Outlining Process Monitoring and Fault Detection in a Wastewater Treatment and Reuse System*

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***Abstract*— Process control is an important part of any industrial system. In a wastewater reuse system this remains true. Process monitoring and fault detection (FD) are important to ensure that the control system has access to reliable data which can be used in making decisions about the operation of the process. The reuse scenario being considered in this work is that of utilizing the nutrients from the wastewater as fertilizer to agricultural soil along with using the water for irrigation purposes. This paper identifies variables that are important to the control of the process and should be a focus of monitoring and FD. In wastewater treatment these variables include temperatures, pressures, liquid levels, flow rates, pH, conductivity, biomass content, suspended solids concentration, dissolved oxygen content, total organic carbon, and the concentrations of nitrate and ammonium. The variables of interest in the reuse of nutrients and water for agriculture include soil moisture, ambient conditions, plant height, biomass content, photosynthetic activity of the crop, leaf area and leaf water content, as well as the concentrations of several ions both in the soil and in the plant. Challenges associated with process monitoring and FD specific to the two processes are also discussed, examples of these are the high dimensionality of the problem, the harsh conditions that sensors must operate in and the non-linear relationships between variables. This information will be used in future work when comparing specific FD methods to ensure that methods chosen are capable of overcoming the commonly encountered problems.**

I. Introduction

One of the UN's sustainable development goals is clean water and sanitation. It states that everyone on the planet should have access to safe drinking water. However, according to Mekonnen & Hoekstra [1], a large part of the global population (66%) live under conditions of severe water scarcity at least 1 month every year. In Europe by 2014 at least 11% of the population had been affected by water scarcity [2]. The areas that have high water scarcity levels are typically areas with high population density or areas that have agriculture that use a lot of water for irrigation [1]. One way to reduce the pressure on freshwater resources is to use reclaimed water for irrigation of agricultural fields and industrial need and save the freshwater for use as drinking water. Wastewater is already reused in many countries around the world, for example the US and Australia [3] and several of the European countries [4]. Apart from water scarcity another challenge is nutrient scarcity. The amount of phosphorous is finite and today most of the phosphorous used for fertilizer is produced through mining phosphate rock. Use of reclaimed water makes it possible to reclaim nutrients from the wastewater streams that otherwise might be lost. In addition, it is important to use phosphorous efficiently since it can pollute water streams and cause unwanted algae growth [5]. Nitrogen, which is of great importance in fertilizer and can also be reclaimed from wastewater, can be particularly hazardous if an excess is allowed to build up in the soil. The risk of N_2O emissions, surface and ground water contamination, eutrophication of water sources, are all possibilities that should be avoided [6].

Ideally a system for reuse of treated wastewater would include a wastewater treatment plant (WWTP) that tailors the quality of the water to the need of the agricultural fields that it delivers reclaimed water to. Such a system would not only include process monitoring and control of the WWTP but also monitoring and control of the crop growth and crop quality and the system as a whole. For process monitoring and control it is important to have reliable data to base decisions upon. In this context fault detection (FD) becomes very important.

The aim of this work is to outline the importance of process monitoring specific to FD in the wastewater treatment (WWT) and reuse process.

II. Process Monitoring

Process monitoring is an important part of the supervisory control system in industrial processes. All process outputs are required to be within quality and safety standards, and process monitoring systems are necessary to allow for counteraction when disturbances occur which can negatively affect the process [7]. Modern processes are collecting more data as technology allows for the measurement of more process variables (for example, improvements in sensors that can measure nutrient concentrations [8]) and it is becoming increasingly important to develop systems that can extract information from these large amounts of data as operators cannot manually extract sufficient information [9]. An additional reason for the rise in process monitoring is the

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increased focus on model-based process control [10]. Often the models require measured on-line data as inputs. This makes it necessary to monitor more variables with regularity and reliability.

There are several components that contribute to process monitoring: detection, isolation, and interpretation being the main ones of interest. Detection (fault detection) involves recognizing that the process is not operating in the normal operational state of the plant, while isolation and interpretation (combined known as fault diagnosis) relate to identifying which variables are responsible for the change in operating state, as well as finding the physical cause of the problem [9].

As mentioned, in a system that reuses treated wastewater in agriculture process monitoring is crucial. The two components of the system, the WWTP and the agricultural fields containing crops, are fundamentally very different and will rely on different processes and principles for their respective process monitoring. It is important to understand the challenges that are inherent to the respective processes in order to design better and more reliable monitoring systems.

A. Process Monitoring in WWT Processes

As with other industrial processes WWT processes also have requirements placed on the process output, where the output is the effluent in the case of a WWT process. The requirements are perhaps even more stringent and the consequences of failing to meet them higher. Additionally, as the global awareness of the need for sustainability increases the demand on the quality of effluent becomes stricter. This makes it even more relevant to have adequate process monitoring systems in place in order to meet the demands.

There are several factors which make WWT processes unique and make efficient process monitoring all the more important. Perhaps the most noticeable is the influent. WWT processes are required to accept all influent, regardless of the quality, and to process it to the same standard of effluent [11]. As the influent is highly variable it is the source of many disturbances to the WWT process which must be detected and compensated for. In a WWT process the disturbances can have a large effect on the process, in the past plants have been designed with large volumes to act as a damper and reduce the impact that the disturbances have [12]. This requires a large capital investment and is hardly a reliable system.

In addition to the influent flow rate and quality, some of the most common variables that are monitored in WWT systems are temperature, pressure, liquid level, flow rate, pH, conductivity, biomass content, suspended solids, NO_3^-, NH_4^+, DO, and total organic carbon (TOC) [10, 13, 14]. These variables are relevant to several common control strategies (aeration phase length, nitrate recirculation, sludge recycle, and chemical precipitation [12]) and are important to ensuring the effluent is of sufficient quality.

Sensors in WWT Processes

As stated previously, advances in monitoring technology has made it possible to measure more variables and to do so more accurately. However, the sensors and technologies are not designed specifically for the WWT environment which leads to several difficulties. Li et al. [15] state that for systems dealing with wastewater, sensors should be capable of withstanding the hostile environment for a significant amount of time, they should have designs that minimize blockage by solid particles and discourage surface contamination and biofouling, as well as being self-contained and requiring no reagent or continuous calibration.

The types of sensors that are commonly used vary greatly. Temperature can be measured with thermistors, liquid level with floats, differential pressure transducers, capacitance measurements, and ultrasonic level detection, flow rates are measured with electromagnetic sensors or rotameters depending on the state of the stream, pH with glass electrodes, biomass and suspended solids with optical measurements or ultrasound, [10] and DO with membrane electrochemical or optical fluorescent techniques [16].

All of these sensors have failings, for example ultrasonic level sensing being sensitive to foaming, or air bubbles causing interference with optical sensors [10]. However, contamination and biofouling are of particular concern in the WWT process, with conductivity sensors, suspended solids probes, fluorosensors, and dissolved oxygen (DO) probes being particularly susceptible to biofouling [10]. Samuelsson et al. [16] demonstrated that unless sensors are manually cleaned or faults are well detected it is most probable that the DO probes will report incorrect values due to the biofouling.

Aside from WWT specific problems, all sensor signals are susceptible to errors such as noise, drift, catastrophic failure, power outages, and transmission problems. These errors can be identified by looking for signals that are outside the 4 to 20 mA range, by finding constant signals (constant signals are unexpected in a wastewater treatment plant and can be indicative of malfunctioning, dirty, or offline sensors), and by identifying sudden changes in the signals which can suggest unreliable measurements or sensor failure [17]. Sensor signals must also often be filtered due to the high frequency parts caused by electrical interference or measurement noise.

B. Monitoring of Crop Growth

One of the motivating factors for monitoring crop growth and nutrient content is to reduce the loss of water and nutrients to the environment [18]. Additionally, monitoring the growth of crops is important in order to ensure that the crops are healthy and producing as high a yield as possible. The growth of crops is often nonoptimal due to numerous factors such as insufficient nutrients, insufficient water, hostile ambient conditions (extreme cold and extreme heat), insects, and disease [19]. If these factors, along with the growth of the crops, are being monitored the cause of the problem can be identified and in some cases steps can be taken to reduce the stress on the crops.

Some commonly monitored variables relevant to characterizing and predicting crop growth include light intensity, soil moisture, soil temperature, ambient temperature and humidity [20, 21], plant height [22], biomass content, photosynthetic activity, light interception by the crop, leaf area index, leaf water content, canopy cover, and water use [6, 18, 23]. To predict the fertilizer requirements concentrations of ions, in both the soil and in the crop, is beneficial, these include Na^+, K^+, Ca^{2+}, NH_4^+, Cl^-, NO_3^-, $H_2PO_4^-$, SO_4^{2-} [18]. These parameters can be separated into three main categories: soil based, plant based, and weather based [24].

Sensors in Crop Monitoring

While there are many variables that are important to monitor, not all are directly measured. Many are inferred from relationships that exist between the variables, for example Freeman et al. [22] showed that reflectance of near-infrared (NIR) and red radiation combined with knowledge of the plant height can be used to determine nitrogen uptake by the plant.

Spectroscopic techniques, such as NIR reflectance measurements, are commonly used in monitoring plant growth. Measurements of reflected and absorbed radiation can be used to estimate light interception, leaf area index [25], nitrogen content using the relationship between nitrogen and chlorophyll [6], and photosynthetic parameters by combining the spectroscopic techniques with chlorophyll-fluorescence [18]. These measurements can even be taken using unmanned aircraft systems (UAS) [19].

UAS have also been used to measure plant height [23], and to determine biomass content using photographic methods based on color analyses [26]. Methods such as terrestrial laser scanning are also used for measurements of plant height [27].

There are numerous complications and difficulties that are present in these monitoring systems. Some examples include the sensitivity of spectroscopic measurements to the illumination source which makes them easily influenced by cloud cover, the presence of excess water can obscure the nitrogen absorption band when measuring reflected radiation [6], and many methods are sensitive to excessive dust on the crop leaves as it can cause unusual absorption peaks and corrupt the colors. Additionally, soil moisture sensors, which are important for scheduling irrigation, most commonly operate using the capacitance method [28]. This method is sensitive to soil type and temperature, which means that a buildup of ions in the soil can result in erroneous moisture measurements. It is possible to use a soil moisture sensor which makes use of the heat-pulse principle in combination with a capacitance-based sensor in order to avoid some of the problems of soil dependency [28]. Soil moisture sensors using the heat-pulse method are robust and independent of soil type, however, they have slow sampling rates and so must be used as a complimentary sensor [28].

III. Fault Detection

Fault detection is an important part of process monitoring and must precede fault diagnosis; a fault cannot be diagnosed if it is not detected. A fault can be considered as the deviation of a parameter from a predetermined range of normal values. There are three main types of faults: process faults, structural faults, and sensor/actuator faults [29]. Process faults are generally due to disturbances in the process and structural faults are due to equipment failures [29]. These two types of faults, along with actuator malfunctions, directly influence the process dynamics which are monitored by the sensors.

An important part of FD is proving reliability of data to avoid making poor decisions due to inaccurate information about the state of the process. As model-based process control becomes more widely used the accuracy of the data that is provided to the control system becomes more important [10, 17]. Variables used in common control strategies in WWT processes should then be variables of the highest importance in FD systems.

In the previous sections some specific sensor faults and complications were discussed relating to commonly measured, and controlled, variables in the two systems. If sensor faults are not detected the information about the actual state of the process is not known to be reliable. Sensor faults can be detected through a variety of methods, some of which were mentioned in the previous section (looking for out of range signals, finding constant signals, or identifying sudden changes in signals). Other common methods to detect sensor faults include hardware redundancy like comparing the values of similar or correlated sensors as illustrated by Carlsson and Zambrano [30], or through the use of analytical redundancy using soft sensors to reconcile physical sensor measurements with predicted measurements as demonstrated by Karlsson et al. [31]. These soft sensors can be used for data reconciliation and fault isolation by using continuity equations connecting different signals [31]. Work done by Samuelsson et al. [32] showed that certain sensor faults can be detected using active fault detection which involves the sensor issuing a test signal which can be used specifically for FD. This is a promising technology to move FD away from the traditional methods and make use of improvements in sensor technology along with improvements in traditional FD methods.

When considering an FD system there are several important characteristics that are desirable for the system to possess such as the ability to quickly detect faults, the ability to operate despite noise and uncertainties in the system data, and the ability to adapt to planned changes in process operating conditions. These are only some of the characteristics identified by Venkatasubramanian et al. [29], with the other characteristics being more specific to the diagnostic capability: quality of isolation, identification of novel faults, identification of multiple simultaneous faults, and adequate explanation about propagation of the fault. It is also important to avoid reporting "false faults" as this will confuse the operators and reduce their trust of the system.

A. Classification of FD Methods

When selecting a FD method process specific challenges must be taken into consideration, however, an additional factor to consider is what information is available to describe the process.

Models based on physical definitions, such as mass balances and reaction kinetics, are commonly used to describe a process. Often these are coupled with parameters whose values have been obtained from observation data of the physical process. These are called grey-box models and are particularly useful due to the physical interpretation that exists of the different terms and parameters in the model [33]. Unfortunately, these models are also generally complicated and often not easy to implement in on-line operations. Another common representation of a process is black-box models. These have little to no physical interpretation, they are based on correlations between measured variables and are often simpler to implement due to their simplicity [33].

Fault detection methods can be classified into three primary groups [29]:

1. Quantitative model-based methods – which are based on mathematical models of the process (grey-box models). The faults are characterized as differences between observed and modelled behavior. These can be difficult to implement in on-line fault detection in WWT processes due to the complexity of the models.

2. Qualitative model-based methods – which use knowledge of the process and the relationships between the variables. These are particularly useful when analytical models are not available or easy to implement.

3. Process history-based methods – these make use of extensive amounts of process data to determine a normal operational state and characterize faulty states, the state of the plant is then compared to these pre-determined states.

It is logical that the fault detection technique which is used should be selected partially based on what information is available.

The review conducted by Corominas et al. [11] found that process history-based methods are overwhelmingly the most commonly researched FD techniques for WWT processes. This is likely due to the complexity of the processes, the high levels of interactions between variables, and the amount of computation time required from models which make the first two types of fault detection less common. In new processes, such as the integration of wastewater treatment with irrigation and fertilization, where there is not a large amount of historical data, it will likely be necessary to make use of a combination of methods to achieve good detection performance without overcomplicating the system.

B. FD Challenges in WWT Processes

All processes have challenges when it comes to FD and diagnosis such as noise, missing data points, or extreme outliers. These problems can be addressed quite simply through digital filtering, extrapolation or interpolation depending on if the analysis is done on- or off-line, and with statistical analysis or the use of redundant sensors [33]. However, WWT processes present many additional difficulties due to the nature of the process [9]:

1. The presence of collinear data in both the dependent and independent variables.

2. A high dimensional problem due to the number of process variables that are measured.

3. Poor data quality due to harsh environments for the sensors and measuring equipment.

4. Non-linear relationships between many of the variables.

5. Non-stationary behavior due to the diurnal and seasonal variations

6. Dynamics with wide ranges of time constants (events occurring on scales of minutes like changes in dissolved oxygen content, and events occurring on scales of weeks like changes in microbial population).

Some of these difficulties are easily addressed: collinearity can often compliment the reduction in dimensionality, WWT processes are not very time sensitive so the poor data quality can be dealt with by extensive pre-filtering and processing before analysis, and non-linearities in WWT processes generally display smooth and monotonic behavior [9].

However, some of the problems require additional work. Consider the 2nd and 6th points, for example: in order to deal with the high dimensionality, it is desirable to use dimension reduction methods such as principal component analysis (PCA) [33, 34]. These methods are usually static and so do not consider the dynamics. This means that the time lag between process and inputs and outputs is neglected and must be quantified using cross-covariance or the expression of the lag as a function of another measurable variable to represent the system with quasi-dynamics [33, 34]. Dimension reduction is important to extract information in a manner that can be represented easily to aid operators [9].

Many methods of FD are not well suited to processes with non-stationary behavior (see point 5) as they often assume the data has a constant mean [34]. These methods must be adapted appropriately using a moving time window to only view relevant data or have some recursive model calculation. Care should be taken so as not to allow the model to adapt to common disturbances and faults [34].

Having a good understanding of these challenges will be critical when selecting an appropriate FD method for the WWT process. The method must be tailored to the process in order to produce optimal results.

C. FD Challenges in Crop Monitoring

As spectroscopic techniques are commonly used in monitoring crops, spectral resolution can be a challenge [35]. This is of concern with the soil; soil has many complex physical, biological, and chemical components, resolving the spectra to relate it to specific properties is not trivial. If the spectral resolution is too low the data cannot be used quantitatively and can only be used for qualitative analysis. The high level of interactions and non-linear correlations also adds difficulties to dealing with the data [35].

Another difficulty is the random nature of ambient conditions [24]. This further complicates the dynamics of the crop-soil system which are highly variable due to the growth rate, the disturbance of insects and disease, and the reliance on correct management in terms of irrigation and fertilization [24]. This can make the use of historical data, which is widely used in traditional FD, difficult.

FD for process faults in crop monitoring (such as determining if the crop is not growing at the optimum rate or producing the highest possible yield) would likely need to be model based and highly adaptive which places additional stress on the ability to detect sensor faults. Unfortunately, models require extensive calibration based on the specific location and crop type. The data required for the desired accuracy is often not available [24].

IV. Conclusion

The intention of this work was to outline the importance of process monitoring and FD with regards to a WWT and reuse system that tailors water quality to the need of the agricultural fields. It was observed that process monitoring is an important area of research in both processes, with emphasis being placed on improving sensor performance. In WWT processes specifically, the harsh conditions often result in unreliable sensor measurements, the ability to detect these unreliable measurements is necessary for effective process control.

While many variables were identified as being important to monitor, further research should narrow down this list and highlight the variables that will provide the most useful information. Despite it becoming easier to measure more variables as technology improves, it is not always sensible to collect more data without considering what use it will have. This selection should consider what variables give accurate quality indicators, which are important for safety concerns, as well as looking for variables with quick response times to faults and disturbances. While on-line monitoring in WWTPs is a well-established field, effective on-line monitoring of plant growth in rural farming in combination with modelling must be developed comprehensively.

Concerning FD it can be seen that the two systems, crop growth monitoring and the WWT process, face similar issues: high dimensionality due to the complexity of the systems, poor data due to difficult conditions when taking measurements and low resolution or high sensitivity on the sensors, non-linear relationships between variables, and a wide range of time constants in the dynamics. Unfortunately, the crop monitoring process does not have the luxury of large amounts of historical data with which to overcome many of these challenges. An approach to deal with the lack of historical data should also be a point of focus as many FD methods require that information.

Future research will involve comparisons of different FD methods taking into consideration the challenges and criteria outlined here. While research has been done on FD methods for the individual systems and units within the systems, the additional complexity added by the integration of the two systems will add interesting challenges to the FD and diagnosis process.

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