On Data Preprocessing in Data Mining to Improve Human–Machine Interface Data Visualization

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Abstract

This paper investigates the benefits of utilizing proven data mining techniques for data preprocessing, with the objective of enhancing data visualization in the context of industrial control systems (ICS). In particular, we address a human-machine interface (HMI) as the key component of supervisory control and data acquisition (SCADA) systems that provide crucial insight into a controlled process, thus posing a critical point of potential data misrepresentation. This is particularly emphasized in the ever-increasing data quantity generated on the factory floor under the Industry 4.0 paradigm. Furthermore, we discuss how this approach can impact data quality during the data collection phase, consequently influencing subsequent data mining stages. To illustrate this approach, we present an example related to the graphical representation of data in the HMI for the tension control process within the steel manufacturing industry. The novelty of this paper lies in exploring the application of data preprocessing techniques in the domain of data presentation at the data acquisition and immediate process control level, prior to data storage in databases, and forming of data lakes and data warehouses.

Keywords

data mining, preprocessing, human-machine interface, HMI, process control, industrial automation

1. Introduction

The field of human-machine interface (HMI) design has undergone a gradual transformation influenced by Industry 4.0, resulting in a shift towards incorporating disruptive and open technologies. This evolution has introduced new design approaches such as human-centric, model-driven, data-driven, task-driven, agile, and contextual design [1, 2]. These approaches are tailored to the unique requirements of each project, client, and industry standards. Aiming to generate more flexible, resilient, adaptive, and efficient solutions for industrial control systems (ICS), they consequently increase the complexity in the development and commissioning phases. Moreover, the constant reduction in time-to-market for new development tools and products

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imposes greater demands on expertise for system integrators and solution providers. Consequently, development teams tend to specialize in narrow fields and specific areas, potentially leading to a loss of awareness by individual team members regarding the overall solution's key performance values and how individual project segments influence them.

Although it may initially appear as a minor problem with minimal impact on the user experience and HMI functionality, the negative consequences become more pronounced due to the increased complexity of HMI, the volume of data involved, and the discrepancies that arise between real-world data from the production floor and the system's design throughout the HMI lifecycle.

To effectively tackle these challenges at the HMI level, it is crucial to employ methods that leverage domain knowledge and ensure enhanced data quality and reliability. One approach to achieve this is through the application of data preprocessing techniques in data mining that incorporate rule-based mechanisms. By revising data elements such as real-time signals from field devices, alarm and event definitions, equipment faults, and status messages, and applying data preprocessing, HMI can transform, and present data in a meaningful way, improving its usability and enhancing the user experience.

The rest of the paper is structured as follows: In section II we present methodology, i.e. research selecting strategy, and briefly elaborate on the significance of data context. Section III elaborates on SCADA-based HMI industrial data analytics. Here, we particularly address works emphasizing preprocessing and data quality significance at the lower levels of the data processing pipeline and draw a parallel to the HMI in terms of potential benefit to data presentation and visualization. In section IV, we provide specific points of concern in the domain of HMI data presentation affected by process data quality. Furthermore, we discuss the significance of domain knowledge to differ the final result data at the HMI level, compared to data preprocessing implemented on aggregated data further on in the data processing pipeline. In section V we address related works, and finally, section VI provides a conclusion on the topic in question.

The main contribution of this paper is to introduce and explore the application of data mining, specifically data preprocessing, in the domain of real-time process controls. This domain differs from traditional data mining approaches used in industrial environments, as it concentrates on levels considerably lower than those typically considered for data mining, which are typically regarded solely as data sources. We additionally contribute by identifying critical points of concern related to real-time data presentation and visualization at the HMI level, where these issues can be effectively addressed through the utilization of rule-based techniques in data preprocessing, which fall under the umbrella of data mining. By doing so, our work subsequently contributes to the broader field of human-machine interaction and context awareness.

2. Methodology

There are multiple aspects and views addressing the data quality impact on the data presentation and visualization. From the HMI standpoint, this can be addressed through areas such as graphic design standards, a human-centered approach, heterogeneous data, and cognitive limitations, to name a few. At the top level, in terms of data quality impact, the question is twofold: (1) How data are presented, and (2) How data are perceived. Although the latter is a consequence of the former, both aspects ultimately affect users' situational awareness by interpreting the given context.

Acknowledging the above aspects, in this section we first briefly address the influence of the demands posed on HMI operators on understanding the data context, extending to situational awareness. In continuation, we focus on the research relevant to the core topic of data mining in the industrial environment that defines preprocessing-related tasks of significance for enhancing data quality for the purpose of data presentation at the HMI level.

2.1. Significance of data context

Recognizing the importance of big data impact on user interface and the overwhelming quantity of data presented on the HMI screens, together with increasing process control complexity and in combination with operators' cognitive limitations, multiple studies are dedicated to the field of situational awareness that is crucial on the plant floor.

In this respect, Singh, Vajirkar, and Lee [3] recognize the increasing volume of data and entities that evolve over time, concluding that, due to the dynamic environment, data must be also interpreted accordingly, i.e. contextualized according to the current situation. In the domain of manufacturing, a context-aware control system is proposed to help operators cope with the challenges of monitoring several devices simultaneously and achieve timely reaction [2]. At the HMI level, a survey covering context-aware inference, conducted by Salam *et al.* [4] singled out automatic engagement inference as one of the tasks required to develop successful human-centered HMI. Although the majority of employed HMI applications across the industries do not have the means to implement such techniques, considering the close relationship between engagement inference and understanding the context of observed entities, this work additionally emphasizes the importance of data quality perceived in realtime. In the context of Industry 4.0, and extending to the Industry 5.0 human-centric approach, several works that addressed human-machine interaction [5, 1] pinpointed adaptive human-machine interfaces as crucial in context-aware technologies. All the above works have a common ground in linking context and users' behavior and choices close to data accuracy and adequate data presentation techniques.

2.2. Data preprocessing in industrial environment

Advanced analytics implementing machine learning and data mining is widely used across industries, with the manufacturing industry being an early adopter. Numerous conducted researches are focused on domains such as energy consumption, process optimization, product quality, and predictive maintenance. In this respect, data preprocessing has been well-defined and established in practice.

However, if HMI is introduced as an element of interest, the works available in scientific databases decrease rapidly in number, and more importantly, in relevance. The search string applying expression *"((HMI or human-machine interface) and preprocessing)"* on title, abstract, and keywords, returned a total of 71 papers in the Scopus database. Although this may seem a substantial number of works for such a narrow field, the encompassed research papers are barely related to manufacturing or the industry sector at all. The HMI is mainly addressed in terms of user interaction such as emotion, gesture, and speech recognition, and/or in the domain of medicine and bio-medicine.

Expanding the search to SCADA systems (which inherently encompass the broader portion of ICS that may implicitly relate to HMI) resulted in 473 research papers, but this did not lead to an increase in relevance, as it has shifted the focus to the levels above the HMI, i.e. to the standard fields of data mining implementation such as predictive maintenance, fault diagnostic, product quality, and anomaly detection and cybersecurity that performs data preprocessing on the data already available in data lakes and warehouses.

Narrowing down the filtered research papers for relevance, we considered those papers that address data preprocessing techniques and data mining in ways that are applicable to the topic at hand and that meet the following criteria: (1) Applicable at the HMI level, without requiring additional components within the ICS, except for those serving as data sources. (2) Applicable in realtime with respect to execution of the HMI runtime layer. (3) Potentially implemented as rule-based. (4) Implementable throughout the entire HMI lifecycle, i.e. scalable according to potential ICS expansion and SCADA system modifications (expanding field devices, additional signals, changes in tag naming conventions, graphical representation).

With such an approach, we have extracted a total of 15 works that we have found significant and directly contributing to this research.

3. SCADA-based HMI in industrial Data Analytics

This section elaborates on the HMI role and position within the Data mining process implemented in the industrial domain. We have addressed the relevant papers that refer to data mining implementation and are related to the production floor data preprocessing, thus providing grounds for targeted implementation of data preprocessing at the HMI level.

Fig.1 depicts the first three layers of the standard automaton pyramid, based on ISA-95 model of functional hierarchy: (L0) Factory floor, i.e. field devices, (L1) Process layer, (L2) Data acquisition layer, i.e. SCADA). Although the interlayer communication is significantly disrupted by introducing the IIoT and smart field devices, in a major part of the manufacturing facilities data flow from the production floor (runtime data layer on the figure) reaches the SCADA layer through various PLC devices in charge of the direct process control (data acquisition layer on the figure). An exception to this is a set of unstructured data (static data on the figure) whose context is addressed across the layers but is not exchanged in realtime. In this respect, raw data generated on the factory floor are in various forms and stored in databases across the Data visualization & Storage layer, i.e. SCADA system that is positioned as a major source of process data for the Data aggregation and/or data preprocessing layer. In this context, HMI stations are merely another data source of Production data recorded in realtime, with the addition of limited historical data, such as alarms, events, reports, and HMI systems logs, that are stored at the HMI level and potentially forwarded to the data historian as well.

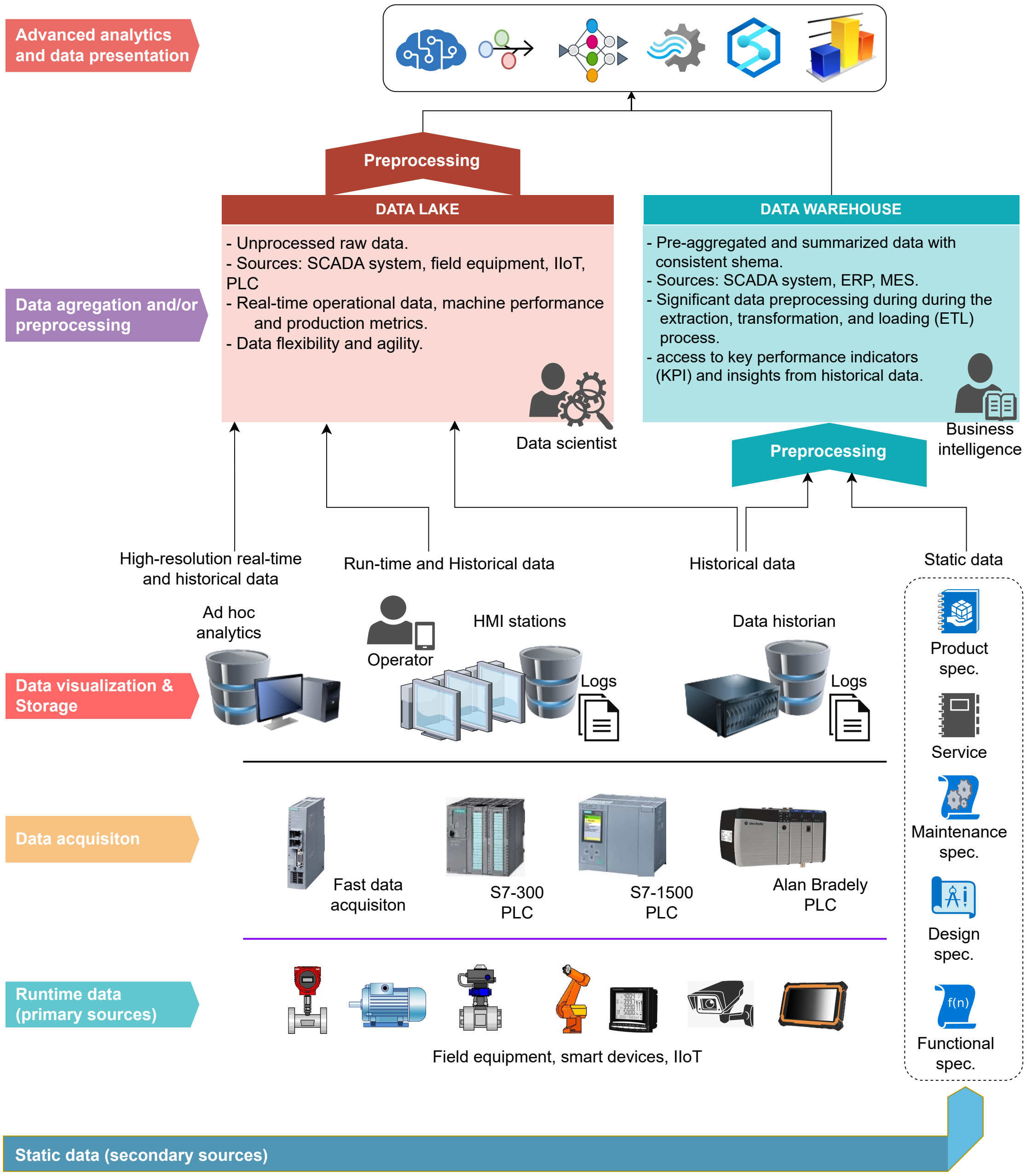

Figure 1: Process control and SCADA roles in providing data for advanced analytics

3.1. User's prespective

From the user's point of view, this is sufficient for the data scientist and business intelligence roles dealing with advanced analytics performed on aggregated data in data lakes and warehouses. However, operators who are in charge of process control, benefit less from such data processing pipelines. The main task of the operator is to supervise and control the ongoing industrial process, and the HMI role is to provide reliable real-time data that enables the operator to be aware of all the aspects of the controlled process. If data preprocessing tasks were implemented on the raw data as early as possible, i.e. at the lowest three levels in the picture, then HMI could benefit from increased data quality in providing more accurate data visualization, thus enhancing users' insight into controlled process.

3.2. Data preprocessing tasks/steps

Several of the selected papers [6, 7, 8] provide a methodology of data preparation as part of their work with a focus on data cleaning, integration, transformation, and data reduction. These four tasks are identified as particularly important for acquired industrial data by [9]. Additionally, Battas *et al.* [6], proposing the data preprocessing method for an industrial prediction process, has elaborated on each step and emphasized the importance of understanding how the data is collected as well as its meaning in order to be able to use it correctly. In this sense, the authors added data understanding as the first task prior to entering the above-defined data preprocessing tasks. The ultimate goal of the tasks defined by the combined above-addressed works is to prepare the data in a manner that maximizes the effectiveness and efficiency of subsequent data mining analysis by uncovering meaningful patterns, relationships, and insights from the raw data.

3.3. Time component and near-source data preprocessing

Discussing the importance of raw data collected from the production floor, Gao *et al.* [10] addresses digital twins and positions data preprocessing in the layer above the digital twin, i.e. when the digital representation of the process is already formed based on the data prior to preprocessing. From the perspective of our research, a parallel can be drawn between the role of digital twins and HMI in terms of real-time insight into the ongoing process. Although, in this case, the discussed data preprocessing is still performed above the HMI level, it is significant for our research because the authors also aim to provide timely feedback to users in order to provide visual monitoring of the process. This emphasizes the importance of a time component and feedback to the users in a way that is not addressed in usual practice, i.e. in implementing advanced analytics with data concentrated in data lakes and warehouses where HMI is only one of the data sources.

Similarly, research discussing data preprocessing with a focus on automated guided vehicles (AGV) [11], proposes a methodology for the aggregation of raw data received from multiple sources exchanging data based on a time-driven paradigm, or by an event-driven paradigm, thus providing data streams that are difficult for data mining tools to directly analyze [12].

Addressing the practical undertaking, Wrembel [7] in comparison of research vs. industrial projects, discusses task orchestration (reordering) techniques called Push down, which implies lowering the critical Extract-Transform-Load (ETL) tasks towards the beginning of data preprocessing. This is primarily oriented to task complexity orchestration aiming to achieve scalability and increase the performance of the overall data mining process. However, it does emphasize the significance of the time component in data preprocessing relevant to real-time process control.

Bearing in mind the implication of task orchestration on the data mining pipeline, i.e. compressing the hierarchical structure by lowering the data presentation layer in Fig.1, the appropriate structure needs to be defined for data preprocessing framework at the HMI level. Based on the comprehensive hierarchical structure of data mining defined by Yuan [13], Fig.2 depicts the hierarchical structure focusing on HMI as a data presentation layer, encompassing five crucial layers: Resource access layer, Resource layer, Data layer, Data preprocessing layer, and user application layer.

The purpose of such a structure is to guarantee the overall process of data mining in terms of resource access, ordering, data sources, implemented tasks, and data presentation, i.e. user application layer in the figure.

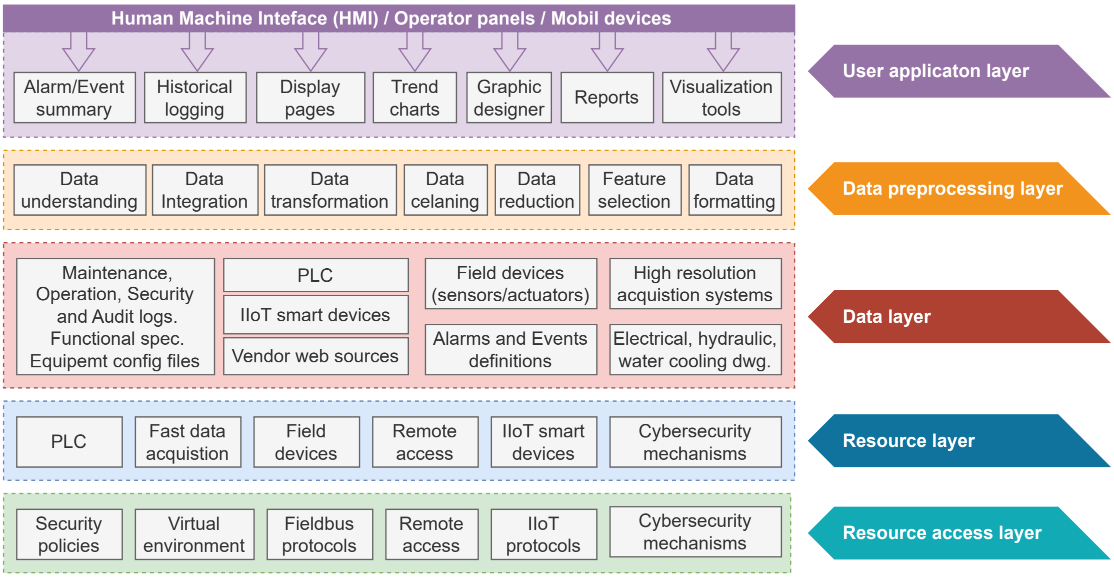

Figure 2: Hierarchical structure of data mining adapted to HMI data preprocessing

3.4. Advanced analytic task applicable to HMI

In consideration of all the above research papers addressing data preprocessing in data mining significant for the topic in question, we have singled out the following AI analytic tasks: (1) Data gathering, (2) Data presentation, (3) Data Analysis, (4) Irregularity detection, (5) Reporting, (6) User interaction. These analytic tasks have an impact on the HMI if applying adequate task orchestration following Wrembel[7], and are in line with research papers dealing with big data in the industrial sector and process mining [8, 14].

Table 1 provides a comparison of targeted segments by the above tasks on the AI-powered analytics vs. HMI, thus indicating HMI segments that can potentially benefit from implementing these tasks directly at the process control domain, i.e. focusing on the HMI as the critical component of user interaction.

Table 1
HMI vs. AI analytics: Comparable tasks in the process control domain with a significant impact of data preprocessing on the final result.

Task	human-machine interface (HMI)	AI-powered analytics
Data gathering	Field devices, PLC, operator inputs, configuration files, L2 automation	Field devices, equipment logs, real-time and historical databases
Data presentation	Representation of the controlled process and equipment status in real-time, graphical and numerical, limited historical data.	Analysis presented as insights, predictions, recommendations, supporting decision-making.
Data Analysis	Visual representation, operators monitor and analyze real-time process variables, equipment status, and trends.	Advanced data analysis, uncover insights and patterns in the data.
Irregularity detection	Alarms and alerts based on predefined conditions enabling immediate action.	Detection of anomalies, deviations, or patterns indicative of faults or abnormal behavior.
Reporting	Customized reports on system performance, alarms/events, production data, and relevant metrics	Automated reports summarizing analysis results, predictions, or performance metrics based on historical or real-time data.
User interaction	Direct interaction between operators and the control system, enabling process control and monitoring based on domain knowledge.	Automated decision support by analyzing data, identifying patterns, and offering recommendations to operators or control systems.

4. Discussion

In this section, we identify the point of concern in terms of HMI data presentation and visualization that can be addressed by the data preprocessing leveraging on the findings in aforementioned research papers and implementing HMI-adapted data mining hierarchical structure depicted in Fig.2.

In regard to data preprocessing tasks and targeted HMI segments addressed in Fig.1, we have identified the following HMI data presentation points of concern that can benefit from the implementation of data preprocessing in compliance with the hierarchical structure shown in Fig.2: (1) **Synoptic view variable refresh cycles** – in case of an increased amount of data it is common practice to apply different refresh cycles for the visualization that, if implemented statically, may affect time stamp in further data analysis. (2) **Signal value range for graphic presentation** – if the value range defined by the field equipment is applied to the graphic element, and the defined range is much larger than the range of values typically encountered in the system, it can lead to insufficient resolution or precision on the display. (3) **Poor IoT input data quality** – addressable by data preprocessing techniques implemented on the field, such as logging practices and sensor placement [15]. (4) **Missing data** – although data streams including missing data may still be of great significance to the data mining process, if they do not correlate with the key indicators, and do not impact output variables of interest for the dedicated graphic display, they should be excluded from visualization. (5) **Outliers** – Some rarely appearing extreme values are crucial for process monitoring, and must be distinguished from random or cyclical disturbance in the measurement. (6) **seemingly redundant data** – in terms of data redundancy, the specific situation with HMI data presentation is that these data are often presented as valuable information confirmation, and should not be confused with data from multiple sources. (7) **Noise** – Some of the data structures and techniques typically used to represent device status, such as bit masks applied on integer value showing variable frequency drive status, can be interpreted as inconsistent, or erroneous variation in data if not properly defined at the HMI level.

Fig.3 shows signals extracted from a dataset containing real-time data of the line tension control of continuous annealing process line demonstrating some of the above points. For this purpose alone, the significance of these signals to the underlying industrial processes is irrelevant.

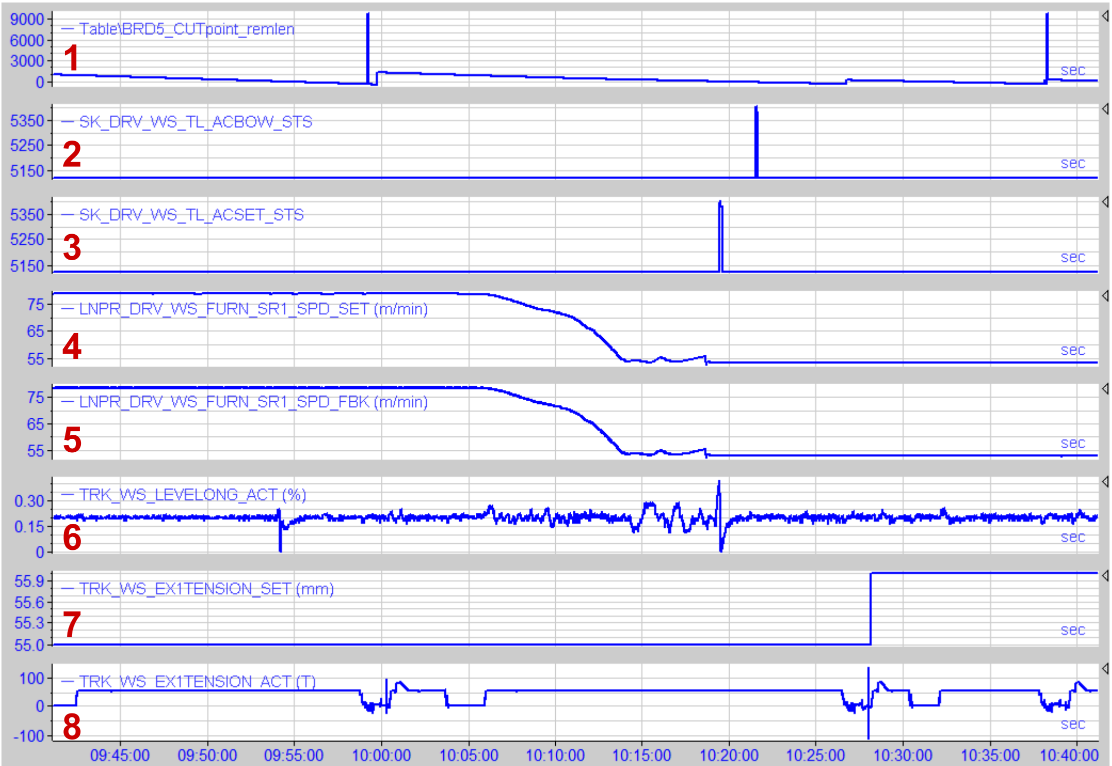

Figure 3: Real-time data of Line tension control of continuous annealing process line

We can regard them as generic analog process values retrieved from the PLC or field devices. In this specific example, they represent (1) strip line remaining length at cut point, (2,3) variable frequency drive status, (4,5) strip line speed over a motorized roll, (6) tension leveler elongation, and (7,8) line tension on exit section. It is important to note that the depicted signals present regular values in relation to the ongoing process.

Regarding the above-defined points of concern, peak values of signals 1, 2, and 3 can easily be interpreted as outliers, although in this case, they provide valid information. In this respect, signals 2 and 3 may additionally be interpreted as noise due to their random peak values, as they are formatted as bit masks, i.e. each bit of the 16-bit word independently signals a different status, thus contributing to seemingly random resulting value. Signals 4 and 5 could easily be interpreted as redundant, although they show opposite directions in terms of device control, i.e. one is a set value toward the device, and the other is device feedback. Additionally, signals 7 and 8 emphasize the scaling issue since both show the same process value (line tension) but in different units (mm and ton) which on the HMI screen results in poor graphic visualization.

These examples additionally emphasize the importance of understanding data prior to engaging in data preprocessing at the HMI level, but also the potential to enhance standard data mining approach by defining rule-based data preprocessing at the lower levels, before data aggregation in the data lakes and warehouses.

Some of the above points may seem trivial to resolve. However, due to reasons stated earlier in the paper affecting HMI development, these points cannot be addressed until the SCADA system is in the production phase. Only then above-identified points are fully manifested on the HMI screen and need further analysis to locate the exact problems and provide adequate solutions that can be implemented in the form of a rule-based approach.

5. Relevant works

A number of research papers were addressed in previous sections that provide insights valuable to the topic in question. Although these insights can be transferred to alternative contexts, and some of them affect HMI data presentation, none of them specifically address data preprocessing at the HMI level. Approaching from a different angle, we applied the search string against the Scopus database, which combines HMI, industrial context, and the aforementioned data preprocessing tasks significant for the topic in hand.

The result of a total of eight papers in the period of ten years (2013 – 2023) has shown a marginal interest in the scientific community compared to the results of the previously applied search string in section II.

From the method standpoint, these works are predominantly focused on artificial intelligence, i.e. neural networks, support vector machine, and hidden Markov model. The fields of interest are in line with works addressed in section II, i.e. HMI is mainly addressed in terms of user interaction such as emotion, gesture, and speech recognition in advancing toward next-generation non-invasive human-machine interface [16]

Although these works do not implement methods that can be integrated at the HMI level without considering additional computational power, i.e. extending to the additional ICS components, they do meet the remaining three criteria defined in section II. In this respect, Wang *et al.* dealing with feature extraction and low accuracy of multi-gesture recognition in real-time human-computer interaction, implemented a convolutional neural network and achieved high accuracy with a delay of less than 300 ms.

Similarly, Ji *et al.* [17] implemented a hidden Markov model dealing with feature extraction in the domain of mechanical acoustic signal asisted translational model for industrial HMI. Verified on typical industrial HMI application, the proposed model achieved 14.3% performance improvement compared with traditional methods.

This shows that similar data preprocessing techniques can be implemented at the HMI level without significantly affecting the real-time performance of the HMI runtime layer.

6. Conclusion

The adoption of data mining techniques for data preprocessing at the SCADA-based HMI level within the Industry 4.0 paradigm has the potential to significantly enhance data visualization and improve data quality in process control within the manufacturing industry. By addressing concerns such as variable refresh cycles, signal value range, poor IoT data quality, missing data, outliers, seemingly redundant data, and noise, operators can make better-informed decisions based on accurate and reliable information. In this respect, the application of data mining techniques at the HMI level, prior to data storage in databases, can optimize data presentation and visualization, potentially leading to increased operational efficiency. Furthermore, the incorporation of domain knowledge in data preprocessing at the HMI level can yield distinct results compared to preprocessing at higher levels of the data processing pipeline. Overall, leveraging data preprocessing techniques in the HMI domain demonstrates promising potential for driving data-driven decision-making and process optimization in the manufacturing industry.

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