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Cybersecurity challenges in downstream steel production processes ⋆

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Abstract: The goal of this paper is to explore proposals coming from different EU-RFCS research funded projects, in such a way that cybersecurity inside the steel industry can be increased from the Operational Technology area, with the current level of adopted Information Technology solutions. The dissemination project ControlInSteel has reviewed different projects with different strategies, including ideas to be developed inside the AutoSurveillance project. An advanced control process strategy is considered and cloud based solutions are the main analysed alternatives. The different steps in the model lifecycle are considered where different cloud configurations provide different solutions. Advanced techniques such as UMAP projection are proposed to be used as detectors for anomalous behaviour in the continuous development / continuous implementation strategy, suitable for integration in processing workflows

Keywords: Modelling, Identification and Signal Processing; Manufacturing Plant Control; Computers for Control; OT cybersecurity; Steel Research control trends;

1. INTRODUCTION

Productivity in modern metals plants and processes depends on sophisticated computer-controlled automation systems that have become powerful, and ubiquitous. It is part of the the Internet of Things (IoT) revolution.

Innovation focused the roadmap toward different objectives, such as producing clean steel, but also Carbon-lean steel-making routes (Sahai, 2016; Quader et al., 2016; Draxler et al., 2020). Enabling technologies have been identified (Rechberger et al., 2020; Souza Filho et al., 2021) involving hydrogen usage but also digitalization techniques (Rieger et al., 2020). A good review for steel related challenges can be found at Branca et al. (2020); Hallin et al. (2022).

Progress is often accompanied by unintended consequences. In the case of automation, the computers that make production smarter also make it more vulnerable to external interference. Metals, chemicals and electronics industries are fast becoming prone to cybersecurity risks as investments in manufacturing systems that incorporate connected devices increase. Manufacturers have become more vulnerable to cyberattacks after shifting to Cloud infrastructure and services; since 2017, there have been approximately 382 new vulnerabilities, and additionally, the crackers have had the tendency of exploring ad targeting vulnerabilities before the security research team and responsible software vendors realise their presence. Increased digital connectivity means manufacturers face threats from various quarters, they said. Undoubtedly, the latest well known electronic attacks have indicated the losses that are likely to happen as ICT and security as a field widens. Denial of Service (DoS) attacks, phishing attacks, backdoors, Zero-Day exploits, and technical flaws are just a few examples of electronic attacks that make it easier for malicious people to exploit these vulnerabilities.

Particular attention must be paid to control processes, because using the "cloud" is not something that is normally considered for process control, but the situation is slightly different when using advanced process control. It uses predictive models of a process to generate set-points and control moves that are better than those generated by typical PID algorithms. Advantages are usually used where responses are nonlinear or even discontinuous and where multiple process values can be required to generate the correct control move. Implementing the Advanced Process Control strategy usually involves three steps: building the model, validating the model using data from a running

⋆ RFCS funded ControlInSteel project.

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system, and executing the model to generate set-points and control moves (Goldin et al., 2017).

Model building is suitable for building from first principles, allowing to use knowledge of the processes to construct mathematical models, accounting for all required product quality attributes and all possible process parameters needed to achieve the attribute targets. Even something as simple as a blending operation may require so much physical modelling as to make it impractical for general use. In these cases, you can use pattern analysis tools to discover the mathematical relationships between the process parameters and the quality attributes to develop an empirical model. A cloud-based solution may be a system as a service (SAAS), in which the cloud service vendor provides an operating system environment that runs your application. Another option is a platform as a service (PAAS), in which the cloud service vendor provides a bare-bones machine that you load with your operating system and application. A third option is an application as a service (AAAS), in which the cloud service vendor provides a full application and the environment. Any one of these options should provide a lower cost solution than locally hosting and maintaining an application that you will use only rarely (Ilin et al., 2019).

Model execution is implemented in real-time control systems and, although in former times was not suitable for moving to the cloud, this situation has changed dramatically. Cloud response times are variable but, together with accessibility improved in recent times, so this is now an environment for any real-time control. Model execution is often performed within a distributed control system (DCS), programmable logic controller (PLC), or an attached PC. Most DCS vendors provide APC elements in their control systems, but these are usually just model execution blocks that assume you have already created and validated the APC model (Jeon et al., 2020).

Cybersecurity is defined as the body of technologies, practices, and processes that are made to help in protecting the networks, devices, data, and programs from any form of attacks, unauthorised access, or damages (Alhayani et al., 2021). Cybersecurity is frequently associated to information technology (IT) security. However, spending efforts from the design phase of Operational Technologies (OT) helps to reduce the overall effort and complexity during the life-cycle of OT systems (ISA/IEC 62443) (Li et al., 2019; Isaksson et al., 2018). The ISA/IEC 62443 is one of the standard series addresses the Security of Industrial Automation and Control Systems (IACS) throughout their life-cycle. Unfortunately, there are many systems in operation for which their design has not considered the potential vulnerabilities derived from their complexity.

With Industry 4.0, machinery, electrical equipment, and contemporary Information Technology (IT) systems are intelligently networked to improve productivity throughout value creation chains while also enabling processes to be optimised. Nürk (2019) explained how steel industry could benefit from the application of lean manufacturing. Some other authors have suggested that some lean principles are probably inapplicable or partially applicable while others are applicable. They suggested that 5S, visual systems, and value stream mapping are applicable

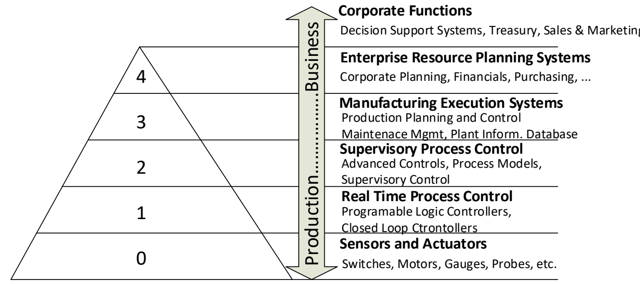


Fig. 1. Architecture based on the Purdue Model for ICS.

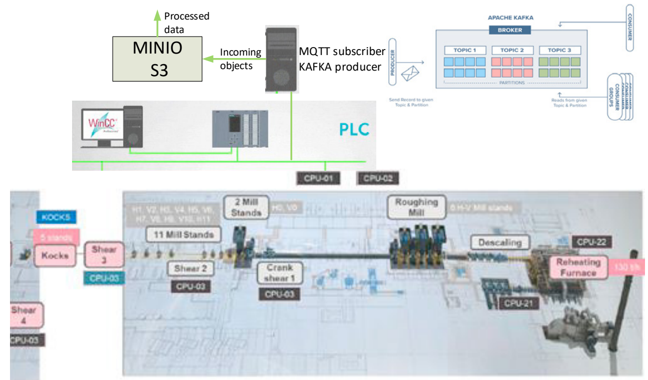


Fig. 2. Structural design compatible with the Purdue model.

in steel industry, while set up time reduction, production leveling, total productive maintenance, and just-in-time are partially applicable (Goshime et al., 2018; Hansen and Bøgh, 2021; Branca et al., 2020).

After reviewing several research projects in the context of the ControlInSteel dissemination project, it becomes clear that many of the created models for forecasting can be useful for estimating bias between expectations and measured values. Unlike earlier analytical attempts to find more effective model representations, combination of methods that only relies on data generated by complex, process-based models (Ordieres-Meré et al., 2010).

The ambition of this paper is to bring some hints at the design phase of the OT architecture, allowing to combine the two main use cases involved. Process monitoring/forecasting and process stability or failure/attack detection.

The main research question is what architecture can be flexible enough to foster the identification of failures / attacks at process level in such a way that can become useful to complement the IT solutions? Indeed, flexibility to accommodate new technologies such as quantum computing and Distributed ledger technologies will be also considered.

2. PROPOSED ARCHITECTURE(S) DEPENDING ON THE USE CASE.

The main hypothesis considers the design to be compatible with cloud infrastructure, whereas it is assumed that existing configuration involving just local components is present. Therefore, an adaptation from the Purdue model (see Fig. 1) was adopted, combining the physical layer in-

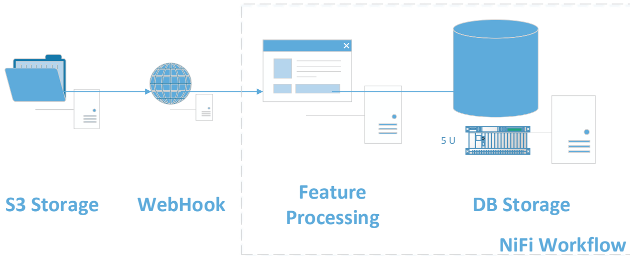


Fig. 3. NiFi approach for Minio based data capture.

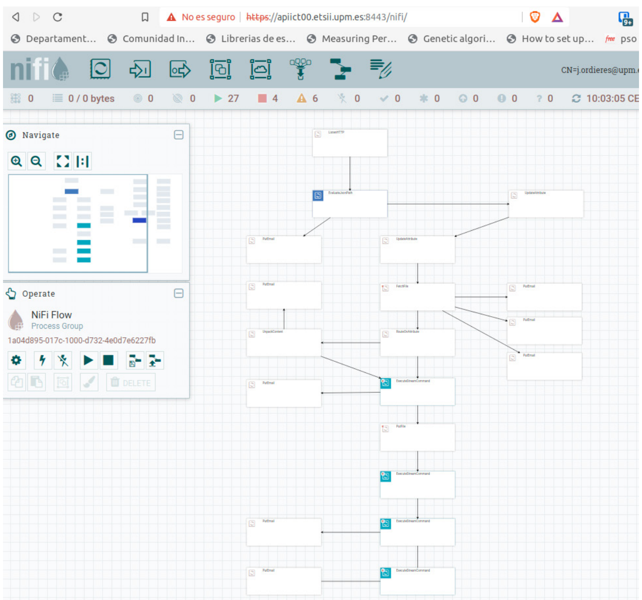


Fig. 4. NiFi workflow defining the ingestion procedure.

volving Sensors and actuators with the Real Time Control layer where PLCs and Scada systems are located in the local infrastructure. Alternatives enabling hybrid Supervisory Process Control accommodating the existing local configuration but allowing an on-Cloud based extension exists and some of them are presented in Fig. 2.

In Fig. 2 different mechanisms to feed data to Cloud have been considered, including synchronous alternatives based on JMS, AMQP, MQTT or Kafka producers (Hugo et al., 2020), but also S3 storage of a set of records through Minio S3 compatible (Naranjo et al., 2021).

Such hybrid configuration becomes rather suitable for these Cibersecurity additional applications, since they allow to keep the originally defined functionality untouched, and the extra monitoring actions are going to be handled from a complementary perspective (see Fig. 3).

3. ON CLOUD DATA PROCESSING STRATEGY.

Recent advances in cloud technologies and on-demand network circuits have created an unprecedented opportunity to enable complex scientific workflow applications to run on dynamic, networked cloud infrastructure. However, it is challenging to reliably execute workflows on distributed clouds because performance anomalies and faults are frequent in these systems (Gaikwad et al., 2016; Naqvi et al., 2017). To operate in such environments an IoT compatible database, namely InfluxDB was selected (Nasar and

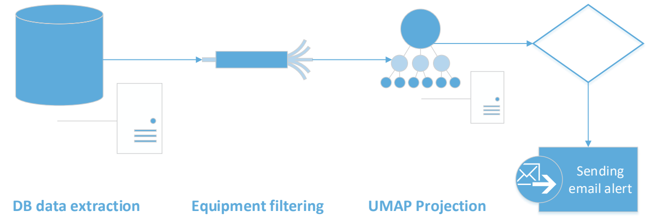


Fig. 5. Conceptual model supporting different processing workflows.

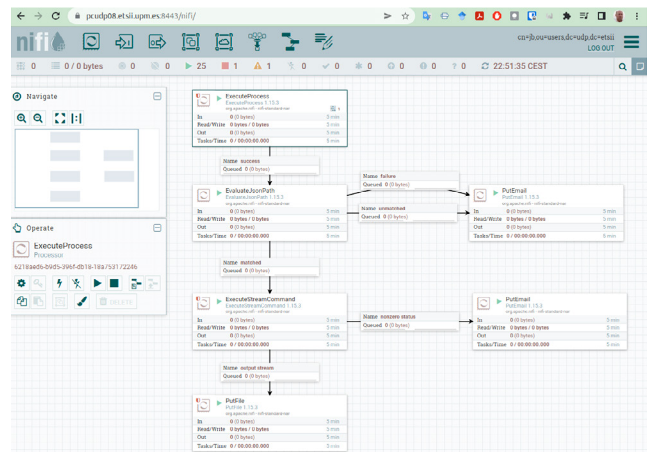


Fig. 6. Subprocess for time consistency analysis between process units.

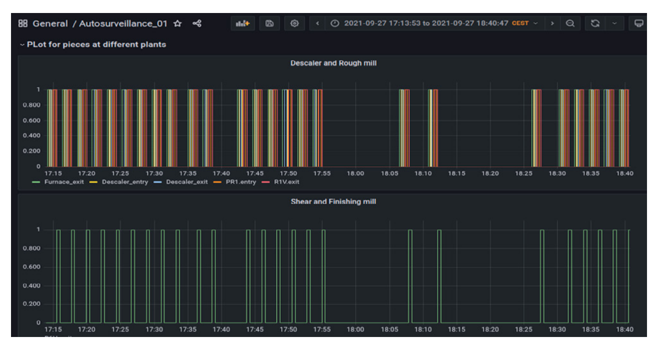


Fig. 7. Time series for material processing in different process units.

Kausar, 2019). It has an agent named Telegraf able to inject data-flows from frequent brokers (Rattanatamrong et al., 2020), but also it allows an specific client language, InfluxQL, to insert properly time-series oriented data flows (Chang et al., 2017). This is the proposed strategy to process inputs from batch data sources, where NiFi solutions have been implemented (Badii et al., 2020) for flow management as presented in Fig. 4.

Having established the process data ingestion, another significant aspect is to provide consistence between the different processing units along the process (see Fig. 5 and Fig. 6). Then, analysis at process unit level and product level can be carried out.

Process semantic is defined by the sequence of the process units, the digital signal linked to material presence at such unit, process variables related to the process units, and the distance between units. Such information, although relevant is not too much invasive and it will be a significant advantage when these supervisory strategy is under consideration, because it does not require an intensive description of the existing relationships or process unit characteristics. Consistency between process units can be verified by using tools able to query directly InfluxDB time-series database and present the evolution visually (Kindratenko et al., 2020), such as the Grafana dashboard presented at Fig. 7.

The consistency check for time passing through each process unit and identifying the next time arrival to the next process unit is the first step in the process. In this way, lasting periods per process unit can be estimated, and elapsed time between process units can be also measured. The analysis of the consistency enables to identify activation of sensor of material presence when due to spurious causes, but it helps to estimate mean duration, as well as standard deviations. From such figures, singular disruptions for delays, etc., can be identified.

Based on the previous step, specific analysis for variable trend when active in processing material can be carried out to identify regular processing from anomalous one. The major issue is because the intrinsic multidimensional characteristics requires extra processing for reducing its dimension. Dimension reduction plays an important role in data science, being a fundamental technique in both visualisation and as pre-processing for machine learning. Dimension reduction techniques are being applied in a broadening range of fields and on ever increasing sizes of data-sets. Because of the significant amount of data and high number of equipment is desirable to have an algorithm that is both scalable to massive data and able to cope with the diversity of data available. Dimension reduction algorithms tend to fall into two categories; those that seek to preserve the pairwise distance structure amongst all the data samples and those that over-weights the preservation of local distances over global distance. For this work the Uniform Manifold Approximation and Projection (UMAP) technique will be adopted (Becht et al., 2019).

UMAP is an algorithm to find a representation of a given dataset D in R^N in a lower-dimensional space R^m. The process datapoints are being drawn from some Riemannian manifold M, then mapped into R^N by some embedding $\phi : \mathrm{M} \rightarrow \mathrm{R}^N$. The ambition of UMAP technique is to reconstruct M in a lower dimension space R^m. To do this, we assume that D is uniformly drawn from M and approximates it well, which does not imply that parts of M might be stretched out or compressed under the embedding into R^N, It is also assumed that M is locally connected with enough datapoints in D, where the metric is locally constant. As we have assumed our data is uniformly distributed on M , any ball of a fixed volume R on M should contain the same number of datapoints. Working backwards, let $\mathrm{N}_k(x)$ be the ball in R^N around a datapoint x that contains its k nearest neighbours in R^N (with respect to the distance in R^N). Then for any datapoint x_i, consider the neighbourhood of M that is sent to $\mathrm{N}_k(x)$ in R^N. This ball should have the same volume as if we followed the same procedure for any other datapoint x_j . For k small enough, we can approximate distances in M from x_i to one of its k nearest neighbours x_j as follows. Fix k as a hyperparameter, and write $\{x_{i1}, \cdots, x_{ik}\}$ for the k nearest neighbours of x_i. Then, we can derive that the distance in M from x_i to x_j is approximately $\frac{1}{r_i} d_{\mathrm{R}^N}(x_i, x_j)$, where r_i is the distance to the kth nearest neighbour of x_i. To smooth this value, and reduce the impact of happening to have the kth nearest neighbour be very far away while the (k - 1)th nearest neighbours are clustered close to x_i, we take r_i to be the value such that

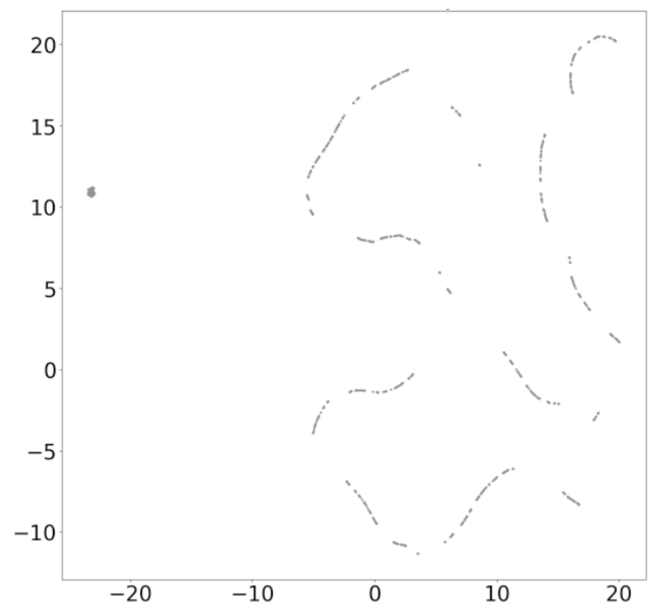
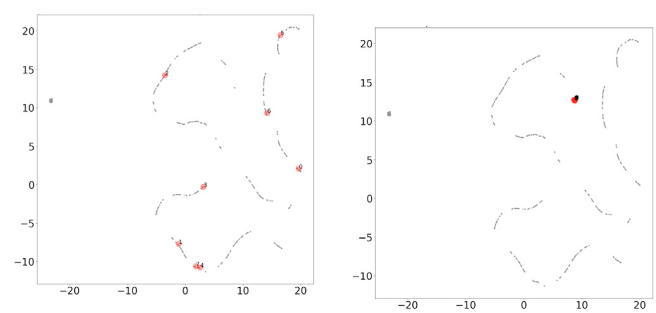


Fig. 8. UMAP projection for one day samples from descaler process unit.



(a) Regular projection for a normal product.

(b) Effect of a DDoS attack.

Fig. 9. UMAP projection for one product process lasting eight seconds over the day before map in gray.

$$\sum_{j=1}^{k} e^{\frac{|x_i - x_{i_j}|}{r_i}} = log_2(k) \tag{1}$$

The distance we get from x_i to x_j using this method will in general be different to that from x_j to x_i, as $r_j \neq r_i$. Therefore, it is needed a technique for combining a family of locally-defined finite metric spaces to get a global structure, where we have some idea of uncertainty on the metric spaces. For this, we will use fuzzy simplicial sets. A simplicial complex describes a topological space9 in a combinatorial way. A (geometric) *n-simplex* is the convex hull spanned by a set of n + 1 linearly independent vertices $\{x_0, \cdots, x_n\}$ in Euclidean space. The convex hull spanned by a n-vertex subset of the $\{x_i\}$ is itself an (n - 1)-dimensional simplex. We call this a face of the n-simplex.

Let E be a low-dimensional representation of our dataset D in R^m, for m ¡ N . To evaluate how good E is as a representation of D, we compare the fuzzy simplicial set X constructed from D to one constructed from E. In constructing a fuzzy simplicial set Y from E, note that we already know the metric of the underlying manifold as it is R^m itself. Consider the sets of edges in X and Y as fuzzy sets. Note that they have the same underlying set of elements, which is all edges whose vertices are labelled by elements of D, and differ only in the membership strength of the simplices. We define the cross-entropy C of two fuzzy sets with the same underlying elements set, (A, μ) and (A, ν).

$$C((A,\mu),(A,\nu)) = \sum_{a\in A}(\mu(a)\cdot log(\frac{\mu(a)}{\nu(a)})+ (1-\mu(a))\cdot log(\frac{(1-\mu(a))}{(1-\nu(a))}) \tag{2}$$

Then optimise the embedding using stochastic gradient descent becomes applicable. Note that X and Y contain many simplices of high dimension. For reasons of computational cost, the implementation of UMAP only looks at the cross-entropy of the one-dimensional simplices in X and Y.

In Fig. 8 the one day projection for descaler equipment is presented, where inter-distance in local Riemann manifold is preserved. Once the distribution of data is established, new coming data can be regularly projected and distance between current status and previous ones, looking for similar behaviours (see Fig. 9a). In similar way, when a DDoS (Distributed DoS) attack is observed, the situation is presented in Fig. 9b. By comparing projections on different days it is possible to realise how UMAP projection is rather stable (out of space rotations) (see Fig. 8 and Fig. 9 which make possible to use previous days behaviours as reference to analyse the behaviour of the current process, item over item. Therefore, DoS attack blocking the activity of the PLCs appears as all the porjection collapsed in a single point, while a man in the middle will make the points to shift far away from the previous day references. In this way, the combination of local deployment of controllers able to handle whatever heavy real time constraint combined with a connected cloud service running a fully scalable and elastic workflow service, providing global overview for the process, either at plant or facility levels will give the manufacturer a powerful but yet confident context for both security issue detection but also process anomaly identification in almost real time, which reduces a lot the reaction time. It opens also the floor to consider physical twin behaviours as an industry can have several lines or plant doing a similar job, where intercomparison is a must.

4. CONCLUSION

In this work a cloud oriented architecture has been proposed, including the description of different ingestion routes as well as the storage and processing of the data, based on continuous sequence data flow. The processing flows attend both to the data processing and maintenance of suitable projections. Therefore, regular projections as per equipment and product behaviours have been implemented through the UMAP projector, which can be implemented either CPU based or GPU based hardware. Significant events are delivered asynchronously to the relevant processes and users.

In addition, this the proposed method, which combines local and cloud resources to extend the perspective of the production, not just based on the single sensor values, but considering wider time windows and several sensors either related to the same plant or to several connected plants. Indeed, the concept can be extended to the product level and deriving the landmark of the variables related to the manufacturing of a single product. The good thing is also that the method involves projectors that, when trained, are very fast and responsive. On the cloud, retraining of projectors can be carried out in parallel with the normal flow activities, which makes the solution perfectly valid.

This work has had benefits to compare different mechanisms proposed by different RFCS funded research projects through out the ControlInSteel initiative, which helped in contributing to propose a seamless adoption for cloud based processing initiative. Combinations with different types of workflow can be easily derived in such a way that they contribute to the value creation for the steel industry. Application areas can be extended further away than cybersecurity and cover accountability for product specific green steel initiative, among several others.

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