatically. At first, **ATS** were implemented in 1949 by Richard Donchian[13] in the form of a set of rules to follow when making trades. During the following decades until the end of the 1990s, the sets of rules for trading became popular, but it was not until the arrival and expansion of the internet in the late 1990s that these systems were implemented in computers that were autonomous and directly connected with the market they made trading transactions with. At the beginning of the 21st century and with the increase in the computing capacity when the stock market expanded the use of **ATS** with its first implementation by the Betterment company[20].

Currently and due to the implementation of the IT sector[4]. **ATS** have the ability to execute extremely complex algorithms in very short periods of time. These systems are called **High-frequency trading (HFT)**. **HFTs** are the most current trend in the stock market and define the current operation of transactions [21][22]

### 1.5.4. Criticism to the state of the arts

Among the different studies carried out in the ETSINF school of the Polytechnic University of Valencia (UPV), two related papers should be highlighted. The first, used for the detection of anomalies in electricity consumption[5], highlights that the results for very long periods of time are poor since **LSTM** networks increase their precision in close periods of time. The second, called "Audio Effects Emulation with Neural Networks"[6], demonstrates the great advantage of **LSTM** networks over other types of networks with input data corresponding to sequences, but its application in this case is not possible due to the requirements specific to the problem.





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## CHAPTER 2

# Proposal

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The project developed below proposes a solution for the existing volatility in the **EURUSD** currency pair implementing the combination of two technologies. The first is the **RNN** with **LSTM** nodes in the forecasting of time series and the second technology is the **Automated trading system (ATS)**.

The project also offers a solution to a problem that has possibly already been proposed but which, considering the value and operation of automated trading systems, is not accessible to any user other than the owner. In summary, it is quite possible that many companies have developed **ATS** for the **EURUSD** currency pair using **LSTM** networks, but knowing the potential benefit of obtaining these **ATS**, companies have not made that information public. Therefore this project offers a public solution and that is the knowledge gap that it fills in this domain.

### 2.1 Problem analysis

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The problem that is currently evident in the currency market is the same that is present in the rest of stock markets. The problem is volatility. Volatility (symbolized by  $\sigma$ ) is the measure used in **FOREX** to quantify changes in the value of different currencies over time taking into account the variation that has occurred in the past. It should be noted that volatility is usually represented by the standard deviation.

The volatility therefore reflects the current great complexity of stock markets and, more specifically, of **FOREX**. It is commonly said that **FOREX** is a flatter market. The flat adjective is used because if we compared for example, the **EURUSD** currency pair chart and another chart from for example the Microsoft Stock, we could observe that the currency market does not suffer from high volatility, but all volatility has its value for each user intrinsically connected to the volume invested by that user. This means, therefore, that although the volatility of the **FOREX** market compared to other markets may be lower, the volume of business operated in this market is exceptionally greater than that of the remaining markets. The foreign exchange market reached a trading value of 6.6 trillion dollars per day in April of 2019, while during the whole year period in 2016, 2017 and 2018 the average value was of 5 trillion per day[23]. During the same time frame, the stock market had a volume of just under 200 million dollars.

Additionally, it is necessary to highlight several characteristics that make **FOREX** the most attractive market for investors.

- High liquidity with respect to the stock market.

- **FOREX** is open 24 hours a day (it opens 5pm Eastern Time- **ET** Sunday and ends 5pm **ET** Friday) compared to the availability from 8h of stock market.
- Main focus point: In **FOREX** there are only a certain number of currency pairs. In stock market, there are hundreds of stocks to invest in.

All these characteristics make **Foreign exchange market (FOREX)** a sector with great business opportunities, where innovation is in the order of the day and where large companies with large resources constantly invest in solutions that allow them to stand out from their competitors.

### 2.1.1. Analysis of the legal and ethical framework

There are specific regulations and laws related to the scope of stock market that should be complied with by any person or entity that wishes to trade . These rules must be previously made available by a “Broker”, who works as an intermediate entity between the market and the traders. The intention of this text is not to inform about all the rules to follow, as this is not important information for the trader. The trader must understand and accept a clause called "Risk disclosure" or "Risk disclaimer". For example, the rules of the Broker selected to carry out these tests[24]. To have an idea of the general meaning of this clause, you can read the first sentences of this section on the website of one of the main European Brokers TD Ameritrade[25] “Before investing carefully consider the underlying fund’s objectives, risks, charges, and expenses”.

## 2.2 Identification and analysis of solutions

In order to obtain the most appropriate solution for the volatility problem, the first step is to analyze the type of solutions, and as has been detailed in previous sections, these solutions are divided into two types, fundamentalist analysis and technical analysis. The advantages of each of these approaches are well known[26][17].

FUNDAMENTAL ANALYSIS	TECHNICAL ANALYSIS
<i>Market valuation(undervalued / overvalued)</i>	<i>Trade timing(entry/exitpoints)</i>
<i>Solid understanding of the market / industry</i>	<i>Can be used on most trading instruments</i>
<i>Geared at more longer – term trades</i>	<i>Favours shorter – term trades</i>
<i>Extensive research required</i>	<i>Encompasses all current information</i>

**Table 2.1:** Advantages of fundamental and technical analysis.

Considering the nature of the project, any fundamentalist analysis solution is ruled out. This is the case except for small decisions based on the fundamentalist analysis, such as the hours in which the volatility is the greatest taking into account that from 13:00 to 16:00 **GMT** the New York and London markets are open. Therefore the problem is approached from a technical analysis point of view. In this sense, there are infinite solutions and approaches, most of them based on statistical methods or mathematical prediction models[14].

Given the domain of the project and taking into account the nature of this research, it is worth mentioning that there are numerous types of machine learning processes are applicable to the prediction of currency exchange and numerous projects where different

models with different topologies are compared[15][16] but the goal is to put the model presented by Neelabh Pant.

The following step is to improve the model and create an architecture that allows you to use this model in a practical way.

## 2.3 Article review

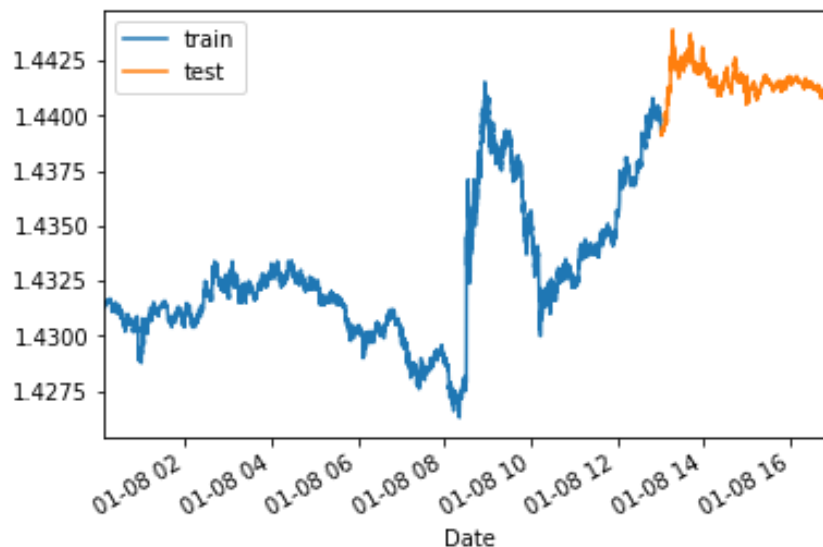
In order to check for the feasibility of the solution proposed in *A Guide For Time Series Prediction Using Recurrent Neural Networks (LSTMs)*, the exact executions of the code provided in that article were carried out and the differences obtained can be seen below.

	Source article value	Verification value
Scalar test loss	0.000275	0.000695

**Table 2.2:** Compared scalar test loss between the source and the review.

At this point, the data history of the last 10 years was obtained [33]. Since the article model is trained and tested with a dataset of 9697 entries, we have to truncate the available dataset in a dataframe of similar magnitude. In order to achieve this, the period of time from 2010-01-08 00:07:19 to 2010-01-08 17:00:00 corresponding to 11721 entries has been carried out.

Considering the following division in train and test dataframes.



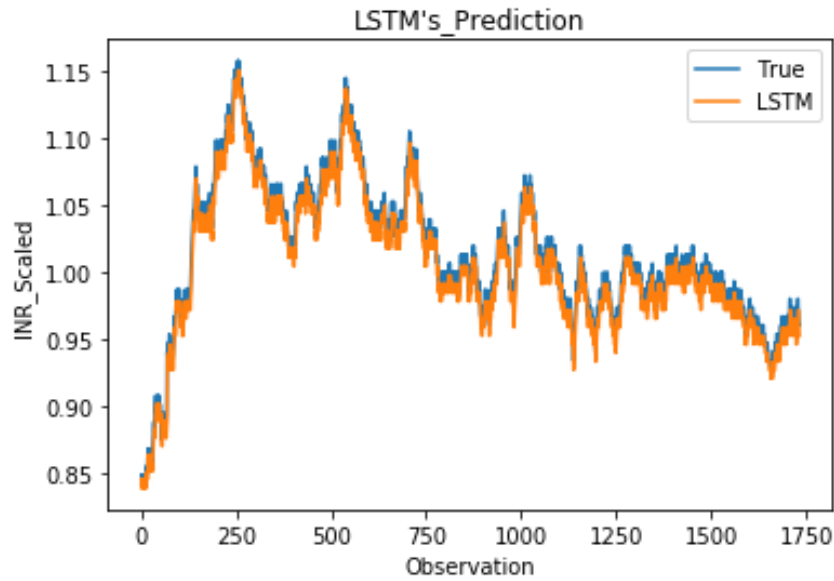
**Figure 2.1:** Graphic of the dataset divided in two dataframes of training and test respectively.

In this case, the result obtained using the model proposed above is:

	Model using EURUSD dataset
Scalar test loss	0.000118

**Table 2.3:** Scalar test loss using EURUSD historical data.

This result is quite surprising if we compare the test prediction that was previously made with the real data:



**Figure 2.2:** Graphic of prediction made compared with the historical values of EURUSD between 2010-01-08 00:07:19 to 2010-01-08 17:00:00.

### 2.3.1. Review analysis

If we read the article and pay attention to the graphs that are presented in it, we will probably be mistakenly surprised by the results. The error lies in the fact that we might think that the values shown in orange in the graph correspond to predicted values, and yes, that is correct, but with which information those values have been preceded is the important issue here. Ideally, to predict the value  $t+1$ , the value  $t$  would be used, resulting in the value  $t+1'$ , and to predict the value  $t+2'$  two values could be used:

- A. The  $t$  value and the  $t+1'$  value predicted above.
- B. The  $t$  value and the actual  $t+1$  value.

The difference is that with option A, we can predict the value  $t+2$  at the instant of time  $t$ , that is, we can predict two future values. On the other hand, in option B, the value  $t+2$  can only be predicted at the instant of time  $t+1$ , this means that only one future value can be predicted.

Therefore the results obtained in the previous article have an analytical value but lack a practical value as far as HFT is concerned, and this can lead to confusion in the real usefulness of the presented model.

## 2.4 Proposed solution

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The solution of choice is based on the use of LSTM cells in a recurrent neural network. This model uses the values of the currency pair EURUSD in the M1 format or one minute periodicity as data entry. This means that each entry in the database corresponds to the average value of said currency pair in the FOREX market for sixty seconds. The model, in addition to being trained initially with the data from the past, will be constantly re-adjusted automatically based on the information obtained in short term. This means that considering a model that was previously trained, the input data for obtaining the

predictions will itself be obtained automatically using communication with the Broker system.

Ideally the system will run with an already given trained model. It communicates asynchronously with the Broker using a packet **TCP** architecture. The Broker system will therefore provide information related to the short-term history, in order to make a prediction. The handling of buying or selling trade orders depends on the situation, which can include: creation, closing, modification and current status.

## 2.5 Solution design

Conceptually and in more detail, the system must perform the following steps for the different tasks to be performed:

**Task 1 - Training of the **RNN**** With the goal of initial training and constant learning of the weights associated with the **RNN** model, the system must provide the tools that allow for the **RNN** to receive the historical data in a specific format as input. Later on, that model is loaded for future use.

**Task 2 - Prediction of a certain time** The system must provide access to data for a definite period of time in order to use it as input for making a prediction.

**Task 3 - Decision making and conducting a trade** Taking into account the obtaining of a prediction in Task 2, the system must analyze and decide which type and when to carry out the corresponding trade to maximize the benefit obtained.

### 2.5.1. System architecture

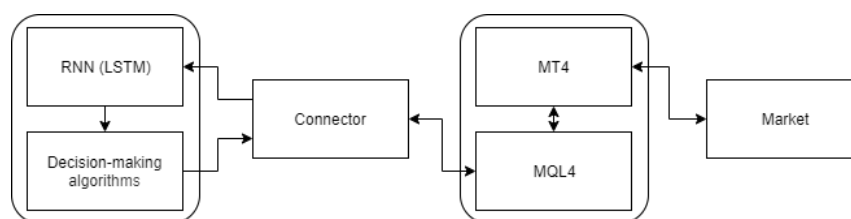


Figure 2.3: System architecture concept schema.

The components that make up the system are conceptually divided into four parts:

- **Logical component:** This component is divided into two parts, the **RNN** model and the part where the decision-making algorithms are located in which, from the results obtained in the **RNN**, actions are carried out in the market by communicating with the connector.
- **Connector:** This component provides the system with a tool for communication between the logical component and the Electronic trading platform. This connection allows for obtaining input data for the **RNN** and the execution of actions by the decision-making algorithms.

- **Electronic trading platform:** This component offers a user interface in which to monitor the tasks that are carried out and, more importantly, it executes a programming language called **MQL4** that allows for the execution of orders through messages received by another component.
- **Market:** It consists of the **FOREX** market where the data will be obtained and where buy and sell orders will be executed.

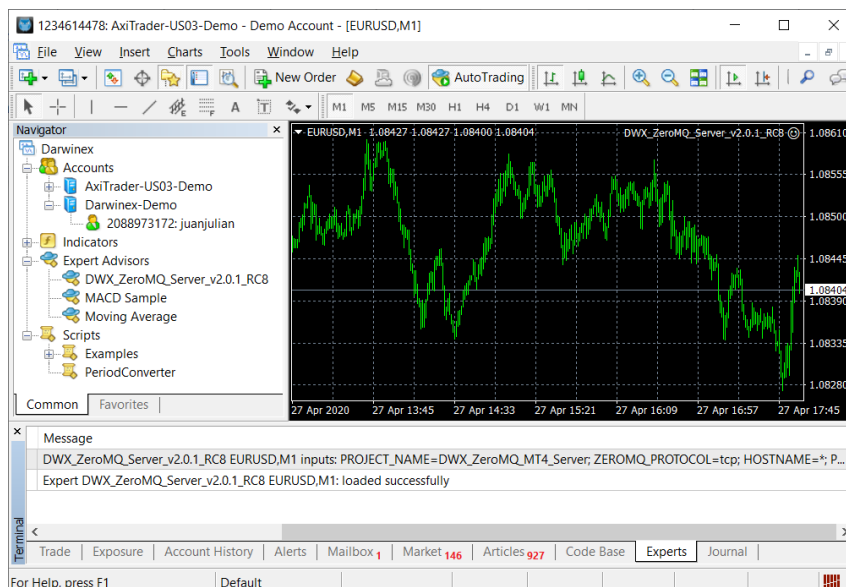
## 2.5.2. Detailed design

### Broker connection

The way in which the “Electronic trading platform” communicates with the market is completely transparent to the trader. This means that once the authentication credentials are associated with the corresponding Broker, the system can carry out transactions.

The selected platform is called **Metatrader 4 (MT4)**. This platform is undoubtedly the most used in the domain of stock market [27]. In this project **MT4** offers two main tools, interface and script execution. The first aims to provide a friendly user interface where it is possible to:

- Access through credentials to the Broker system.
- Monitor active trades in real time.
- Check the balance and transaction history.
- Monitoring of "Experts".



**Figure 2.4:** MT4 user interface where the Experts monitoring tab can be seen.

Secondly and more importantly, **MT4** allows the execution of commands and functions through its own programming language called **MQL4** [28]. Therefore, using a tool called “Expert Advisor” **MT4** makes it possible to execute the functions developed in **MQL4**. These functions enable the possibility to perform a multitude of tasks and it is possible to develop investment strategies and complex decision algorithms through these

functions, but currently we must highlight the functions or methods related to external communication, that is, the input and output of information on these executions with other systems outside of **MT4**.

## Communication

This section corresponds to the communication that takes place between the component corresponding to the execution of an **Expert Advisor (EA)** described above and the logical component. The development carried out by the Darwinex Team with the ZeroMQ library should be greatly highlighted. This development is the communications component used in this project as follows.<sup>1 2</sup>

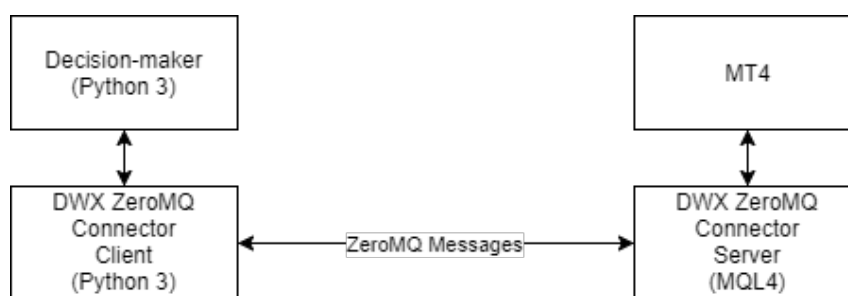


Figure 2.5: Schema of connector component of the system.

ZeroMQ provides a queuing system based on asynchronous **TCP** messages between executions on different platforms or programming languages, giving the option to automatically execute transactions on the market using the Python programming language, passing through the **MQL4** programming language.

This way, the communication that is carried out for the tasks described above is as follows:

### Task 1 - Training of the RNN

The logical component, obtained by executing the Python connector function [31]:

```
DWX_MTX_SEND_MARKETDATA_REQUEST_ (self, _symbol, _timeframe, _start, _end)
```

It makes the request for the data history corresponding to a certain period of time. This request accesses the socket of the ZeroMQ client and is transported through the **TCP** protocol to the ZeroMQ server applied through the **MQL4** connector, which then executes the function corresponding to the Obtaining the market history and this information is returned by an asynchronous message in the opposite direction. (During the tests the address that was used has been the loopback address since the component corresponding to the client and the server are on the same machine).

Additionally, it is worth noting that there is a limitation detected during the tests regarding this way of obtaining the data history for feeding the **RNN**. In order to execute an **EA** script, this **EA** must be connected to a chart in the **MT4** interface. Therefore the **MQL4** CopyClose() function [32] that is executed in a certain chart, can only obtain the data corresponding to the information loaded in said chart by **MT4** at the moment of creation. This information is limited and governed by a number of values. This means that if the selected chart is W1 (Weekly), older information can be obtained compared to selecting a chart that corresponds to M1 (Minute).

<sup>1</sup>Darwinex team *Darwinex Github site*. <https://github.com/darwinex>.

<sup>2</sup>ZeroMQ *High-performance asynchronous messaging library*. <https://zeromq.org/>.

Considering the limitation described above and taking into account that the execution of the task corresponding to the training of the **RNN** is carried out manually, in case the data history is greater than that loaded by **MT4**, the dataset is obtained from an external source[33].

### Task 2 - Prediction of a certain time

In this case, since the objective is to obtain input data that will serve as input to make the prediction in the **NN**, the data can be obtained directly from **MT4** considering its size.

The mechanism to follow will be exactly the same described in Task 1, since the **NN** output data will be used by the logical component itself.

### Task 3 - Decision making and conducting a trade

In this case, and after completing Task 1, the decision-making system will use the information obtained from the forecast to carry out transactions in the market. These transactions may be of the buy or sell type and the following function available on the Python side of the connector will be used:

```
DWX_MTX_NEW_TRADE_ (self, _order = None)
```

This function will return a confirmation message following the path described for the information obtained in Task 1 and return, a trade identification number called "ticket" that will later be used to close with the following function:

```
DWX_MTX_CLOSE_TRADE_BY_TICKET_ (self, _ticket)
```

## Logical application

Considering the following premises:

- Non-viable results obtained using the model presented in the article described previously[18].
- Following **HFT**, the trades to be carried out use information obtained in short-term predictions.

A different operating model is proposed, where the variation does not reside in the **NN** topology but rather in the results obtained when using several **NNs**.

The model described below has the characteristic of not making a single continuous prediction. Instead it makes many predictions of which, by combining the output information, practical prediction results can be obtained.

The objective is that with the following values:

- Period of time to be predicted
- Period of time to be used to predict.

A system is generated where both time fragments are divided and for each pair of fragments (A,B) an **RNN (LSTM)** is generated and the precision obtained in scalar test loss is analyzed. Then set out to use that information to obtain the most beneficial dataframe for each future prediction.

This means that an  $A * B$  number of **NN** is generated, of which after analyzing their precision, a number equal to the length of A is selected. For each pair (A,B) an h5 file is generated containing the weights that correspond to a trained **NN** with an input of n values corresponding to  $t - B$  length, where t is the current instant and with an output corresponding to the exact value of  $t + A$ .



## 2.6 Development of solutions

During the development and following the described design of the “Logical application” the following dataframes have been selected.

A. Period of time that you want to predict: 8h (480 minutes) giving greater importance to the first hour in particular, which is where the trades will be carried out.

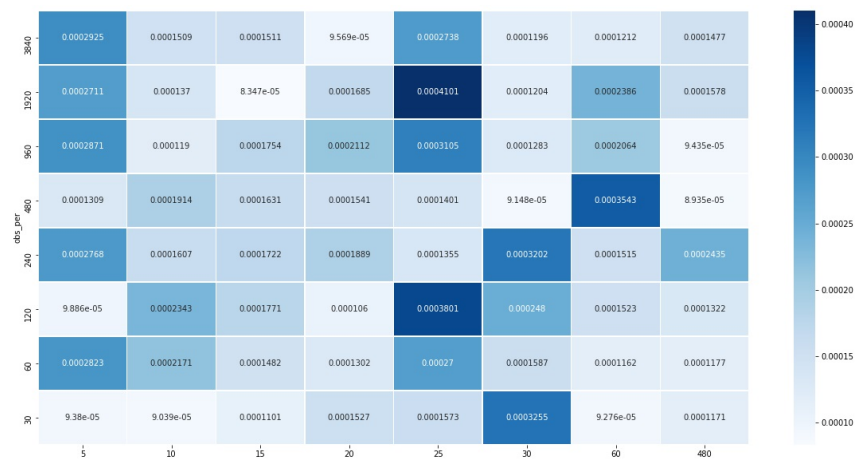
B. Period of time to be used to predict: 64h (3840 minutes) where the most recent time is of greatest importance.

Therefore, each dataframe has been arbitrarily divided into the following order:

<b>A</b>	5	10	15	20	25	30	60	480
<b>B</b>	30	60	120	240	480	960	1920	3840

**Table 2.4:** 8 and 64 hours divided respectively into A and B.

And 64 results corresponding to the scalar test loss of the 64 **NN** will be obtained from the automatic creation of this system.



**Figure 2.6:** Heat-map of the results obtained on 2019-12-31 7:59:00.

From this, it can be determined that the observation time that generates the best results for each point of the prediction time is as follows:

<b>Forecast period</b>	5	10	15	20	25	30	60	480
<b>Observable period</b>	30	30	1920	3840	240	480	30	480

**Table 2.5:** Results obtained analysis the heat-map (Figure 2.4).

This means that the prediction that will obtain the best results will be the one generated by combining the (A,B) pairs:

(5.30); (10.30); (15.1920); (20.3840); (25,240); (30,480); (60.30); (480,480)

### 2.6.1. Model improvement

In order to obtain better results, it is convenient to modify the previous approach. Once again the topology will not be modified instead, the training parameters will be modified. The modified parameter is the Patience in the Early Stopping:

Previous value:

```
EarlyStopping(monitor='loss', patience=2, verbose=1)
```

Valued modified:

```
EarlyStopping(monitor='loss', patience=10, verbose=1)
```

This means that the number of times a certain set is trained, when the training result is worse than the previous one, will increase from 2 to 10 times.<sup>3</sup>

This modification is due to the fact that there is not a very large variation between the different data in the dataset. This can be explained because the data are part of a time series and therefore the change in the scalar test loss will be small. This problem can be palliated with a Patience value.

The results obtained for the same dataset with the modification described above are in Figure 2.5.

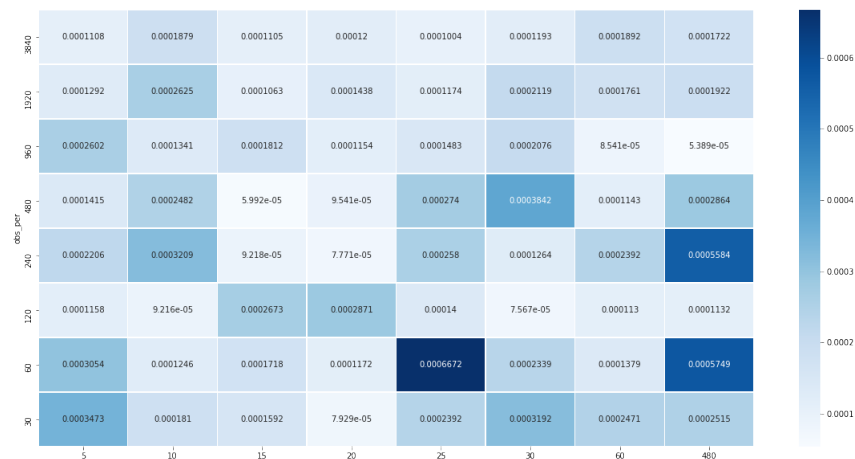


Figure 2.7: Results obtained on 2019-12-31 7:59:00 with the Patience parameter set to 10.

Where it can be determined that the observation time that generates the best results for each point of the prediction time is as follows:

Forecast period	5	10	15	20	25	30	60	480
Observable period	3840	120	480	240	3840	120	960	960

Table 2.6: Results obtained analysis the heat-map (Figure 2.5).

If we compare the observable periods with the best results of the two tests we do not obtain similarity as could be seen in Table 2.4.

## 2.7 Test and results

For the construction of a practical exercise, the NNs in which the model has been trained with the parameter Patience set to 2 were selected because the results obtained in scalar test loss were better as is shown in the following table.

<sup>3</sup>Patience: Number of epochs with no improvement after which training will be stopped(Keras documentation - [https://keras.io/api/callbacks/early\\_stopping/](https://keras.io/api/callbacks/early_stopping/)).

Forecast period	5	10	15	20	25	30	60	480
Observable period Patience 2	30	30	1920	3840	240	480	30	480
Observable period Patience 10	3840	120	480	240	3840	120	960	960

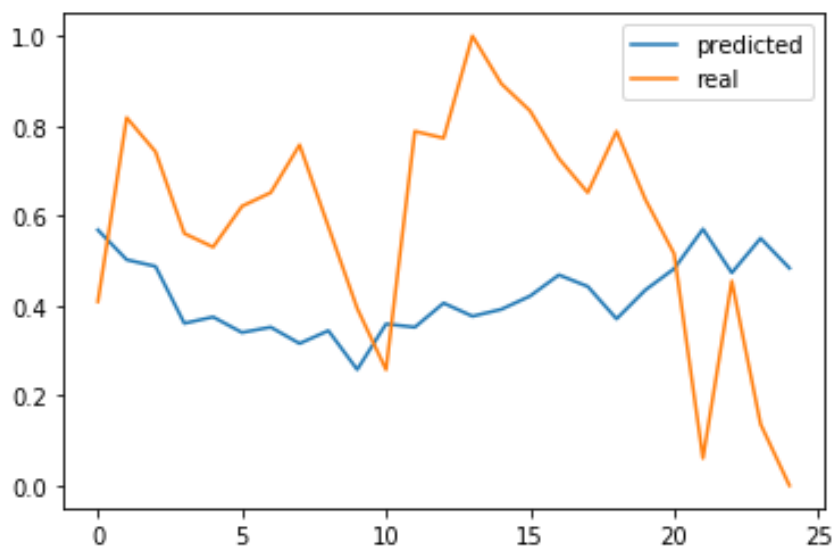
**Table 2.7:** Comparative table of the best observable periods with the Patience parameter set at 2 and 10 respectively.

Forecast period	Patience 2	Patience 10	Difference
5	0,0000938	0,0001108	<b>-0,000017</b>
10	0,0000939	0,00009216	0,00000174
15	0,00008347	0,00005992	0,00002355
20	0,00009569	0,00007771	0,00001798
25	0,0001355	0,0001004	0,0000351
30	0,00009148	0,00007567	0,00001581
60	0,00009276	0,00008541	0,00000735
480	0,00008935	0,00005389	0,00003546

**Table 2.8:** Comparative table of the best observable periods with the Patience parameter set at 2 and 10 respectively.

We can see how, except for the **NN** for the 5 minute period, the rest of the **NN** have reported better precision.

In the following figure we can see the results obtained by carrying out this test on 2020.04.22 12:59:



**Figure 2.8:** Comparison graph of results obtained during a real test.



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## CHAPTER 3

# Conclusions and implications

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Analyzing the results obtained with respect to the objectives initially defined in the project, it could be said that the objectives have been largely achieved, with the exception of the objective of automating a practical application. The following lines describe more fully the conclusions obtained from each of the objectives.

### 3.0.1. Corroborate with the information presented in the article

During the tests, the values that were obtained are less precise. This is due to the fact that the weights before the training of a **NN** are defined in a random way. Still, the difference in these values is minimal.

### 3.0.2. Check the feasibility with EURUSD

In the application of the model on the currency pair **EURUSD**, very promising results have been observed, as we can see in Figure 2.8. Therefore we can state that the model is valid for other currency pairs and within different periods of time.

### 3.0.3. Analyze the weaknesses and develop possible improvements

The most remarkable conclusion related to the analysis of the article is strongly related to the interpretation that can be done of the results described in it.. The very positive a priori results do not correspond to a real application, since they are obtained from a model that only predicts the next instant of time. In a practical way, this solution offers no benefit. Therefore, the model and the system have been modified so that its practical application is possible using different **NNs**, instead of just one.

### 3.0.4. Implement the architecture in the practical application of an automated trading system.

In this phase, an asynchronous communication system with the market has been successfully developed and implemented, which allowed for the execution of a decision algorithm that operates automatically through the data obtained by the use of **RNN (LSTM)**. In practice, the results that were obtained differed substantially from the real market values and this has prevented a valid decision algorithm from being applied automatically.

### 3.1 Integration of the project with academic qualifications

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The project has been a good extension of the knowledge acquired during my studies. The software development branch has been especially useful in terms of learning a new programming language.

It has been a great challenge, especially in terms of how to approach this project, the topic in question and the technologies on which it is developed on. It has been useful to learn about Python and its libraries focused on machine learning. It was also necessary to understand the operation of the whole environment related to **FOREX** and its platforms, including the **MQL4** programming language and the ZeroMQ application. There have been several particularly complicated barriers. Migration to Google Colab has been necessary, for example, since the computing capacity of a personal computer is insufficient for many tests. On the other hand, the project has been carried out in an exceptionally long period of time, which has led to version and update problems. Finally, the fact that the paper this project was based on was not valid due to its interpretation has changed the final results.

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## CHAPTER 4

# Further research

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The first step that can be taken in the direction of expanding this project would have the intention of meeting the objective that was not reached in its development :the implementation of an automatic trading system. Therefore all improvements would be oriented to this goal. Many variables present the possibility of improvement in this type of system, first with the aim of improving the precision of the predictions. These variables include different topologies, different training methods or different **NNs** as was proposed. Secondly, and even though the precision will increase considerably, there are different ways to approach the decision algorithms in order to maximize the benefit. Finally, considering a communication system for **HFT**, an asynchronous messaging system may not be the fastest and in some cases this can make a big difference.





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CHAPTER 5  
Terminology

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# Acronyms

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**ATS** Automated trading system. 1, 5, 7

**EA** Expert Advisor. 13

**ET** Eastern Time. 8

**EURUSD** Shortened term for the euro against U.S. dollar pair. vii, 1, 3, 4, 7, 10, 19

**FOREX** Foreign exchange market. 1, 2, 4, 7, 8, 10, 12, 20

**GMT** Greenwich Mean Time. 8

**HFT** High-frequency trading. 5, 10, 14, 21

**LSTM** Long Short-term Memory. 1–5, 7, 10, 14, 19

**MAE** mean of absolute errors. 4

**MQL4** MetaQuotes Language version 4. 12, 13, 20

**MSE** Mean squared errors. 4

**MT4** Metatrader 4. 12–14

**NN** Neural Networks. 14–17, 19, 21

**RNN** Recurrent Neural Networks. 7, 11, 13, 14, 19

**TCP** Transmission Control Protocol. 11, 13