Volatility Change Point Detection Using Stochastic Differential Equations and Time Series Control Charts

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***Abstract*—**The article focuses on volatility change point detection using SPC (Statistical Process Control), specifically through time series control charts, and stochastic differential equations (SDEs). In the paper, recent advances in timechange point for process volatility component satisfying a stochastic differential equation (SDE) based on discrete observations and also using time series control charts will be reviewed. Theoretical part will discuss the methodology of time series control charts and SDEs driven by a Brownian motion. Research part will demonstrate the methodologies using a case study focusing on analysis of Slovak currency during the period of 2000 – 2004 from the perspective of its usefulness for generating profits for company management through time series control charts and SDEs. The aim of the paper is to demonstrate use of change point detection in time series of the Slovak crown. It also aims to highlight versatility of control charts not only in manufacturing but also in managing financial stability of cash flows.

***Keywords*—** Change point, Statistical process control, Stochastic differential equations, Time series control charts.

I. Introduction

In finance, the volatility of the market or of the asset prices plays a crucial role in many aspects. For example, in option pricing, although the very basic Black and Scholes (1973) [1] and Merton (1974) [2] model assumes a constant volatility, it is well known that this assumption is unrealistic when one works with real financial data. This fact causes well-known effects like implied volatility and volatility smiles. Change point analysis was initially introduced in the framework of independent and identically distributed data (see, e.g., Hinkley, 1971 in [3]; Inclan and Tiao, 1994 in [4]; Bai, 1994, 1997 in [5], [28]; Csörgö and Horváth, 1997 in [34]), and quickly applied to the analysis of time series (see, e.g., Kim, Cho and Lee, 2000 in [6]; Lee, Ha and Na, 2003 in [7]; Chen, Choi and Zhou, 2005 in [8]). Kutoyants (1994, 2004) in [39], [40]; Lee, Nishiyama and Yoshida, (2006) in [9] studied structural change point problems for the drift term for continuous observations from ergodic diffusion processes. Due to the fact that volatility can be estimated without error in continuous time, the change point analysis in this setup is not very interesting.

In this paper, there will be review recent advances for the problem of timechange point for the volatility component of a process satisfying a stochastic differential equation (SDE) based on discrete observations (Chapter V) and also using time series control charts (Chapter IV).

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II. Literature Review

In fact, change point problems have originally arisen in the context of quality control, but the problem of abrupt changes in general arises in many contexts like epidemiology, rhythm analysis in electrocardiograms, seismic signal processing, study of archeological sites and financial markets. In particular, in the analysis of financial time series, the knowledge of the change in the volatility structure of the process under consideration is of a certain interest.

Various authors have studied change point detection problems using parametric and non-parametric procedures quite extensively. In some cases, the study was carried out for known underlying distributions, namely the binomial, Poisson, Gaussian and normal distributions, amongst others. This chapter discusses some of the work that has been done on change point detection.

CUSUM is one of the widely used change point detection algorithms. Basseville & Nikiforov (1993) in [10] described four different derivations for the CUSUM algorithm. The first is more intuition-based, and uses ideas connected to a simple integration of signals with an adaptive threshold. The second derivation is based on a repeated use of a sequential probability ration test. The third derivation comes from the use of the off-line point of view for multiple hypotheses testing. The fourth derivation is based upon the concept of open ended tests. The principle of CUSUM stems from stochastic hypothesis testing method.

Nazario, Ramirez and Tep (1997) in [11] developed a sequential test procedure for transient detections in a stochastic process that can be expressed as an autoregressive moving average (ARMA) model. Preliminary analysis shows that if an ARMA(p,q) time series exhibits a transient behavior, then its residuals behave as an ARMA(Q,Q) process, where: $Q \leq p + q$. They showed that residuals from the model before the parameter change behave approximately as a sequence of independent random variables - after a parameter change, the residuals become correlated. Based on this fact, they derived a new sequential test to determine when a transient behavior occurs in a given ARMA time series.

Blazek, HongJoong, Boris and Alexander (2001) in [12] developed efficient adaptive sequential and batch-sequential methods for an early detection of attacks from the class of “denial-of-service attacks". Both the sequential and batch-sequential algorithms used thresholding of test statistics to achieve a fixed rate of false alarms. The algorithms are developed on the basis of the change point detection theory: to detect a change in statistical models as soon as possible, controlling the rate of false alarms. There are three attractive features of the approach. First, both methods are self-learning, which enables them to adapt to various network loads and usage patterns. Second, they allow for detecting attacks with a small average delay for a given false alarm rate. Third, they are computationally simple, and hence, can be implemented online. For more about false alarm rates e.g. for the Shewhart control charts see in [29].

Huat and Midi (2010) in [33] examine a process-monitoring tool that not only provides speedy detection regardless of the magnitude of the process shift, but also provides useful change point statistics.

Lund, Xiaolan, Lu, Reeves, Gallagher and Feng (2007) in [13] looked at the change point detection in periodic and auto correlated time series using classic change point tests based on sums of squared errors. This method was successfully applied in the analyses of two climate changes.

Moskvina and Zhigljavsky (2003) in [14] developed an algorithm of change point detection in time series, based on sequential application of the singular-spectrum analysis (SSA). The main idea of SSA is performing singular value decomposition (SVD) of the trajectory matrix obtained from the original time series with a subsequent reconstruction of the series.

Mboup, Join and Fliess (2008) in [15] presented a change point detection method based on a direct online estimation of the signal’s singularity points. Using a piecewise local polynomial representation of the signal, the problem is cast into a delay estimation. A change point instant is characterized as a solution of a polynomial equation, the coefficients of which are composed by short time window iterated integrals of the noisy signal. The change point detector showed good robustness to various types of noises.

Auret and Aldrich (2010) in [16] used random forest models to detect change points in dynamic systems. Wei, Hanping, Yue and Wang (2010) in [17] used Lyapunov exponent and the change point detection theory to judge whether anomalies have happened. Aldrich and Jemwa, (2007) in [18] used phase methods to detect change in complex process systems.

Vincent (1998) in [19] presented a new technique for the identification of inhomogeneities in Canadian temperature series. The technique is based on the application of four linear regression models in order to determine whether the tested series is homogeneous. Vincent’s procedure is a type of “forward regression” algorithm in that the significance of the non-change point parameters in the regression model is assessed before (and after) a possible change point is introduced. In the end, the most parsimonious model is used to describe the data. The chosen model is then used to generate residuals. It uses the autocorrelation in the residuals to determine whether there are inhomogeneities in the tested series. At first, it considers the entire period of time and then it systematically divides the series into homogeneous segments. Each segment is defined by some change points, and each change point corresponds to either an abrupt change in mean level or a change in the behavior of the trend.

III. PROBLEM FORMULATION

The aim of the paper is to demonstrate use of change point detection in time series of the Slovak crown through the time series control charts and SDEs.

Slovak crown was analyzed due to accessibility of primary statistical data (currency rates, interest rates on whole time scale from Overnight to 1 year) and also due to availability of fast communication channels with the statistical department of the National bank of Slovakia in case there was a need for any clarification.

Box-Jenkins methodology was utilized as the main analytical and mathematical-statistical method to analyze time series. The output will be used to construct SPC control charts for detection of change in variance structure. Furthermore, this approach will be confronted with change point detection by modeling the SDEs, covered in Chapter VI.

The following theoretical chapters (Chapter IV and Chapter V) provide a description of mathematical-statistical tools used to verify the formulated research aim.

IV. TIME SERIES CONTROL CHARTS

A. ARIMA control charts

Classic Shewhart SPC concept assumes the measured data are not autocorrelated. Even very low degree of autocorrelation causes failure of the classic Shewhart control charts in a form of a large number of points outside the regulatory limits in control diagram [30]. The phenomenon is not unique to continuous processes, where the inertia processes determine the autocorrelation data in time (chemical and climate processes etc.). Autocorrelation of data becomes increasingly frequent in discrete processes, in particular manufacturing with short production cycles, high speed production with high degree of production automation and also in test and control operations. In these conditions, it is possible to obtain data about each product, with the consequence that the time interval between measurements (recording) of two consecutive values of the monitored variables is very short. One of the ways to tackle autocorrelated data is the concept of stochastic modeling of time series using autoregressive integrated moving average models, the ARIMA model. Linear stochastic autoregressive models (models AR), moving average (model MA), mixed models (the ARMA models), and ARIMA models, based on Box-Jenkins methodology are seen as a time series realization of stochastic process. Box-Jenkins methodology represents a modern analysis of stationary and nonstationary time series based on probability theory. Linear models AR, ARMA and MA are modeling tool for the stationary processes. These models have a characteristic shape of the autocorrelation function (Autocorrelation Function – ACF) and partial autocorrelation function (Partial Autocorrelation Function – PACF), essential tools for providing information about the stochastic process. ACF and PACF estimates are used to identify the time series model. Very often, there are non-stationary processes in practice. Nonstationarity can be present due to the mean value changing over time or process variance changing over time. If, after the transformation of nonstationary process variance of "random walk" (so-called integrated process) using differential *d*-th order is the final process model to describe the stationary ARMA (p, q), the original integrated process is called an autoregressive integrated moving average process of order *p*, *d*, *q*, i.e. ARIMA (p, d, q) [44].

ARIMA control chart (Autoregresive Integrated Moving Average) is based on the principle of finding a suitable time series model and the use of control chart for the model's residuals (deviations from the values actually measured values from calculated values with the model use).

The general shape of the model ARIMA (p, d, q) is such

$$\Phi_p(B)\cdot\nabla^d\cdot x_t=\Theta_q(B)\varepsilon_t, \tag{1}$$

where

$\Phi_p(B)=\left(1-\phi_1B-\phi_2B^2\ldots-\phi_pB^p\right)$ is autoregressive polynomial of *p*-th order,

$\Theta_q(B)=\left(1-\theta_1B-\theta_2B^2\ldots-\theta_qB^q\right)$ is moving averages polynomial of *q*-th order,

∇ operator denoted a backward difference (introduced when the model exhibits nonstationarity of the process),

d difference order,

t time,

B back shift operator $B\cdot x_t=(x_{t-1})$,

$\phi_1,\phi_2,\ldots,\phi_p$ parameters of autoregressive model,

$\theta_1,\theta_2,\ldots,\theta_q$ parameters of moving averages model,

ε_t is a white noise, unpredictable, normally distributed fluctuations in the data with mean equal to zero and constant variance, and uncorrelated values.

If $\hat{x}_t$ is an estimate of empirical value of x_t calculated with help of right chosen ARIMA model, residuals of the model $e_t=x_t-\hat{x}_t$ will be uncorrelated, normally distributed random variables.

Most commonly used in applications are ARIMA models. Let us consider the model

$$x_t=\xi+\phi x_{t-1}+\varepsilon_t \tag{2}$$

where ξ a $\varphi(-1<\phi<1)$ are unknown constants and ε_t is normally distributed and uncorrelated variable with the mean equal to zero and the constant standard deviation σ. This model is called autoregressive model of the first order and is denoted as AR(1). The values of the reference mark of quality, which are mutually shifted of *k* time periods (x_t and x_{t-k}) have the correlation coefficient □^{k}. This means that autocorrelation function ACF should fall exponentially. If we expand the previous equation in the form

$$x_t=\xi+\phi_1x_{t-1}+\phi_2x_{t-2}+\varepsilon_t, \tag{3}$$

we get equation of second order autoregressive model AR(2). Generally, variable x_t is directly dependent on the values preceding x_{t-1}, x_{t-2}, etc. in the autoregressive model AR (p). If we model the dependence of data using the random component ε_t, then we get moving average model MA (q). Moving average model first order has an equation:

$$x_t=\mu+\varepsilon_t-\theta\varepsilon_{t-1}. \tag{4}$$

There is some correlation only between two values x_t and x_{t-1}. It can be described as follows: $\rho_1=-\theta/(1+\theta^2)$. This corresponds to the shape of the autocorrelation function ACF [44]. For modeling of practical problems, it is often suitable to model compound containing both autoregressive and the moving averages component. The model is generally known as ARMA (p, q) [45]. ARMA of the first order, i.e., ARMA (1, 1) is described by the equation:

$$x_t=\xi+\phi x_{t-1}+\varepsilon_t-\theta\varepsilon_{t-1}. \tag{5}$$

It is often suitable for chemical and other continuous processes, where many quality characteristics can be easily modeled by AR (1). Measurement errors are described by model's random component we assume to be random and uncorrelated. The ARMA model assumes process stationarity, i.e., that the character quality reference values are around a stable mean. But often, in practice, there are processes (e.g. in the chemical industry), where the values of monitored variable are "running away". It is then convenient to model processes using appropriate model with the operator of backward difference ∇, such as the ARIMA model (0, 1, 1) whose equation is

$$x_t=x_{t-1}+\varepsilon_t-\theta\varepsilon_{t-1}. \tag{6}$$

ARIMA are different from Shewhart model ($x_t=\mu+\varepsilon_t$ for t = 1, 2, …). However, if we put $\varphi = 0$ in the equation $x_t=\xi+\phi x_{t-1}+\varepsilon_t$ or $\theta=0$ in the equation $x_t=\mu+\varepsilon_t-\theta\varepsilon_{t-1}$, we get the Shewhart model process.

Another important step in the use of ARIMA models is the choice of the appropriate SPC control chart. When residuals testing are deemed not autocorrelated and coming from a normal distribution, it is possible to use them to verify whether or not the process is statistically stable. Because the number of observations equals one (original empirical values x_t were detected by each unit) control charts for individual values and moving range takes priority. Location of the mean value CL and upper and lower control limits (*UCL, LCL*) for the ARIMA chart for individual values can be determined from the formula

$$CL = \overline{e}\left(\cong 0\right), \tag{7}$$

$$UCL = \overline{e} + \frac{3}{1{,}128}\overline{R}_{kl}, \tag{8}$$

$$LCL = \overline{e} - \frac{3}{1{,}128}\overline{R}_{kl}, \tag{9}$$

where

$\overline{e}$ is average value of residuals,

$\overline{R}_{kl}$ is average moving range.

Values CL, UCL and LCL can be calculated as follows

$$CL = \overline{R}_{kl}, \tag{10}$$

$$UCL = 3{,}267 \cdot \overline{R}_{kl}, \tag{11}$$

$$LCL = 0. \tag{12}$$

To increase the sensitivity of control charts ARIMA, it is recommended to use two-sided CUSUM control chart with the decision interval $\pm H$ or standard EWMA chart, both applied to the residuals of the model. If we pursue more quality characteristics simultaneously on a single product to multiple, we can apply Hotelling chart or CUSUM or EWMA charts for more variables [44].

B. CUSUM control chart

CUSUM (Cumulative Sum) is a sequential analysis technique that is used in the detection of abrupt changes [32].

When applying CUSUM method, a diagram is constructed. On x axis of this diagram a selective order is recorded. On axis y test criterion values Y_k are recorded. The value of test criterion after k-th selective y_k can be defined by formula

$$C_k = \sum_{j=1}^{k}\left(\overline{x}_j - \mu_0\right) = C_{k-1} + \left(\overline{x}_k - \mu_0\right),\ C_0 = 0, \tag{13}$$

where k is the selective order k = 1, 2, ...), $\overline{x}_j$ is the selective average from values of regulated value in j-th selection (j = 1, 2, …, k). The study of CUSUM will not answer the question whether the change of diagram progression signals a significant deviation (indicating a definable influence on process) or whether the influence is random. Therefore decision criteria need to be added.

There are two basic types of criteria, through which a decision can be made, whether the process is statistically viable or not. These are:

I. decision mask,
II. decision interval.

These procedures are described in detail in publication [7].

- *CUSUM chart for individual values and for samples means from normally distributed data*

Values of x_i are independent with the same normal distribution $N(\mu, \sigma^2)$ with the known population mean and with the known population standard deviation σ. We assume logical subgroups with the same volume n. Cumulative sum – CUSUM C_n is defined for individual values (n = 1) as:

On a base of original scale:

$$C_n = \sum_{j=1}^{n}(x_j - \mu)\cdot \tag{14}$$

On a base of normal distribution where the mean μ = 0 and the standard deviation σ = 1:

$$U_j = \frac{(x_j - \mu)}{\sigma},\ S_n = \sum_{j=1}^{n} U_i \cdot \tag{15}$$

The CUSUM C_n is almost the same as CUSUM S_n measured in the units of standard deviation σ. Equation for C_n can be rewritten recurrently [20]: $C_0 = 0$, $C_n = C_{n-1} + (x_n - \mu)$; and with the same principle for S_n: $S_0 = 0$, $S_n = S_{n-1} + U_n$.

Suppose that the original distribution of observed variable $N(\mu, \sigma^2)$ changes into $N(\mu + \delta, \sigma^2)$ distribution for integer t (at arbitrary moment). It means that the population mean μ will face a certain shift of δ.

It also means that the shift starts at point (m, C_m) and grows linearly with the slope δ. But the population means shift can be more complicated. The CUSUM control chart can reflect all these changes [21].

- *CUSUM for sample means*

We have considered mainly the individual values until now. Now, we will consider subgroups with m observations and calculate the sample means from subgroups. We have to work with the sample mean standard deviation $\sigma_{\bar{x}} = \dfrac{\sigma}{\sqrt{m}}$.

A shift of mean Δ will not be measured in the units of σ but in the units of $\sigma_{\bar{x}}$ in this case. We will substitute the individual values of x_i with the sample means $\overline{x}_j$ and the process standard deviation σ with the sample mean standard deviation $\sigma_{\bar{x}}$ in abovementioned formulas [22].

New Process Mean Estimate

If there is a shift we can estimate a new process mean from the next formula:

$$\hat{\mu} = \begin{cases} \mu_0 + K + \dfrac{C_I^+}{N^+} & \text{pro} \quad C_I^+ > H \\[2ex] \mu_0 - K + \dfrac{C_I^-}{N^-} & \text{pro} \quad C_I^- < -H \end{cases}, \tag{16}$$

where N^+ and N^- is a number of selected points from a moment [23], when $C_n^+ = 0$, resp. when $C_n^- = 0$.

- *Comparsion of CUSUM and Shewhart´s Control Charts*

This example shows practically sensitivity of the CUSUM control chart in comparison with the Shewhart´s control chart for the sample means. The CUSUM control chart detects process mean deviation towards the lower values (around the subgroup 20 – see Fig. 1) while the Shewhart´s control chart does not detect this deviation [21]. It does not detect a shift towards the upper values (around the subgroup 56). It only detects a big shift around the subgroup 70 (see both Fig. 1 and Fig. 2) [22].

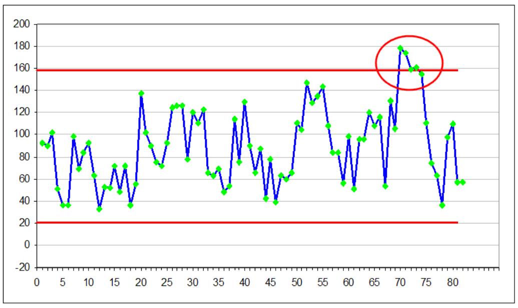

Fig. 1 Shewhart´s Control Chart. Source: QC Expert 2.5Cz

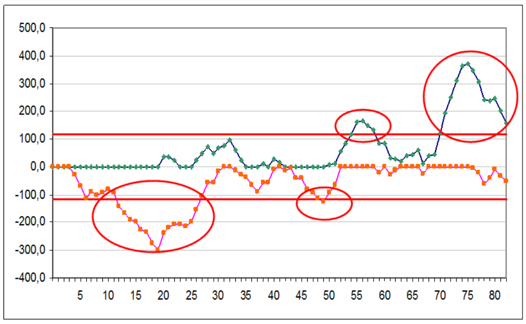

Fig. 2 Control Chart CUSUM. Source: QC Expert 2.5Cz

C. EWMA control charts

Similarly to CUSUM diagram, also EWMA diagram is feasible for situations in which the process is impacted by sudden, small but prevailing changes and the values of observed characteristic are not dependent. Unlike standard diagrams, the regulation bounds depend on the selective moment.

The author of the EWMA diagram is Roberts (1959) in [24]. This diagram works with test criterion Y_k. The value after k-th selection is defined as follows:

$$y_k = (1-\lambda)^k \cdot Y_0 + \lambda \cdot \sum_{j=1}^{k} (1-\lambda)^{k-j} \cdot f(x_j) \qquad (17)$$

for $j = 1, 2, \ldots, k$ and for $0 < \lambda < 1$, $f(x_j)$ is the value of selective characteristic, k is the selection order, Y_0 is the required level of distribution parameter of regulated value.

When dealing with Shewhart regulation diagrams for individual values, we observed that the diagram for individual values is very sensitive to data non-normality in the sense that real, under the ARL (ARL_0) control, would be significantly smaller than the expected value based on the assumption of normal distribution. Borror, Montgomery and Runger (1999) in [25] compared the behavior of ARL Shewhart diagrams for individual values and EWMA diagrams for the case of asymmetric distribution. Features of individuals control charts for Burr distributed and Weibull distributed data see in [31].

In the following text a specific gamma distribution representing the case of asymmetric distribution and t distribution representing symmetrical distribution N(0, 1) will be utilized. ARL_0 values of Shewhart regulation diagrams for individual values and EWMA diagrams for these distributions are denoted in the following tables.

Two aspects in these tables are bewildering. Firstly, even slight non-normality in distribution leads to significant decrease of ARL value in Shewhart diagram for individual values. Subsequently the number of false alarms increases. Secondly EWMA with $\lambda = 0.05$ or $\lambda = 0.10$, and appropriately selected regulation bound can work very well on both symmetric and asymmetric distribution.

With parameters $\lambda = 0.05$ and $K = 2.492$ the ARL_0 value for EWMA is approximately 8% of the limit emphasized by theory of normal distribution of value $ARL_0 = 370$, with the exception of extreme cases [26].

Tab. 1 ARL values for the EWMA chart and a chart of individual values for different gamma distribution. Source: [26]

	EWMA			Shewhart
λ	**0.05**	**0.1**	**0.2**	**1**
K	**2.492**	**2.703**	**2.86**	**3.00**
Standard	370.4	370.8	370.5	370.4
Gamma (4, 1)	372	341	259	97
Gamma (3, 1)	372	332	238	85
Gamma (2, 1)	372	315	208	71
Gamma (1, 1)	369	274	163	55
Gamma (5, 1)	357	229	131	45

Tab. 2 ARL values for the EWMA chart and a chart of individual values for different t distribution. Source: [26]

	EWMA			Shewhart
λ	**0.05**	**0.1**	**0.2**	**1**
K	**2.492**	**2.703**	**2.86**	**3.00**
Standard	370.4	370.8	370.5	370.4
t_{50}	369	365	353	283
t_{40}	369	363	348	266
t_{30}	368	361	341	242
t_8	358	324	259	117
t_6	351	305	229	96
t_4	343	274	188	76

Based on this information the properly designed EWMA is recommended as a control chart for individual values in a wide range of applications, particularly in process monitoring. It is almost a completely nonparametric (independent of distribution) procedure. In addition, EWMA charts are definitely better than Shewhart charts for individual values as well as for the features of the mean shift detection [26], [27].

V. CHANGE POINT DETECTION USING STOCHASTIC DIFFERENTIAL EQUATIONS

Change point estimation consists in the identification of the instant in which a change occurs in the parameter of some model. There are several approaches to the solution of this problem, and here we consider a least squares solution (see, e.g., [4], [5], [8]), but other approaches, such as maximum likelihood change point estimation, are also possible (see, e.g., [28], [34]). We assume we have a diffusion process[1] solution to

$$dX_t = b(X_t)dt + \theta\sigma(X_t)dW_t, \tag{18}$$

where $b(\cdot)$ and $\sigma(\cdot)$ are known functions and $\theta \in \Theta \subset \mathbb{R}$ is the parameter of interest. As in [36], given discrete observations from (18) on $[0, T = n\Delta_n]$, we want to identify retrospectively if and when a change in value of the parameter θ occurred and estimate consistently the parameter before and after the change point. The asymptotics is $\Delta_n \to 0$ as $n \to \infty$ and $n\Delta_n = T$ fixed.[2] For simplicity, we assume that the change occurs at instant k_0, which is one of the integers in 1, …, n. This is a problem of volatility change point estimation that frequently occurs in finance applications. We assume that $\theta = \theta_1$ before the time change and $\theta = \theta_2$ after the time change with $\theta_1 < \theta_2$ (but this does not matter in the final results). In order to obtain a simple least squares estimator, we use Euler approximation. So, from now on, we assume all the hypotheses necessary to have the Euler approximation in place. Namely, we can write the Euler scheme as

$$X_{i+1} = X_i + b(X_i)\Delta_n + \theta\sigma(X_i)(W_{i+1} - W_i)$$

and introduce the standardized residuals

$$Z_i = \frac{(X_{i+1} - X_i) - b(X_i)\Delta_n}{\sqrt{\Delta_n}\sigma(X_i)} = \theta\frac{(W_{i+1} - W_i)}{\sqrt{\Delta_n}}.$$

The Z_i's are i.i.d. (independent and identically distributed) Gaussian random variables. The change point estimator is obtained as

$$\hat{k}_0 = \arg\ \min_k \left(\min_{\theta_1, \theta_2} \left\{ \sum_{i=1}^{k} \left(Z_i^2 - \theta_1^2\right)^2 + \sum_{i=k+1}^{n} \left(Z_i^2 - \theta_2^2\right)^2 \right\} \right), \tag{19}$$

with, $k = 2, \ldots, n-1$. We denote by $[x]$ the integer part of the real x, and sometimes we write $k_0 = [n\tau_0]$ and $k = [n\tau]$, $\tau, \tau_0 \in (0,1)$ to indicate the change point in the continuous timescale. Define the partial sums

$$S_n = \sum_{i=1}^{n} Z_i^2, \quad S_k = \sum_{i=1}^{k} Z_i^2, \quad S_{n-k} = \sum_{i=k+1}^{n} Z_i^2,$$

and denote by $\bar{\theta}_1^2$ and $\bar{\theta}_2^2$ the initial least squares estimators of θ_1^2 and θ_2^2 for any given value of k in (19),

$$\bar{\theta}_1^2 = \frac{S_k}{k} = \frac{1}{k}\sum_{i=1}^{k} Z_i^2,$$

and

$$\bar{\theta}_2^2 = \frac{S_{n-k}}{n-k} = \frac{1}{n-k}\sum_{i=k+1}^{n} Z_i^2.$$

These estimators will be refined once a consistent estimator of k_0 is obtained. Denote by U_k^2 the quantity

$$U_k^2 = \sum_{i=1}^{k} \left(Z_i^2 - \bar{\theta}_1^2\right)^2 + \sum_{i=k+1}^{n} \left(Z_i^2 - \bar{\theta}_2^2\right)^2.$$

Then, $\hat{k}_0$ is defined as

$$\hat{k}_0 = \arg\ \min_k U_k^2.$$

To study the asymptotic properties of U_k^2, it is better to rewrite it as

$$U_k^2 = \sum_{i=1}^{n} \left(Z_i^2 - \bar{Z}_n\right)^2 - nV_k^2,$$

where

$$\bar{Z}_n = \frac{1}{n}\sum_{i=1}^{n} Z_i^2$$

and

$$V_k = \left(\frac{k(n-k)}{n^2}\right)^{\frac{1}{2}} \left(\bar{\theta}_2^2 - \bar{\theta}_1^2\right) = \frac{S_n D_k}{\sqrt{k(n-k)}},$$

with

$$D_k = \frac{k}{n} - \frac{S_k}{S_n}.$$

This representations of U_k^2 is obtained by lengthy but straightforward algebra, and it is rather useful because minimization of U_k^2 is equivalent to the maximization of V_k and hence of D_k. So it is easier to consider the following estimator of k_0

$$\hat{k}_0 = \arg\ \max_k |D_k| = \arg\ \max_k \left(k(n-k)\right)^{\frac{1}{2}} |V_k|. \tag{20}$$

As a side remark, it can be noted that, for fixed k (and under suitable hypotheses), D_k is also an approximate likelihood ratio statistic for testing the null hypothesis of no change in volatility (see, e.g., [4]). Once $\hat{k}_0$, has been obtained, the following estimators of the parameters θ_1 and θ_2 can be used:

$$\hat{\theta}_1^2 = \frac{S_{\hat{k}_0}}{\hat{k}_0}, \tag{21}$$

$$\hat{\theta}_2^2 = \frac{S_{n-\hat{k}_0}}{n-\hat{k}_0}. \tag{22}$$

Next results provide consistency of $\hat{k}_0$, $\hat{\theta}_1^2$ and $\hat{\theta}_2^2$ as well as their asymptotic distributions.

[1] For continuous-time observations this problem was studied in [9]. A bayesian approach for discrete-time observations can be found in [35].

[2] For ergodic diffusion processes and $n\Delta_n = T \to \infty$, under additional mild regularity conditions, the results mentioned here are still valid.

Fact 1 ([34]) Under $H_0 : \theta_1 = \theta_2 = 1$, we have that

$$\sqrt{\frac{n}{2}}|D_k| \xrightarrow{d} |W^0(\tau)|, \tag{23}$$

where $\{W^0(\tau), 0 \le \tau \le 1\}$ is the Gaussian stochastic process – Brownian bridge, which is useful when we need to model variable, which starts at some point, and that must return to a specific point at a specific time in the future.

The asymptotic result above is useful to test if a change point doesn't exist. In particular, it is possible to obtain the asymptotic critical values for the distribution of the statistic by means of the same arguments used in [34].

Fact 2 ([34]) The estimator $\hat{\tau}_0 = \frac{\hat{k}_0}{n}$ satisfies

$$|\hat{\tau}_0 - \tau_0| = n^{-1/2}\left(\theta_2^2 - \theta_1^2\right)^{-1} O_p\left(\sqrt{\log n}\right). \tag{24}$$

Moreover, for any $\beta \in (0, 1/2)$,

$n^{\beta}\left(\hat{\tau}_0 - \tau_0\right) \xrightarrow{p} 0$.

Finally,

$$\hat{\tau}_0 - \tau_0 = O_p\left(\frac{1}{n\left(\theta_2^2 - \theta_1^2\right)^2}\right). \tag{25}$$

It is also interesting to know the asymptotic distribution of $\hat{\tau}_0$ for small discrepancies between θ_1 and θ_2. The case $\vartheta_n = \theta_2^2 - \theta_1^2$ equal to a constant is less interesting because when ϑ_n is large the estimate of k_0 is quite precise.

Assumption 1 $\vartheta_n \to 0$ in such a way that $\frac{\sqrt{n}\vartheta_n}{\sqrt{\log n}} \to \infty$.

Assumption 1 and Fact 2 imply the consistency of $\hat{\tau}_0$.

Fact 3 ([34]) Under Assumption 1, for $\Delta_n \to 0$ as $n \to \infty$, we have that

$$\frac{n\vartheta_n^2\left(\hat{\tau}_0 - \tau_0\right)}{2\left(\tilde{\theta}_n^2\right)^2} \xrightarrow{d} \arg\max_v \left\{W(v) - \frac{|v|}{2}\right\}, \tag{26}$$

where $W(u)$ is a two-sided Brownian motion,

$$W(u) = \begin{cases} W_1(-u), & u < 0 \\ W_2(u), & u \ge 0 \end{cases}, \tag{27}$$

with W_1 and W_2 two independent Brownian motions and $\tilde{\theta}_n^2$ a consistent estimator for θ_1^2 or θ_2^2.

Finally we have the asymptotic distributions for the estimators $\hat{\theta}_1^2$ and $\hat{\theta}_2^2$ defined in (21) a (22). We denote by θ_0 the common limiting value of θ_1 and θ_2.

Fact 4 ([34]) Under Assumption 1, we have that

$$\sqrt{n}\begin{pmatrix} \hat{\theta}_1^2 - \theta_1^2 \\ \hat{\theta}_2^2 - \theta_2^2 \end{pmatrix} \xrightarrow{d} N(0, \Sigma), \tag{28}$$

where

$$\Sigma = \begin{pmatrix} 2\tau_0^{-1}\theta_0^4 & 0 \\ 0 & 2\left(1-\tau_0\right)^{-1}\theta_0^4 \end{pmatrix}. \tag{29}$$

- *Estimation of the change point with unknown drift*

When both $b(x)$ and $\sigma^2(x)$ are unknown, it is necessary to assume that at least $\sigma(x)$ is constant, and hence we consider the stochastic differential equation

$$dX_t = b(X_t)dt + \theta dW_t. \tag{30}$$

Then $b(x)$ can be estimated nonparametrically with

$$\hat{b}_n(x) = \frac{\sum_{i=0}^{n-1} K\left(\frac{x - X_i}{h_n}\right)\left(X_{i+1} - X_i\right)}{\Delta_n \sum_{i=0}^{n-1} K\left(\frac{x - X_i}{h_n}\right)} \tag{31}$$

and Z_i are estimated as

$$\hat{Z}_i = \frac{X_{i+1} - X_i}{\sqrt{\Delta_n}} - \hat{b}_n(X_i)\sqrt{\Delta_n}.$$

Remark 1 In Stanton's approach [34], the two estimators are nothing but Nadaraya-Watson kernel regression estimators of the following conditional expectations

$$b(x) = \lim_{t \to 0}\frac{1}{t}\mathrm{E}\left\{X_t - x \mid X_0 = x\right\},$$

$$\sigma^2(x) = \lim_{t \to 0}\frac{1}{t}\mathrm{E}\left\{\left(X_t - x\right)^2 \mid X_0 = x\right\}.$$

In this approach, $b(x)$ and $\sigma^2(x)$ are seen as instantaneous conditional means and variances of the process when $X_0 = x$. The two quantities can be rewritten, for fixed Δ_n as

$$b(x) = \frac{1}{\Delta_n}\mathrm{E}\left\{X_{i+1} - X_i \mid X_i = x\right\} + \frac{o(\Delta_n)}{\Delta_n},$$

$$\sigma^2(x) = \frac{1}{\Delta_n}\mathrm{E}\left\{\left(X_{i+1} - X_i\right)^2 \mid X_i = x\right\} + \frac{o(\Delta_n)}{\Delta_n}.$$

So if we have estimated residues Z_i, in this case, we can use the following contrast to identify the change point:

$$\tilde{k}_0 = \arg\min_k \left\{\sum_{i=1}^{k}\left(\hat{Z}_i^2 - \frac{\hat{S}_k}{k}\right)^2 + \sum_{i=k+1}^{n}\left(\hat{Z}_i^2 - \frac{\hat{S}_{n-k}}{n-k}\right)^2\right\}, \tag{32}$$

where

$\hat{S}_k = \sum_{i=1}^{k}\hat{Z}_i^2$ a $\hat{S}_{n-k} = \sum_{i=k+1}^{n}\hat{Z}_i^2$.

We obtain the new statistic

$$\hat{V}_k = \left(\frac{k(n-k)}{n^2}\right)^{\frac{1}{2}}\left(\frac{\hat{S}_{n-k}}{n-k} - \frac{\hat{S}_k}{k}\right) = \frac{\hat{S}_n\hat{D}_k}{\sqrt{k(n-k)}},$$

where

$$\hat{D}_k = \frac{k}{n} - \frac{\hat{S}_k}{\hat{S}_n},$$

and the change point is identified as the solution to

$$\hat{k}_0 = \arg \max_k \left|\hat{D}_k\right|.$$

Consistency and distributional results mentioned in [34], [37] and [38].

This paper will be dealt with a change point problem for the volatility of a process solution to a stochastic differential equation, when observations are collected at discrete times. The instant of the change in volatility regime is identified retrospectively by maximum likelihood method on the approximated likelihood. For continuous time observations of diffusion processes Lee, Nishiyama and Yoshida (2006) in [9] considered the change point estimation problem for the drift. In the present work, there will be only assume regularity conditions on the drift process.

VI. PROBLEM SOLUTION

Most data analysis procedures and the resulting conclusions are dependent on fulfilling basic assumptions on which these procedures were based. If not met, all other standard procedures such as calculating an average, confidence intervals, percentiles, most tests, classical Shewhart control charts, design of models for the description of time series, etc., are questionable and impugnable. They usually provide incorrect results and conclusions. A typical breach of conditions for application of control by Shewhart charts or different technologies, but also for the construction of models describing time series, is shown in [41]. The assumptions must be verified by statistical tests, which involve the *basic assumptions for statistical process control:*

- normal data distribution, symmetry,
- constant mean of the process,
- constant variance (standard deviation) of data,
- independence, non-correlation of data,
- absence of outliers and extreme values.

If these assumptions are infringed, conventional regression methods for the time series analysis provide biased and often incorrect results.

Let us now analyze the time series of O/N rate of the Slovak crown for the period 2000 – 2008 (used in [43]). For this purpose the ARIMA model will be used, which is applied if a resulting process is showing such autocorrelation and partial autocorrelation after the transformation of the integrated process using differentiation of d-th order that it is expressed in the form of stationary and invertible ARMA model (p,q). The course of time series is illustrated in the following figure. The graph shows that the time series is non-stationary, but it is not clear whether it contains a seasonal component.

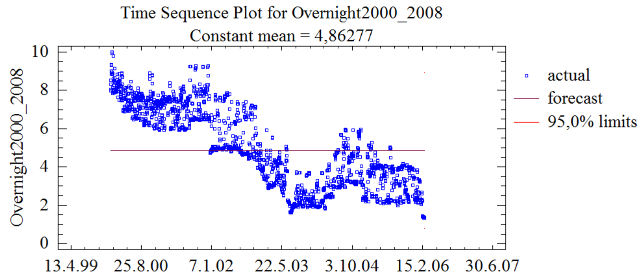

Fig. 3 Time series of O/N rate of the Slovak crown for the period 2000 – 2008. Source: Own Processing

Non-stationarity of the time series is also confirmed by the shape of the ACF and PACF. ACF values fall very slowly and the first value, as well as the PACF, is close to one. The periodogram has a significant peak in the zero (non-seasonal) frequency. Seasonality indicates neither the ACF and PACF, or the periodogram.

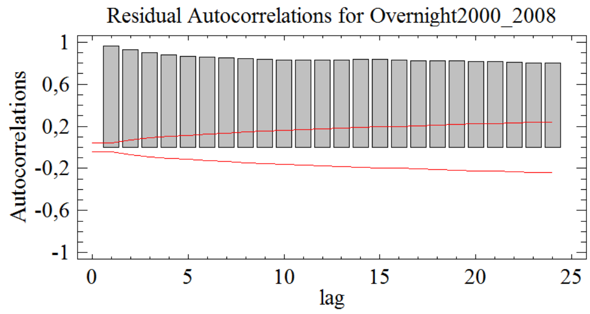

Fig. 4 ACF of the original time series. Source: Own Processing

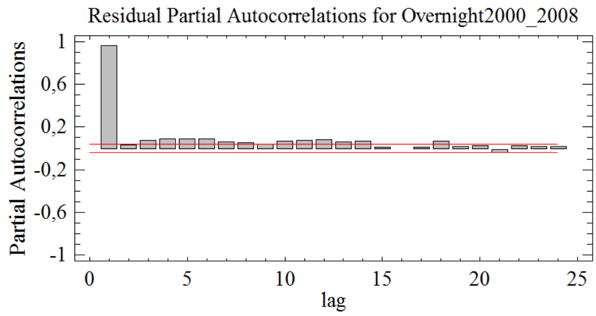

Fig. 5 PACF of the original time series. Source: Own Processing

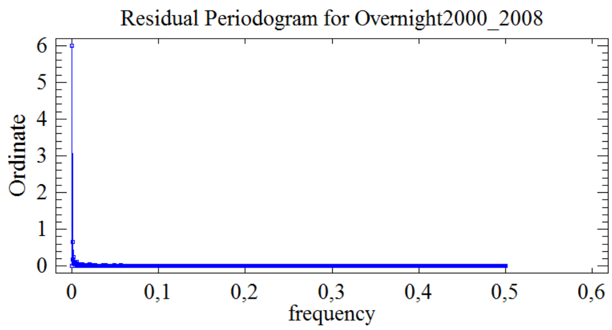

Fig. 6 Periodogram of the original time series. Source: Own Processing

The time series will be again stationarized by the I. non-seasonal difference. Let us skip the elementary steps of the analysis and go directly to the analysis of two ideal models to describe this time series. The first model is after the power linearization ARIMA $(1,1,2)_c$ and the second model is after the logarithmic linearization of the original time series SARIMA$(1,1,2)(1,1,1)_c20$.

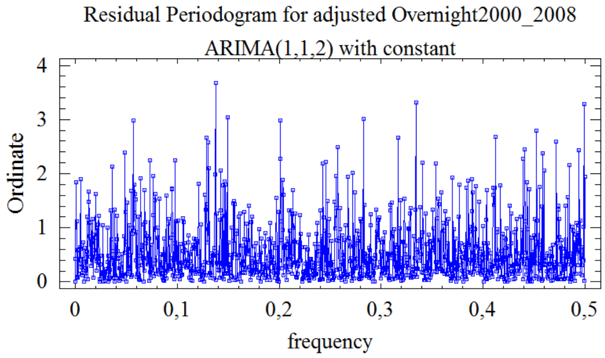

Fig. 7 Residual periodogram for ARIMA model $(1,1,2)_c$. Source: Own Processing

Residual periodogram for ARIMA model $(1,1,2)_c$ shows that residuals are stationary. Now the focus is on the extended SARIMA model (1,1,2) $(1,1,1)_c20$, followed by tables of estimates and interpolation criteria and the very estimates of the model's parameters.

Tab. 3 Estimates of the interpolation criteria of SARIMA model $(1,1,2)(1,1,1)_c20$. Source: Own Processing

	Estimation	*Validation*
Statistic	*Period*	*Period*
RMSE	0.536932	0.145012
MAE	0.327448	0.140548
MAPE	7.23435	10.2761
ME	0.0380698	-0.140548
MPE	-0.398906	-10.2761

Tab. 4 Estimates of parameters of SARIMA model $(1,1,2)(1,1,1)_c20$. Source: Own Processing

Parameter	*Estimate*	*Stand. Error*	*T*	*P-value*
AR(1)	0.752851	0.021549	34.9367	0.000000
MA(1)	0.850656	0.0291219	29.2102	0.000000
MA(2)	0.112643	0.0264917	4.25202	0.000021
SAR(1)	0.046946	0.021776	2.15587	0.031094
SMA(1)	0.974709	0.001605	607.074	0.000000
Mean	-0.00000	0.0000172	-0.420	0.674417
Constant	-0.00000			

Estimated white noise variance = 0.0143047
Estimated white noise standard deviation = 0.1196
Box-Pierce Test
Test based on first 24 autocorrelations
Large sample test statistic = 23.3012
P-value = 0.224336, AIC = -1.25429

Interpolation criteria shows SARIMA $(1,1,2)(1,1,1)_c20$ as much more suitable than ARIMA $(1,1,2)_c$ for the description of this time series.

The figures below show graphs with the time series forecast, autocorrelation and partial autocorrelation functions of unsystematic component for estimated model and residual periodogram.

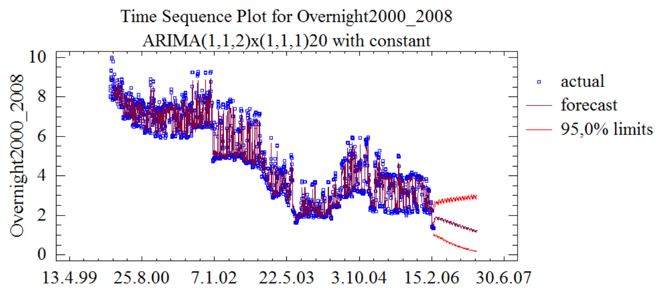

Fig. 8 Graph of the time series with forecast and confidence interval for forecast. Source: Own Processing

According to Akaike information criteria, the Box-Pierce test of autocorrelation of unsystematic component and interpolation criteria, SARIMA model $(1,1,2)(1,1,1)_c20$ appears to be better for the description of this time series than ARIMA model $(1,1,2)_c$.

The following figure illustrates the residual ACF and PACF of the estimated model. P-value of the Box-Pierce test and both of these graphs indicate non-autocorrelation of unsystematic component, thus the estimated model appears to be correct.

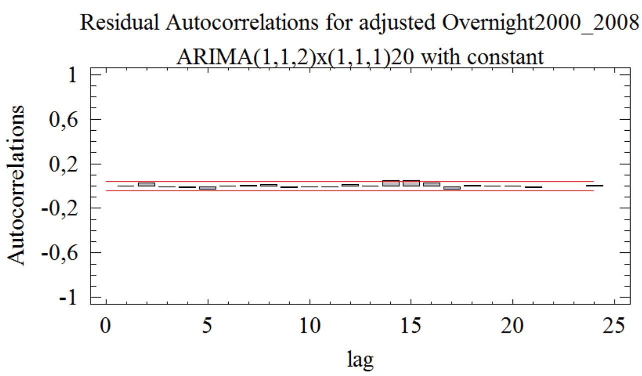

Fig. 9 Residual ACF of SARIMA model $(1,1,2)(1,1,1)_c20$. Source: Own Processing

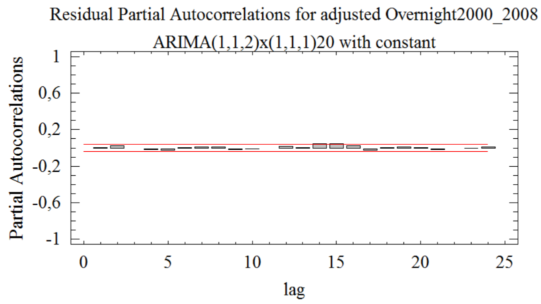

Fig. 10 Residual PACF of SARIMA model (1,1,2)(1,1,1)$_c$20. Source: Own Processing

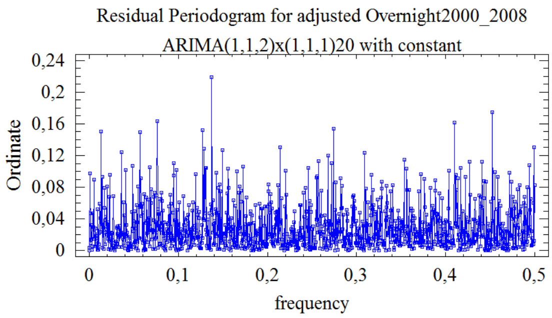

Fig. 11 Residual periodogram of SARIMA model (1,1,2)(1,1,1)$_c$20. Source: Own Processing

Now that we have information on the process due to a statistical model, it can be used to construct control charts for detecting changes in the mean. This detection will be demonstrated on the time series of Overnight values of the Slovak crown during 20 January 2000 – 16 June 2004.

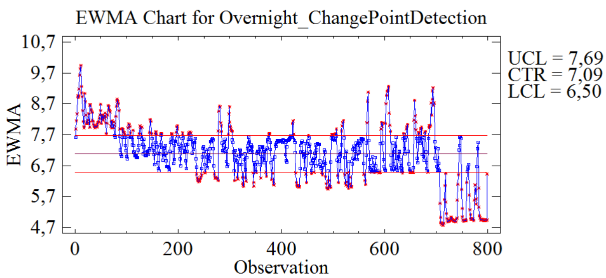

Fig. 12 EWMA control chart for mean shift detection with $\lambda = 0.6$. Source: Own Processing

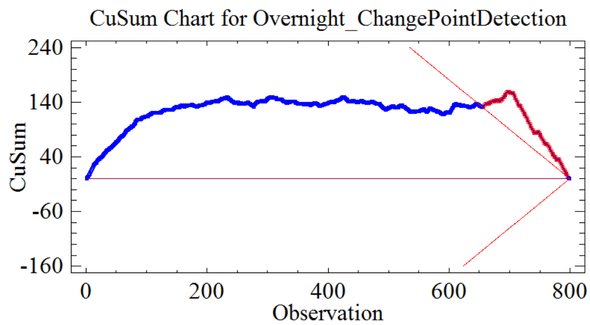

Fig. 13 CUSUM control chart for mean shift detection in 6σ. Source: Own Processing

As evident from the previous images, the EWMA control chart and CUSUM were able to detect changes in the mean almost immediately (EWMA: 13 November 2002; CUSUM: 4 September 2002). These are control charts with memory, therefore information on variability in the time series of SARIMA model (1,1,2)(1,1,1)$_c$20 was used for parameter estimation to construct these diagrams very effectively. The ARIMA control chart detected a shift of mean and therefore high heteroscedasticity in 5 August 2002, which corresponds to fluctuations of Slovak crown.

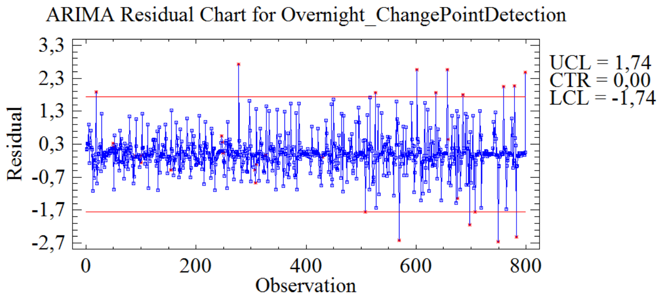

Fig. 14 ARIMA control chart for volatility change point detection. Source: Own Processing

Then we look at the volatility change point detection using the SDEs least squares approach.

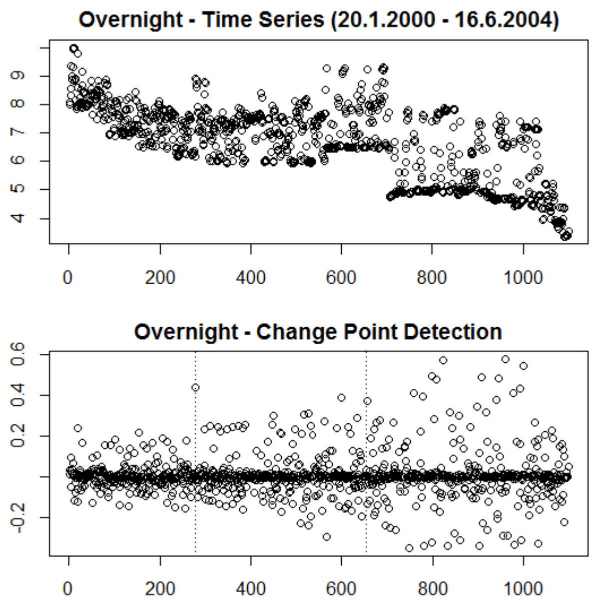

Fig. 15 Overnight values change point analysis of Overnight values of the Slovak crown in the period 20 January 2000 – 16 June 2004. Source: Own Processing

All the analysis using SDEs have been done using the R statistical environment (R Development Core Team, 2009) and the package `sde` (see in [37]) and Yuima (see in [42]).

Following is the output of the R programming language environment using the `sde` package.

```
$k0
[1] 655
$tau0
[1] 655 (2 September 2002)
$theta1
[1] 0.07893081
$theta2
[1] 0.124977
```

Looking at the previous figure, another change point may be present. So we reanalyze the first part of the series to spot the second change point.

```
$k0
[1] 276
$tau0
[1] 276 (23 February 2001)
$theta1
[1] 0.05829864
$theta2
[1] 0.08956524
```

Both change points (23 February 2001 and 2 September 2002) correspond to fluctuations of Slovak crown.

VII. Discussion

Most traditional control charting procedures are grounded on the assumption that the process observations being monitored are independent and identically distributed. With the advent of high-speed data collection schemes, the assumption of independence is usually violated. That is, autocorrelation among measurements becomes an inherent characteristic of a stable process. This autocorrelation causes significant deterioration in control charting performance. To address this problem, several approaches for handling autocorrelated processes have been proposed. The most popular procedure utilizes either a Shewhart, CUSUM or EWMA chart of the residuals of the appropriately fitted ARMA model. However, procedures of this type possess poor sensitivity especially when dealing with positively autocorrelated processes. As an alternative, we have explored the application of the statistics used in a time series procedure for detecting outliers and level shifts in process monitoring. The study focused on the detection of level shifts of autocorrelated processes with particular emphasis on the important AR(1) model. The results presented showed that time series charts are found to be sensitive in detecting small shifts and we utilize the fact that these control charts can be used in certain situations where the data are autocorrelated.

As for the two sub-series identified by the change point estimate and estimators of these parameters: both are consistent and asymptotically normal at the usual rate $\sqrt{n}$, with n the number of observations. The least squares estimator $\hat{\tau}_0$ seems to have a good performance in terms of bias and variability for models with constant or bounded drift, while it behaves badly in the presence of unbounded drift as time T grows.

VIII. Conclusion

In financial markets it is crucial to have an accurate description of the volatility of the market and/or the different financial products. All pricing formulas make use of the historical values of the volatility as a fundamental ingredient. It is well known, however, that volatility is not constant over time, even short time, and thus the monitoring of the volatility is one of the primary tasks in empirical finance. The statistical way to monitor structural changes is called change point analysis or change point estimation.

The paper dealt with the control charts and SDEs applications in financial data. This kind of data is very sensitive to mean shifting and strong autocorrelation appears very often. Therefore we put a focus on dynamic regulation charts CUSUM, EWMA and ARIMA models. We highlighted the versatility of control charts not only in manufacturing but also in managing the financial stability of financial flows. A refined identification of the type of intervention affecting the process will allow users to effectively track the source of an out-of-control situation, which is an important step in eliminating the special causes of variation. It is also important to note that the proposed procedure can also be applied when dealing with a more general autoregressive integrated moving average model. Autocorrelated process observations mainly arise under automated data collection schemes. Such collection schemes are typically controlled by software upgradeable to handle SPC functions. Under such an integrated scheme, the usefulness of the proposed procedure will be optimized. Based on information from chapter 4, we would recommend a properly designed time series control charts as control charts for individual measurements in a wide range of applications. They are almost perfectly nonparametric (distribution-free) procedures.

Stochastic differential equations are among the most used stochastic models to describe continuous time financial time series. Although data are collected in discrete time, the underlying structure of the continuous model allows for very detailed analysis of these data. In the analysis of the Slovak crown, the approach revealed (unlike time series control charts) another change point in the structure of variability, thus appearing to be preferable for the change point detection. It also shows that the use of SDEs provides robustness in the estimation results.

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