End-to-end process monitoring: Challenges and framework for case study design

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Abstract: The theory and practice of process monitoring are diverging. Practical process monitoring requires fault detection, identification, diagnosis, and the implementation of process recovery actions. Algorithmic design and automation of all these steps are required if the future promise of more autonomous plants is to be realised. In contrast, theoretical research in data-driven process monitoring is overwhelmingly focused on fault detection. This paper discusses the current challenges of data-driven process monitoring research and presents a conceptual framework for improved experimentation of end-to-end process monitoring approaches. An end-to-end process monitoring solution is defined as the complete set of automated algorithms that is able to execute (in real-time) fault detection, fault identification, fault diagnosis, as well as process recovery intervention advisories. The major contribution of this framework is in the increased relevance added to the process monitoring problem to be solved, particularly in the extent of autonomy that is required by any proposed process monitoring solution.

Keywords: process monitoring; fault detection, identification, and diagnosis; process recovery

1. INTRODUCTION

Effective process control requires accurate measurements, reliable actuation equipment, and (for more advanced control) predictable process behaviour. Faults negatively impact the accuracy of sensor measurements, the functioning of actuation equipment, and the predictability of process behaviour. Process monitoring is necessary to ensure and sustain the benefit of process plant automation. A series of process monitoring tasks needs to be executed efficiently and accurately to aid effective plant automation (Ge et al. (2013)). Table 1 provides an overview of process monitoring tasks, their performance criteria, and the extent to which these tasks are typically the subject of data-driven process monitoring case studies.

Fault detection is the most popular task targeted by data-driven process monitoring - evaluated in terms of false/missing alarm rates. *Fault identification* is challenging to define performance criteria for - due in part to the challenge of distinguishing between measurements related to fault causes versus symptoms. *Fault diagnosis* is a challenging task for data-driven methods if all fault types, locations, or magnitudes are not represented in historical data. Note: Some literature sources group detection and identification as diagnosis.

Process recovery interventions include maintenance actions on sensors and actuators, reconfiguration of control systems, or other process-specific adjustments. Research focused on process recovery interventions is noticeably lacking in the data-driven process monitoring research field. Exceptions include fault-tolerant control research that incorporates data-driven process monitoring, e.g., the Monitoring, Analysis, Diagnosis, and Control with Agent-Based Systems (MADCABS) latent variable approach MacGregor and Cinar (2012). The outcome of Prognostics and Health Management (PHM) is to support maintenance decisions for efficient, reliable, and safe operations Zio (2022), therefore incorporating interventions. Reinforcement learning (RL) for industrial control explicitly targets interventions - e.g., a RL industrial task suite for industrial cooling system control Chervonyi et al. (2022).

Typical data-driven process monitoring case studies are conducted on passive historical data sets without information on available/previously applied interventions, or simulations that do not explicitly incorporate interventions. Therefore, definitions of process recovery performance criteria are typically absent from process monitoring literature. From an operational perspective, successful process recovery would be characterised by minimising the harmful effects of faults - optimising the key performance indicators of the process (financial, environmental, and safety sustainability).

The true value of process monitoring is in ensuring appropriate (accurate and timely) process recovery interventions. Detection, identification, and diagnosis may contribute to this outcome, but optimal performance criteria for such tasks are not sufficient to guarantee a practical and valuable process monitoring deployment. The term *end-to-end process monitoring* (E2E-PM) is introduced to capture the emphasis on the complete set of process monitoring tasks, from detection to process recovery.

An E2E-PM solution is defined as the complete set of automated algorithms that is able to execute (in real-time)

Table 1. Process monitoring tasks with their ideal performance criteria and extent of prevalence in data-driven process monitoring case studies - definitions from Qin (2012); Bayar et al. (2015)

Task	Definition	Ideal performance criteria	Prevalence
Fault detection	Determines whether a fault has occurred	Missing and false alarm rates; detection delay	High
Fault identification	Identifies which observed measurements are most relevant in determining which fault is occurring	Missing and false variable identifications	Low
Fault diagnosis	Determines exactly which fault occurred, including fault type, location, and magnitude	Accuracy and sensitivity of fault classification	Medium
Process recovery	Applies the appropriate intervention to the process to remove the effect of the fault	Minimize impact of faults; optimise long-term process performance	Very low

fault detection, fault identification, fault diagnosis, as well as the generation of process recovery intervention advisories. The difference between E2E-PM and traditional monitoring methods is the targeted output: traditional monitoring methods typically focus on only one or two aspects of fault detection, identification, or diagnosis, while the goal of E2E-PM is to link these tasks to automatically generate the appropriate process recovery interventions exactly when required.

The goals of this paper are to discuss the current challenges of data-driven process monitoring research (section 2), and to present a conceptual framework for improved evaluation of E2E-PM approaches (section 3), demonstrated on a case study (section 4). The major contribution of the proposed framework is in the increased relevance added to the process monitoring problem to be solved, particularly in the extent of autonomy that is required. This paper does not present a candidate for an E2E-PM solution, but rather discusses a framework that can improve the design and testing of E2E-PM solutions. It is envisioned that the wide-spread adoption of the E2E-PM evaluation framework proposed in this work will realign process monitoring research with practice.

2. CURRENT CHALLENGES IN DATA-DRIVEN PROCESS MONITORING RESEARCH

A typical data-based process monitoring research study involves the design of an improved process monitoring approach, application to case studies, and evaluation of detection and identification *performance criteria* of the proposed approach in comparison to existing approaches (e.g., see Yin et al. (2012) as a typical example). The case studies are typically simulation-based, or require real-world historical data.

The majority of simulation-based case studies are passive, i.e., simulation data for various fault conditions and process variability manifestations are analysed. No *active interventions* to correct the detected faults are made during the simulation. Kerremans et al. (2018) provides a case study where interventions are incorporated in an active simulation. Only a limited number of simulation case studies are widely used.

The *de facto* benchmark simulation-based case study for data-driven process monitoring is the Tennessee Eastman process simulator. Efforts have been made recently (Reinartz et al. (2021)) to improve the benchmark by dramatically increasing the *fault variability* (types, locations, and especially magnitudes) and *process variability* (disturbance and set point perturbation), manifesting in a large database of different simulation results. However, these improved data sets have not been widely adopted in process monitoring research yet and *accessible interventions* are not available.

The benefit of real-world case studies is the realistic nature of collected process data - (Schubert et al. (2011), for example, consider three real-world case studies in-depth). However, the ground truth of fault occurrences (*diagnosis*: type, location, and magnitude) is challenging to verify, the specific manifestation of the historical data set presents only one snapshot of potential *process variability*, and *available interventions* are typically not reported.

Process monitoring case studies, at the minimum, include information on whether specific observations are classified as normal or faulty, which can be used to evaluate *detection performance*. Some case studies include further information on the *location of the fault* (e.g., which sensor, actuator, or process unit is affected), while information on the *magnitude of the fault* is less common. Many case studies do not provide ground truth information on the measurements associated with the fault (causal or symptomatic), limiting the objective evaluation of *identification performance*.

No popular data-driven process monitoring case studies provide information on *available interventions*, which prohibit the objective evaluation of *process recovery performance*. Faults are difficult to diagnose in practice, resulting in delayed or absent interventions, and therefore such interventions are not easily captured in available data. Interventions may include actions such as manually changing set points, tuning controllers, and scheduling specific maintenance action, with such details not typically captured or easily recognised in process historian data.

The case study limitations above constrain the evaluation of E2E-PM. It is natural that research studies would focus on optimising objective and measurable performance metrics. This manifests in a local optimum of prioritising *detection performance*, without consideration of the requirements of identification, diagnosis, and process recovery tasks. These challenges are relevant for model-based and data-based process monitoring, the latter being the focus of this paper. The framework developed in section 3 is appropriate for a combination of different approaches.

3. E2E-PM FRAMEWORK DESIGN

3.1 Desired characteristics

A conceptual framework is required which may be used to design and implement simulation-based case studies for the evaluation of E2E-PM solutions. Such a framework will support researchers in developing industry relevant case studies that target relevant performance metrics. Based on current challenges in section 2, desired characteristics of an improved E2E-PM framework are proposed, and discussed below.

Accessible interventions imply that the process monitoring approach to be designed and tested should produce as output not only an alarm (fault detection output), but the appropriate intervention required for process recovery. As such, an ideal case study should be an active simulation which allows the triggering of interventions informed by fault detection, identification, and diagnosis tasks. This addresses the challenge of lack of *available interventions*.

Appropriate performance criteria for an E2E-PM problem should relate to operational objectives, i.e., minimising the harmful effects of faults on financial, environmental, and safety performance indicators. Such indicators should reflect savings due to correct interventions made by the process monitoring solution, but also losses/costs due to incorrect interventions. The evaluation of such indicators only make sense for extended durations of process operation. This addresses the challenge of lack of appropriate *performance criteria*.

Sufficient process variability is required to reflect the challenge of practical process monitoring: real-world operations are characterised by variation in disturbances, operational modes, operator adjustments, and manifestation of fault occurrences. Realistic process variation requires longer periods of time to manifest (i.e., weeks and longer). This addresses the challenge of lack of sufficient process and fault *variability*.

Reproducibility and extendability is a requirement for responsible research: existing baseline techniques as well as proposed techniques can be applied to a E2E-PM case study, with reproducible results. The E2E-PM case study should also be easily extendable by other researchers.

3.2 Framework

A proposed framework designed to meet the criteria above is depicted in Figure 1. Within this framework, a case study consists of modular components which interact to mimic automated plant operation and maintenance states. Eight interacting modular components (referred to as models) are proposed to facilitate E2E-PM. The strength of the proposed framework resides not in the definition of the models, but rather in constraining the *purposes* of each and the *relationships* between them, to support effective and unbiased comparisons between E2E-PM solutions.

A (1) *disturbance model* generates suitable process disturbances $\mathbf{d}(t)$ over the required timescales. The disturbances are independent of the rest of the simulation and may take various forms, e.g., deterministic, stochastic, seasonal, etc.

Process dynamics are captured in the (2) *process model*, which accepts process disturbances $\mathbf{d}(t)$, control signals $\mathbf{u}$, and fault conditions $\mathbf{f}$ as inputs, and generates process states $\mathbf{x}$ as outputs. The process model is most often represented by a system of differential-algebraic equations which integrates the process dynamics over time, and includes all physical processes, including (potentially faulty) actuator dynamics.

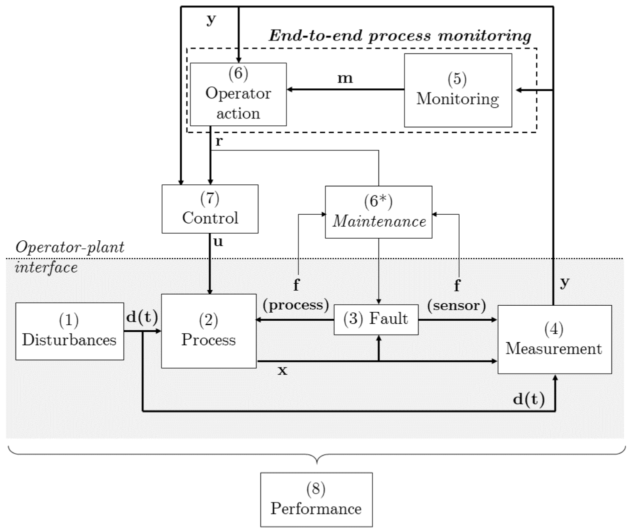


Fig. 1. Framework for modular components of E2E-PM simulation

Process, actuator, and sensor faults are simulated using the (3) *fault model*, generating a fault state signal $\mathbf{f}$. The fault state depends on the current process state $\mathbf{x}$, representing the fact that faults may be triggered by process conditions. More complex failure models (e.g. stochastic component failure) may also be simulated. The fault signal $\mathbf{f}$ serves as input to the (2) process model as well as the (4) measurement model, where it may alter process dynamics and sensor accuracy, respectively.

Measurement is simulated in the (4) *measurement model*, which accepts the true process state $\mathbf{x}$ and current fault state $\mathbf{f}$ as inputs, and produces measured values $\mathbf{y}$ as output. The measurement model simulates the effects of time delays, variable sampling rates, measurement noise as well as gross sensor errors such as drift.

The first four models (disturbance, process, fault, and measurement) constitute the plant, whereas the next three models (monitoring, operator actions, and control) simulate the operator and the systems available to interact with the plant. Under normal conditions, only two signals are allowed to cross the operator-plant interface: control signals $\mathbf{u}$ (which include the operators' handles on the plant) and measurement signals $\mathbf{y}$ (which represent raw insights on the plant). Additionally, a special submodel (6*) *maintenance* may directly modify the fault model through the operator actions $\mathbf{r}$, but only under special conditions (e.g., plant shutdown) as will be discussed shortly. Explicitly limiting the signals that cross the operator-plant interface ensures that the protection against data leakage is baked into the simulation framework.

The (5) *monitoring model* is responsible for those activities most often associated with process monitoring. It only has access to process measurements $\mathbf{y}$, and produces typical outputs of detection, identification, and diagnosis, summarised in the monitoring signal $\mathbf{m}$. These outputs may range from a non-specific warning or alarm to flagging a particular component as faulty.

The $\mathbf{m}$ signal is supplied as input to the (6) *operator actions model*, along with the raw measurements contained in $\mathbf{y}$. The operator actions model is responsible for all inputs to the plant that are not managed by automated control: this includes start-up and shut-down procedures, activation of regulatory control, set point adjustments, etc. Most importantly for the current context, this model must also capture operator interventions resulting from monitoring signals e.g., adjusting the planned maintenance schedule following the detection of a component fault. Despite the fact that process monitoring research has traditionally focused on detection, identification, and diagnosis (the *monitoring model*), we argue that the simulation of follow-up interventions is essential in evaluating the performance of a process monitoring method; it is therefore the combined *monitoring-* and *operator actions* models that constitute E2E-PM, as indicated in Figure 1.

Operator actions are summarised by the signal $\mathbf{r}$, which serve as input to the control model as well as the (6*) *maintenance model.* The maintenance model is a submodel of operator actions that is only invoked under special circumstances (typically plant shut-downs), and facilitates direct interaction with fault states $\mathbf{f}$. This aims to simulate plant personnel directly interacting with the plant e.g., inspecting and replacing components. This submodel provides a third link across the operator-plant interface, but data leakage may be limited by only allowing the model to run under special circumstances.

The (7) *control model* simulates automated control (including interlocks, regulatory, supervisory, and optimisation control), and may range from simple PI control to real-time optimisation with model-predictive control and more. Manual control settings contained in $\mathbf{r}$ and measured variables $\mathbf{y}$ constitute the inputs to the control model, and control outputs $\mathbf{u}$ in the form of desired actuation are produced. Recall that $\mathbf{u}$, along with disturbances $\mathbf{d}(\mathrm{t})$ and faults $\mathbf{f}$ serve as the sole inputs to the process model.

Finally, the (8) *performance model* calculates the operational performance (financial, environmental, and safety indicators) of the plant. The plant is subject to external disturbances, automated control, automated interventions as enacted by the process monitoring model, and maintenance resulting in downtime. The performance model is the final evaluation of whether process monitoring is successful in minimising the harmful effects of faults in the presence of realistic process variability. The inputs to the performance model are all relevant process states and intervention details which have an effect on revenues, costs, and other impacts. The performance model is a reflection of the ground truth, or the true process performance; it is not an online metric based on plant measurements available to plant operators. In practice, the definition of a suitable performance model constitutes a challenging task requiring inputs from a variety of stakeholders.

The proposed framework is significantly different to existing frameworks for process monitoring experimentation. Importantly, the modular framework allows for the evaluation of different process monitoring and control strategies without the need to modify other aspects of the simulation, such as the process- or fault-models, thereby providing a safeguard against (unintentionally) biased comparisons. Further, the requirement to explicitly define interventions extends the evaluation of process monitoring strategies beyond fault detection and diagnosis by means of the *performance measure*, which not only requires accurate detection, identification, and diagnosis, but also recovery.

A case study simulation spans several simulated weeks in order to capture short, medium, and longer term dynamics and operational rhythms. The sampling time of the simulation must be short enough to capture sufficient detail of closed-loop control and fault dynamics (i.e., in the order of seconds or minutes), but the extent of the simulation should also be long enough to capture important operational rhythms that are related to process monitoring interventions and operational performance (i.e., in the order of weeks or months), such as planned maintenance cycles.

3.3 Framework evaluation against desired characteristics

Accessible interventions are explicitly encoded in the nature of the proposed framework: the operator actions model produces interventions which are enacted in the simulation. Potential interventions must therefore be defined up front in the case study design and should consider interventions affected through control signals during plant operation, as well as maintenance planning.

Appropriate performance criteria are ensured by the performance model: the ultimate performance of the monitoring model (through its enacted intervention) is measured in financial, safety, and environmental terms. Defining the performance model is by no means straightforward, but must be considered carefully in order to objectively evaluate process monitoring strategies. Overfitting and subsequent overestimation of monitoring performance is also limited by explicitly preventing data-leakage across the operator-plant interface.

Sufficient process variability is introduced through probabilistic (and potentially process state dependent) generators for disturbances and fault states, as well as by considering sufficiently long periods of simulated process operation. Furthermore, essential process operations such as start-up and shut-down procedures are built into the framework through the operator actions model, further increasing the range of process states considered.

To ensure *reproducibility* and *extendability*, the goal of this framework is to create a communal reference for similar E2E-PM case studies, and to encourage the publication of open-access manifestations of such case studies. The inherent modularity of the proposed framework enables researchers to develop and share baseline simulations, and evaluate the impact of proposed solutions. By conforming to the required input/output structures of the modular components, such components can be expanded to incorporate new contexts (e.g., different plant models), different control schemes, and an expanding library of fault types. The impact of a particular monitoring approach may be evaluated by modifying the monitoring- and/or operator actions models only, without changing any of the other models. This concept can be extended beyond process monitoring: for example, different control strategies may be evaluated by simply changing the control model while maintaining all other models as is, allowing for a reliably objective comparison.

4. EXAMPLE CASE STUDY

4.1 Case study description

To illustrate the proposed framework, a toy-problem is presented in the form of a variable volume mixing tank, depicted in Figure 2. The overall case study may be described by considering each model in Figure 1 individually.

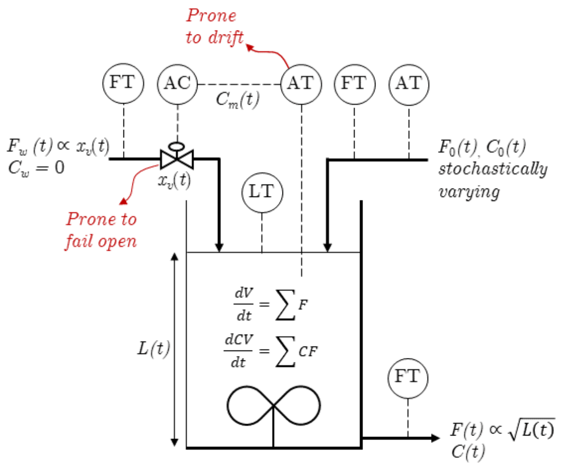


Fig. 2. Case study: Variable volume mixing tank

(1) *Disturbances*: The mixing tank is fed by two streams: one consisting of pure water (zero solute concentration) with a controlled flow rate F_w, and another stream with a stochastically varying flow rate F_0 and solute concentration C_0; the latter stream properties constitute the process disturbances.

(2) *Process*: The liquid level L and solute concentration C in the tank are modelled using appropriate conservation laws. The tank is treated as perfectly mixed and the outlet flow rate F is proportional to the square root of the liquid level. The pure water flow rate F_w is proportional to the control valve position x_v, which dynamically tracks the supplied control signal u in an overdamped fashion. The control objective is to maintain the solute concentration C at set-point by minimising the difference between the measured- and set-point concentrations, $|C_m - C^{sp}|$.

(3) *Fault*: Two possible faults are considered. First, the control valve may fail, forcing $x_v = 1$ and rendering control ineffectual. Second, the measured solute concentration C_m sensor may drift such that $C_m = C + \delta t + \varepsilon$, where δ represents the drift rate and ε represents normally distributed noise. Both faults are stochastically initiated following a bathtub shaped failure rate.

(4) *Measurements*: The flow rates F_0, F_w and F, concentrations C_0 and C, and liquid level L are all measured, with the measurements subject to normally distributed random noise. No time delays were incorporated, and a sampling period of 100 s was assumed for all measurements.

(5) *Monitoring*: Principal Component Analysis (PCA) was used for detection and diagnosis Chiang et al. (2000) The method was trained using data from the first seven days of simulation, with two components retained. Hotelling's T^2 statistics and squared prediction errors were calculated and compared to a predefined threshold. If either threshold were exceeded, a rudimentary diagnosis strategy was implemented by comparing C_m to the set-point C^{sp}. If $|C_m - C^{sp}| > 4\sigma$, where σ is the standard deviation of C_m during training, then it was assumed that the valve on stream F_w had failed, otherwise it was assumed that the solute concentration sensor C_m had failed (C_m would remain close to C^{sp} if sensor drift occurred due to closed-loop control action). Once the diagnosis was complete, a warning was raised for the relevant component. If a warning was raised more than 80% of the time over the course of one-hour, then the relevant component alarm was raised. The framework allows for different monitoring approaches during the various phases of plant operation: in this study, alarms during start-up and shut-down were ignored, but a more sophisticated approach may be implemented as necessary.

(6) *Operator actions and maintenance*: During start-up, streams F_0 and F were closed while stream F_w was fully open, until the measured liquid level exceeded a predefined threshold, at which point all valves were opened. A similar procedure was followed for shut-down, except all valves except F were closed. Three different intervention and maintenance strategies were considered.

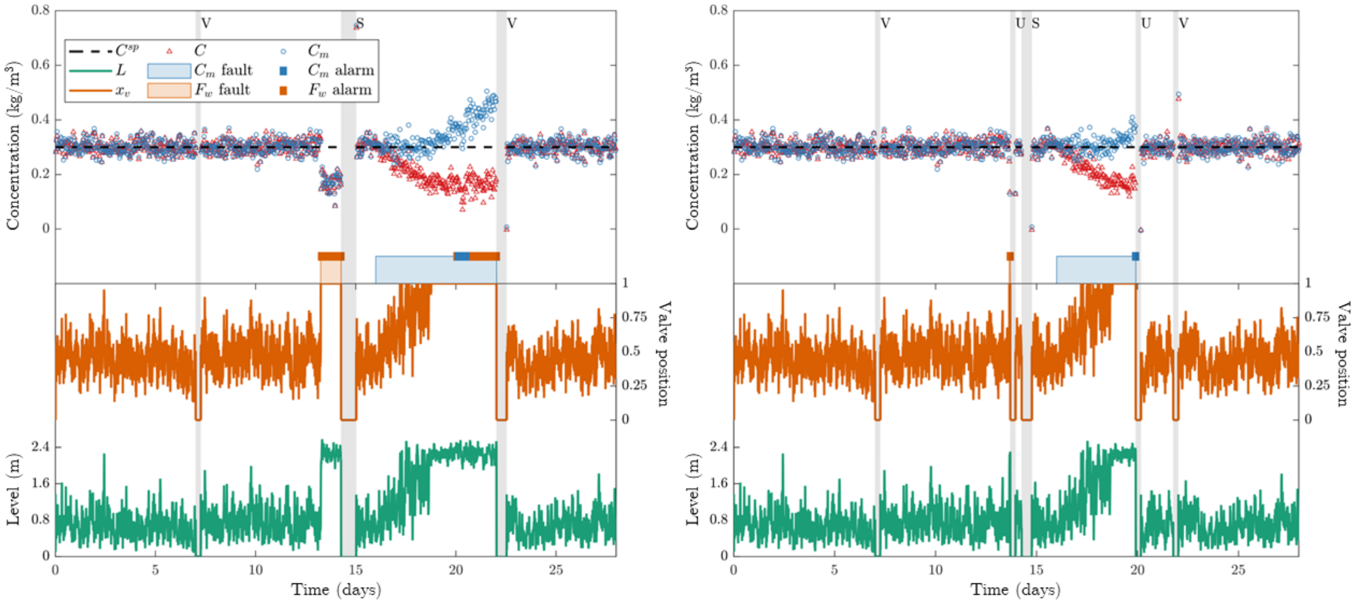
Case study 1: All alarms were ignored and planned maintenance was scheduled once every seven days during which all components (three valves and six sensors) were checked and faulty components replaced. The shut-down period depended on the number of components to be evaluated, assuming it takes 2 hrs to check a component for faults and 4 hrs to replace a faulty component.

Case study 2: Planned maintenance was scheduled once every seven days and alternated between checking sensors and checking valves (i.e., one week all valves would be checked, the next week all sensors), resulting in less plant down time. However, if an alarm sounded for a particular component, that component would be flagged and replaced during the next planned maintenance, regardless of type.

Case study 3: A similar maintenance strategy to (2) was followed. However, if an alarm sounded, the plant was immediately shut down and the faulty component replaced.

(7) *Control*: A simple PI-controller was used to regulate C_m by adjusting the control signal sent to x_v.

(8) *Performance*: A trivial performance model was implemented where the plant generated profit according to distance to set point, $P = 3600\exp\left(-\alpha(C - C^{sp})^2\right)$, where the profit P has units of \$/hr. It is important to note that the plant profitability is not accessible to plant operators at any given moment in time: P cannot be calculated online based on measurements. Rather, it is a measure of the true profitability of the plant which depends on the ground truth, not the measurements. The true solute concentration C was therefore used in the calculation of P. In addition to lost revenue, maintenance induces additional costs and safety concerns. To capture this effect, we used $P = -100$ \$/hr and $P = -250$ \$/hr during planned- and unplanned maintenance, respectively.



(a) Case study 2: Planned maintenance only

(b) Case study 3: Planned and unplanned maintenance

Fig. 3. Time series data for simulation case studies. Plant shut-downs are indicated by grey shaded regions, with either (V)alves or (S)ensors checked during planned maintenance, or (U)nplanned maintenance occurring.

It is worth noting that only the operator action and maintenance models were modified when comparing the three case studies; all other models were fixed (thereby demonstrating reproducibility and extendibility). The case studies are implemented in MATLAB and available at github.com/Stellenbosch-University-Process-Eng/End-to-end-process-monitoring.

4.2 Comparison of simulated case studies

Each case study was simulated for a period of 28 days. The results for Case 1 are not shown as it is qualitatively similar to the results for Case 2, which is shown in Figure 3 (a). However, the cumulative effect of small variations between Case 1 and Case 2 are significant, as can be seen from Figure 4.

In Figure 3 (a), the shaded grey regions indicate plant shut-downs, and the associated letter indicates whether (V)alves or (S)ensors were checked for faults during the planned maintenance. The F_w valve fails on day 12 (indicated by the shaded orange region), resulting in a sudden decrease in solute concentration below the $C^{sp} = 0.3$. The fault is immediately diagnosed as a valve fault, and the F_w valve is flagged for replacement during the next shutdown, which alleviates the problem.

On day 16, the C sensor starts to drift (indicated by the blue shaded region). Initially, C_m remains close to C^{sp} due to controller action, but as the drift increase the controller fails to maintain set-point. The fault is initially diagnosed as a sensor fault and the C sensor is flagged. Later on, the valve is also erroneously flagged as faulty. The sensor is replaced during the next planned maintenance, resolving the issue.

The results for Case 3 are shown in Figure 3 (b). The only major difference to note is that unplanned maintenance is initiated as soon as an alarm sounds and the faulty components are replaced. This does, however, result in increased down time.

The overall performance of the three case studies was compared by integrating the profit over time to find the cumulative profit $\int_0^t P(s)ds$. Given the stochastic nature of the simulations, a Monte Carlo approach was followed whereby each case study was simulated 50 times to estimated the expected cumulative profit. Figure 4 shows the mean cumulative profit for each of the three case studies, as well as the mean $\pm$ one standard deviation.

While Case 3 (unplanned maintenance on alarm) outperforms the no intervention strategy on average, the variability using this approach is significantly higher. The variability is not only a result of the fault detection and diagnosis method, but also the intervention strategy followed. Immediately shutting down the plant for unplanned maintenance minimises plant operation under faulty conditions, but also upsets day-to-day operations, as reflected by the greater penalty incurred for unplanned maintenance by the performance model.

It is clear that Case 2 (flagging faulty components and waiting for next planned maintenance) results in the best performing case. Case 2 outperforms the no intervention strategy due to a reduction in planned maintenance time: only a subset of components (including flagged components) are checked per maintenance event. Case 3 did outperform Case 2 in a limited number of trials when process faults drastically degraded plant performance and unplanned maintenance could quickly rectify the issue. However, on average, the additional cost of unplanned maintenance exceeded the benefit of rapidly addressing faults, leading to a greater expected profit for Case 2.

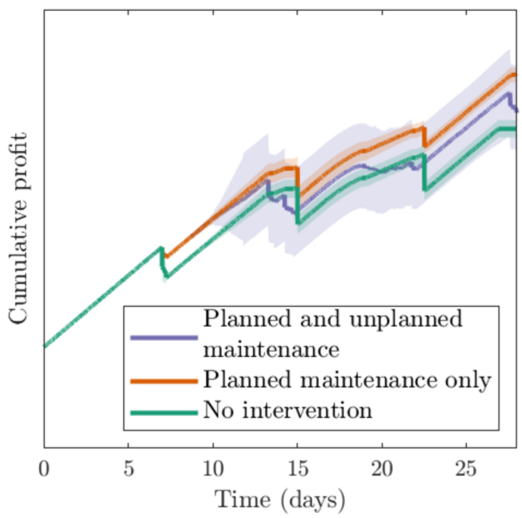


Fig. 4. Mean and standard deviation (shaded area) of cumulative profit for each case study, simulated 50 times.

The intervention strategy followed in Case 3 leads to highly variable performance, while Case 2 provides consistently good performance. It is clear that many other intervention strategies could be devised to enhance process performance, but such an endeavour is beyond the scope of this article. Importantly, neither the case study results nor the performance of any other E2E-PM solutions can be obtained without simulating the entire process, highlighting the necessity of the proposed framework.

5. CONCLUSIONS

Any process monitoring approach can only be considered effective if it leads to appropriate interventions, as evaluated by financial, environmental, and safety indicators. The framework for E2E-PM developed in this work aims to improve the development of process monitoring techniques by introducing mechanisms for accessible interventions, appropriate performance criteria, and sufficient process variability, within an ecosystem designed for reproducibility and extendability.

The case study results emphasise the importance of the proposed framework in evaluating E2E-PM solutions. In particular, it was shown that the benefit to plant profitability does not only depend on the monitoring method, but also the proposed interventions following fault detection, identification, and diagnosis. Following a PCA-based monitoring approach with immediate unplanned maintenance (Case 3) serves to improve the *expected* cumulative plant profitability as compared to no process monitoring (Case 1), but the variance in plant profitability was significantly higher for Case 3 compared to Case 1. It is trivial to show that a more severe penalty for unplanned maintenance will further decrease the expected cumulative profitability for Case 3. These results clearly demonstrate the need for a holistic evaluation framework for E2E-PM solutions that extend beyond commonly reported performance metrics which emphasise fault detection, identification, and diagnosis only, and requires careful consideration of suitable interventions as well as plant performance metrics. It is believed that the proposed framework addresses the requirements to effectively evaluate E2E-PM strategies.

The complexity of the proposed framework remains challenging: even the trivial case study presented here requires substantial implementation effort. Scaling the framework to complex, integrated processes will not be straightforward. However, we hope that the modularity of the framework serves to partially ameliorate the issue by supporting collaborative development of independent but interactive models.

Future work will include development and expansion of further case studies using the proposed framework, and design of process monitoring approaches that explicitly target appropriate interventions. The proposed framework (especially its action space and active simulation nature) also lends itself to exploitation by reinforcement learning.

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