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Differentiation between Process and Equipment Drifts in Chemical Plants

Linda Eydam[a]*, Lukas Furtner[a], Julius Lorenz[b] and Leon Urbas[ab]*

[a] TU Dresden, Process-to-Order Group, Process Systems Engineering Group, Dresden, 01069, Germany
[b] TU Dresden, Process-to-Order Group, Chair of Process Control Systems, Dresden, 01069, Germany
* Corresponding Author: linda.eydam@tu-dresden.de

ABSTRACT

The performance of chemical plants is inevitably related to knowledge about the current state of the system. However, both process and equipment drifts may distort state information. Deviations of process values caused by equipment malfunction may be misinterpreted as process drifts and vice versa. Determining the cause of the drift is further complicated by the fact that equipment drifts typically occur in combination with process drifts. This paper presents a method that uses available additional equipment data to reliably detect and decouple combined equipment and process drifts in chemical plants by combining statistical methods with model-based approaches. The utility of additional equipment information is assessed based on its effect on the decoupling of process and equipment drifts. First results demonstrate the feasibility of the approach in a real plant.

Keywords: Fault Detection, Modelling, Process Monitoring, Coupled Drifts, Namur Open Architecture

1 MOTIVATION

In the chemical industry a combination of high plant availability and desired product quality is required to operate economically. This is achieved if the desired operating point is maintained, which requires accurate information about the state of both the process and the equipment. If inaccurate process information is used, the plant cannot be operated with sufficient accuracy. The result is loss of quality and, in the worst case, plant shutdowns and a reduction in plant availability. Equipment drifts, such as fouling or wear in sensors or actuators, can lead to inaccurate process information. Measurement deviations that are caused by equipment malfunction or insufficient calibration can be misinterpreted as process drifts and vice versa. When this happens, the operating point is updated even though the process has not changed. As a result, the quality of the product is reduced.

Such equipment drifts typically occur in combination with process drifts. Very often, the data collected in the process control systems and historians is not sufficient to clearly determine the causes of the drifts. However, additional equipment information, such as device health information, is typically collected in modern devices. It has the potential to enable the differentiation and decoupling of coupled drifts. For this reason, a method is developed that uses this additional information to detect and decouple combined process and equipment drifts.

This paper is organized as follows: first, fundamentals of drift types and their detection methods are presented. Then, the developed methodology is explained by describing its assumptions, requirements and workflow for detecting and decoupling of coupled drifts. Furthermore, the evaluation of additional equipment information is explained. A case study in a real plant demonstrates the applicability and feasibility of the approach. Finally, the method is critically evaluated.

2 BACKGROUND

2.1 Definition of Drifts

In the literature various definitions of process drift and equipment drift can be found. According to Kadlec et al. [1], process drifts affect the measured data and the state of the process. Sensor drifts only affect the measured data. Actuator drifts are not mentioned. In contrast, the NAMUR Recommendation 107 on Self-Monitoring and

Diagnosis of Field Devices [2] describes status signals for the diagnosis of appliances and field devices. Diagnostic bits are used to differentiate between possible error sources. However, only equipment failures are considered. In addition, the International Electrotechnical Commission defines a drift as a “change in the indication of a measuring instrument, generally slow, continuous, not necessarily in the same direction and not related to a change in the measurand” [3]. This definition corresponds to equipment drift.

Each of these definitions is missing some type of drift, and if both process and equipment drift were defined, the definitions would no longer work. Therefore, the information on process drifts affecting the state of the process is taken from Kadlec et al. [1]. In addition, NAMUR Recommendation 107 [2] and the International Electrotechnical Commission [3] provide necessary information on equipment drifts.

Based on this information and in the context of this research, process drift and equipment drift are defined as occurrences with the following results:

Process drift:

> unacceptable, unforeseen variation of predefined critical process parameters from their desired operating point for an unacceptable period of time

Equipment drift:

> unacceptable, unforeseen variation in the operating principle of measuring or control devices for an unacceptable period of time

2.2 Drift Detection Approaches

In the literature, various approaches have been found to detect drifts, some of which also diagnose the cause of the drifts. According to Venkatasubramanian et al. [4], methods of detection are divided into model-based and data-based.

Common model-based approaches are observers and redundancy-based methods. Observers are models that continuously update and improve an estimate of the system state [5]. Redundancy-based methods generate optimal reference values for measured sensor data [6]. Residuals, the differences between the estimated and measured states or the redundant values, are calculated and compared to drift detection thresholds [5], [6]. As model-based approaches describe the system using equipment and process knowledge the modeling effort increases significantly with the complexity of the system. For applications in large chemical plants, it can be concluded that high system complexity can lead to a disproportionate modeling effort [4].

Common data-based approaches are statistical methods and machine learning. Statistical methods are utilized to reduce the dimensions of the data. For instance, cluster analysis is used to divide the data into clusters of normal and abnormal variation. A cluster is an area with specific characteristics, such as an area with a certain drift or an area without any drift. Drifts are detected by analyzing if data points belong to the cluster with normal or abnormal variation [7], [8], [9]. The difficulty with statistical methods is that enough data must be available from the time a drift occurs. Machine learning trains and tweaks models such as neural networks to classify the data. The outputs are different categories such as no drift or drift [10]. However, to build a data-based model, classified data is needed for training, which is very often not available for chemical plants. The reason for this is that it is not known when a drift occurs and what kind of drift it is.

None of these approaches addresses combined drifts and their decoupling. In recent years, the amount of available data has increased greatly due to digitalization. This is not considered in the proposed approaches of the relevant literature. Modern devices record a range of additional information complementing the primary measurement value. If these additional information streams can be accessed, e.g. via the process control system or a side-channel such as the NAMUR open architecture, and utilized, they can help to differentiate between process and equipment drifts and their coupling.

3 METHODOLOGY

Due to the large amount of data available in chemical plants nowadays, it is reasonable to use data-based methods such as statistical methods. These methods divide the data into clusters. But there is a problem - after such a cluster analysis it is not possible to assign which cluster belongs to which drift. The solution is to combine statistical methods with model-based approaches. Possible drifts are modeled and compared with the clusters to assign them to the drifts. The idea of decoupling is to reconstruct the individual drifts and span drift vectors to characterize them. Data points that are drift couplings are then also represented as vectors. Drift decomposition splits these data point vectors into individual drifts and decoupling is complete.

However, the combination of these approaches and the decoupling of combined drifts is only possible if process data and additional equipment information are available and can be used.

3.1 Assumptions and Requirements

First, assumptions are made about the method being developed. They also address the process and equipment for which the method can be used.

1. Data from the equipment under consideration is accessible. This includes primary measurement

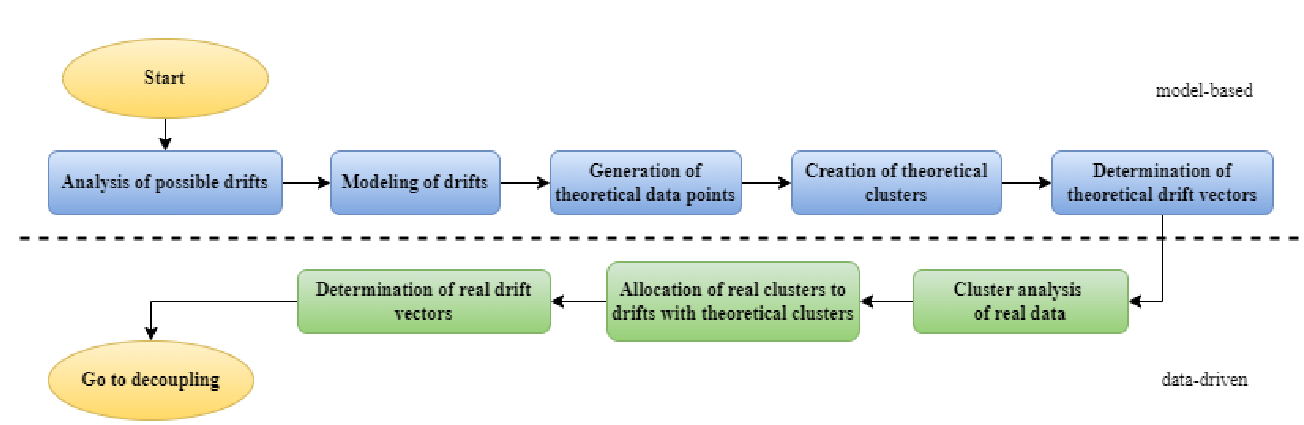

Figure 1: Workflow for the identification of drift areas. These steps are necessary to decouple coupled drifts. Yellow is the start and end of the workflow, blue is the model-based part, and green is the data-driven part.

values as well as additional equipment information.

2. Devices without additional equipment information can also be used with this method. Primary measurement values and the information streams of other devices in the chemical plant help to compensate for the lack of additional equipment information.
3. It is known what drifts can occur on the equipment under consideration and their approximate impact on the data streams.
4. The drifts are considered to be independent.
5. The available data can be separated by cluster analysis.
6. The process must be continuous with a steady state setpoint and low dynamics. The method cannot be used for processes with varying process conditions, changing target states or high dynamics.

Requirements related to the goal are:

1. Drift detection.
2. Distinguishing between process and equipment drifts.
3. Determining the cause of the drift.
4. Detecting and unambiguous decoupling of combinations of known drifts.
5. Evaluation of what additional equipment information is needed to decouple the drift combinations.

3.2 Drift Areas Identification/Characterization

At the beginning, it is necessary to identify and characterize the areas of the drifts to perform the developed method. The workflow for this is shown in Figure 1. The first step is to analyze possible drifts in the equipment and plant under consideration. These drifts are then modeled mechanistically, allowing the creation of theoretical data points. These theoretical data points are used to build theoretical clusters as a reference for specific clusters. When modeling, it is important to ensure that the theoretical clusters do not overlap. If they overlap during the modeling process, increase the modeling dimension with the help of additional equipment information until they no longer overlap. After that, the centers of the theoretical clusters are formed, e.g. if the theoretical data points are uniformly distributed, as the geometric center of their theoretical data points. To characterize the theoretical drift clusters, vectors are drawn from the center of the cluster without drift to the centers of the drift clusters. These theoretical drift vectors are determined by their direction and their length is positive.

Next, real data is used to perform a cluster analysis. The real clusters are assigned to the drifts by comparison with the theoretical clusters. Then, their centers are calculated, e.g. as the geometric center of their real data points. To characterize the real drift clusters, vectors are drawn from the center of the cluster without drift to the centers of the drift clusters. These real drift vectors are determined by their direction and their length is positive.

3.3 Decoupling of Coupled Drifts

When the drift areas are identified and characterized, new data points can be categorized. The first step is to check if the data point belongs to a real cluster. If so, the new data point is assigned to that cluster and the associated drift. Drift detection is complete.

However, if the data point does not belong to a real cluster, there is a high probability of a coupled drift, because only a combination of at least two drifts leads to this area. Vector decomposition and vector addition are used to determine the individual drifts that are combined. First, a vector is drawn from the center of the cluster without drift to the data point to be categorized. This vector is called the data point vector $\boldsymbol{v}_{\mathrm{DP}}$. Then $\boldsymbol{v}_{\mathrm{DP}}$ is decomposed into individual drifts. This is shown schematically in Figure 2. To decompose $\boldsymbol{v}_{\mathrm{DP}}$, it is compared with the existing real drift vectors $\boldsymbol{v}_{\mathrm{r}}$. The real drift vector that is most parallel to $\boldsymbol{v}_{\mathrm{DP}}$ is selected. In Figure 2 $\boldsymbol{v}_{\mathrm{r1}}$ is more parallel to $\boldsymbol{v}_{\mathrm{DP}}$ than $\boldsymbol{v}_{\mathrm{r2}}$. Therefore, $\boldsymbol{v}_{\mathrm{r1}}$ is chosen. The selected vector is then weighted by projecting $\boldsymbol{v}_{\mathrm{DP}}$ onto it. The resulting vector $\boldsymbol{v}_{\mathrm{rG}}$ corresponds to the first decomposition vector or factor $\boldsymbol{v}_{\mathrm{F1}}$.

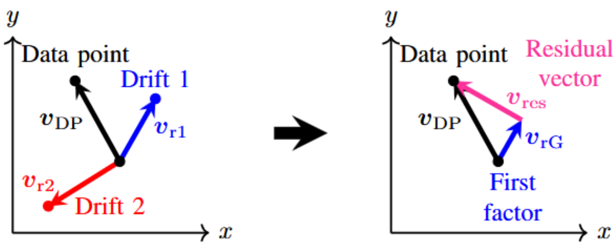

Figure 2: Schematic of the decomposition of a data point vector $\boldsymbol{v}_{\mathrm{DP}}$ into individual drift vectors $\boldsymbol{v}_{\mathrm{r}}$. The first factor of the decomposition $\boldsymbol{v}_{\mathrm{rG}}$ and the remaining residual vector $\boldsymbol{v}_{\mathrm{res}}$ are calculated.

Then, it is determined whether this resulting first factor $\boldsymbol{v}_{\mathrm{F1}}$ points to a point within a specified boundary around the data point. For this purpose, the residual vector $\boldsymbol{v}_{\mathrm{res}}$ is spanned from the superposition of the previously determined factors to the new data point. If the square sum of the length of $\boldsymbol{v}_{\mathrm{res}}$ is less than a specified threshold, it is inside the boundary and the decomposition is complete. However, if the computed square sum is greater than a specified threshold, it is outside the boundary. In this case, $\boldsymbol{v}_{\mathrm{res}}$ is used to perform the steps like $\boldsymbol{v}_{\mathrm{DP}}$, from comparing $\boldsymbol{v}_{\mathrm{res}}$ with the existing real drift vectors $\boldsymbol{v}_{\mathrm{r}}$ up to calculating more decomposition factors $\boldsymbol{v}_{F2}, \ldots, \boldsymbol{v}_{Fn}$. At the end of each determination of a new factor, it is checked whether the superposition of the decomposition factors points to a point within the specified boundary around the data point. If this is the case, the decomposition is complete. The calculated factors are the individual drifts that together form the drift coupling:

$$\boldsymbol{v}_{\mathrm{DP}} = \boldsymbol{v}_{\mathrm{F1}} + \cdots + \boldsymbol{v}_{\mathrm{Fn}}. \tag{1}$$

3.4 Derivation and Evaluation of Additional Equipment Information

The space with its dimension and axis in which the drifts are modeled and the cluster analysis and decoupling will be performed, is defined with the help of additional equipment information. This can include signal-to-noise ratio, a measurement gain, position feedback, a control value or energy data about the device.

In an ideal world, the combined drifts should be uniquely decoupled. This is the case when the coupled drifts can be unambiguously decomposed into any combination of individual drifts. To achieve this, the drift vectors of the possible individual drifts must be linearly independent. Thus, n drift vectors must span a n-dimensional space. If for example only two drifts occur, a 2-dimensional space is needed. In this space, combinations of the two occurring drifts can be unambiguously decomposed as shown in Figure 3. The vector $\boldsymbol{v}_{\mathrm{DP}}$ of the coupled drift is a combination of the drift vectors $\boldsymbol{v}_{\mathrm{D1}}$and $\boldsymbol{v}_{\mathrm{D2}}$:

$$\boldsymbol{v}_{\mathrm{DP}} = \mathrm{a}\boldsymbol{v}_{D1} + \mathrm{b}\boldsymbol{v}_{D2}. \tag{2}$$

The drift vectors are linearly independent when

$$\mathbf{0} = \lambda_1 \boldsymbol{v}_{D1} + \lambda_2 \boldsymbol{v}_{D2} \tag{3}$$

and the only solution of the system of equations is $\lambda_1 = \lambda_2 = 0$. So $\boldsymbol{v}_{\mathrm{D1}}$and $\boldsymbol{v}_{\mathrm{D2}}$ span the 2-dimensional space. They are defined by their direction and their length is positive. This means that every data point lies in the positive range of both drift vectors.

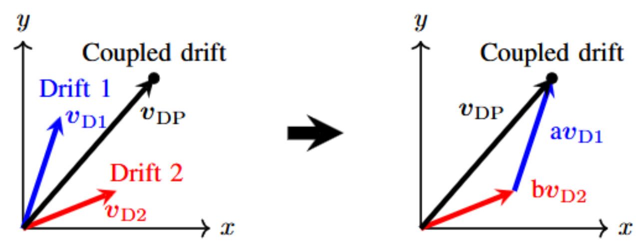

Figure 3: Schematic decomposition of a coupled drift vector $\boldsymbol{v}_{\mathrm{DP}}$ in two individual drifts $\boldsymbol{v}_{\mathrm{D1}}$ and $\boldsymbol{v}_{\mathrm{D2}}$.

When the number of occurring drifts become larger than the dimension of the space, the decomposition becomes ambiguous. The drift vectors get linearly dependent. To get from such an ambiguous to an unambiguous decomposition, more additional equipment information is needed. The dimension of the space must be increased to the number of occurring drifts. To derive the necessary information that increases this dimension, available additional information of the equipment under consideration is analyzed. Using assumed connections in the real data, an estimate of the most useful additional information is made. The data used for cluster analysis is extended with the selected information, cluster analysis is performed, and the drift vectors are calculated. The independence of the drift vectors is checked. If they are still linearly dependent, other additional information must be examined until they are linearly independent or no more information is available.

The value of the additional equipment information is judged by its contribution to spanning the n-dimensional space. If the information provides a dimension, it can be used immediately. If not, it is examined to see if it can contribute in combination with other information.

4 CASE STUDY

A case study on a real-world brownfield chemical plant is performed to demonstrate the applicability and feasibility of the method. Consider a control valve in a chemical plant through which a fluid flows. Due to the presence of solids, an abrasive mixture is formed. Gas bubbles may also be present. Under the assumption that the control valve is recently installed, four independent drifts may occur in the valve:

- Equipmentdrift 1: Increased amounts of gas bubbles that cause inaccuracy in measuring the flow through the valve.
- Equipmentdrift 2: Increased amounts of solids that cause inaccuracy in measuring the flow through the valve.
- Processdrift 1: Reduced density of the fluid.
- Processdrift 2: Increased density of the fluid.

These four drifts are modelled, and theoretical clusters and drift vectors are determined, as Figure 4 shows. The white areas outside the clusters are where unclassified and unknown drifts or couplings of drifts can occur.

The modeling space is defined with the help of additional equipment information. In particular, the measurement gain and the signal-to-noise ratio of the valve are used along with the main measurements of density and temperature of the mixture. The reason for this is that this additional information adds dimensions to the space so that the theoretical clusters and drift vectors can be well distinguished. The emerging four theoretical drift vectors are linearly independent and span a 4-dimensional space.

The cluster analysis of the real data from the control valve is performed in the 4-dimensional space of the theoretical drift vectors. In this context, the statistical part benefits from the modeling part of the method. The result of the cluster analysis shows only three clusters and outliers. Together with the modelled drifts, these real clusters can be assigned to the drifts. One of the real clusters is the cluster without drift, the other two are drift clusters. Only Equipmentdrift 1, the gas bubbles, and Processdrift 1, a reduced density, occur in the data. These results are shown in the 2-dimensional space of density and measurement gain in Figure 5.

The outliers from the cluster analysis are passed to the method as possible drift combinations. However, if some drifts are not represented in the data, a combination of real and theoretical drift vectors is required. Otherwise, some drift coupling may not be detected and decoupled. This is because drift coupling can only be diagnosed if the drift vectors of the individual drifts that are combined are present. Thus, a 4-dimensional space is created from the real drift vectors of Equipmentdrift 1 and Processdrift 1 and the theoretical drift vectors of Equipmentdrift 2 and Processdrift 2. When the outliers are categorized by the method in this 4-dimensional space, different combinations of drifts are detected and diagnosed. For example, there are couplings of individually occurring drifts, such as the drift coupling data point in Figure 5. This data point is a combination of Equipmentdrift 1 and Processdrift 1. Thus, the vector of the data point $\boldsymbol{v}_{\mathrm{DP}}$ is a linear combination of the vectors of Equipmentdrift 1 $\boldsymbol{v}_{\mathrm{Eq1}}$ and Processdrift 1 $\boldsymbol{v}_{\mathrm{Pd1}}$:

$$\boldsymbol{v}_{\mathrm{DP}} = a\boldsymbol{v}_{\mathrm{Eq1}} + b\boldsymbol{v}_{\mathrm{Pd1}}. \tag{4}$$

This linear equation system is solved, and the parameters a and b are uniquely determined. There are also other combinations of drifts, such as Equipmentdrift 1 and Processdrift 2.

Finally, this use case demonstrates that drift couplings can be detected with the help of additional equipment information. The cause of these drift couplings can also be diagnosed with a high degree of certainty.

5 DISCUSSION AND OUTLOOK

In this paper, a method is developed to detect and decouple combined process and equipment drifts. To achieve this goal, statistical methods are combined with model-based approaches. Cluster analysis is performed, and the real clusters are assigned to the drifts using previously modeled clusters. To characterize these theoretical and real clusters, drift vectors are spanned. Drift combinations are then diagnosed using vector decomposition. The key to getting the right data space for the unambiguously decoupling of drift couples is the use of additional equipment information. The n drift vectors of the n possible drifts must span an n-dimensional space. For this purpose, a combination of theoretical and real drift vectors is used. Additional equipment information helps to obtain the required n-dimensional space.

The application of the method on a control valve in a brownfield chemical plant demonstrated that the detection and diagnosis of simultaneously appearing process and equipment drifts is successful. Thus, the feasibility of the approach is shown.

The critical evaluation shows that the developed approach is successful in plants with a continuous process, a steady state setpoint and low dynamics. However, most chemical plants do not meet these requirements. Often there are varied process conditions and changes in the target state. In addition, existing drifts change, and new drifts occur. If the drifts are dependent on each other, this is not considered.

Future directions of research are the development of new strategies to deal with changing process conditions and high dynamics as well as the detection and handling of dependent drifts. Furthermore, the development

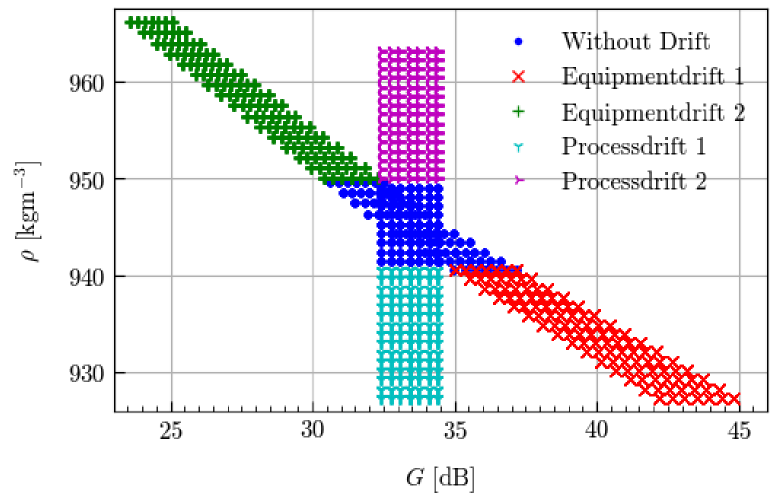

Figure 4: Modeled clusters – one cluster with no drift and four with different drifts. The process parameter ρ, the density, is the main measured value. The variable G, the measurement gain, is a typical additional information from the same equipment.

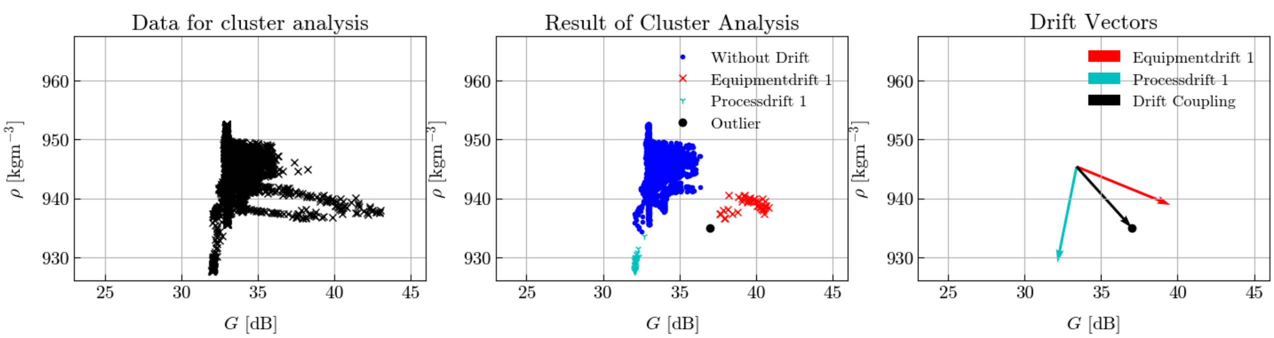

Figure 5: Data and results of the case study. Two drifts with their drift vectors and outliers as drift couplings were detected. The process parameter ρ , the density, is the main measured value of the equipment. The variable G, the measurement gain, is a typical additional information from the same equipment.

of a unified equipment data standard deserves to be a topic of future research.

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