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Energy and process data processing and visualisation for optimising wastewater treatment plants

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Abstract

For complex systems such as wastewater treatment plants (WWTPs), effective data communication is an important step to enable operators to assess their plant. However, examples in practice show that this step is insufficiently considered. In this article, we describe a fast, relevant, and intuitive decision-support tool for operators. We have developed a key performance indicator (KPI) visualisation tool for energy and process data embedded in a larger process optimisation software. The KPI set consists of indicator values relating to energy and effluent quality. In order to ensure that the visualisation tool will be used and cover the needs of the plant staff, we developed this part of the software in collaboration with two WWTPs. At the time of writing, the tool is used in the daily operation of both plants. The operators see the tool's most important advantages as its ability to quickly assess current plant performance and to simplify the tracking and analysis of inter- and intra-process relationships and dynamics.

Key words: data quality, data visualisation, decision support systems, optimisation, performance indicators, wastewater treatment

INTRODUCTION

Energy and resources are important cost factors for wastewater treatment (Hernandez-Sancho & Sala-Garrido 2008). The implementation of new energy-intensive treatment technologies such as post-ozonation (Hollender *et al*. 2009) makes it essential to optimise not only the design but also the operation of wastewater treatment plants (WWTPs) towards energy and resource efficiency. On a daily basis, operation optimisation requires a keener awareness of the process characteristics and energy consumption of the plant. Moreover, various studies in other engineering areas claim that energy savings can be achieved simply by providing more frequent or real-time energy data to the decision-makers (Siero *et al*. 1996; Fischer 2008). However, limited efforts have gone into the effective communication of this data. For a broader and complex indicator set, such as ours, the actual visualisation and arrangement of the individual graphical elements is a crucial step in attracting the operator's attention.

In the current literature, visualisation in wastewater treatment is often linked only to methods of processing data and does not discuss its on-site deployment. Popular approaches are based on unsupervised learning models such as principal component analysis (e.g. Aguado & Rosen 2008; Maere *et al*. 2012) or self-organising maps (e.g. García & González 2004; Dürrenmatt & Gujer 2012) and have been studied intensively in the academic community.

In the visualisation concept presented in this paper, visualisation also includes intuitive communication of relevant and processed (smoothed, filtered) data. Research about the communication of data

Water Practice & Technology Vol 10 No 1
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from WWTPs to operators has been limited. Publications such as those of Andrienko & Andrienko (2006) and Aigner *et al.* (2007), for example, discuss general rules for the visualisation of temporal data which may be transferable to wastewater practice. In this paper, we present a novel approach to the accurate and intuitive visualisation of key performance indicators (KPI) taking into account energy and process data on WWTPs. This approach deals not only with computational and graphical issues, but also considers the integration of heterogeneous data sources, varying data quality and quantity, as well as computational requirements. With the aid of this novel KPI-focused approach, we aim to support operators in assessing and optimising the performance of their plants.

SOFTWARE DESIGN PHILOSOPHY

Modularity

The visualisation tool fits into a larger project in which software is developed for optimising WWTP operation. A key observation in this context is that numerous techniques for data analysis and visualisation are available today. They include generic techniques as well as tools which are highly specific to particular data sources (e.g. discrete/continuous, univariate/multivariate sources). It is expected that the demand for these tools will vary over time and for different WWTPs because of their scale, their location or additional plant-specific conditions and requirements. For this reason, a core element of the design philosophy is that the resulting software, including data visualisation tools, is modular. Such modularity aims to limit the extra efforts needed to implement the same software in new plants. Unavoidable plant-specific software changes are limited to differences in data acquisition, plant configuration, and data availability. It is important that any visualisation tool, including the one proposed in this work, should be flexible enough to be used for a wide range of WWTP designs and even for other systems (e.g. sewer networks and water production systems).

Data quality

An important aspect of data visualisation in wastewater treatment practice is that the displayed data must be of guaranteed quality in order to prevent errors in the decision-making process. Therefore, the software is built in such a way that the visualisation module discussed in this paper is fed only with data already analysed by a data quality module. Although this module is not discussed in detail in this paper, its specifications account for the following elements:

(1) Hardware redundancy, such as sensors measuring the same variable in the same location or a sensor measuring the controlled variable of an actuator (e.g. flow rate set point and flow rate measurement), is exploited for fault detection (to indicate a fault) and fault isolation (to indicate a faulty sensor) to allow appropriate sensor maintenance. Furthermore, automatic fault identification (e.g. identifying calibration errors, fouling, bias, and the associated parameter values) should lead to automated data correction schemes (e.g. Ali & Narasimhan 1995; Rieger *et al.* 2010).
(2) Process redundancy based on mechanistic knowledge in the form of flow, mass, and energy balances (static redundancy) is used to reconcile online data, so that the reconciled data satisfy the balance equations as described in, e.g. Ali & Narasimhan (1995) or Narasimhan & Jordache (1999). Furthermore, gross error detection schemes are put in place for fault detection, isolation, and identification based on balance equations (e.g. Villez *et al.* 2013).
(3) Empirical redundancy, discovered only by means of data mining or data-driven pattern recognition methods, is used to detect anomalies in the measurements where the methods mentioned above fail (e.g. Dunia *et al.* 1996; Villez *et al.* 2009).

Water Practice & Technology Vol 10 No 1
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Data granularity

During the development of a data visualisation tool, several aspects of full-scale data have to be addressed. One is that not all data are measured at the same frequency. As such, it is very obvious that the updating interval for visualisation cannot be shorter than the collection interval for the data. This is especially relevant for off-line measurements, as they are typically available at irregularly spaced time intervals. This is less of a concern for on-line data. However, the visualisation of energy-related and general process data at high frequency (e.g. scale of seconds) makes little sense if the data visualisation is only requested on an hourly or daily basis. Indeed, the granularity of the visualisation data itself needs to be adjusted to a lower scale (less detail) so that it captures the important variations in the plant, which can be influenced by the operator, but no small timescale variations, which have limited relation to the plant performance. This applies especially to systems with a long delay between inputs (control signals) and outputs (measurements). Typical time constants for wastewater treatment are daily cycles (e.g. flow and energy) or hydraulic or solid residence times (e.g. digester). Excessively frequent computation may give the operator an erroneous picture, possibly leading to aggressive action or distrust of the software. This is to be set off against a potentially slower response of the visualisation tool if the chosen granularity is so low (not enough detail) that important events are detected more quickly by the operator instead of the software or, even worse, missed entirely.

VISUALISATION CONCEPT

Visual design elements

Two graphical elements help to visualise the KPI, the ‘colour bar’ and the ‘calendar view’. The colour bar (cf. Figure 1(b)) has a numerical scale for the indicator with an arbitrary number of markers. Each colour of the colour gradient from red to yellow to green is fixed to specific numerical values for each indicator and includes no additional information. However, the colours are designed to allow a faster and more intuitive understanding of the numerical scale. The colours of this colour bar are basically matched to the EU energy label for household appliances (European Union 2013), which is also an official label in Switzerland and is therefore well-known (cf. Figure 1(a)). Each colour bar contains a description of the calculation, the data sources used, and the time of the last calculated value (not shown). The calendar view is based on an idea of Wicklin & Allison (2009) and consists of a calendar where weekdays are arranged in columns and each row represents a week (cf. Figure 1(c)). Each day is a small box coloured according to the characteristic day value (e.g. daily average). The colour scale corresponds to that in the colour bar. If an indicator is not calculated, the respective day remains blank. The form and arrangement of the calendar view elements supports the operator in finding weekly and seasonal patterns within one or among several indicators. The calendar view offers interactive options (e.g. mouse hover effects) to gain a better understanding of the indicated value with respect to the nutrient and hydraulic loads and other KPIs on the selected day. During hovering, the corresponding calendar view value is displayed on the corresponding colour bar (H).

If the operator wants to study some indicators in more detail, a second graphical interface can be opened (not shown). On this level, the user can visualise multiple indicator trends on any timescale and with various options to show statistical key figures. The second level is still in the process of development and has not yet been released.

Water Practice & Technology Vol 10 No 1
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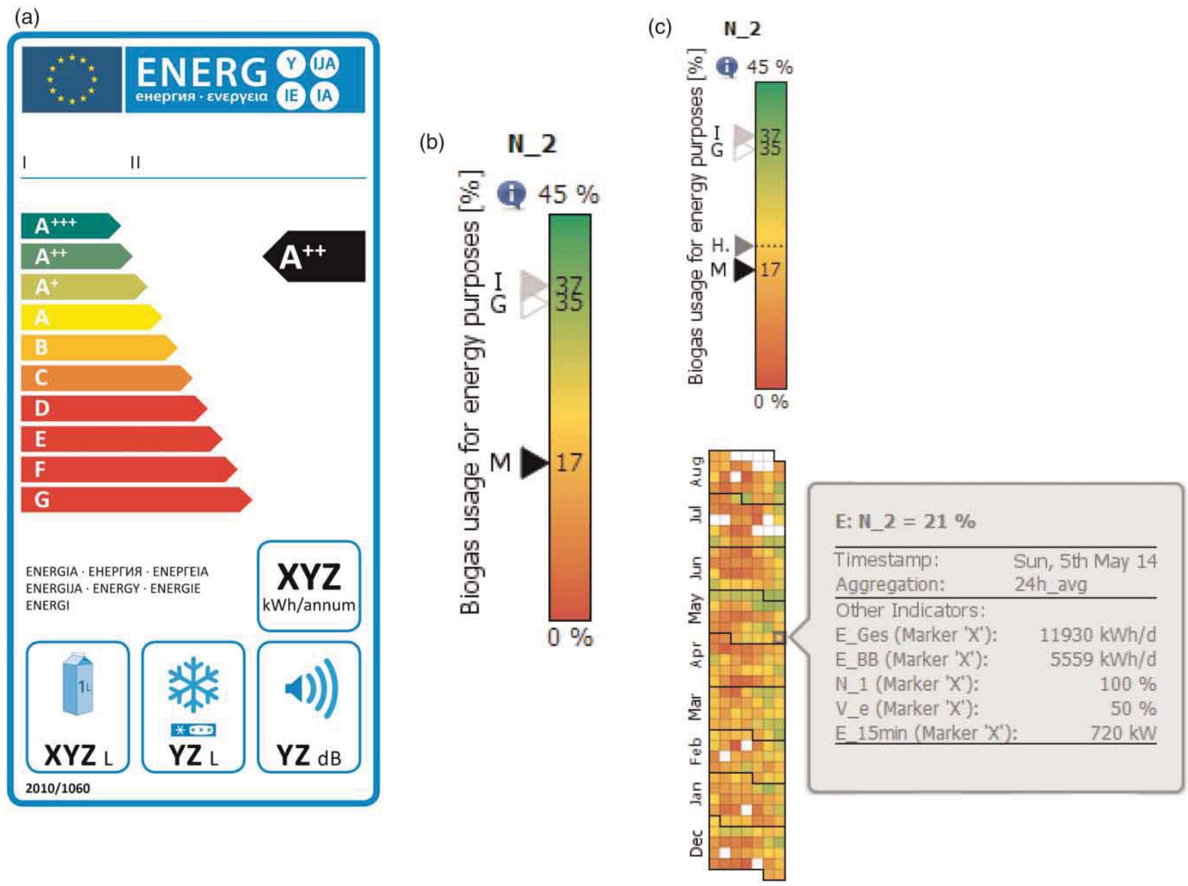

Figure 1 | (a) European energy label for household appliances (European Union 2013). (b) Colour bar component. (c) Calendar view with interactive mouse hover information. Colour bar markers: I, ideal value; G, guideline value; M, measured value; and H, historical value.

FULL-SCALE IMPLEMENTATION

To ensure relevant, intuitive, and user-friendly visualisation, the software module was developed in close collaboration with two Swiss WWTPs, namely, WWTP Hard in Winterthur and WWTP Pfungen. The former is a conventional activated sludge treatment plant and is equipped with a pre-denitrification stage, iron-based phosphorus precipitation and effluent sand filters. The average load is approximately 130,000 population equivalents (p.e.). The plant mainly receives municipal wastewater and has strict discharge requirements due to its relatively small receiving water body. The WWTP Pfungen is a conventional municipal activated sludge treatment plant and is equipped with a pre-denitrification stage and iron-based phosphorus precipitation. It is designed for 12,000 p.e. The software module is similarly configured for both plants.

Indicators

The data chosen for visualisation can be separated into two groups, energy indicators, and process indicators. In our implementation, the energy indicators are based on existing guidelines from the Swiss Water Association (BFE & VSA 2010). The German Association for Water, Wastewater and Waste provides an equally valid alternative (DWA 2013). These indicator sets help operators to benchmark their plants against ideal and guideline values. The guidelines suggest calculating consumption per population equivalent (p.e.) assuming 120 g COD/p.e./day. Due to the variability of

Water Practice & Technology Vol 10 No 1
doi: 10.2166/wpt.2015.002

the COD influent concentrations, the WWTP operators favoured absolute values in our initial evaluation experiments. This is discussed in more detail in the Evaluation section below.

The set of energy indicators was extended by an additional indicator of peak electricity load, as this is subject to fees and thus relevant for the operators. Process and elimination performance as well as resource efficiency are also visualised by appropriate indicators. Instead of guideline and ideal values, however, they are benchmarked against effluent limits and internal quality objectives. An overview of the implemented indicators is given in Table 1.

Table 1 | Key performance indicators selected for deployment

Indicator	Unit	Colour bar value
Modified energy indicators (BFE & VSA 2010)		
Total electricity consumption per day	kWh/d	Daily value
Electricity consumption of the biological treatment step (aeration, recirculation, stirrers) per day	kWh/d	Daily value
Litre of biogas produced per kilogram of VSS loaded into the digester	l/kg VSS	Ratio of average daily gas production (l) to average daily VSS measurements (kg) within a single solid retention time of the digester
Degree of biogas usage for energy purposes	%	Daily value
Degree of biogas usage for electricity or direct motive force purposes	%	Daily value
Self-sufficiency in electrical energy	%	Daily value
Self-sufficiency in thermal energy	%	Daily value
Custom Energy Indicators		
15 min of peak electricity load	kW	Daily maximum 15 min average value
Plant performance indicators		
Elimination performance COD, N & P, whole plant	%	Value of last daily composite sample
Elimination performance COD, N & P, biological step	%	Value of last daily composite sample
Effluent concentrations TSS, COD, DOC, nitrite, nitrate, ammonia & total nitrogen	mg/l	Value of last daily composite sample
Fraction of COD, N & P plant capacity in use	%	Value of last daily composite sample
Absolute and relative denitrification performance	kg/d & %	Value of last daily composite sample
Precipitant usage per mole of P precipitated	mol/mol P	Value of last daily composite samples or daily average (online P-sensor).

Implementation and deployment

Systematic integration of software modules designed for WWTP staff is crucial for successful deployment on-site. While systematic integration eases the use of the modules by providing uniform and intuitive user interfaces, it is also a key factor for cost-effective deployment if embedded within a broader software framework.

Consequently, the visualisation module presented in this paper is deployed as an optimisation software module within the commercially available RITUNE platform (http://www.rittmeyer.com/ritune) shown in Figure 2. The software has a client-server architecture, where client and server communicate by means of HTTP requests. This enables and simplifies deployment over the internet, thus also facilitating remote applications. The RITUNE platform connects to supervisory, control, and data

Water Practice & Technology Vol 10 No 1
doi: 10.2166/wpt.2015.002

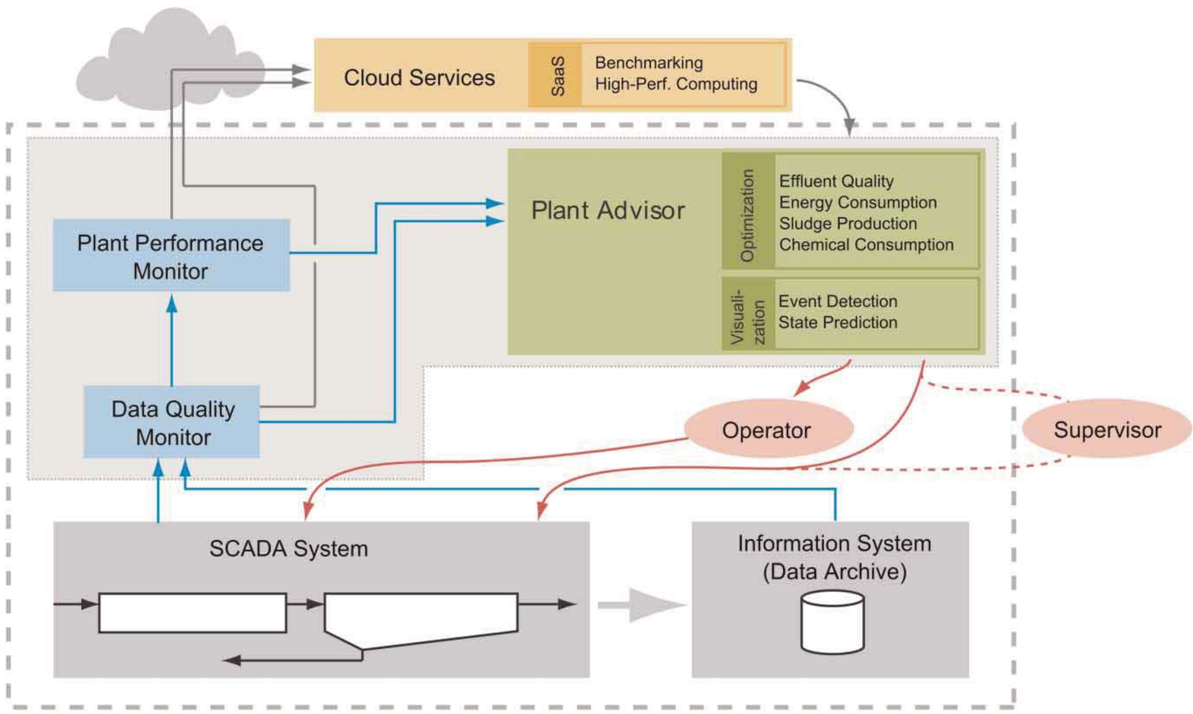

Figure 2 | Implementation of the optimisation software (brighter grey area) within the WWTP. The plant's fence is indicated by the dashed grey line.

acquisition (SCADA) systems, plant information systems, and other data sources via industry-standard interfaces such as OPC, OBDC, SQL, and XML-RPC. The quality of the incoming data is first analysed (data quality monitor; Figure 2) and the performance of the plant is assessed (plant performance monitor). Data of ascertained quality are hierarchically aggregated for fast data access, taking advantage of the map-reduction capabilities of the database. Both aggregated data and performance measures are then fed into the plant advisor, where they are utilised by modules performing specific tasks, e.g. visualising KPIs as in our case. Insights gained from data analysis and recommendations made by the optimisation software are either (i) manually applied to the plant by the operator, (ii) directly sent to the SCADA system, or (iii) verified by an external supervisor. Cloud services allow direct benchmarking data among different plants as well as the use of computationally intensive optimisation modules; thus, the local server and clients normally only require standard computers to run on. The initial installation of the server and clients and the configuration of the visualisation module take less than a day.

The module visualising energy and process data on WWTPs is shown in Figure 3. Horizontally arranged gauges indicating KPIs and guideline values facilitate obtaining an overview of the plant's state. For each gauge, a calendar view allows the analysis of temporal variations by emphasising weekly and seasonal patterns. A typical interface on common screens can contain up to 15 gauges and display historic data for the last 12 months. The user login concept of the RITUNE platform allows to personalise the visualised KPIs according to the individual needs (e.g. operator vs. manager). Configuration masks allow any user with appropriate permissions to create and configure new and existing indicators, to arrange indicators within dashboards and also to define additional dashboards. There are no limitations in terms of number of indicators per dashboard and dashboards per installation.

Application

The following application example shows a typical use case of the tool shown in Figure 3. The red dashed line indicates a period where the second-largest biogas consumer in the plant, namely the

Water Practice & Technology Vol 10 No 1
doi: 10.2166/wpt.2015.002

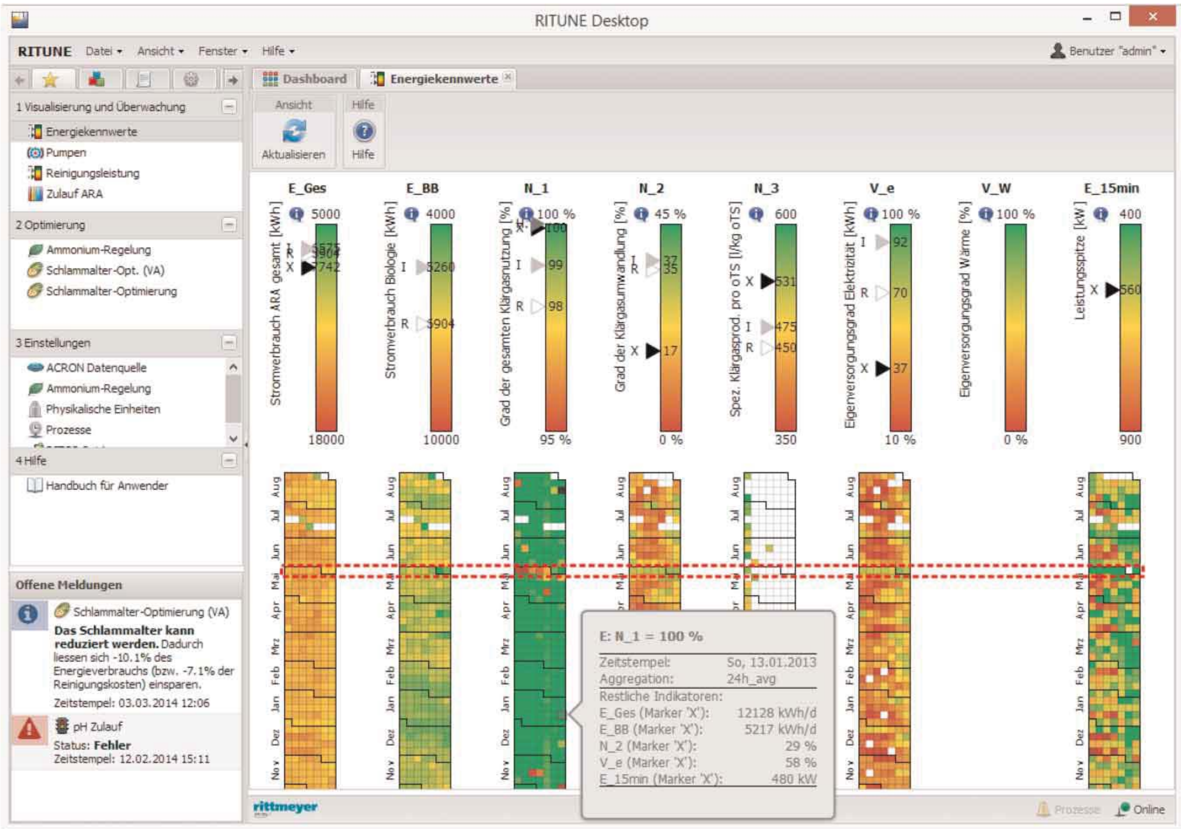

Figure 3 | Screenshot of the dashboard prototype implemented on the WWTP Hard, Winterthur. It indicates the current state of the plant by means of KPIs, embedded as a plugin module within the optimisation software platform. The red dashed line indicates a phase where the sludge incineration, a large biogas consumer, was shut down (cf. Application section).

sludge incinerator, was shut down due to maintenance. This decline in gas consumption with constant gas production led to various effects, which are easy to explore as the relevant data are already intuitively arranged. One observed effect is that some gas was diverted to the gas flare to relieve a lack of storage capacity, thereby causing a decline in the percentage of gas used for energy production (N_1). A second effect is that the high gas surplus allowed the cogeneration plant to be operated during a larger fraction of each day. Indeed, the higher electricity production led in turn to a higher percentage of gas used for electricity production (N_2) as well as a higher level of self-sufficiency in electricity consumption (V_e). The peak kilowatt consumption from the public electricity grid was consequently also below normal weekday levels (E_15 min). This example shows that the effects of planned changes can be tracked effectively. In addition, the visualisation tool can be used as a monitoring device to detect and identify unintentional process disruptions. It is intended to add a plugin to the RITUNE platform which allows to write and read entries to already existing event databases such as the SCADA system in order to keep track of event meta data.

EVALUATION

The visualisation tool presented in this paper offers the user a faster and more intuitive way of extracting relevant information from process data compared to the conventional tools in use today (cf. Figure 4). Figure 4 shows daily values from five out of seven indicators we show in Figure 3. Both visualisations are based on the same data set.

On the basis of initial full-scale tests, the operators of the two WWTPs (Hard and Pfungen) claim that the tool enables them to assess the current state of the plant quickly on a daily basis. In particular

Water Practice & Technology Vol 10 No 1
doi: 10.2166/wpt.2015.002

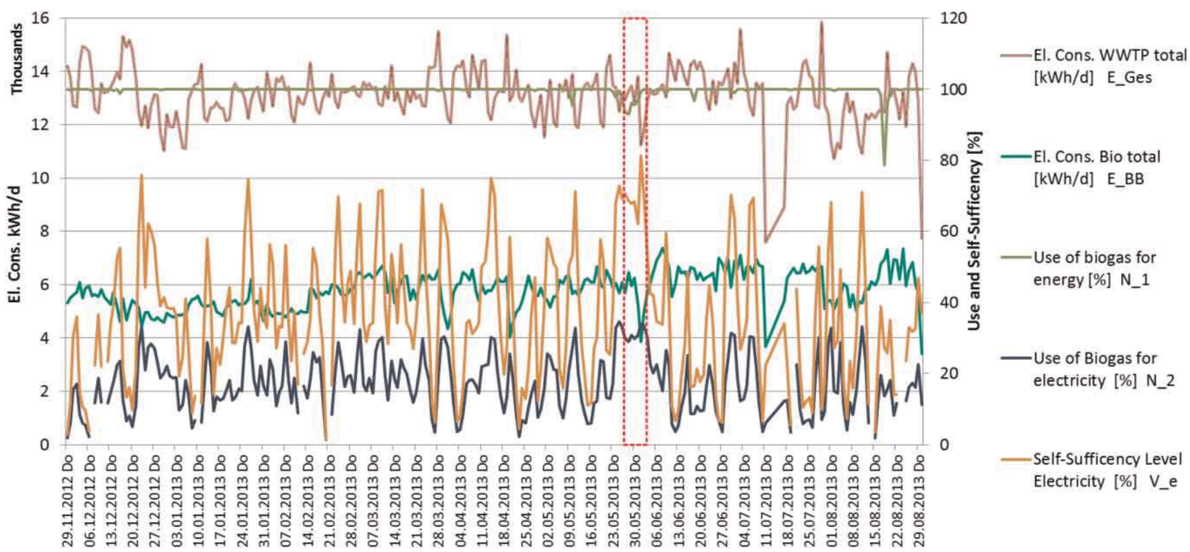

Figure 4 | The graph is based on the same data as the KPIs already visualised in Figure 3 (Autumn 2012–Summer 2013). Five out of seven KPIs plotted. The red dashed line indicates a phase where the sludge incineration, a large biogas consumer, was shut down (cf. Application section).

the automated update of the KPIs and the more intuitive visualisation compared to the classical spreadsheet tools (cf. Figure 4) were mentioned. Furthermore, the calendar view makes it easier for them to study intra- and inter-process effects (see Application section above) without major effort. According to the operators, information can be used not only for operational decisions but also for preliminary strategic decisions as the operators gain more knowledge about the plant load dynamics. Furthermore, the tool allows them to track the success of new operation strategies or to confirm that they are already operating the plant or single processes optimally. Nevertheless, a number of problems remain unsolved. Some challenges are of a technical nature. For example, temporal resolutions of different variables for computation and visualisation are currently set *ad hoc* and thus require further refinement. Annual key indicators are often unsuitable for daily treatment for various reasons such as data noise or data availability. On-going studies are aimed at the evaluation and quantification of operational risks associated with missing and excluded data. A further challenge is to ensure the general applicability of the software. Other challenges relate to the quantification of the benefits of the developed software. While operators value the visualisation tool as a major improvement, it is still unclear whether and how the human–machine interface should be enhanced further. Also the long-term usage of the tool is not evaluated yet. It is for this reason that a broader set of tests on a variety of WWTPs are currently being carried out.

CONCLUSION

A new tool to visualise energy and process data has been presented. Two graphical elements facilitate the assessment of the current and historical state of the plant. In combination, they enable the operator to interactively interpret relevant data, thus leading to better informed decision-making. The approach presented here is flexible enough to accept generic KPIs, even if intuitive ones are available in the literature. On-going tests reveal that it is helpful for plant operators. Reported benefits over traditional data visualisation include: (1) straightforward overview of the plant's performance, (2) effective appreciation of otherwise unknown correlations and patterns, and (3) diagnostic capabilities, leading to decision-making in a well-informed operational setting.

Water Practice & Technology Vol 10 No 1
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