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Abstract

This paper presents a new approach to quality control of wastewater treatment. The first part formulates basic principles of statistical process control (SPC) and Taguchi Method. Then it is shown that the classical SPC technique used in industry, cannot be applied to wastewater treatment plants without adaptation and that the Taguchi Method is inapplicable in this case. This is followed by an example from literature, which demonstrates the problems of applying the SPC method to wastewater treatment. The third part of the paper presents a case study where the performance of a greywater treatment plant is examined. The performance is analyzed by means of cross-correlation between input and output parameters. A new approach to SPC of wastewater treatment, either “Dynamic SPC” or “linear regression SPC”, is presented, and a permeability coefficient is developed (the ratio of the output and input energies). Both are proposed as monitoring tools for wastewater treatment systems.

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1. Introduction

1.1. Background

A bio-system is a symbiotic entity in which bacteria reproduce and die; a bio-cell is the site of about a hundred thousand reactions. Eco-bio-systems differ from their mechanical counterparts in their need for adaptation and in their wide variability. For example, while in a mechanical system a failed part is replaceable, in a bio-system failure is disruption of the biocenosis (i.e. living organisms engaged in conversion of flowing energy) and crash effect, namely death of part or all present microorganisms, whose rehabilitation is a matter of weeks, months or even years.

Wastewater treatment is farthest removed from its standard mechanical counterparts (although not from the biological ones) and the dissimilarity will be emphasized in this work. Our specific objective is extension of the methods of control, with a
view to their application to processes with low adaptability and narrow variability – the biological domain.

Uniqueness of bio-systems from Quality Assurance point of view:

- synergy of living entities as main industrial tools with extreme ability for self-adaptation;
- high variability of the input properties;
- process of involved hundred thousands of reactions and extremely high rates of organic matter utilization;
- process which includes “Tools” death and birth depending on the surrounding medium instead of spare parts replacements (“Tools” in industry are pumps, mixers, aerators, etc.).

The term “wastewater” is descriptive and broad (Manual of Instruction, 1988). Generally it refers to liquids and waterborne solids from domestic, industrial or commercial uses as well as other liquids involved in human activities, whose quality has been degraded, and which are discharged to a sewage system. The term “sewage” has been in use for many years and generally refers to water containing only sanitary wastes, but technically denotes any wastewater which passes through a sewer.

Three general categories of wastewater are recognized: municipal, industrial and agricultural. Municipal wastewater originates principally from domestic activities but usually includes water discharged from commercial and business facilities. Stormwater and groundwater may also be present in municipal wastewater due to infiltration and inflow. Domestic wastewater is usually of predictable quality and quantity. Greywater is domestic wastewater from kitchens, bathrooms and washing machines. Blackwater is wastewater originating from toilets, mainly containing human excreta (urine and faeces). Industrial wastewater originates from manufacturing processes, is usually of a more variable character and in many cases less amenable to treatment. The principal sources of municipal, industrial and agriculture wastewater are shown in Table 1. Biological wastewater treatment can be defined as a process in which bacterial (biochemical) activity serves to stabilize/oxidize unstable organic matter, and remove nitrogen and phosphorus in the feed to produce effluent that comply with discharge regulations (which dependent on the receiving environment).

1.2. Methods of process monitoring in bio-ecological systems

Two key approaches to environmental improvement commonly found in literature are environmental management system standards such as ISO 14000 and the Total Quality Environmental Management philosophy, which focus more on the management and qualitative aspects. With the new and detailed environmental performance data now available thanks to the above approaches, application of quantitative methods is far easier than before (Aliperti et al., 2003; Cameron and Hangos, 1999; Marcus and Willig, 1997).

Since 1990 several statistical methods for process monitoring have been applied to wastewater treatment plants. Some of the more common approaches are Principal Component Analysis, Independent Component Analysis, Partial List Squares or Projection to Latent Structures and Model Predictive Control, and Statistical Process Control (SPC) (Corbett and Pan, 2002; Erbe et al., 2002; Lee et al., 2004; Lee et al., 2004; Olsson and Newell, 1999; Tomita et al., 2002). For better understanding of the problems of SPC applications to wastewater treatment plants in the next chapter, a review of Statistical Process Control and of the Taguchi Method is presented.

1.3. Statistical process control and principles of control design

Statistical process control is part of a company-wide effort towards continuous improvement. Shewhart (1981) explained that a process is said to be controlled when, through use of past experience, one can predict at least approximately the probability that the observed values of a product characteristic (also called process output or product parameter) will fall within given limits. In our case these are control parameters that control the behavior of the WWTP. Such prediction is possible when the probability distribution of the characteristic is known. As variability is always present, the characteristic can be regarded as a random variable characterized by its probability distribution. The parameters of this distribution are referred to as control parameters.

A production process is often considered as a system of interacting components such as the hardware, materials, control system and disturbing...
factors. In the case of wastewater treatment we classify the deviations in two categories: input deviations (external) and system deviations (internal). Input deviations result from variability of the input properties. The internal deviations are due to the vast number reactions, to the extremely high rate of organic matter utilization, and to failures of equipment (pumps, mixers, aerators, etc.). The internal deviations are compensated through adaptation of the bio-ecological–physical–chemical system with its rather significant time constant and high variability. Whereby, the system is relaxed. The external deviations are smoothed out in the system. The residual variability of the output in common cases is controlled by SPC.

Shewhart’s control charts and their various later modifications are aimed at detection of assignable causes of variation, hence at reduction of the overall variability of the control parameters. The Shewhart approach could be characterized by the statement: “Fit the process to the model”, which is the reverse of statistical modeling (Hoerl and Palm, 1992). It is customary to distinguish between two states of the system: the in-control (IC) and the out-of-control (OOC). In our case the first is the example when the control parameters equal their target values (i.e. the system is in control). Otherwise, the bio-system is in the second state (OOC), which is associated with special or assignable causes of variation. The IC can be described by some probability distribution with fixed parameters; as for the OOC, there are two ways of describing it: the first assumes absence of a constant distribution; the second an a priori distribution model of the control parameters, most of which are associated with economic design of control charts; the OOC detected by means of SPC, and the process is adjusted accordingly (Lipnik, 2000; Montgomery, 1996).

1.4. Taguchi method

The Taguchi Method (Chau-Chen et al., 1999; Dale, 1994; Mohan et al., 2005), pioneered by Dr. Genichi Taguchi, greatly improves engineering productivity. By consciously considering the noise factors (environmental changes during use of the product manufacturing, and component deterioration) and the cost of failures, the Taguchi Method helps ensure customer satisfaction. The Method focuses on improving the fundamental function of the process or product (in our case, the process output), thus facilitating flexible designs and concurrent engineering. Indeed, it is the most powerful method available for reducing product cost, improving wastewater quality, and simultaneous reducing the development interval.

Traditionally, quality is viewed as a step function. A product is either good or bad. In the former case, it is assumed to the uniformly good between the lower and upper specification limits – LSL and USL.

Sometimes traditionalists and those using Taguchi’s loss function may arrive at the same decision.
Such is the case if an organization considers both the mean and the variance, and both or either of these parameters is equal. However, the traditional decision-maker calculates the percent defective over time when both the means and the variances are different, as they are in our case.

According to Taguchi’s approach, the customer becomes increasingly dissatisfied as a product’s performance diverges from the target value – the optimum as the customer sees it – which is the midpoint of the quadratic curve representing the dissatisfaction function.

Determination the target (optimal design) involves the mean and variance concepts. The equation for the mean loss reads:

\[
\text{Loss} = \frac{A}{D} \cdot \left( \sigma^2 + (\bar{y} - T)^2 \right),
\]

where \(\text{Loss}\) – average loss; \(A\) – cost of rework or of a defective unit; \(D\) – half of tolerance (Tolerance is an interval covering a fixed proportion of the population with a stated confidence; its application to manufacturing involves comparison of specification limits prescribed by the client against tolerance limits covering a specified proportion of the population); \(\sigma\) – standard deviation of product unit group; \(\bar{y}\) – average size of product unit group; \(T\) – target value.

1.5. Shortcomings of SPC approaches

On the basis of accumulated information, one can see the following shortcomings of the SPC approaches used in bio-processes:

1. Output-based SPC’s are effective only for processes with statistically stable input.
2. SPC is of complex bio-processes with high input variability cannot be based on analysis of the output characteristic alone.
3. The SPC approach for such processes found in literature (Corbett and Pan, 2002) is incompatible with the Taguchi Method.
4. Only proper indices (to be found) permit effective SPC performance for bio-processes.
5. No allowance is made for the biological nature of the processes.

1.6. Objectives of the current paper

This paper addresses exactly the above problems. Once the weaknesses of implementing classical quality control methods used in industrial manufacturing in wastewater treatment are signaled out, adjustments to these methods are suggested in order to fuse them into wastewater treatment control. Then, the modified methods are tested against actual data from a pilot-scale experimental setup. Finally, a method of energy analysis using Fourier transforms is developed and tested against the experimental data.

2. Result of research

2.1. Problems in using standard SPC techniques in environmental performance evaluation

In their paper Corbett and Pan (2002) present an example of Lewis’s data (Table 2) and the way capability indices can be used for quantitative evaluation of the environmental performance of a process with respect to prevailing regulations.

The following facts have been revealed:

1. Nitrate concentrations less than 0.002 are undetectable (see Fig. 1a, \(\ln(0.002) = -6.215\)).
2. The lower control limit for the nitrate concentration is zero and only the upper limit can be calculated (according to the principle “the smaller the better”).
3. A 20-sample set is inadequate for the overall process (about 64 samples).
4. The process is unstable and the probability distribution varies significantly over time (see Fig. 3); the process is out-of-control from the outset and the principle of statistical control has to be non-standard.

Corbett and Pan state that “the first period (first 20 points) is used for estimating the population mean as well as for establishing the tentative or trivial upper control limit (UCL) and lower control limit (LCL)”.

Fig. 1a matches the theoretical and experimental cumulative density functions (cdf) based on 20 samples (first period).

After omission of the 0.002 points (see Fig. 1b), we obtained different parameters of the theoretical function – namely, the standard deviation of the first period as reported by Corbett and Pan was 1.000, while after the omission it became 1.232.

Corbett and Pan also claim that “any out-of-control points for which assignable causes can be found should be removed or eliminated before the trial control limits are calculated” and that “after
removing the outliers the normality tests also improve”. This is reasonable, as the out-of-control points were omitted from the outset for the second period of Lewis’s data. It is also noted that “the distribution is constant and these estimated values (UCL and LCL that were established for the first period) are used for the second period”.

The distribution of the 42 remaining points after omission of the 0.002’s for the second period is shown in Fig. 2a. Fig. 2b compares the theoretical and experimental curves based on 57 samples (both periods minus the 0.002 points).

Analysis of the parameters of the theoretical functions for the first and second periods shows that the probability distribution changes very significantly over time. The mean value for the first period is \(\bar{X} = 3.800\) and for the second – 1.830. The standard deviation for the first period is \(\sigma = 1.232\) and for the second \(1.668\).

### Table 2: Nitrate blank results (Lewis, 1996)

<table>
<thead>
<tr>
<th>Blank number</th>
<th>Nitrate concentration</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>First period</strong></td>
<td><strong>Second period</strong></td>
</tr>
<tr>
<td>1</td>
<td>0.033</td>
</tr>
<tr>
<td>2</td>
<td>0.049</td>
</tr>
<tr>
<td>3</td>
<td>0.002</td>
</tr>
<tr>
<td>4</td>
<td>0.002</td>
</tr>
<tr>
<td>5</td>
<td>0.008</td>
</tr>
<tr>
<td>6</td>
<td>0.002</td>
</tr>
<tr>
<td>7</td>
<td>0.014</td>
</tr>
<tr>
<td>8</td>
<td>0.016</td>
</tr>
<tr>
<td>9</td>
<td>0.009</td>
</tr>
<tr>
<td>10</td>
<td>0.009</td>
</tr>
<tr>
<td>11</td>
<td>1.631</td>
</tr>
<tr>
<td>12</td>
<td>0.063</td>
</tr>
<tr>
<td>13</td>
<td>0.042</td>
</tr>
<tr>
<td>14</td>
<td>0.022</td>
</tr>
<tr>
<td>15</td>
<td>0.093</td>
</tr>
<tr>
<td>16</td>
<td>0.022</td>
</tr>
<tr>
<td>17</td>
<td>0.002</td>
</tr>
<tr>
<td>18</td>
<td>0.002</td>
</tr>
<tr>
<td>19</td>
<td>0.031</td>
</tr>
<tr>
<td>20</td>
<td>0.004</td>
</tr>
<tr>
<td>21</td>
<td>0.066</td>
</tr>
<tr>
<td>22</td>
<td>0.731</td>
</tr>
</tbody>
</table>

Fig. 1. Nitrate concentration cumulative distribution densities: (a) first period and (b) first period minus 0.002 points.
second 1.500. Based on these data, we conclude that the mean value does not shift “downwards” as claimed, but rather upwards, and so does the standard deviation.

The standard deviation of the 57 points (Fig. 2b) is calculated based on that of the first period and on the variance of the uniform distribution, and can be calculated using the following overall equation:

$$
\sigma_2 = \sqrt{\frac{(b \cdot N)^2}{12}} + \sigma_1^2,
$$

where $\sigma_2$ – standard deviation for both periods (57 points); $\sigma_1$ – standard deviation for first period (in our example $\sigma_1 = 1.232$); $b$ – slope of regression line; $N$ – number of points (in our example $N = 57$).

Based on the above equation and on the theoretical function for both periods (Fig. 2b), we obtain the standard deviation $\sigma_2$ equal to 1.510.

As shown in Fig. 3, apart from the variability, nitrate concentration exhibits an underlying pattern of increase with time. The linear regression line drawn on the figure and proven to be statistically significant (slope ($b$) = 0.056; $R^2 = 0.279; p < 0.0001$), strengthens this observation. The control limits of Corbett and Pan, covering a wide range, do not allow for the dynamicity of the process, but only consider the apparent overall variability. It should be stressed that the linear regression presented in Fig. 3 was derived only in order to reveal the underlying trend. A smoothing spline curve ($\lambda = 0.1; R^2 = 0.929$) is also shown in Fig. 3. This spline curve, which was found to be statistically significant (Shapiro-Wilk Test for residuals), better models the underlying upwards trend of the data, and thus strengthen the above observation.

The cumulative-sum control chart (CUSUM) detects a small process shift. In the paper of Corbett and Pan the CUSUM chart shows an example of the second period, and they say that “the trial limits are based on the first period”. As was explained above, the parameters of the theoretical functions for the two periods differ significantly.

Based on the results of our research, we conclude that the process is unstable and that it shifts and widens. The “appropriate modification of existing statistical quality control techniques” proposed by
Corbett and Pan is unsuitable for the management and monitoring of environmental processes. Direct transfer of the SPC from industry to bio-systems is unfeasible since in industry a production plant behaves as a function of the input parameters, with a statistical input/output relationship, while in bio-systems, as in all eco-systems most parameters vary according to process conditions, to the components involved, and to the state of the system.

The next section shows application of SPC, cross-correlation and energy analyses to a case study of an on-site wastewater treatment plant that treats domestic greywater.

2.2. Description of pilot plant

The pilot plant treats the greywater of 14 flats in a residential building which was retrofitted in order to separate light greywater (greywater from baths, showers and washbasins) from the other wastewater streams. The treatment plant comprised of a pretreatment step followed by three separate treatment trains (Fig. 4). Pretreatment included fine screen (1 mm square shaped mesh) for removal of coarse solids, hair etc., followed by an equalization basin that regulated between the raw greywater inflow (instantaneous, highly variable) and withdrawal to the treatment units (continuous and steady), and equalised the temperature and quality of the raw greywater. After pretreatment, greywater was distributed to three parallel processes:

1. Stand alone sand filtration unit – 0.7 m deep gravity filter, filled with size 0 quartz sand media ($d_{10}$ 0.63 mm, UC 1.24 and porosity 0.36). The sand was supported by 0.1 m deep gravel layer (diameter 2.2 mm). Filtration rate was set at 8.3 m$^3$ h$^{-1}$ (equivalent to 0.065 m$^3$ h$^{-1}$).

2. Membrane bioreactor (MBR, Triqua B.V., Netherlands) – The unit consisted of a circular aeration tank (100 L) connected to a side cross-flow UF membranes unit (tubular polysulphone membranes; molecular weight...
cut-off 100,000 Dalton; Berghoff GmbH, Germany) in series. Hydraulic residence time in the aeration tank ranged from 8 to 5 h (in correspondence with the permeate flux), and sludge age was set to 15–20 d. Mixed liquor of the aeration basin was circulated through the membranes by a centrifugal pump (head 3 atm, discharge 6 m$^3$ h$^{-1}$), creating a cross-flow velocity of 4.0 m s$^{-1}$ at the membrane unit. Permeate (treated effluent) flux varied from 20 L h$^{-1}$ (clean membranes) to 13 L h$^{-1}$ (clogged membranes just before cleaning). Membranes were cleaned periodically with hypochlorite solution.

(3) Rotating biological contactor system (RBC) – This system comprised of two RBC basins in series (15 L each), followed by a sedimentation basin (7.5 L). Each RBC basin was equipped with 13 circular discs (1 m$^2$ total surface area), 40% submerged in the liquid. The rotational speed was set at 13 rpm. Flow was perpendicular to the rotation axis, at a discharge of 7.5 L h$^{-1}$. The resultant mean residence times were 2 h in each RBC basin, and 1 h in the sedimentation basin. After sedimentation there was an option to pass the effluent through a dedicated sand filtration unit which was identical to the stand alone sand filtration unit (see #1 above).

A more detailed description of the system can be found in Friedler et al. (2005, 2006).

2.3. Analysis of chemical data of greywater pilot

2.3.1. Statistical analysis

The object of WWT is reduction of all biodegradable organics to a very low level (below discharge limits set by authorities), whereas that of industrial processes is realization of a product. In WWT, the concentration of the feed is usually variable, and that of the output should comply with discharge standards which require very low values. In an industrial process the pattern is reversed – no changes at the inlet, changes at the output. These characterizations suffice to show that "blind" application of the classical SPC to bio-processes is impracticable and the usual statistical control limits are unsuitable as they obscure the true picture. This is the very reason for our suggestion that SPC control limits have to match the process. Our task consists in observing the current state of the system and predicting its course in the immediate future.

Fig. 5 shows that the Total Kjeldahl Nitrogen (TKN) in the raw greywater entering the treatment plant increases with time, as is the case with the nitrate concentration. In addition we see regularity, dictated by seasonal variations with a period of
three/four months. Any industrial process does not have the same variability of input quality characteristics. It is seen that the control limits of the classical SPC do not reflect the changing nature of the process. We suggest a new approach which we propose to call “Dynamic SPC” (DSPC) – an SPC with variable control limits and a simpler one which we propose to call “Linear regression SPC” (LSPC). For example, the LSPC control limits were derived based on a linear regression line, represented by an equation of the form:

$$Y = a + b \cdot X,$$

where $X$ is the explanatory variable, $Y$ the dependent variable, $b$ the slope of the line, and $a$ the $Y$ intercept.

Now the UCL and LCL can then be described by the following equations:

$$UCL = a + b \cdot X + Z_{\delta} \cdot \sigma_X,$$

$$LCL = a + b \cdot X - Z_{\delta} \cdot \sigma_X,$$

where $\sigma_X = \frac{\sigma}{\sqrt{n}}$, $\sigma$ – the standard deviation, $\delta$ – the confidence level, $Z_\delta$ – the upper $100 \cdot (1 - \delta)$ percentage point of the standard normal distribution (in our case $Z_{\delta} = 2$).

The control limits of the DSPC model were derived in a similar way.

Fig. 5 shows that although the control limits classical SPC and the proposed LSPC and DSPC do not seem to differ that much, only the latter two are able to trace the long-term upward shift of the TKN concentration in the raw greywater. Nevertheless, the differences between the three models deserve further investigation.

In order to quantify the differences between the classical SPC, LSPC and DSPC models, they were compared using residual plots (Fig. 6a–c) and by autocorrelation plots (Fig. 6d and e). The residual plot of the classical SPC model (Fig. 6a) shows a clear non-random pattern, where residuals tend to be more negative at the beginning of the period and less negative or positive towards its end. This indicates that the classical SPC model fails to identify the underlying trend of increase in the process, i.e. increasing concentrations in TKN in the raw greywater entering the treatment plant. On the other hand, the residuals of LSPC and DSPC (Fig. 6b and c) exhibit random distribution around 0 and are generally lower than the residuals of the classical SPC. The autocorrelation plots of the residuals clearly demonstrate that both LSPC and DSPC (Fig. 6e and f) have similar random distributions with zero mean value, while such function for classical SPC decreases with non-zero mean (Fig. 6d).
Furthermore, the variances of the LSPC and DSPC models had the same values (0.111) while the variance of classical SPC was higher (0.135). All the above results strongly indicate that the DSPC and LSPC models are more suitable for the control and prediction of wastewater treatment than classical SPC.

2.4. Cross-correlation analysis

Cross-correlation is a standard method of estimating the degree to which two parameters are correlated. The correlation coefficient is a measure of the linear association between a pair of variables measured on an interval or a ratio scale. If there is no relationship between the two variables the correlation coefficient is 0 or very low, and the stronger the relationship, the higher the correlation coefficient. A perfect fit gives a coefficient of 1.0. In the case of wastewater treatment, a high correlation coefficient between the feed and effluent concentrations indicates that the treatment process may be faulty.

Based on the above data, the cross-correlation between the feed and treated effluent concentrations was examined (Table 3). For example, the correlation coefficient for Total Kjeldahl Nitrogen shows that the RBC + sand filtration and membrane reactor are operating similarly (the correlation coefficients are 0.295 and 0.243 respectively). We also see the highest correlation coefficient (0.752) for

<table>
<thead>
<tr>
<th>Contaminant</th>
<th>Step in treatment process (see Fig. 4)</th>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>NO₃</td>
<td>Input/Deep sand filtration effluent</td>
<td>Insufficient data</td>
</tr>
<tr>
<td></td>
<td>Input/RBC + sand filtration effluent</td>
<td>−0.557</td>
</tr>
<tr>
<td></td>
<td>Input/MBR effluent</td>
<td>0.389</td>
</tr>
<tr>
<td>NH₃</td>
<td>Input/Deep sand filtration effluent</td>
<td>0.752</td>
</tr>
<tr>
<td></td>
<td>Input/RBC + sand filtration effluent</td>
<td>0.412</td>
</tr>
<tr>
<td></td>
<td>Input/MBR effluent</td>
<td>0.508</td>
</tr>
<tr>
<td>Total Kjeldahl nitrogen (TKN)</td>
<td>Input/Deep sand filtration effluent</td>
<td>0.576</td>
</tr>
<tr>
<td></td>
<td>Input/RBC + sand filtration effluent</td>
<td>0.295</td>
</tr>
<tr>
<td></td>
<td>Input/MBR effluent</td>
<td>0.243</td>
</tr>
<tr>
<td>pH</td>
<td>Input/Deep sand filtration effluent</td>
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<td>Input/RBC + sand filtration effluent</td>
<td>−0.008</td>
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<tr>
<td></td>
<td>Input/MBR effluent</td>
<td>0.139</td>
</tr>
<tr>
<td>Total phosphorus (TP)</td>
<td>Input/Deep sand filtration effluent</td>
<td>0.596</td>
</tr>
<tr>
<td></td>
<td>Input/RBC + sand filtration effluent</td>
<td>0.132</td>
</tr>
<tr>
<td></td>
<td>Input/MBR effluent</td>
<td>0.342</td>
</tr>
<tr>
<td>Total chemical oxygen demand (CODₐ)</td>
<td>Input/Deep sand filtration effluent</td>
<td>0.041</td>
</tr>
<tr>
<td></td>
<td>Input/RBC + sand filtration effluent</td>
<td>0.232</td>
</tr>
<tr>
<td></td>
<td>Input/MBR effluent</td>
<td>−0.059</td>
</tr>
<tr>
<td>COD dissolved (CODₐ)</td>
<td>Input/Deep sand filtration effluent</td>
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</tr>
<tr>
<td></td>
<td>Input/RBC + sand filtration effluent</td>
<td>0.570</td>
</tr>
<tr>
<td></td>
<td>Input/MBR effluent</td>
<td>−0.009</td>
</tr>
<tr>
<td>Total biological oxygen demand (BODₐ)</td>
<td>Input/Deep sand filtration effluent</td>
<td>0.414</td>
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<td>Input/RBC + sand filtration effluent</td>
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<tr>
<td></td>
<td>Input/MBR effluent</td>
<td>−0.27</td>
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<tr>
<td>Total suspended solids (TSS)</td>
<td>Input/Deep sand filtration effluent</td>
<td>0.006</td>
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<td>Input/RBC + sand filtration effluent</td>
<td>0.026</td>
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<td>Input/MBR effluent</td>
<td>0.034</td>
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<td>Volatile suspended solids (VSS)</td>
<td>Input/Deep sand filtration effluent</td>
<td>−0.036</td>
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<tr>
<td></td>
<td>Input/RBC + sand filtration effluent</td>
<td>0.056</td>
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<td>Input/MBR effluent</td>
<td>0.029</td>
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<tr>
<td>Turbidity (TURB)</td>
<td>Input/Deep sand filtration effluent</td>
<td>−0.055</td>
</tr>
<tr>
<td></td>
<td>Input/RBC + sand filtration effluent</td>
<td>−0.318</td>
</tr>
<tr>
<td></td>
<td>Input/MBR effluent</td>
<td>0.169</td>
</tr>
</tbody>
</table>
NH₃ concentration after the deep sand filtration. The fact that filtration removes suspended compounds, but not dissolved ones is also reflected in the different correlation coefficients for total COD and dissolved COD (0.041 and 0.491 respectively).

Finally, it is of interest to plot the data along with a constant density curve (ellipse), using a method described by Grabov and Ingman (1996). The curve is the boundary of the true control region representing a set of points with a given common property (the mutual orthogonality of the sample means and standard deviations is taken into account in constructing it). To accomplish this, we can set the probability density function for multinomial distribution equal to the control parameter. The result equation is the ellipse (for more details see Appendix A). An alternative method described by D’Ambrosio, consists in setting the bivariate (two random variables) Gaussian probability density function equal to \( k^2 \) and taking the natural logarithm of both sides; the resulting equation is that of an oblique ellipse. Coordinate transformation is used for determining the orientation of the ellipse and the lengths of its major and minor axes (for more details see D’Ambrosio, 1998).

As examples, constant density curves for phosphorus before and after the deep sand filtration, and for the total suspended solids before and after the membrane reactor, are presented in Fig. 7, showing the deviations from the average input/output. It is seen that the longer the minor axis, the wider the data spread; that the spread for the TSS is wider than for the phosphorus; and finally, that the steeper the slope of the major axis, the larger the correlation coefficient (very large for phosphorus, very small for TSS, both of them positive). The process is “in control” for any point falling within the boundary and “out-of-control” for any others. Based on Fig. 7, one can see that the sand filtration unit does not operate as required for phosphorus removal, while the MBR is very efficient regarding TSS.

2.5 Energy analysis

Monitoring methods used today are normally based on time series charts, where the operator can view the different variables as historical trends. We propose a new approach to monitoring of wastewater treatment based on energy analysis using Fourier transforms, namely a set of observed data measured over a number of samples and expressed in terms of frequency. In this case discrete Fourier transforms were used for the discrete samples from a continuous process with the sampled data contained in a vector \( \mathbf{x} \), the \( k \)th element of its transform is computed as a sum of the form:

\[
x_k = \sum_{m} x_m \cdot \exp \left( \pm 2 \cdot \pi \cdot \mathbf{i} \cdot \left( \frac{k}{N} \right) \cdot m \right),
\]

where \( N \) denotes the number of data points sampled, \( m \) the runs over the indices of \( x \), and

![Fig. 7. Constant density curves: (a) phosphorus I/O in the sand filtration unit; (b) TSS I/O in the MBR unit.](image-url)
\[ i = \sqrt{-1} \]. The sum may also include a scaling factor such as \( 1/N \).

Fourier transforms were used for both the feed and effluent concentrations. The quotient of the output and input energies of the chemical compounds is the permeability coefficient \( \mu(\omega) \). Fig. 8 shows the distribution of this coefficient for volatile suspended solids.

The figure shows that the system has two statuses. One is represented by the spectrum of low frequency and show that system operates as required. The other is represented by the spectrum of high frequency, and show that system does not operate as required. At zero frequency (continuous flow) the permeability coefficient is also zero, which means that the system removes impurities of medium concentration. For example, Fig. 8b shows that the “RBC + sedimentation + filtration” satisfactorily removes the VSS, but at frequencies 0, ±3, ±5 (frequency 3 being approximately equivalent to 1 month and frequency 5–2.5 months) such a system is inefficient. We conclude that a membrane reactor (Fig. 8d) is preferable for VSS removal.

3. Conclusions

This paper analyzed the possibility of implementing classical SPC used in industrial manufacturing to the field of wastewater treatment. It showed that direct transfer of classical SPC from industry to biosystems is unfeasible as it does not account for long-term underlying trends of change. Processes of wastewater treatment are self-adaptive, dynamic, undergoing shifts and extension. Not considering these characteristics, masks long-term changes, prevents observation of what is happening in the system in reality and thus hampers recognition of alarm situations. Further, control of a single parameter also cannot provide sufficient information for recognition of alarm situations (bio-overload).

As an alternative to the classical SPC either “linear regression SPC” (LSPC) or “dynamic SPC” (DSPC) methods are proposed, both permit better application of the SPC approach to bio-systems. By applying these two modified SPC methods the control limits become narrower and vary according to the underlying trends of change in the process. These in turn, enable using input–output correlations as control parameters while taking into account the dynamic character and high variability of the wastewater treatment plant inputs.

Another approach developed is based on mass-energy analysis using Fourier transforms. This approach helps identifying whether the general performance of the system is efficient and the frequency of events where the treatment system becomes inefficient (e.g. does not produce effluent of the desired quality).

It is suggested to use LSPC or DSPC (when appropriate) and energy analysis methods as monitoring tools for wastewater treatment plants or for other systems that exhibit long-term changes. These will have sufficiently narrow control ranges that will enable better detection of out-of-control situations (alarm situations), will help revealing underlying trends of change, help in analysing the periodicity of system failure, and be used for predicting the immediate coming developments.

**Fig. 8.** Permeability coefficients of VSS concentration I/O deviation statistics: (a) input/after RBC + sedimentation; (b) input/after RBC + sedimentation + filtration; (c) input/after filtration; (d) input/after MBR.
Appendix A. Construction of the constant density curve – example

The following application of Mathcad in constructing the constant density curve for phosphorus is presented. More details can be found in (Grabov and Ingman, 1996; D’Ambrosio, 1998)

\[
\begin{pmatrix}
2.53 & 2.81 \\
2.15 & 2.81 \\
3.09 & 2.72 \\
3.92 & 3.54 \\
2.46 & 1.61 \\
3.59 & 2.55
\end{pmatrix}
\]

TPLsi is the matrix of phosphorus concentrations in input and output;

\[ N := \text{length}(\text{TPLsi}^{(0)}) \]  
number of elements in vector \( \text{TPLsi}^{(0)} \);

\[ i := 0 \ldots N-1 \]  
range variable;

\[ A := \text{TPLsi}^{(0)} \]  
phosphorus concentration vector of input;

\[ B := \text{TPLsi}^{(1)} \]  
phosphorus concentration vector of output.

Covariance matrix for \( A \) and \( B \)

\[
\text{Cov} := \begin{pmatrix}
\text{Var}(A) & \text{cvar}(A, B) \\
\text{cvar}(A, B) & \text{Var}(B)
\end{pmatrix}, \quad \text{Cov} = \begin{pmatrix}
1.084 & 0.507 \\
0.507 & 0.472
\end{pmatrix}
\]

\[
\begin{pmatrix}
1.084 \\
0.507
\end{pmatrix}^{-1} = \begin{pmatrix}
1.854 & -1.991 \\
-1.991 & 4.258
\end{pmatrix}
\]

Probability density function for multinomial normal distribution

\[
\left( \begin{pmatrix}
x_1 \\
y_1
\end{pmatrix} \right)^T \cdot \begin{pmatrix}
1.854 & -1.991 \\
-1.991 & 4.258
\end{pmatrix} \cdot \begin{pmatrix}
x_1 \\
y_1
\end{pmatrix} \rightarrow (1.854 \cdot x_1 - 1.991 \cdot y_1) \cdot x_1 + (-1.991 \cdot x_1 + 4.258 \cdot y_1) \cdot y_1.
\]

Given

\[ 1.854 \cdot x_1^2 - 3.982 \cdot x_1 \cdot y_1 + 4.258 \cdot y_1^2 = C \]

C – Control Constant (Parameter),

\[
\text{Find}(y_1) \rightarrow \left[ \frac{1991}{4258} \cdot x_1 + \frac{1}{4258} \cdot (-3930251 \cdot x_1^2 + 4258000 \cdot C) \right] \left[ \frac{1991}{4258} \cdot x_1 - \frac{1}{4258} \cdot (-3930251 \cdot x_1^2 + 4258000 \cdot C) \right]
\]

\[
\left[ \frac{1991}{4258} \cdot x_1 + \frac{1}{4258} \cdot (-3930251 \cdot x_1^2 + 4258000 \cdot C) \right] \left[ \frac{1991}{4258} \cdot x_1 - \frac{1}{4258} \cdot (-3930251 \cdot x_1^2 + 4258000 \cdot C) \right]
\]

C := 4 \cdot 5

\[
y_{11}(x_1) := \frac{1991}{4258} \cdot x_1 + \frac{1}{4258} \cdot (-3930251 \cdot x_1^2 + 4258000 \cdot C)
\]

\[
y_{12}(x_1) := \frac{1991}{4258} \cdot x_1 - \frac{1}{4258} \cdot (-3930251 \cdot x_1^2 + 4258000 \cdot C)
\]
References


