Applying FSSAM for Currency Rates Forecasting

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ABSTRACT

Currency rates forecasting in real-time is a milestone in the process of financial decision making. Assessing the historical performance of currency rates is a major concept in financial management. In this paper Fuzzy Software System for Asset Management (FSSAM) is briefly described. This system is applied on real data of currency rates and some of the results are shown.

***Keywords*:** FSSAM; Soft Computing; Fuzzy Inference System, Currency Rates

1 Introduction

Currency rates forecasting in real-time is a milestone in the process of financial decision making. Assessing the historical performance of currency rates is a major concept in financial management. Traditionally, financial investors use mainly two methods when managing assets: fundamental analysis and/or technical analysis. While the former approach is based on exploring the numerous macroeconomic events, the latter is concentrated on finding patterns in currency rates time series. Practically, both approaches aim to predict the future behavior of currency rates and thus to make investment decisions.

However, new methods of financial analysis are emerging nowadays, attempting to take into consideration the fluctuations in the rate series. The Fuzzy Software System for Asset Management (FSSAM) is originally designed to work with asset prices and is considered to be able to offer new solutions to longstanding problems. [7]

The core of FSSAM is fuzzy logic with the tools and techniques that it provides for dealing with large amounts of data (such as time series) and vague or imprecise information (as is economic information).

FSSAM steps on a simple concept: every investor has one ultimate goal and it is achieving maximum return at minimum risk. Therefore, the key point in the process of managing financial investments is finding a reliable estimator for changes in asset prices, an estimator that takes into account both return and risk. FSSAM is an independent software system in which the procedures for the collection and storage of data, the evaluation of assets and the construction of investment portfolios are implemented. It is a fuzzy rule-based software system, and following the general structure of a fuzzy system, consists of a knowledge base (rule base and database) and an inference machine. [4, 5, 6, 14]

Conceptually, fuzzy logic is the basis of Soft Computing (SC) [1, 3, 9, 12, 13], enriched with neural networks, evolutionary computing, probabilistic calculations and conclusions [10, 11].

SC consists of several computing paradigms: Fuzzy Logic (FL), Neural Networks (NN), approximate reasoning and non-differential optimization methods such as Genetic Algorithms (GA) and Simulated Annealing (SA).

2 FSSAM

2.1 Fuzzy Rule-based Software Systems

Following the general structure of a fuzzy system, a fuzzy rule-based software system consists of a knowledge base (rule base and database) and an inference machine (Fig. 1).

Let N be the number of the input fuzzy variables K_i, $i = 1, 2, 3, \dots, N$, and n_i be the number of terms X_{ij} of K_i for each i with $j = 1, 2, 3, \dots, n_i$. Let S be the number of output fuzzy variables Q_s, $s = 1, 2, 3, \dots, S$, and p_s be the number of terms Y_{sp} of Q_s for each s with $p = 1, 2, 3, \dots, p_s$.

Let $\mu_{ij}(x)$ be the membership function of the term X_{ij} and $\mu_{sp}(y)$ be the membership function of Y_{sp} . Then the overall number of the membership functions in the knowledge base is

$$N.\sum_{i=1}^{N} n_i + S.\sum_{s=1}^{S} p_s.$$

The crisp input values form a vector $x^* = (x_1^*,\ x_2^*, \dots, x_N^*\ )$. This vector is fuzzified by calculating $\mu_{ij}(x_i^*)$ for each i and j. At this point there are

$$N.\sum_{i=1}^{N} n_i$$

membership values, stored in the database after that calculation.

The next step is to aggregate. For simplicity let *min* operator be used for the *T-norm* and *T-norm* be used for the *AND* operator. Let *M* be the number of rules and the m-th rule R_m has the form:

$$if\ \left\{K_{m_1}\ is\ X_{m_1 j_{m_1}}\right\} and\ \left\{K_{m_2}\ is\ X_{m_2 j_{m_2}}\right\} and\ \dots\ and \left\{K_{m_k}\ is\ X_{m_k j_{m_k}}\right\}\ then\ \left\{Q_{m_1}\ is\ Y_{m_1 j_{m_1}}\right\} and$$
$$\left\{Q_{m_2}\ is\ Y_{m_2 j_{m_2}}\right\} and\ \dots\ and \left\{Q_{m_l}\ is\ Y_{m_l j_{m_l}}\right\}$$

and each rule has its weight w_m, $m = 1, 2, 3, \dots, M$.

Once the *m*-th rule is selected and put into the template (Figure 2), two consecutive calculations are made:

I. $\Theta_m = \min\left\{\ \mu_{m_1 j_{m_1}}(x_1^*),\ \mu_{m_2 j_{m_2}}(x_2^*), \dots, \mu_{m_k j_{m_k}}(x_k^*)\ \right\}$ and then

II. $\Theta_m{}^o = \Theta_m . w_m$.

After firing all the rules the corresponding values of the membership functions $\mu_{sp}{}^m = \Theta_m{}^o$ for each term Y_{sp} of the output variables are obtained. The number of these values depends on the number of rules in which they are used.

The aggregation applies after calculating

$$\mathrm{P}_{sp} = \max\{\ \mu_{s\,p}{}^1,\ \mu_{s\,p}{}^2, \dots, \mu_{s\,p}{}^M\ \}$$

for each Y_{sp}, $s = 1, 2, 3, \dots, S$ and $p = 1, 2, 3, \dots, p_s$.

The last step is defuzzification. For implementing any of the methods for defuzzification, shown earlier, a numerical integration could be applied.

This procedure is illustrated on Figure 1.

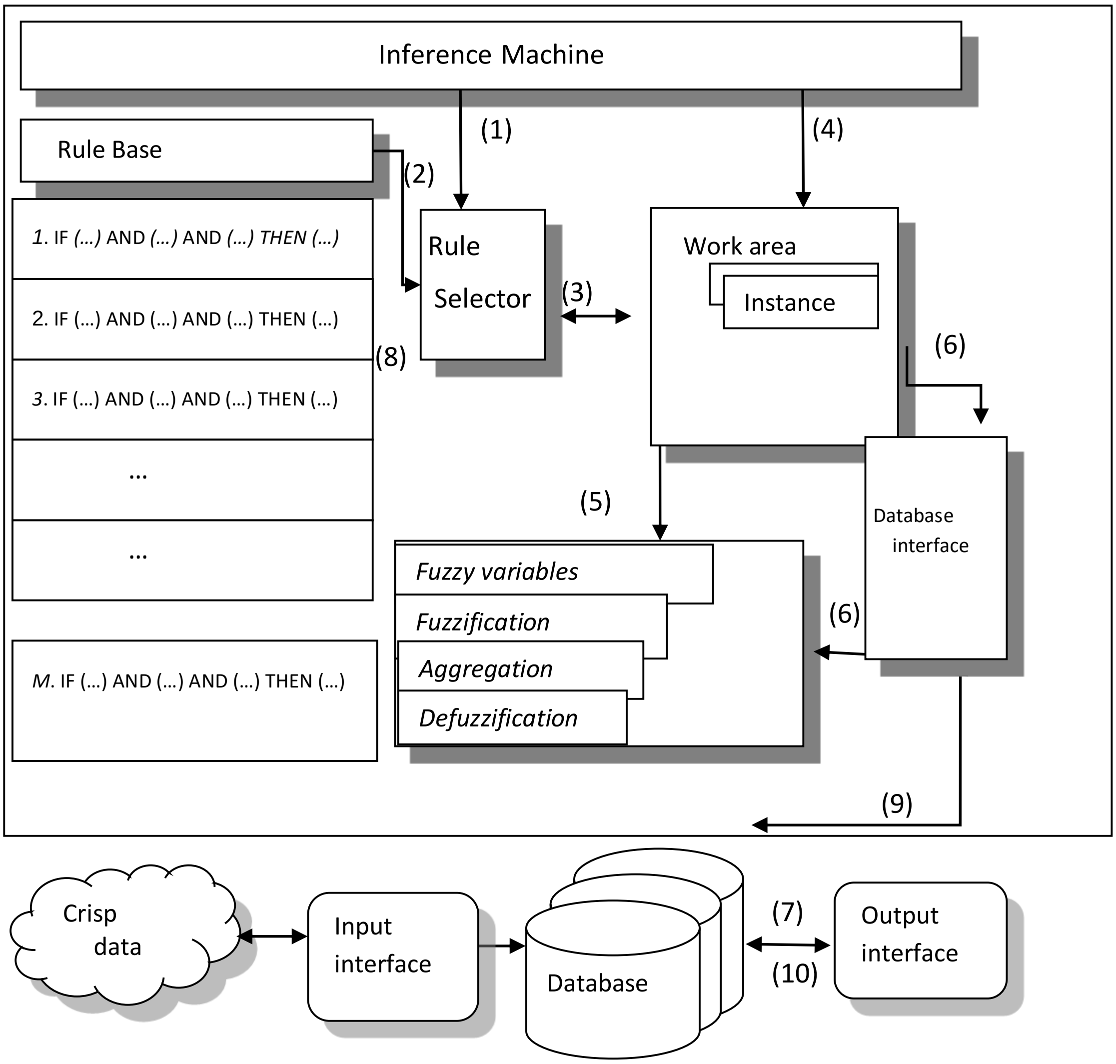

Figure 1 Inference Machine

(1) selector activation;
(2) rule choice;
(3) template;
(4) rule activation;
(5) go to: Fuzzy variables, fuzzy aggregation, defuzzification;

(6) interface connection;
(7) reading from the database;
(8) processing the next rule;
(9) writing the results in the database;
(10) output.

2.2 Fuzzy Software System for Asset Management (FSSAM)

FSSAM is an independent software system which consists of procedures for data collection and data storage, asset evaluation and investment portfolios construction. [15]

The application software system consists of three modules (Fig. 2):

(1) *data managing module* (*DMM*) with the following features: automatically submits queries to the Web server of a particular stock exchange; extracts data from the downloaded pages; writes data to the database; fills in the missing data; calculates *return*, *risk* and *q-ratio* for each asset in the database.

(2) *Q-measure fuzzy logic module* (*QFLM*), which is an application, based on fuzzy logic. Input data are the crisp numerical values of asset characteristics, obtained from *DMM*. These crisp values are fuzzified and after applying the aggregation rules, a fuzzy variable (*Q-measure)* for each of the assets is derived. The output is a defuzzified crisp value of *Q-measure*. The linguistic variables are four: three input variables and one output variable. Input variables describe the characteristics of an asset: *K1 = {return}*, *K2 = {risk} and K3 = {q-ratio}*. The output variable is *Q = {Q-measure}*. The input variables *K1 = {return}* and *K2 = {risk}* consist of five terms, each with corresponding parameters: *Very low*, *Low*, *Neutral*, *High*, and *Very high*. *K3* consists of three terms: *Small*, *Neutral*, and *Big*. The output variable *Q* consists of five terms: *Bad*, *Not good*, *Neutral*, *Good* and *Very Good*. There are 24 fuzzy rules implemented in the system. All fuzzy rules in this module have the form:

IF {K1 is high} AND {K2 is low} AND {K3 is big} THEN (Q is good).

As a defuzzification method, the method of center of gravity has been chosen, the composite trapezoidal rule for numerical calculation of the integrals is used and thus a crisp value for the asset quality is obtained as an output of *QFLM*.

(3) *portfolio construction module* (*PCM*), in which various portfolios are constructed.

The modules are described in detail in [5] and [8].

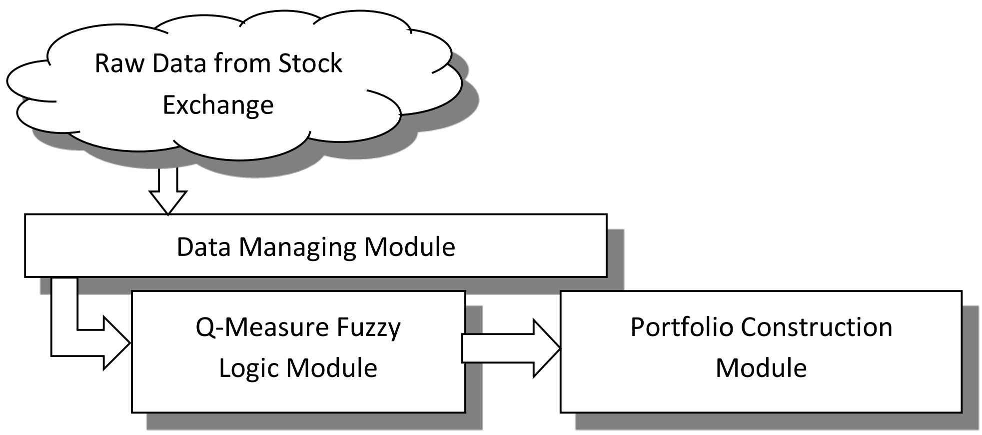

Figure 2 Conceptual scheme of FSSAM

2.3 Return, Risk and r/r Ratio

Let $P_1, P_2, \ldots, P_T$ be the sequence of daily rates P_t of a currency pair A/B, $t = 1, 2, \ldots, T$. Then the geometric mean of returns is an accurate measure for the change of the sum used to buy certain amount of A or B:

$$R_g = \sqrt[T-1]{\prod_{t=2}^{T} r_t} \ ,$$

where $r_t = \frac{P_t}{P_{t-1}}$ is the return for day t, $t = 1, 2, \ldots, T$.

Nevertheless, if one needs to study the dynamics of rate changes and the standard deviation of the returns, it is appropriate to take the logarithms of returns and then the next formulae are derived:

$$\ln(r_t) = \ln\left(\frac{P_t}{P_{t-1}}\right) = \ln(P_t) - \ln(P_{t-1}),$$

which is called log return for day t, $t = 1, 2, \dots, T$; and

$$\overline{r_g} = \ln(R_g) = \ln\left(\sqrt[T-1]{\prod_{t=2}^{T} r_t}\right) = \frac{1}{T-1}\sum_{t=2}^{T}\ln(r_t),$$

which is the arithmetic mean of log returns.

In time series formed from rates, some data may be missing, e.g. there may have not been any trading activities. One way to compensate these missing values is to add the last non-missing rate the corresponding number of times $P_{t-1}, P_{t-1}, \dots, P_{t-1}, P_t$. Then the annual return is calculated as follows:

$$AR = \sqrt[s]{\prod_{t=2}^{T} r_t} = \sqrt[s]{\frac{P_T}{P_1}},$$

where $s = \frac{\sum_{t=2}^{T}\Delta_t}{D}$; Δ_t is the number of days between the non-missing at days $t-1$ and t decreased by 1 and D is the number of days in the financial year.

And the mean annual norm of return is $ANR = AR - 1 = \sqrt[s]{TR} - 1$.

In case one uses log returns, the above considerations should be made very carefully because of the different number of days between the observations. Thus, if the return for the period Δ_t is $r_t^* = \frac{r_t - 1}{\Delta_t} + 1$, then the log return at the moment t is $\ln(r_t^*)$ and so the arithmetic mean of log returns is calculated as:

$$\overline{r_g^*} = \ln(AR) = \ln\left(\sqrt[T-1]{\prod_{t=2}^{T} r_t^*}\right) = \frac{1}{T-1}\sum_{t=2}^{T}\ln(r_t^*) \quad (1)$$

$AR^* = \left(e^{\overline{r_g^*}} - 1\right).D$ is the annual return and

$ANR^* = \left(e^{\overline{r_g^*}} - 1\right).D - 1$ is the annual norm of return. [4]

The annual norm of return ANR^* is an adequate estimator for the exact annual return.

The commonly used measure of risk in investment theory is the variability of returns. The variability shows to what extent returns change over time and thus estimates the probability of gain or loss in future moment. The variability is calculated by different statistical tools, based on probability distributions and most often the variance of the returns [2, 11].

If log returns are used, then the estimator of variance as an arithmetic mean of log-returns is calculated as follows:

$$s^2 = \frac{1}{T-2}\sum_{t=2}^{T}\left(\ln(r_t) - \overline{r_g}\right) \quad (2)$$

and the r/R ratio [5] equals the quotient of return and risk:

$$q = \frac{\overline{r_g^*}}{s} \quad (3)$$

2.4 Q-measure Fuzzy Logic Module (QFLM)

The final goal in the process of decision making is to find an optimal solution for a situation in which a number of possible solutions exists. Bellman and Zadeh proposed a fuzzy model for decision-making in which objectives and goals are described as fuzzy sets and the solution is an adequate aggregation of these sets. There are various algorithms for building a fuzzy system.

QFLM is an application based on fuzzy logic. Input data for this module are the crisp numerical values of asset characteristics from DMM. These crisp values are fuzzified and after applying the aggregation rules a fuzzy variable *Q-measure* for each of the assets is obtained. The output of this module is a defuzzified crisp value of *Q-measure*.

Input variables of QFLM. The calculations of the crisp values of the input variables: annual return, risk and q-ratio are derived in DMM. These crisp values are fuzzified with the predefined linguistic variables (LVs). The output variable is one: *Q-measure* of an asset.

The names of LVs are $X_1 \triangleq return$, $X_2 \triangleq Risk$, $X_3 \triangleq q\text{-}ratio$, $Y \triangleq Q\text{-}measure$. The term-sets of LVs are $T(X_1) = \{X_{1j}\}$, $T(X_2) = \{X_{2j}\}$, $T(X_3) = \{X_{3k}\}$, $T(Y) = \{Y_j\}$ *for* $j=1,\ldots,5$; $k=1,2,3$ and

$$X_{ij} \triangleq \begin{pmatrix} Very\ low & i=1,2 & j=1 \\ Low & i=1,2 & j=2 \\ Neutral & i=1,2 & j=3 \\ High & i=1,2 & j=4 \\ Very\ high & i=1,2 & j=5 \\ Small & i=3 & j=1 \\ Neutral & i=3 & j=2 \\ Big & i=3 & j=3 \end{pmatrix}; \qquad Y_j \triangleq \begin{pmatrix} Bad & j=1 \\ Not\ bad & j=2 \\ Neutral & j=3 \\ Good & j=4 \\ Very\ good & j=5 \end{pmatrix}$$

The universes of discourse of LVs are $U_{X1}=U_{X2}=U_{X3}=U_Y=R$.

Three types of membership functions are used:

- Gaussian membership function $\mu_G(x) = e^{-\frac{1}{2}\left(\frac{x-\beta}{\alpha}\right)^2}$;
- Bell membership function $\mu_B(x) = \frac{1}{1+\left|\frac{x-\gamma}{\alpha}\right|^{2\beta}}$ and
- Sigmoid membership function $\mu_S(x) = \frac{1}{1+e^{-\alpha(x-\beta)}}$.

The corresponding type of membership functions (MF) and values of the parameters can be found in [6].

Fuzzy inference. In this application, a Mamdani-type fuzzy inference (MFIS) system is chosen [14]. As a result of MFIS, a fuzzy output is obtained and this is the major reason for which MFIS are widely used in decision support applications. There are four stages in the fuzzy inference process:

(1) evaluation of the antecedent for each rule;

(2) obtaining a conclusion for each rule;

(3) aggregation of all conclusions;

(4) defuzzifying.

The *AND* and *THEN* operators are implemented by *min* fuzzy *T-norm*, whereas the aggregation is implemented by *max* fuzzy *T-conorm*. Center of gravity method is used for defuzzification of the output.

As there are three input variables with 5, 5 and 3 terms accordingly, the universe of all possible rules consists of 75 rules. In the system, 24 of the rules are chosen by experts. Although these rules adequately describe the most important possible situations that might arise in the process of investment decision-making, the list of fuzzy rules can be extended without changing the system's architecture. The fuzzy rules model the decision making process intuitively and have IF-THEN form:

$$if\ \ (r^*\ is\ X_{1i})\ and\ (s^*\ is\ X_{2j})\ and\ (q^*\ is\ X_{3k})\ \ then\ (Q-measure\ is\ \ Y_p)$$

for $i=1,\dots,5$; $j=1,\dots,5$; $k=1,\dots,3$ and $p=1,\dots,5$.

In the next step the fuzzy rules are fired. At this point additional expert knowledge is taken into account by assigning weights to each rule in the structure. In this way for a crisp input $(r^*,\ s^*,\ q^*)$ the obtained membership values are:

$$\theta^* = min\{\mu_i(r^*), \mu_i(s^*), \mu_i(q^*)\}$$

and then respectively

$$\theta^{**} = w.\theta^*,$$

where w is the corresponding weight of the rule.

After applying all the rules, several values for each term of the output variable *Q-measure* are calculated. Aggregation is the process of bringing together the outcomes of all the fuzzy rules. Choosing a suitable aggregation operator is a key issue when a fuzzy system is designed. As an aggregation method the *max* fuzzy *T-conorm* is applied in the proposed model and thus the fuzzy output variable is obtained.

The overall fuzzy output generally constitutes a multimodal non-zero distribution of possible crisp values over a subset of the output space. In the defuzzication stage, one of those possible crisp values has to be selected. The design of a sound defuzzication method is important as it affects the interpretation of the fuzzy response. A desirable defuzzication procedure should require a low computational effort to allow its implementation in real-time applications. At the same time, it should allow a smooth response and mapping accuracy to be obtained over all or most of the output space. What is more, a defuzzication method should ease the design of the fuzzy system and keep the decision making logic transparent to the user. The center of gravity (*CoG*) has been chosen as a defuzzification method. According to it, the crisp output value is calculated as:

$$\hat{Q} = C_oG(Q) = \frac{\int_{-\propto}^{+\propto} x.Q(x).dx}{\int_{-\propto}^{+\propto} Q(x).dx},$$

which is illustrated on Figure 3.

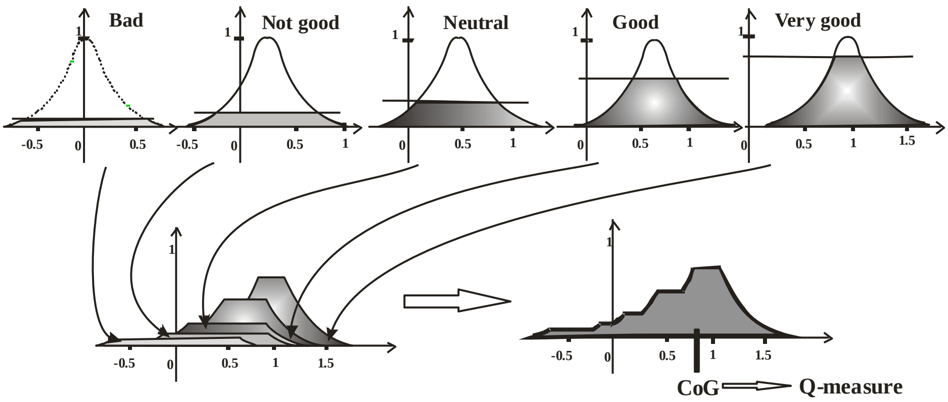

Figure 3 Aggregation and defuzzification for obtaining the Q-measure of an asset

3 Experiments and Results

In this section, FSSAM is applied on time series of currency rates. The results are obtained from real data from [16]. The data are rates of currency pairs – EUR/USD and AUD/USD. The goal is to assess the performance of FSSAM if applied for forecasting the rates. Part of the source code is provided below.

```
Price = xlsread('tempor.xlsx'); [TT,l]=size(Price);  P=Price;
   r0=0.055;sigma0=0;
   num1=9; L=1;
for k=1:TT-1
```

```
            T=num1-1;  T1=k;  T2=T1+num1;
        for i=T1+1:T2-1
            rt(i)=P(i)/P(i-1);
            rlog(i)=log(rt(i));
        end
TR=0;
        for i=T1+1:T2-1
            TR=TR+rlog(i);
        end
   rg=TR*(1/(T-1));
   AR=exp(rg*(T-1));
   ANR=(AR-1)*360/T;
.....
     FSSAM
                ……..
end
```

3.1 Currency pair EUR/USD

The observations of rates of the pair EUR/USD are from 30 October 2015 till 30 April 2016. The changes in rates are graphically shown on Figure 4 and, as can be seen, there are fluctuations over time.

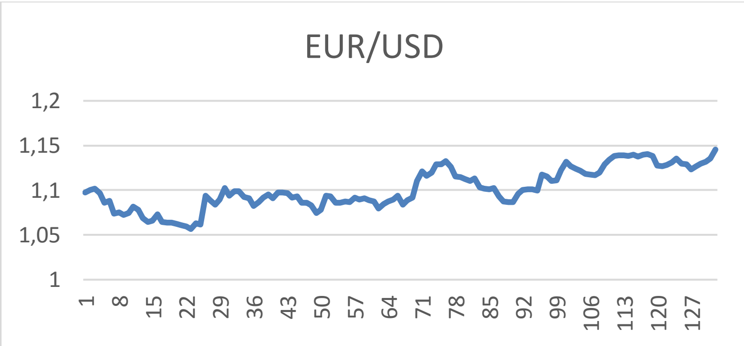

Figure 4 Changes in rates of EUR/USD

FSSAM is used to assess the tendencies in these changes. It is applied for different sequential periods – 5 days period, 6 days period, 7 days period, 8 days period and 9 days period. Thus an array of values of *Q-measure* is obtained. These arrays are visualized on Figure 5.

The obtained results can be used to evaluate possible changes in the currency pair rates. The value of *Q-measure* obtained from FSSAM shows a tendency to indicate the substantial decrease in the pair rates. There is, however, little or no evidence that the increase of the value of *Q-measure* indicates growth in currency rates.

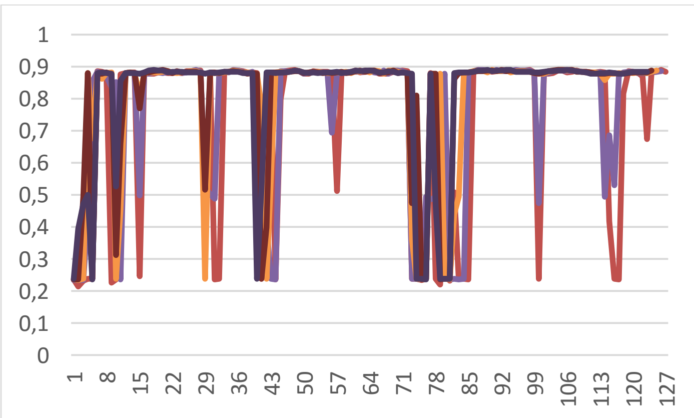

Figure 5 *Q-measure* obtained from FSSAM for EUR/USD

3.1 Currency pair AUS/USD

The observations of rates of the pair AUS/USD are again from 30 October 2015 till 30 April 2016. The changes in rates are graphically shown on Figure 5.

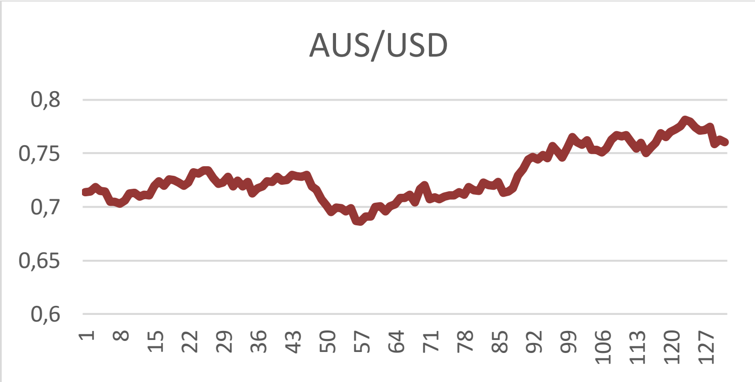

Figure 5 Changes in rates of EUR/USD

FSSAM is again applied to assess the tendencies in these changes. It is applied for different sequential periods – 5 days period, 6 days period, 7 days period, 8 days period and 9 days period, but for simplicity Figure 6 contains only the results from 5 days period, 7 days period and 9 days period. Thus another array of values of *Q-measure* is obtained.

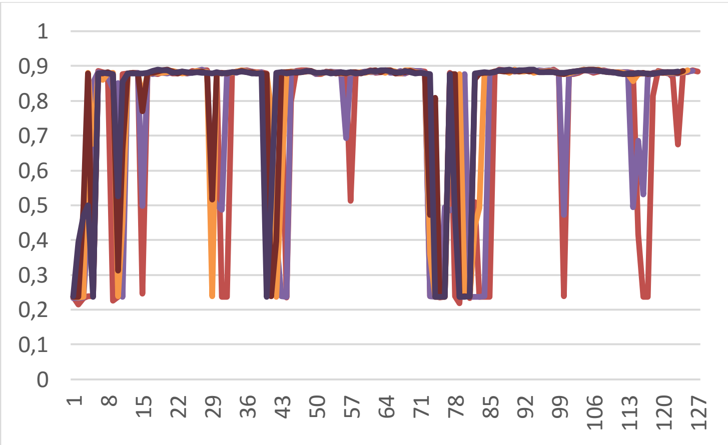

Figure 6 Q-measure obtained from FSSAM for AUD/USD

On Figure 7 the Q-measure for 6 day period and the rates are displayed together.

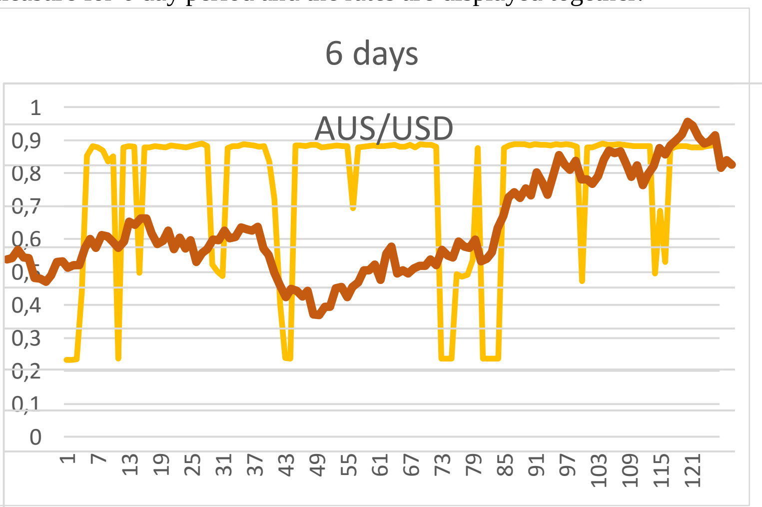

Figure 7 *Q-measure* obtained from FSSAM and rates series for AUD/USD

4 Conclusion and Future Development

FSSAM is designed and originally used for assessing financial assets – individual as well as financial portfolio investments. This model is based on the Q-measure of an asset: a characteristic which combines return, risk and their ratio, and being modelled with fuzzy logic tools, it intuitively reflects the process of investment decisions in economic environment with an enormous amount of data, which is often incomplete and imprecise.

The application of FSSAM on currency rates shows that changes in *Q-measure* can be used (so far) only as an indicator in case of decrease. And this is one possible direction for refining the system if it is to be used for currency forecasting.

Another direction for improvement is connected with the fact that the fuzzy systems have one disadvantage in general: they are not flexible to changes. There are various possibilities for the future improvement of the model: adjusting the parameters of the membership function with a neural network; using genetic algorithms for improving the architecture of the Fuzzy system etc.

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