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An Artificial Neural Network Model to Forecast Exchange Rates[#]

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ABSTRACT

For the purposes of this research, the optimal MLP neural network topology has been designed and tested by means the specific genetic algorithm multi-objective Pareto-Based. The objective of the research is to predict the trend of the exchange rate Euro/USD up to three days ahead of last data available. The variable of output of the ANN designed is then the daily exchange rate Euro/Dollar and the frequency of data collection of variables of input and the output is daily. By the analysis of the data it is possible to conclude that the ANN model developed can largely predict the trend to three days of exchange rate Euro/USD.

Keywords**:** *Exchange Rates*, *Forecasting*, *Artificial Neural Networks*, *Financial Markets*

1. Introduction

The recent international economic crisis has highlighted the need for banks to implement effective systems for estimating risks of market. In particular, the international activity of the largest banks and the increasing volatility of exchange rates emphasize the importance of exchange rate risk, whose active management by the banks require the use of effective forecasting models.

The study of the topic of forecasting in financial markets is based on the research hypotheses that:

(h_1) the process of pricing in financial markets is not random;

(h_2) the degree of information efficiency at Fama of the financial markets is not strong or semi-strong.

If the two research hypotheses proposed were not considered valid, it would be highly redundant and useless to study the issue of forecasting in financial markets.

If the first hypothesis (h_1) was invalid, in fact, it would assume that the processes of pricing in financial markets are governed by the random walk model, whereby the price dynamics are determined by the interaction of an indefinite variety of interacting causes not modelling and among them not ordered by relevance. In other words, we assume that the processes of pricing in financial markets are governed by the noise. This would make it useless to study models of forecasting because the case is not predictable.

If the second hypothesis (h_2) was invalid, however, it would assume that all relevant information are instantly incorporated in the pricing of financial products, making essentially unnecessary and economically inconvenient any efforts to develop models to predict the future based on present information.

This research aims to analyze the ability of mathematical models of nonlinear nature, such as artificial neural networks, to highlight non-random and therefore predictable behaviour in a highly liquid market and therefore characterized by high efficiency, such as the exchange rate Euro/US dollar. To this end, it was developed and empirically tested a non-linear model for forecasting exchange rates.

Economic theory has not yet provided econometric models to produce efficient forecasts of exchange rates, although many studies have been devoted to the estimation of equilibrium of exchange rates, including:

1) Cassel [1], Samuelson [2], Frankel [3], MacDonald [4], Alba and Papell [5], Alba and Park [6], Coacley, Flood, Fuertes and Taylor [7], Kim B.H., Kim H.K. and Oh [8], Taylor [9], Grossmann, Simpson and Brown [10] on the theory of Purchasing Power Parity (PPP);

[#]Although the research has been conducted jointly by the three authors, paragraphs 1, 2 and 7 can be attributed to Vincenzo Pacelli, paragraph 5 is due to Vitoantonio Bevilacqua, while paragraphs 3, 4 and 6 are a collaborative effort of the three authors.

2) Mundell [11], Dornbusch [12,13], Frenkel [14], Frenkel and Mussa [15], Rogoff [16] on the monetary approach;

3) Branson [17], Branson and Henderson [18], Allen and Kenen [19], Cifarelli and Paladino [20] on the approach of financial assets or balance of the portfolio.

Despite significant advances in econometric theory on the estimation of exchange rates, empirical results emerging from many studies, among others, Frankel [21] and Froot and Rogoff [22] to refute the theory of purchasing power parity; Frankel [23] against the monetary model, Branson, Halttunen and Masson [24] and Frenkel [25] to refute the theory of financial assets do not provide special support to the theories mentioned, except in the long term.

In particular, Meese and Rogoff [26] found that none of the forecasting models of the exchange rate established by economic theory has a better ability to forecast, over a period lower than 12 months, rather than the forward rate models or random walk, emphasizing the paradox that the variations of exchange rates are completely random. In the wake of the study of Meese and Rogoff [26], some authors, including Hsieh [27], Vassilicos, Demos, Tata [28], Leroy, Nottola [29], Refenes, Azema Barac, Chen, Karoussos [30], Nabney, Dunis, Dallaway, Leong, Redshaw [31,32], Brooks [33], Tenti [34], Dersch, Flower, Pickard [35], Lawrence, Giles, Tsoi [36], Rauscher [37], El Shazly MR, El Shazly HE [38], Gabbi [39], Gencay [40], Soofi, Cao [41], Sarno [42], Alvarez and Alvarez-Diaz [43-45] Alvarez-Diaz [46], Reitz and Taylor [47], Anastakis and Mort [48], Majhi, Panda and Sahoo [49], Bereau, Lopez and Villavicencio [50], Norman [51], Bildirici, Alp and Ersen [52], have studied the predictability of the dynamics of exchange rates of non-linear models such as neural networks, genetic algorithms, expert systems or fuzzy models, leading however to conflicting results.

It is unnecessary to underline that the theme of forecasting in financial markets is not confined to the specific case of foreign exchange markets, but it is extended to all financial assets. This is because the mechanisms that determine and influence the pricing in financial markets are still largely unknown, although many studies have been devoted over the years at this issue as early as by Keynes in chapter 12 of Book IV of his The General Theory of Employment, Interest and Money in March of 1936 [53]. After Keynes, some authors (Meese and Rogoff [26]; Schiller [54]; Soros [55], Obstfeld and Rogoff, [56]; Rogoff [57]) have highlighted the inability of economic theory to unravel the mechanisms that determine price movements in financial markets, highlighting the inadequacy for the purpose of both models of fundamental analysis and technical one.

In general, the prediction of financial time series requires the prior identification of a specific portfolio of variables (input data for forecasting models) which are explanatory of the phenomenon to be foreseen and therefore significantly influence the pricing (output for forecasting models). The forecasting models, in fact, will learn the characteristics of the phenomenon to be foreseen by the variables of input selected and by historical data that represent the phenomenon analyzed. Models predicting the financial phenomena, developed by economic theory over the years, can be classified into two main categories:

- structural prediction models or linear ones, such as econometric models as Autoregressive Conditional Heteroschedasticity (ARCH), Generalized Autoregressive Conditional Heteroschedasticity (GARCH), State Space, which are based on the general view that every action of traders can be explained by a model of behaviour and thus by a definite, explicit function that can bind variables determinants of the phenomenon to be foreseen;
- black box forecasting models or non-linear ones, such as neural networks, genetic algorithms, expert systems or fuzzy models, which, through the learning of the problem analyzed, attempting to identify and predict the non random and non-linear dynamics of prices, but without explicit ties and logical functions that bind the variables analyzed.

This paper will deepen in particular the second class of forecasting models, through the development and empirical application of a neural network model for forecasting the exchange rate EUR/USD for up to three days ahead of last data available.

2. A Literature Review

The literature on the application of artificial intelligence systems (such as neural networks, expert systems, fuzzy models and genetic algorithms) to the fields of economics and finance has explored various aspects. In particular lots of studies have analyzed the application of these models on time series forecasting.

Over the years, the literature has produced several studies to highlight both the critical factors and point of strengths of artificial intelligence models in the forecasting of financial phenomena and to propose tools to facilitate trading in financial markets.

Among the most significant contributions we can mention Yu and Bang [58], Zhang, Patuwo and Hu [59], Kashei, Hejazi and Bijari [60], Wong, Xia and Chu [61], Yu and Huarng [62].

In the paper of H. Y. Yu and S. Y. Bang [58], the authors develop a new learning algorithm for the FIR neural network model by applying the idea of the optimization layer by layer to the model. The results of the experiment, using two popular time series prediction problems, show that the new algorithm is far better in learning time and more accurate in prediction performance than the original learning algorithm. The FIR neural network model can be proposed for time series prediction giving good results. However, the learning algorithm used for the FIR network is a kind of gradient descent method and hence inherits all the well-known problems of the method.

G. P. Zhang, B. E. Patuwo and M. Y. Hu [59] presents an experimental evaluation of neural networks for nonlinear time-series forecasting. The effects of three main factors (input nodes, hidden nodes and sample size) are examined through a simulated computer experiment. Results show that neural networks are valuable tools for modelling and forecasting nonlinear time series while traditional linear methods are not as competent for this task. The number of input nodes is much more important than the number of hidden nodes in neural network model building for forecasting. Moreover, large sample is helpful to ease the over fitting problem.

In the paper of M. Khashei, S. R. Hejazi and M. Bijari [60], based on the basic concepts of ANNs and fuzzy regression models, a new hybrid method is proposed that yields more accurate results with incomplete data sets. In their proposed model, the advantages of ANNs and fuzzy regression are combined to overcome the limitations in both ANNs and fuzzy regression models. The empirical results of financial market forecasting indicate that the proposed model can be an effective way of improving forecasting accuracy.

In the study of W. K. Wong, M. Xia and W. C. Chu [61], a novel adaptive neural network (ADNN) with the adaptive metrics of inputs and a new mechanism for admixture of outputs is proposed for time-series prediction. The adaptive metrics of inputs can solve the problems of amplitude changing and trend determination, and avoid the over-fitting of networks. The new mechanism for admixture of outputs can adjust forecasting results by the relative error and make them more accurate. The proposed ADNN method can predict periodical time-series with a complicated structure. The experimental results show that the proposed model outperforms the auto-regression (AR), artificial neural network (ANN), and adaptive k-nearest neighbors (AKN) models. The ADNN model is proved to benefit from the merits of the ANN and the AKN through its' novel structure with high robustness particularly for both chaotic and real time-series predictions.

The paper of T. H. K. Yu and K. H. Huarng [62] intends to apply neural networks to implement a new fuzzy time series model to improve forecasting. Differing from previous studies, this study includes the various degrees of membership in establishing fuzzy relationships, which assist in capturing the relationships more properly. These fuzzy relationships are then used to forecast the stock index in Taiwan. This study performs out-of-sample forecasting and the results are compared with those of previous studies to demonstrate the performance of the proposed model.

3. The Construction of the Data Base

The construction of the data base used to train the artificial neural network (ANN) developed was divided into the following three phases:

- data collection;
- data analysis;
- variable selection.

The phase of data collection must achieve the following objectives:

- regularity in the frequency of the data collection by the markets;
- homogeneity between the information provided to the ANN and that available for the market operators.

In the phase of the data collection, we were, therefore, initially considered, as variables of input, both macroeconomic variables (fundamental data) and market data, from which it was assumed that the behaviour of the exchange rate euro-dollar was conditional. The data were collected from January 1999 to December 31, 2009[1]. The variables of input are listed in the **Table 1**, indicating the frequency of the data collection and the acronyms of variables used in the tables of the similarity matrix.

Once collected all the data, we moved to the stage of their analysis, which aims to select the data that will be used to train ANN among those initially collected. This phase is crucial, because the learning capacity of the ANN depends on the quality of information provided, which is the capacity of this information to provide a true representation of the phenomenon without producing ambiguous, distorting or amplifying effects in the phases of training networks.

In this phase, the observation of the correlation or similarity coefficients (shown below in **Tables 2** and **3**) allow to evaluate the nature of relations between the variables of input considered, suggesting the elimination of the variables highly correlated with each other and therefore capable to product amplifying or distorting effects during the training phases.

Tables 2 and **3** show, respectively, the coefficients of

[1]Source of data are Bloomberg and Borsa Italiana.

Table 1. Variables of input initially selected.

Variables	Frequency
Dow Jones Euro Stoxx 50 Index	Daily
FTSE 100 Index	Daily
National Association of Securities Dealers Automated Quotation - Nasdaq Composite Index (NASDAQ)	Daily
Cotation Assistée en Continu – CAC 40 index (CAC)	Daily
Deutscher Aktien Index (DAX)	Daily
Dow Jones Industrial Average (DOW JONES)	Daily
Standard and Poor's 500 Index (SP)	Daily
Exchange Rate EUR/GBP (GBP)	Daily
Exchange Rate EUR/YEN (YEN)	Daily
Exchange Rate EUR/USD (USD)	Daily
Exchange Rate EUR/NZD (NZD)	Daily
Gold Spot Price USA (GOLDS)	Daily
Silver Spot Price USA (SILV)	Daily
Oil Price (CLA)	Daily
Natural Gas Accounts (NGA)	Daily
LIBOR Rate 3m $ (L3M)	Daily
EURIBOR Rate 3M € (EU3M)	Daily
Avarage yield on Government Bond to 2 years in U.S. area (usgg2yr)	Daily
Avarage yield on Government Bond to 5 years in U.S. area (usgg5yr)	Daily
Avarage yield on Government Bond to 5 years in Eurozone (gecu5yr)	Daily
Avarage yield on Government Bond to 2 years in Eurozone (gecu2yr)	Daily
Monetary Aggregate M1 USA $ (M1$YOY)	Monthly
Monetary Aggregate M2 USA $ (M2$YOY)	Monthly
Monetary Aggregate M1 Euro € (M1€ YOY)	Monthly
Monetary Aggregate M2 Euro € (M2€ YOY)	Monthly
Consumer Price Indices Euro a/a (ECCPEMUY)	Monthly
Consumer Price Indices USA a/a (CPI YOY)	Monthly
Eur Trade Balance (XTSBEZ)	Monthly
USA Trade Balance (USTBTOT)	Monthly
Eur Consumer Confidence (EUCCEMU)	Monthly
USA Consumer Confidence (CONCCONF)	Monthly
Eur Investor Confidence (EUBCI)	Monthly
Eur Industrial Confidence (EUICEMU)	Monthly
Eur Unemployment Rate (UMRTEMU)	Monthly
USA Unemployment Rate (USURTOT)	Monthly
Eurostat Eurozone Monthly Production in Construction SA (EUPREMU)	Monthly
USA Index of real estate - Nahb Stati Uniti (USHBMIDX)	Monthly
USA Retail Sales (RSTAMOM)	Monthly
USA Government Debt (DEBPTOTL)	Monthly
Eur Industrial Production (EUIPEMUY)	Monthly
USA Industrial Production (IP YOY)	Monthly
Deficit/surplus % Pil USA (FDDSGDP)	Monthly

correlation or similarity of the daily and monthly initial variables.

Following the analysis of the correlation coefficients, we moved to the stage of selection of variables and we eliminated the variables with the following characteristics:

- variables characterized by a Pearson correlation coefficient with at least one other variable considered above the threshold level of acceptance equal to 0.80[2];
- monthly variables, because, having developed a neural network with a daily frequency of data collection of variables of input and output, they were considered potentially able to produce ambiguous or redundant signals during the training of ANN.

As a result of the selection of variables conducted according to the criteria outlined above, we have the final set of seven input variables to train the neural network, which is in the next section. In establishing the final data set with data of the seven input variables, exceptional values, as the outliers, were also removed related to special historical events such as the terrorist attacks of September 11, 2001.

4. The Methodology for the Development of the Artificial Neural Network Model

The objective of the ANN is to predict the trend of the exchange rate Euro/USD up to three days ahead of last data available. The variable of output of the ANN designed is then the daily exchange rate Euro/Dollar and the frequency of data collection of variables of input and the output is daily.

In drawing up the network it was considered that the exchange rate is characterized by the so-called phenomenon of mean reversion[3], or by the tendency not to maintain a trend up or down for a long time[4].

As noted in paragraph 3, as a result of the processing steps of the data base, we have selected the following seven variables of input of the ANN.

[2]Since the coefficient of correlation or similarity between two variables analyzed both at the time "t" is merely indicate what the change of a variable "x" is similar to the change of a variable "y", which follow the same trend, it was considered necessary to eliminate the variables most strongly correlated with each other in order to avoid potentially ambiguous or amplifying signals in the stages of training. The fact of considering as input of a neural network two or more variables strongly correlated (*i.e*. Pearson's coefficient > 0.80), would artificially boost the information provided by the neural network variables in question.

[3]See Gabbi (1999), pag. 241.

[4]Empirical evidence shows that exchange rates tend to remain sufficiently stable in the medium term around a mean value of equilibrium. It occurs that too high values compared with the average period reflect a tendency to return later to the media. The prediction of these variables, therefore, may be affected by distorting effects produced by historical dynamic, as the typical behaviour of the series is precisely to reverse the trend.

Table 2. Similarity matrix of daily variables.

	USD	DJ Stoxx50	FTSE	NASDAQ	CAC	DAX	DOW JONES	SP	GBP	YEN	NZD	GOLDS	SILV	3M	usgg2yr	usgg5yr	EU3M	gecu5yr	gecu2yr	CLA	NGA
USD	1.000																				
DJ_Stoxx50	–0.012	1.000																			
FTSE00	0.053	0.983	1.000																		
NASDAQ	0.244	0.920	0.939	1.000																	
CAC	–0.073	0.985	0.970	0.914	1.000																
DAX	0.314	0.905	0.900	0.953	0.889	1.000															
DOW JONES	0.201	0.958	0.956	0.964	0.951	0.964	1.000														
SP	0.112	0.975	0.973	0.964	0.977	0.938	0.991	1.000													
GBP	0.363	–0.872	–0.820	–0.723	–0.903	–0.664	–0.785	–0.842	1.000												
YEN	0.371	0.842	0.831	0.884	0.829	0.898	0.908	0.901	–0.682	1.000											
NZD	–0.051	–0.890	–0.900	–0.903	–0.895	–0.844	–0.885	–0.904	0.777	–0.759	1.000										
GOLDS	0.708	–0.607	–0.531	–0.364	–0.653	–0.303	–0.447	–0.527	0.846	–0.328	0.460	1.000									
SILV	0.836	0.016	0.114	0.254	–0.022	0.260	0.179	0.123	0.296	0.289	–0.146	0.705	1.000								
L3M	–0.416	0.837	0.768	0.645	0.866	0.619	0.738	0.790	–0.962	0.634	–0.667	–0.877	–0.404	1.000							
usgg2yr	–0.475	0.819	0.787	0.656	0.863	0.563	0.698	0.775	–0.951	0.590	–0.704	–0.890	–0.368	0.937	1.000						
usgg5yr	–0.435	0.807	0.787	0.680	0.853	0.570	0.697	0.775	–0.939	0.595	–0.737	–0.845	–0.316	0.897	0.986	1.000					
EU3M	1.000	0.007	0.072	0.263	–0.053	0.331	0.219	0.130	0.346	0.385	–0.071	0.700	0.840	–0.401	–0.458	–0.416	1.000				
gecu5yr	0.094	0.841	0.806	0.798	0.850	0.808	0.863	0.875	–0.812	0.911	–0.696	–0.576	–0.012	0.806	0.750	0.747	0.105	1.000			
gecu2yr	0.051	0.852	0.812	0.780	0.860	0.790	0.865	0.879	–0.833	0.894	–0.686	–0.619	–0.053	0.840	0.767	0.743	0.061	0.987	1.000		
CLA	0.768	0.130	0.184	0.330	0.096	0.329	0.308	0.266	0.041	0.539	–0.147	0.331	0.588	–0.092	–0.139	–0.097	0.765	0.436	0.405	1.000	
NGA	0.098	0.644	0.624	0.560	0.646	0.558	0.664	0.680	–0.666	0.735	–0.476	–0.511	–0.007	0.682	0.613	0.588	0.102	0.861	0.883	0.560	1.000

Table 3(a). Similarity matrix of monthly variables.

	M1$YOY	M2$YOY	M1€YOY	M2€YOY	eccpemuy	CPI_YOY	xtsbez	euccemu	eubci	euicemu	umrtemu	rstamom	ushbmidx	ustbtot	concconf	usurtot	debptotl	eupremu	euipemuy	ip_yoy	Fddsgdp
M1$YOY	1.000																				
M2$YOY	0.789	1.000																			
M1€YOY	0.797	0.427	1.000																		
M2€YOY	–0.865	–0.481	–0.931	1.000																	
eccpemuy	–0.930	–0.676	–0.921	0.942	1.000																
CPI_YOY	–0.939	–0.753	–0.879	0.882	0.985	1.000															
xtsbez	0.710	0.326	0.859	–0.822	–0.827	–0.788	1.000														
euccemu	–0.746	–0.851	–0.322	0.464	0.592	0.643	–0.210	1.000													
eubci	–0.942	–0.842	–0.690	0.796	0.886	0.901	–0.589	0.890	1.000												
euicemu	–0.922	–0.865	–0.616	0.730	0.837	0.864	–0.519	0.932	0.993	1.000											
umrtemu	0.909	0.570	0.937	–0.982	–0.971	–0.930	0.812	–0.569	–0.868	–0.812	1.000										
rstamom	0.094	0.134	0.307	–0.186	–0.214	–0.190	–0.002	0.105	–0.045	0.010	0.174	1.000									
ushbmidx	–0.466	–0.740	0.055	0.070	0.253	0.343	0.158	0.872	0.618	0.701	–0.190	0.209	1.000								
ustbtot	0.917	0.787	0.807	–0.850	–0.941	–0.954	0.652	–0.759	–0.949	–0.918	0.910	0.256	–0.451	1.000							
concconf	–0.526	–0.725	–0.182	0.258	0.390	0.450	–0.028	0.873	0.700	0.753	–0.379	0.205	0.858	–0.561	1.000						
usurtot	0.921	0.581	0.916	–0.977	–0.962	–0.921	0.792	–0.596	–0.879	–0.827	0.995	0.164	–0.217	0.911	–0.382	1.000					
debptotl	0.943	0.610	0.905	–0.943	–0.955	–0.931	0.816	–0.613	–0.881	–0.840	0.974	0.038	–0.274	0.888	–0.427	0.975	1.000				
eupremu	–0.952	–0.635	–0.881	0.938	0.957	0.933	–0.825	0.622	0.892	0.853	–0.965	–0.057	0.296	–0.892	0.431	–0.964	–0.975	1.000			
euipemuy	–0.921	–0.819	–0.726	0.804	0.883	0.899	–0.556	0.867	0.981	0.968	–0.877	–0.139	0.574	–0.962	0.692	–0.887	–0.870	0.864	1.000		
ip_yoy	–0.926	–0.820	–0.677	0.781	0.865	0.869	–0.593	0.843	0.969	0.953	–0.846	–0.155	0.547	–0.928	0.604	–0.865	–0.851	0.861	0.953	1.000	
fddsgdp	–0.900	–0.523	–0.944	0.985	0.960	0.913	–0.837	0.503	0.826	0.765	–0.992	–0.165	0.121	–0.868	0.307	–0.989	–0.971	0.955	0.835	0.812	1.000
USD	–0.721	–0.764	–0.354	0.414	0.573	0.636	–0.278	0.909	0.828	0.873	–0.545	0.203	0.818	–0.710	0.787	–0.568	–0.646	0.617	0.798	0.793	0.487
DJ_Stoxx50	–0.869	–0.842	–0.547	0.654	0.763	0.791	–0.432	0.943	0.953	0.971	–0.745	0.085	0.751	–0.857	0.804	–0.764	–0.805	0.784	0.925	0.911	0.696
FTSE00	–0.821	–0.824	–0.472	0.574	0.693	0.728	–0.384	0.935	0.908	0.934	–0.670	0.149	0.766	–0.791	0.802	–0.693	–0.752	0.714	0.874	0.872	0.625
NASDAQ	–0.770	–0.886	–0.389	0.464	0.642	0.715	–0.311	0.938	0.872	0.914	–0.578	0.173	0.843	–0.762	0.832	–0.591	–0.666	0.647	0.835	0.803	0.519
CAC	–0.880	–0.855	–0.553	0.656	0.769	0.801	–0.446	0.944	0.956	0.974	–0.746	0.082	0.748	–0.857	0.797	–0.764	–0.806	0.787	0.930	0.913	0.700
DOWJONES	–0.879	–0.848	–0.565	0.666	0.779	0.811	–0.454	0.944	0.962	0.978	–0.759	0.086	0.740	–0.870	0.800	–0.776	–0.815	0.795	0.937	0.914	0.711
SP	–0.869	–0.868	–0.541	0.629	0.763	0.807	–0.440	0.944	0.950	0.972	–0.728	0.102	0.766	–0.856	0.805	–0.744	–0.795	0.775	0.921	0.897	0.679
DAX	–0.827	–0.870	–0.484	0.570	0.715	0.763	–0.387	0.952	0.926	0.955	–0.675	0.117	0.795	–0.823	0.832	–0.690	–0.746	0.723	0.896	0.875	0.621
CLA	–0.840	–0.854	–0.621	0.627	0.807	0.866	–0.578	0.817	0.894	0.905	–0.727	0.036	0.632	–0.863	0.655	–0.723	–0.786	0.781	0.867	0.836	0.673
GBP	0.844	0.822	0.605	–0.713	–0.817	–0.851	0.498	–0.825	–0.912	–0.914	0.771	0.055	–0.619	0.874	–0.665	0.764	0.753	–0.805	–0.899	–0.835	–0.717
YEN	–0.844	–0.862	–0.559	0.574	0.750	0.817	–0.475	0.853	0.886	0.912	–0.687	0.104	0.730	–0.819	0.733	–0.691	–0.773	0.766	0.857	0.819	0.638
NGA	–0.921	–0.703	–0.860	0.882	0.952	0.945	–0.784	0.693	0.917	0.886	–0.936	–0.089	0.367	–0.928	0.483	–0.931	–0.951	0.935	0.908	0.890	0.907
NZD	0.648	0.843	0.190	–0.330	–0.485	–0.549	0.108	–0.973	–0.817	–0.870	0.442	–0.125	–0.922	0.673	–0.894	0.463	0.483	–0.527	–0.779	–0.765	–0.364
GOLDS	0.176	0.034	0.563	–0.531	–0.413	–0.337	0.401	0.154	–0.141	–0.050	0.445	0.475	0.436	0.332	0.139	0.401	0.296	–0.299	–0.209	–0.114	–0.439
SILV	–0.551	–0.570	–0.095	0.167	0.317	0.380	–0.164	0.733	0.594	0.661	–0.287	0.387	0.754	–0.394	0.610	–0.324	–0.435	0.434	0.524	0.597	0.264
L3M	–0.836	–0.580	–0.878	0.913	0.936	0.914	–0.718	0.476	0.786	0.726	–0.911	–0.393	0.164	–0.897	0.277	–0.897	–0.838	0.872	0.809	0.759	0.897
usgg2yr	–0.874	–0.838	–0.700	0.704	0.861	0.909	–0.646	0.749	0.882	0.881	–0.779	–0.022	0.535	–0.874	0.553	–0.772	–0.829	0.818	0.862	0.826	0.740
usgg5yr	–0.688	–0.849	–0.391	0.424	0.624	0.710	–0.356	0.804	0.777	0.811	–0.518	0.058	0.706	–0.720	0.648	–0.510	–0.562	0.582	0.757	0.700	0.451
EU3M	–0.711	–0.763	–0.339	0.400	0.561	0.626	–0.263	0.909	0.821	0.868	–0.532	0.205	0.825	–0.702	0.788	–0.555	–0.633	0.605	0.791	0.786	0.474
gecu5yr	–0.887	–0.819	–0.758	0.756	0.902	0.941	–0.665	0.753	0.908	0.899	–0.834	–0.088	0.519	–0.924	0.579	–0.823	–0.860	0.855	0.902	0.852	0.789
gecu2yr	–0.919	–0.791	–0.833	0.834	0.951	0.972	–0.726	0.726	0.925	0.902	–0.902	–0.128	0.443	–0.952	0.547	–0.893	–0.918	0.906	0.923	0.879	0.867

Table 3(b). Similarity matrix of monthly variables.

	USD	DJ Stoxx	FTSE	NASDAQ	CAC	DOW JONES	SP	DAX	CLA	GBP	YEN	NGA	NZD	GOLDS	SILV	L3M	usgg2yr	usgg5yr	EU3M	gecu5yr	gecu2yr
M1$YOY																					
M2$YOY																					
M1€YOY																					
M2€YOY																					
eccpemuy																					
CPI_YOY																					
xtsbez																					
euccemu																					
eubci																					
euicemu																					
umrtemu																					
rstamom																					
ushbmidx																					
ustbtot																					
concconf																					
usurtot																					
debptotl																					
eupremu																					
euipemuy																					
ip_yoy																					
fddsgdp																					
USD	1.000																				
DJ_Stoxx50	0.924	1.000																			
FTSE00	0.938	0.989	1.000																		
NASDAQ	0.947	0.950	0.957	1.000																	
CAC	0.918	0.997	0.988	0.954	1.000																
DOWJONE	0.922	0.998	0.985	0.954	0.998	1.000															
SP	0.937	0.993	0.984	0.974	0.995	0.996	1.000														
DAX	0.944	0.988	0.989	0.982	0.990	0.989	0.995	1.000													
CLA	0.865	0.888	0.870	0.920	0.898	0.902	0.923	0.916	1.000												
GBP	–0.696	–0.823	–0.753	–0.803	–0.835	–0.841	–0.842	–0.819	–0.857	1.000											
YEN	0.927	0.918	0.903	0.953	0.922	0.926	0.949	0.939	0.965	–0.824	1.000										
NGA	0.720	0.846	0.800	0.753	0.852	0.858	0.849	0.818	0.902	–0.828	0.844	1.000									
NZD	–0.871	–0.874	–0.863	–0.905	–0.873	–0.872	–0.880	–0.898	–0.774	0.797	–0.817	–0.591	1.000								
GOLDS	0.328	0.029	0.116	0.160	0.026	0.016	0.054	0.085	–0.040	0.202	0.095	–0.290	–0.212	1.000							
SILV	0.867	0.711	0.755	0.756	0.713	0.704	0.728	0.738	0.635	–0.468	0.742	0.467	–0.728	0.682	1.000						
L3M	0.378	0.609	0.505	0.472	0.616	0.627	0.603	0.547	0.658	–0.798	0.588	0.833	–0.390	–0.564	0.088	1.000					
usgg2yr	0.785	0.851	0.826	0.869	0.867	0.868	0.887	0.869	0.980	–0.860	0.934	0.928	–0.685	–0.150	0.545	0.733	1.000				
usgg5yr	0.777	0.776	0.763	0.880	0.798	0.794	0.828	0.835	0.923	–0.861	0.878	0.734	–0.807	0.021	0.581	0.533	0.906	1.000			
EU3M	1.000	0.920	0.935	0.945	0.913	0.917	0.933	0.941	0.860	–0.691	0.923	0.710	–0.874	0.339	0.870	0.367	0.778	0.776	1.000		
gecu5yr	0.773	0.857	0.814	0.844	0.867	0.873	0.884	0.863	0.972	–0.890	0.921	0.953	–0.690	–0.218	0.501	0.802	0.985	0.878	0.765	1.000	
gecu2yr	0.740	0.859	0.809	0.808	0.866	0.875	0.876	0.846	0.941	–0.872	0.892	0.977	–0.640	–0.291	0.454	0.848	0.965	0.803	0.731	0.987	1.000

- Nasdaq Index;
- Daily Exchange Rate Eur/USD New Zeland;
- Gold Spot Price USA;
- Average returns of Government Bonds—5 years in the USA zone;
- Average returns of Government Bonds—5 years in the Eurozone;
- Crude Oil Price—CLA (Crude oil);
- Exchange rate Euro/US dollar of the previous day compared to the day of the output.

For each of these variables of input historical memory was calculated, which is the number of daily observations in which it is very high the possibility that the daily value of the variables is self-correlated with the values of n days[5].

The historical memory was calculated by an polynomial interpolation with coefficient R^2 equal to 0.98 for 90% of cases. The historical memories calculated for each variable are:

- Nasdaq index: eight surveys;
- Daily exchange rate Euro/NZ Dollar: five surveys;
- Spot price of gold expressed in dollars per ounce: six surveys;
- Average returns of government bonds—5 years in the USA: eight surveys;
- Average returns of government bonds—5 years in the Eurozone: seven surveys;
- The price of crude oil (CLA): eight surveys;
- Exchange rate Euro/USD: seven surveys more output[6];

In order to predict the trend of historical memories of individual variables by determining the angular coefficients (m), it was used by the software MatLab the function Polyfit[7], whereas for the first experiments a degree of the polynomial approximation of 1[8].

Since the ANN uses values between –1 and 1 where it is used the activation function Tansig[9], it was necessary to normalize data through the interpolation performed with MatLab assigning values between –1 and 1 to vary of the value of the angular coefficient (m) produced by the Polyfit, according to the following summary:

IF	0 <= m <= 0.1	Then	value = 0.2
IF	0.1 < m <= 1.1	Then	value = 0.4
IF	1.1 < m <= 3.1	Then	value = 0.6
IF	3.1 < m <= 7.1	Then	value = 0.8
IF	m > 7.1	Then	value = 1
IF	–0.1 <= m < 0	Then	value = –0.2
IF	–1.1 <= m < –0.1	Then	value = –0.4
IF	–3.1 <= m < –0.1	Then	value = –0.6
IF	–7.1 <= m < 3.1	Then	value = –0.8
IF	m < –7.1	Then	value = –1

As shown by the previous scheme, the change of the angular coefficient determines the change in trend growth or reduction of the exchange rate Euro/USD USA.

The inputs of the network were reduced by 49 (*i.e.* 7 input with their historical memories) to 7, while the records[10] are 547.

To optimize the performance of the network we have reduced the data set to avoid signal of distortion or enhancement of some information, using 160 examples of maximum variance, of which 75% (120 examples) for training set and 25% (40 samples) for the validation set.

5. Optimal Topology Design Multi Layer Perceptron Neural (MLP) through a Multi-Objective Genetic Algorithm

The problem of finding the optimal topology of a Multi Layer Perceptron (MLP) neural network as a trade-off between the performance in terms of precision and the performance in terms of generalization, avoiding the problems of overfitting during the training phase, has been analyzed in the literature very accurately [63] and described in details in terms of an innovative genetic algorithm multi-objective Pareto-Based optimization problems [64] in which a bi-objective functions problems has been formulated and implemented. In fact decisions made in the network designing phase could turn out to be critical and choices non coherent with the problem could influence negatively learning or generalization ability of the Intelligent System. In this field evolutionary techniques have proven to be a great support in exploring the complex spaces that characterize the designing process. The setup of a neural network can be thought of as an optimization problem, indeed. The employment of such techniques appeared to be the optimal method in order to find a competitive solution.

Genetic Algorithms (GAs) are well established bio-inspired computational optimization approaches with a wide range of applications that spans from finance to medicine, inspired by the evolutionist theory explaining the origin of species. Following what happens in nature,

[5]The construction of the data set the neural network is based on the concept of historical memory as the objective of the ANN is to predict the trend of the exchange rate Euro/Dollar.

[6]To train the neural network it is considered as current moment t-2 for each variable, so as to obtain two readings back in order to predict a trend output rate Eur/U.S. dollar equal to three days.

[7]Function polyfit: polyfit $p = (x, fx, n)$. The polyfit is a function used for the construction of polynomial interpolation, where x is the vector that contains the nodes of the grid, fx is the vector containing the values to interpolate on the grid nodes, n is the degree of the polynomial interpolation.

[8]A function polyfit degree of approximation equal to 1 (*i.e.* $n = 1$) is a polynomial of first degree which interpolates the data as if making a linear regression values.

[9]Hyperbolic tangent sigmoid activation function. Tansig $(n) = 2/(1 + \exp(-2 * n)) - 1$, where n is the matrix of inputs. The results of a function Tansig can vary between –1 and 1.

[10]A record is a set of values of input variables and output.

weak species within their environment are faced with extinction by natural selection. The strong ones have greater opportunity to pass their genes to future generations via reproduction. If these changes provide additional advantages in the challenge for survival, new species evolve from the old ones. Unsuccessful changes are eliminated by natural selection. In GA terminology, a solution vector X is called an individual or a chromosome. Chromosomes are made of discrete units called genes. Each gene controls one or more features of the chromosome. In the original implementation of GA by Holland, genes are assumed to be binary digits. In later implementations, more varied gene types have been introduced. Normally, a chromosome corresponds to a unique solution X in the solution space. This requires a mapping mechanism between the solution space and the chromosomes. Being a population-based approach, GA are well suited to solve multi-objective optimization problems. A generic single-objective GA can be modified to find a set of multiple non-dominated solutions in a single run. The ability of GA to simultaneously search different regions of a solution space makes it possible to find a different set of solutions for difficult problems with non-convex, discontinuous, and multi-modal solutions spaces. In particular, Multi-Objective Genetic Algorithms are an extension of GAs and show their best performance when other common methods to simultaneously consider multiple objectives combining them linearly with fixed weights fail. In non MOGA strategy a linear combinations actually transform multiple objectives into a single objective, unfortunately such combinations cause the loss of diversity in potential solutions and then to overcome this shortcoming, Pareto optimal solutions are applied to retain the diversity.

Definition: Pareto Optimal Solutions

Let $x_0, x_1, x_2 \in F$, and F is a feasible region. And x_0 is called the Pareto optimal solution in the minimization problem if the following conditions are satisfied.

- If $f(x_1)$ is said to be partially greater than $f(x_2)$, *i.e.* $f_i(x_1) \geq f_i(x_2), \forall\, i = 1, 2, \cdots, n$ and $f_i(x_1) > f_i(x_2), \exists\, i = 1, 2, \cdots, n$, Then x_1 is said to be dominated by x_2.
- If there is no $x \in F$ s.t. x dominates x_0, then x_0 is the Pareto optimal solutions.

The geometric interpretation of Pareto optimal solutions for a bi-objective problem is demonstrated in **Figure 1**.

Then the definition of Pareto optimal solution is applied to determine which solutions in the set are Pareto optimal. The step repeats in every generation in MOGA.

The complete MOGA algorithm is introduced in **Figure 2** and the details of each step are explained in the following.

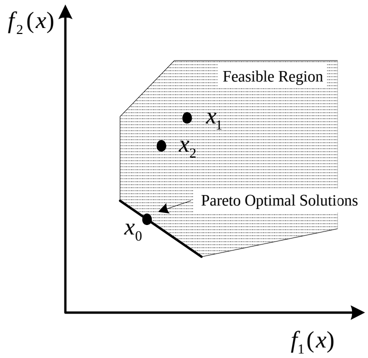

Figure 1. Pareto optimal solutions in the bi-objective problem.

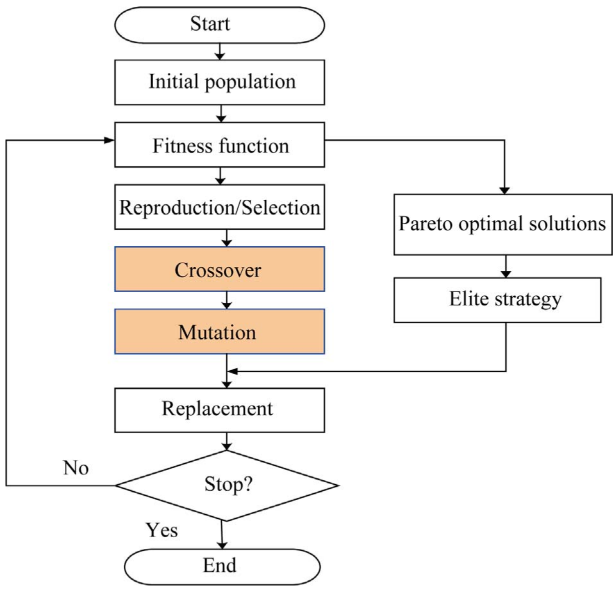

Figure 2. Steps of MOGA.

Moreover, it is well known that 90% of the approaches to multi-objective optimization aimed to approximate the true Pareto front for the underlying problem. A majority of these used a meta-heuristic technique, and 70% of all meta-heuristics approaches were based on evolutionary approaches. From this perspective it could be easily intended how MOGAs can be used in order to carry out a MLP topology optimization. In this paper each MLP neural topology developed for this research was trained on data sets described in paragraph 3 by monitoring two parameters of precision and generalization, which can be considered indicators of network quality, capacity or indices of the same set of learning of training data and generalize a set of separate data, not participating in the training phase. Generalization and accuracy were calculated as mean square error over all 120 training examples and all 40 examples of validation considered. In particular, for the purposes of this research, the optimal MLP neural network topology has been designed and tested by means the specific genetic algorithm multi-objective Pareto-Based designed from Bevilacqua *et al.* [64], taking into account the following parameters:

- number of neurons for layer;
- number of layers;
- activation functions of all neurons per each layer;

value of the learning rate.

The proposed solution proved to be able to reach a good level of optimization in terms of generalization performance and showed to be able to prune several original architectures designed formerly.

6. Analysis of the Results

In **Table 4** below it is summarized the characteristics and performance of the three best ANN designed for the purpose of this research which have provided, at the same performance of the training set of 100%, the best results for validation sets, respectively 70%, 60% and 80%.

The first two ANN are designed with the construction technique trial and error and the third network with optimized construction technique mentioned above in paragraph 5.

The third topology neural network designed with an optimized construction technique gives the best performance since it classifies correctly 120 examples of 120 in the training phase (performance of 100%) and 32 examples of 40 during validation (performance of 80%) using as classification decreasing range [–0.2; –0.04] and as a growing range of classification [0.04; 0.2]. The bandwidth of the network indecision is then amplitude namely 0.08 [–0.04; +0.04].

Table 5 shows some indicators of statistical error that can provide useful information on good predictive power of the third neural network topology designed with optimized design and manufacturing. By the analysis of the data it is possible to say that the ANN model developed can largely predict the trend to three days of exchange rate Euro/USD.

Table 4. Characteristics and performance of the three best topologies of neural networks designed.

First ANN Topology with Technology Building designed trial and error				
N° inputs	First Layer	Second Layer	N° output	Performance
7	11	8	1	120/120 28/40
Activation Function	Tansig	Tansig	Tansig	
Second ANN Topology with Technology Building designed trial and error				
N° inputs	First Layer	Second Layer	N° output	Performance
7	12	9	1	120/120 24/40
Activation Function	Tansig	Tansig	Tansig	
Third and optimal ANN Topology designed with optimized construction technique				
N° inputs	First Layer	Second Layer	N° output	Performance
7	12	9	1	120/120 32/40
Activation Function	Tansig	Tansig	Tansig	

7. Conclusions

By the empirical results it is possible to say, first of all, that empirical research conducted largely support the two research hypothesis discussed in section 1, justifying the attempt to forecast the exchange rate Euro/USD performed in this research through a non-linear methodology. The good forecasting performance of the network developed show that the process of formation of rate exchange is not completely governed by noise.

The research therefore provides evidence to support the hypothesis of serial dependence of prices in financial markets, according to which prices evolve according to a trend not completely random, and then, at least in part, predictable. This hypothesis, which draws its origins from chaos theory applied to financial systems [46,65-72], is based on the idea that what the theory of random walk considers noise, it is probably the result of complex interaction between different market players, who react to the dynamics of price with behaviours that can be better identified by models of nonlinear nature. Therefore, the analysis provides evidence to support the research hypothesis that the processes of pricing in financial markets have seemingly ruled by chance but in reality are determined by interaction between actors and relationships between variables of nonlinear nature, which are difficult to detect because of the chaotic component that

Table 5. Statistical indicators of performance of the best ANN topology designed with optimized design.

Coefficient	Result
Coefficient of determination R^2	0.946
MAE (Mean Absolute Error)	0.0835
MSE (Mean Square Error)	0.0316
MSEP (Mean Square Percentage Error)	0.7911
RMSE (Root Mean Square Error)	0.1779
RMSEP (Root Mean Square Percentage Error)	0.8895

characterizes the process of pricing in financial markets, the non-exhaustive information available to build effective predictive models and the inadequacy of many forecasting models. The considerations highlighted above lead to a final consideration [73], which is essentially methodological and is about the effectiveness of an integrated approach, which is based on the joint use of linear and non-linear methods of analysis to study the phenomenon of the forecasting of financial prices.

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