Bridging both Worlds in Semantics and Time: Domain Knowledge Based Analysis and Correlation of Industrial Process Attacks

ABSTRACT

Modern industrial control systems (ICS) attacks infect supervisory control and data acquisition (Scada) hosts to *stealthily* alter industrial processes, causing damage. To detect attacks with low false alarms, recent work detects attacks in both Scada and process data. Unfortunately, this led to the same problem - disjointed (false) alerts, due to the semantic and time gap in Scada and process behavior, i.e., Scada execution does not map to process dynamics nor evolve at similar time scales. We propose Bridge to analyze and correlate Scada and industrial process attacks using domain knowledge to bridge their unique semantic and time evolution. This enables operators to tie malicious Scada operations to their adverse process effects, which reduces false alarms and improves attack understanding. Bridge (i) identifies process constraints violations in Scada by measuring actuation dependencies in Scada process-control, and (ii) detects malicious Scada effects in processes via a physics-informed neural network that embeds generic knowledge of *inertial process dynamics*. Bridge then dynamically *aligns* both analysis (*i* and *ii*) in a time-window that *adjusts* their time evolution based on process inertial delays. We applied Bridge to 11 diverse real-world industrial processes, and adaptive attacks inspired by past events. Bridge correlated 98.3% of attacks with 0.8% false positives (FP), compared to 78.3% detection accuracy and 13.7% FP of recent work.

CCS CONCEPTS

• **Security and privacy → Software and application security**.

KEYWORDS

industrial processes, industrial control system, SCADA

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1 INTRODUCTION

Industrial control systems (ICS) operate life-essential industrial processes such as water treatment and manufacturing plants. In ICS networks, supervisory control and data acquisition (Scada) hosts manage processes, comprised of actuators, sensors, and programmable logic controllers (PLCs). Processes are governed by the dynamics (or physics) of their actuators. Scada runs software and Human Machine Interfaces (HMI) to control processes (called *process-control* [1]). Unfortunately, modern attacks (e.g., Industroyer, Stuxnet [2, 3]) infect Scada to disrupt processes [4–8]. For example, the 2021 Oldsmar water treatment attack infected a Scada HMI to alter process parameters and poison the water supply [1, 9–12].

To accurately detect industrial process attacks, it is essential to connect the *causal* software action in Scada to the adverse physical *effect* on the process. On one hand, process anomaly detection [13–15] such as Invariant [16] can detect abnormal sensor data, but is evaded by small/*stealthy* process deviations by Scada adversaries, which over time causes damages [17–19]. On the other hand, host anomaly detection [20, 21] cannot know if abnormal Scada execution (e.g., system calls) has adverse process effects. Because these (disjointed) techniques cannot tie the Scada *cause* and process *effect* of attacks, they cause high false alarms due to benign faults and errors [1]. Further, PLC defenses (e.g., VetPLC [22]) can detect altered PLC logic but are not suited for Scada adversaries, who can alter PLC parameters at run-time without touching its logic.

Identifying malicious Scada actions *that cause* adverse process effects, and tying them *in time* to the process behavior is challenging because Scada and industrial processes differ in *semantics* and *time* evolution. That is, while Scada runs *discrete* software at CPU speed, processes are governed by *continuous* physics laws, which constrain their actuation (e.g., *inertial* delays). A recent work, Scaphy [1], analyzed both Scada and process data to detect attacks. Scaphy used Open Platform Communication (OPC) events [23–27] to induce system call signatures unique to Scada phases and physical states. However, its analysis in each domain was disjointed and not connected in semantics or time. This led to high false alarms from isolated alerts. In addition, Scaphy's reliance on signatures limits it to only known attacks, i.e., it cannot detect unknown attacks. As demonstrated in our experiments, attacks that use normal Scada tools/system calls (e.g., Oldsmar) will evade Scaphy's signatures.

Connecting Scada and processes semantically involves understanding process constraints in Scada operation, and alternatively, identifying Scada effects in process behavior. To control processes, Scada adheres to physics dependencies intrinsic to process tasks i.e., how actuators *depend on* each together to achieve a task [28]. Therefore, an ideal semantic relationship can be formulated from this "process adherence" in software. However, *discrete* system calls (used in Scaphy) cannot capture process dynamics, which are *continuous*. At a high level, we first inspect relevant program-flow dependencies in process-control logic. For example, if Scada *monitors* device A to *actuate* device B, then B depends on A. Then, we statistically measure the *continuous* behavior of these dependencies in process-control executions. Through this, an attacker's violations of intrinsic process constraints in Scada, will result in adverse process effects, which can now be selectively flagged in Scada.

To detect adverse process effects (i.e., due to Scada attack), neural networks such as autoencoders (AE) [29, 30] can learn normal process behavior via sensor-actuator time-series data. An AE aims

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to reconstruct its input as its output. Since there is compression in the AE inner layers, it is forced to learn relationships in the input distribution. This way, AEs trained on benign time series will have *errors* reconstructing anomalous sequences (via a loss function), allowing adverse change effects to be detected. However, training data are limited in practice, which can limit AE's accuracy [31, 32].

Further, processes experience *inertial* forces (due to physics factors e.g., friction/momentum [33]) which *resists change* in actuators. This introduces irregularities/noise to process dynamics [33–35]. This not only impairs AE's correctness but impedes the ability to analyze malicious Scada effects on processes, especially stealthy perturbations that blend with noise [17–19].

In addition, connecting Scada and processes in time aims to determine *where* or *when* a Scada attack can be noticeably detected in process behaviors. This is critical to *tie* both attacks *in time*. Recall that inertial forces can maintain process behavior for a while even when under attack. For example, a conveyor belt actuated by large discs will not stop/slow down at once after a *stop* command. As such, when Scada attacks are flagged, the adverse effect may not be present in the same time window, which leads to false negatives (when correlated), but *later* causes damage. Further, because AEs analyze process inputs *sequentially*, this causes more time discrepancies in correlating with the faster Scada side. We present Bridge, a domain knowledge-based analysis and correlation of Scada and industrial process attacks that bridges their unique semantic and time evolution. This enables operators to tie malicious Scada execution to their adverse process effects, which reduces false alarms and improves attack understanding. At the Scada side, Bridge analyzes the physical dependency constraints of Scada process-control and measures their statistical behavior such as control frequencies and bursts. Because process-control behavior *vary* based on a process setpoint (e.g., what level to fill a tank), Bridge develops a statistical solution based on *coefficient of variations* [36, 37], which aggregates measured constraints to work for processes regardless of their calibrated setpoints. Using these constraints, Bridge selectively monitors and flags a Scada attacker's executions that violate intrinsic process semantics.

On the process side, Bridge develops a *physics-informed* neural network (PINN) [38, 39] that embeds physical laws on *inertial process dynamics* via a partial differential equation (PDE) loss function. This facilitates it to capture the right solutions and generalize well even in limited data. To mitigate sequential delays in process time-series, Bridge implements the PINN in a Transformer-based architecture, which instantiates parallel *Attention* processes [40] for each sequence input, enabling timely correlation with Scada.

To align Scada and process evolution in time (to know where Scada attacks can be noticeably detected in processes), Bridge first uses a hybrid data-driven approach to derive the inertia delay associated with a process task, called *inertia time-block* (ITB). It does this by analyzing the *rate of change* of relevant process values. After a Scada attack is flagged, Bridge waits for one ITB before checking for process anomalies (i.e., process effects lag behind Scada by at least 1 ITB). Then, it continues to analyze anomalies using a dynamic process evolution window, which interleaves multiple ITBs until the process rate of change reaches a steady state (i.e., no change). Through this, Bridge derives an evolution window that *bounds* the temporal lifespan of Scada effects on processes.

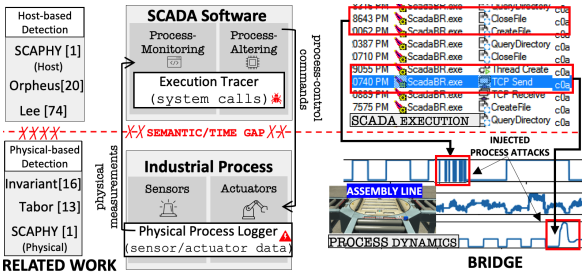


Figure 1: Showing how Bridge ties malicious Scada operation to adverse process effects in contrast to existing (disjointed) techniques

Bridge's correlation approach (shown in Fig. 1) detects attacks that current work miss such as attacks that infect benign Scada tools to *stealthily alter* processes (e.g., Oldsmar attack), but over time cause damages. In these stealthy attacks, recent tools such as Invariant and Scaphy will either discard the small deviation as false alarms or (if they narrow their thresholds), will trigger other benign deviations as attacks. This is because additional evidence (i.e., Bridge's semantic connection of a prior Scada anomaly in the process evolution window) is needed to *confirm* the attack and discard false alarms by current (disjointed) analysis. Since modern attacks [4–8] infects Scada to attack processes, we leverage this real-world ICS threat-model to apply process anomalies as a *filter* for Scada attacks. That is, although process anomalies are analyzed, they are not used unless a Scada attack is flagged in the process evolution, i.e., the effect cannot happen before the cause.

Since Bridge uses generic Scada and sensor/actuator data, it is *device-agnostic* and applies to industrial processes based on the widely-deployed ICS Purdue model [41]. Further, since inertia is a physics property of actuation systems, our PINN is generic to ICS processes but vital for correlation with Scada. Unlike Scaphy, which makes attack assumptions using signatures, Bridge *generalizes* attacks by detecting anomalies that *violates* intrinsic semantic constraints in industrial processes. We make these contributions:

(1) We present a new technique to correlate Scada and process attacks both semantically and time-wise via domain knowledge that bridges their unique behavior and time evolution.
(2) We introduce a physics-informed learning architecture that captures inertial dynamism in processes via a domain PDE loss function deployed in a Transformer-based AE. This not only increases the learning robustness in limited data, but enables it to timely and accurately correlate with Scada.
(3) We propose a new technique to derive intrinsic process constraints from Scada execution, which works for unique processes regardless of their setpoint calibration.
(4) We performed extensive experiments and case studies to validate Bridge using public real-world data from 11 diverse industrial processes[1] and attacks inspired by past events. We compared Bridge to Scaphy [1] and Invariant [16]. Bridge correlated 98.3% of attacks with 0.8% false positives (FP), compared to 78.3% detection and 13.7% FP in the second best work, Scaphy. Bridge is available online[2].

[1] https://github.com/lordmoses/Scaphy
[2] https://anonymous.4open.science/r/bridge/

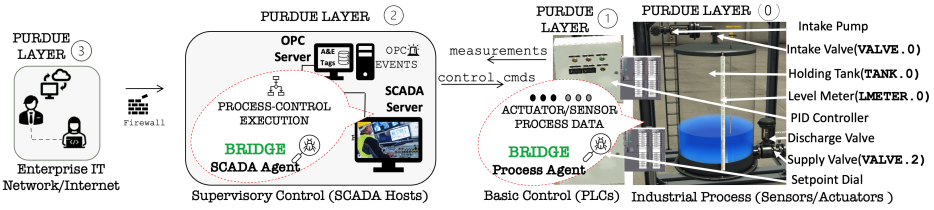
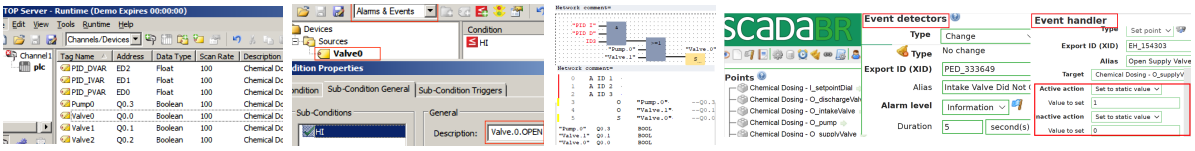


Figure 2: Showing where BRIDGE is applied in real-world ICS environments, i.e., to analyze the SCADA and process logs of the whole ICS



(a) OPC Device Tags (b) OPC Event Config (c) FBD and STL (d) Industrial configurations of SCADA event-Handlers

Figure 3: Showing real-world SCADA configurations of process sensors, actuators, and OPC events in Industrial Environments

2 BACKGROUND AND MOTIVATION

In this section, we describe ICS operations based on the Purdue network model. To motivate our problem, we use a real-world attack running example to show how BRIDGE is applied in the SCADA and process sides. We then analyze the challenges of detecting modern attacks and existing work limitations in comparison to BRIDGE.

2.1 Industrial Processes and Control Operations

Physical tasks in industrial plants are called processes [1]. Without loss of generality, Fig. 2 describes the SCADA and physical domain of ICS using a *chemical dosing* process in a real-world water treatment plant. Actuators (e.g., pumps, valves) at Purdue layer 0 work together to achieve the process task, such as filling a tank to a *setpoint* level (S_V). Actuating systems are governed by physics laws such as inertia. For example, the opening (speed) of a solenoid valve depends on the strength of induced electromagnetic fields. These dynamic physics factors constrain industrial process behaviors (called *process dynamics*) and time evolution. Further, PLCs at layer 1 set the *basic* inputs of actuators at every scan cycle. SCADA hosts at layer 2 perform *supervisory* control of all actuators and PLCs. They run special software to monitor/respond to process events and manage processes to achieve their task [28, 42]. This is called *process-control*. For example, Siemens SIMATIC water systems manage entire transition operations in water treatment plants [42, 73].

2.1.1 SCADA Event-Based Process-Control. When process events occur, SCADA executes event-handling process-control routines. This involves reading and writing relevant parameters to resolve the event (e.g., fault correction, process transition). As such, SCADA events can be used to artificially induce its process-control execution, allowing it to be analyzed [1]. SCADA events are specified using OPC event tags [23, 24]. OPC is a widely deployed service in ICS plants to enable data compatibility in common formats called tags [25–27]. As an example, Fig. 3 shows relevant SCADA settings in a real-world chemical dosing process [1]. Fig. 3a shows the actuators and parameters. Fig. 3b shows the OPC event tags, one of which is *Valve.0* (*Intake Valve*). The shown tag, *Valve0.open*, means that SCADA responds to device states that trigger the *Intake Valve* to open (called *event-trigger* states). Fig. 3c shows a function block diagram (FBD) of the process. FBD is a graphical logic that describes how devices are connected and operated. FBD can be converted to readable text, called *statement list* (STL). As shown in Fig. 3c, the STL logic evaluates to *Valve.0*. This means that *Valve.0* is dependent on all devices in the STL block. Hence, the union of all *states* of these devices is the event states SCADA responds to. Fig. 3d shows SCADA event-handling settings for the water treatment example.

2.1.2 Real-World Attack Running Example. In 2021, an attacker compromised the SCADA HMI in the City of Oldsmar's water treatment plant via Teamviewer [9–12]. He then ran commands to raise the *dosing rate* of Sodium Hydroxide (NaOH) to toxic levels, endangering citizens. Water plants use NaOH to set water PH, but it is toxic in high doses. This SCADA attack disrupted the *chemical dosing* process, increasing NaOH from 100 ppm level to 11,100 ppm [9–12].

2.2 Industrial Process Attacks and Challenges

Modern attacks on industrial processes are launched from infected SCADA hosts to alter its parameters [4–8]. SCADA adversaries evade detection by blending with normal host/network behavior while stealthily perturbing processes, which over time leads to damages [28]. Stealthy attacks blend well with benign noise/faults, which triggers false alarms in current process anomaly detection tools. To reduce false alarms, it is vital for operators to connect process anomalies to the causal malicious SCADA operation. This requires identifying SCADA actions *that have* adverse process effects, and then tying these actions *in time* to the process behavior. This increases detection accuracy and improves attack understanding. Sadly, this is challenging because SCADA and industrial processes differ in both semantics and time, i.e., their behavior does not map to each other nor evolve at similar time scales. This is because while SCADA executes *discrete* software at CPU speed, processes follow *continuous* physics laws and are subject to *inertial* forces or delays.

SCADA hosts have dedicated connections to devices via secured serial or TCP sessions [1]. As such, SCADA attackers *hitchhike* on their normal operation to avoid triggering host anti-viruses such

Table 1: Taxonomy of representative related works in ICS defense categorized by their techniques and approach

	ICS Traffic Analysis												Physical Behavior Analysis											PLC Logic Analysis								SCADA Host Exec.		+ Physical	
	Sequences												R. Learning			Process-Aware																				
Techniques	Critical [43]	State-IDS [44]	Pattern [45]	SPEAR [46]	Yang [47]	Ihab [48]	Ponoma. [49]	Diversity. [50]	Evolution. [51]	ML PIDS [52]	Experion [53]	Blockchain [54]	Kurt [55]	Zhong [56]	Panfili [57]	Chromik [58]	Nivethan [59]	Remke [60]	Lin [61]	Ghaeini [15]	Dina [62]	Aoudi [63]	OSCIDS [64]	Abbasi [65]	Invariant [16]	TABOR [13]	Niang [66]	Mulder [67]	Formby [68]	PLC-Sleuth [69]	PLCDefend [70]	NoisePrint [71]	TSV [72]	VETPLC [22]	Lee [21]	Orpheus [20]	Scaphy [1]	Bridge
Action Sequence	•																																	•	•	•
State Transitions	•	•	•								•																									
Event-based												•																							•	•
ICS Traffic	•	•	•	•	•		•		•	•	•	•																	•	•						
Response Analysis				•	•	•	•																													
Physics Modelling																				•	•	•	•			•										•
PLC Control Logic																								•			•	•		•	•	•	•			
Logic verification											•													•			•					•	•			
Control register											•	•											•				•		•							
Online POMDP													•																							
Reward weights														•																						
Multi-agent game														•	•																					
Rules/Signatures																•	•	•																	•	
Power-flow rules																		•	•																	
Host Execution								•																										•	•	•	•
Semantic Correlate																																			x	•
Time Correlation																																			x	•

as terminating the Scada program and initiating a new session with devices. For example, Stuxnet [3] infected Siemens Scada to re-program PLCs under the legitimate program context, and the Oldsmar attack used HMIs. Further, due to the presence of re-programmable third-party tools in Scada hosts, defenses such as code-signing may not be easily enforced, allowing attackers to infect Scada programs. Unlike in IT, Scada has many complex physical dependencies. As such, applying current program analysis tools [74, 75] to assess them may be intractable due to hardware-constrained code paths and physical environment need.

2.3 Limitations of Current ICS Defenses

To accurately detect industrial process attacks with low false positives, it is necessary to tie the *causal* malicious Scada operation to the adverse process *effect*. Existing techniques inspect data in hosts, PLCs, and physical domains. However, most analyses are done in isolation (i.e., with no cross-domain correlation) as shown in Table 1. Physical anomaly detection [13–16, 58–61, 76] including reinforcement learning [55–57, 77] can detect anomalous process behavior but cannot tie it to their *cyber cause*, which leads to false alarms due to benign anomalies such as faults/noise. PLC defenses [22, 72] detect altered PLC logic, but are not suited for Scada adversaries, who can modify PLC parameters/coils at run-time without altering its logic. Host anomaly detection [20, 21] can flag abnormal system calls, but cannot know if the flagged calls have adverse physical effects (i.e., discrete system calls does not map to the continuous process behavior). Network analysis tools [78–85] can detect unusual and noisy traffic (e.g., scans and illegal packet fields) but cannot catch semantic-based attacks (e.g., process perturbation) which can use normal tools to emit normal traffic.

2.3.1 SCADA and Process Correlation. Scaphy [1] is a recent work that combined Scada and process signatures to detect attacks. Scaphy used OPC events to induce and learn system calls unique to Scada phases. Then, it created physical signatures based on inconsistent device states. However, Scaphy's analysis of Scada and process behavior were disjointed from each other or not connected either semantically or time-wise. For example, discrete calls do not map or capture any process dynamics behavior, which is continuous in nature. This led to high false alarms from its isolated alerts. In addition, Scaphy's design of relying on signatures limits it to only known attacks, i.e., it cannot detect unknown attacks. In our experiments, we show that attacks that use normal system calls (e.g., infected Scada tools) will evade Scaphy's signatures.

2.4 Threat Model and Assumptions

We assume a similar threat model as current works where an attacker has infected Scada programs and can execute commands to alter devices [1, 16, 20]. Similar to recent work [1], Bridge comprise of two privileged agents that monitor executions in Scada, and another that logs sensor/actuator values from PLCs (depicted in Fig. 1/Fig. 2). As in these works, the agents are assumed to run in a Trusted Computing Base, hence cannot be tampered with. We do not consider non Scada-originated attacks such as side-channels [86, 87] or direct physical access to devices/PLCs. Based on public data [4–8], vast majority of in-the-wild attacks are launched from Scada [1]. We note that PLC Man-in-the-middle attacks have been addressed by previous work [69, 70] and in practice using non-PLC diode gateways [88]. Hence it is outside of our scope.

2.5 Domain Knowledge Analysis of SCADA and Process Semantics and Time Evolution

Our idea to bridge the unique semantic and time evolution of Scada and industrial processes is to first understand process constraints in Scada, and alternatively, identify Scada effects on process dynamics. Then, we use knowledge of how physics factors constrain process time evolution to align it with Scada so their behaviors can be correlated in time. This approach is generic to industrial processes, i.e., only requires logs from actuators/sensors and Scada hosts. Through this, Bridge overcomes current limitations in detecting process attacks such as disjointed analysis (i.e., which causes false alerts) and signature-based detection (e.g. as in Scaphy).

2.5.1 Analyzing Process Constraints in SCADA. Since Scada process-control *adheres* to physics dependencies (i.e., how actuators operate and inter-depend on each other to achieve a physics-governed task) in managing industrial processes, we first used OPC events to induce process-control execution trace, which reveals program-flow dependency of Scada operations on processes. For example (without loss of generality), in a chemical dosing process, the *Supply*

Valve depends on the *Intake Valve* state to operate and transition the water treatment operation [1]. In the process-control trace, we uncover this by tracing READ calls on the *Intake Valve* followed by a predicate check, and then a WRITE call on the *Supply Valve* (called *Read-before-Write* process-control constraint). Then, BRIDGE measures its continuous statistical behavior such as its frequency and bursts (or intermittence). BRIDGE then aggregates these constraints and uses them to selectively monitor the attacker's process-targeted executions that violate intrinsic process constraints, which are as follows: (1) *control-time* or time-interval between two *dependent* WRITE calls (2) *control-burst* or difference in the number of adjacent WRITE calls on a single device, and (3) *control-frequency* of device WRITE calls relative to others. Note that command calls are addressed to devices. Hence dependent commands imply dependent devices. In Windows OS, which dominates SCADA, WRITE and READ operations specify the communication session (e.g., serial or TCP) and the Device-Tag in their arguments.

2.5.2 Embedding Domain Knowledge on Process Dynamics. To analyze anomalous process behavior, BRIDGE develops a physics-informed architecture that embeds knowledge of inertial laws in actuating systems. It uses a PINN that integrates a PDE loss function to minimize inertial irregularities/noise in the process input distribution. This increases the learning algorithm's correctness even in limited training data, facilitating it to detect injected subtle adverse effects. Through this, BRIDGE detects malicious SCADA effects on processes, especially *stealth* perturbations, which would have been otherwise blended with noisy behaviors in process dynamics. Inertial measurement units (IMUs) in industrial plants can measure inertia delays in actuating systems [33, 34]. However, this can also be derived by analyzing the rate of change of process value logs using a data-driven approach. Specifically, for processes in motion (e.g., a moving conveyor/actuating valve), we measure the average time it takes to come to stop/de-energize after a *stop* command. For processes at rest, we measure the time it takes to attain a steady state (e.g., constant speed of conveyor) after a *start* command

2.5.3 Capturing Industrial Process Periodicity. Industrial actuating systems exhibit periodic/repetitive behavior, such as the up/down movement of a piston, cyclical motion of spinning discs, or off/on switching of regulator valves/pumps. Unlike other neural network applications where longer sequences are preferred, intuitively, sequence sizes that capture a process's periodic nature will better learn its behavior and detect anomalous effects. Since inertia captures a process's *reaction time* to changes, BRIDGE uses it to inform its PINN sequence sizes, which aptly fits its periodicity. For example, when stop commands are issued to spinning discs, inertial (centrifugal) forces may enable it to complete its *rotation*. Note that this differs from process to process e.g., a short piston may require a shorter sequence to encode its (periodic) up/down motion. To overcome delays in analyzing periodic sequences (i.e., one after another) and prioritize their causal relationships, BRIDGE implements its PINN in state-of-the-art *Transformer* architectures [89], which learns sequences at once and instantiates multiple *Attention* processes [40] for each input in the periodic sequence.

2.5.4 Aligning SCADA and Process Time Evolution. Because inertia causes processes to react slower to changes even after an attack,

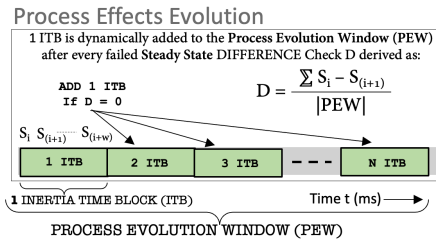


Figure 4: Dynamic Alignment of SCADA and Process Time Evolution

BRIDGE analyzes process inertia delays to inform its correlation of SCADA and process time evolution. When a SCADA attack is detected, we can expect the process effect to be noticeable *after* the inertia time has passed (called *inertia time block* or ITB in milliseconds). A process behavior within an ITB is captured by sensor/actuator time series within the ITB period. After 1 ITB has passed, the lifespan of the anomalous effect (called the *process evolution window*) will vary based on other state conditions. However, it is linear (i.e., non-increasing) for inertial systems [33–35]. Hence, we analyze the rate of change of process values to know when it has reached a steady state (i.e. when the avg. difference in successive changes becomes negligible [1]). We use this to determine when a flagged SCADA attack is done having an effect on a process. Since the ITB captures a process' *reaction time* to changes, BRIDGE performs a steady-state checking after each ITB. If the steady state is not reached, BRIDGE adds 1 ITB to the process evolution window and continues to do so until the steady state is reached. This approach is depicted in Fig. 4. Through this, BRIDGE dynamically aligns a SCADA attack to its resultant process effect, enabling them to be correlated in time.

2.5.5 Calibration-Agnostic Constraints. When a calibrated amount of physical task increases or decreases, dependent devices also increase or decrease their throughput *by the same factor* to maintain operational dependence [90, 91]. When this happens, the *absolute* dependency value (e.g., the time interval) between two dependent devices may change, but the *variation* across different task calibrations remains the same. For example, in a chemical dosing process, no matter how high or low to fill a tank, the ratio of the time interval between *Intake Valve* and *Supply Valve* actions vary by the same factor. Therefore, it is possible to derive a single dependency variability that works for any calibration of the same process, as long as the inter-dependent devices remain the same. To do this, BRIDGE leverages an established mathematical foundation called the coefficient of variation (C_V) [36, 37], which succinctly embodies this physical phenomenon. C_V measures the ratio of standard deviation to the mean to compare *degrees of variation from one data series to another*, even if their means are drastically different. Using C_V, BRIDGE aggregate statistical values for each dependent device pair by computing their *relative dependency* (or R_D) for different runs of the process. Via R_D, BRIDGE process constraints can be applied to detect SCADA attacks in a calibration-agnostic way.

3 DESIGN

In this section, we first describe BRIDGE's end-to-end approach and its input and output. Then, we describe the formal design of its SCADA-side and process-side analysis.

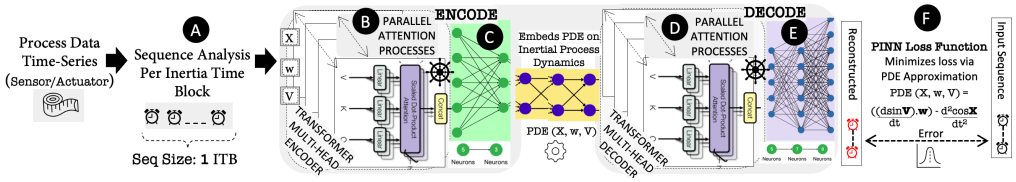


Figure 5: Bridge Process-side: Develops a transformer-based architecture that instantiates parallel attention processes for each input sequence. Bridge PINN embeds a PDE and loss function to capture inertial properties in process dynamics, facilitating its robustness

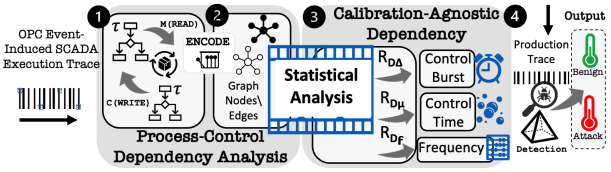


Figure 6: Bridge Scada-side: Statistical behavior of process-control dependencies are analyzed and aggregated to derive a calibration-agnostic R_D constraints to detect attacker's violation of contraints

3.1 End-to-End Approach and Input/Ouput

At the Scada side, Bridge takes as input, OPC event-induced Scada execution trace. It outputs 3 process-control constraints, which map each event to a relative dependency (R_D) measure used to detect Scada attacks, as follows: (*I*) event-to-control time (*II*) event-to-control burst, and (*III*) event-to-control frequency maps. An event-to-control time map, $V_{k(i,j)} \mapsto R_{D\Delta(i,j)}$, means that the time-interval Δ between dependent control commands on devices i and j due to event k in an event set V should not deviate from the benign control time variation $R_{D\Delta(i,j)}$, otherwise, it is anomalous. Similarly, event-to-control burst map, $V_{k(i)} \mapsto R_{D\mu(i)}$, means that the control burst between adjacent command bursts on device i due to event k should not deviate from the control-burst variation $R_{D\mu(i)}$. An event-to-control frequency map, $V_{k,(i)} \mapsto R_{DF(i)}$, means that the frequency of commands on i due to event k should not exceed the benign control frequency ratio $R_{DF(i)}$. Bridge Scada analysis works in 4 phases shown in Fig. 6. ❶ It analyzes the input execution trace and extracts the process-control dependency operations (or *Read-before-Write*). For each dependency pair, ❷ it represents their frequency, burst, and time features in a graph, whereby directed edges connect devices in the direction of their dependency relationships. ❸ Bridge then aggregates these constraints using the calibration-agnostic relative dependency (or R_D) formulation. ❹ During production, Bridge analyzes process-control logs in Scada hosts to detect behaviors that violate the R_D constraints.

At the process side, Bridge takes as input, time-series of sensor/actuator data per second. It outputs a trained PINN model of the industrial process behavior tailored for correlation with Scada side attacks. Bridge process side analysis works in 6 phases shown in Fig. 5. Ⓐ Bridge pre-processes the input sequences (e.g., scaling, one-hot encoding,) and uses the derived inertia delay to inform the sequence size. Ⓑ It then feeds the input into its Transformer-based AE, which uses parallel *multi-head* attention blocks to process each sequence input. The output is then concatenated and Ⓒ compressed via the PINN. At the decode stage, Ⓓ the compressed data is processed again via the multi-head blocks, and then Ⓔ uncompressed. The output is reconstructed and the PINN/PDE loss function is applied to compute the error Ⓕ, and fed back to optimize the training. During production, Bridge processes sequences in the same inertia-informed size. As with existing tools [29, 30], it uses the 75th percentile as the threshold to detect anomalies.

3.2 Analyzing Process-Control Constraints

Bridge analyzes physical process dependency between two devices i and j based on control commands executed on them, and measures their frequency and time features. It then aggregates their relative statistical behavior (of dependent process-control commands) into 3 categories; control time, control burst, and control frequency.

3.2.1 Control Command Dependency. Control command dependency (C_i, C_j) exists when operation to alter device i depends on device j. In Bridge, control commands are WRITEs while *Monitoring* are READs. Scada invokes a monitoring command M_i to read device i state. To formulate control command dependency, we first define a process-control operation $P(V_k)$ as a combination of control and monitoring commands due to event k in the event set V, as follows:

$$P(V_k) := \{C_j, C_{j+1}, ...C_n\} \cup \{M_j, M_{j+1}, ...M_n\} \tag{1}$$

A control command C_j is dependent on C_i, denoted as $(C_i \hookleftarrow C_j)$ if device i was the last device to be *read* before device j was *written to*, called *Read-before-Write Adjacency* and denoted with a comma as in (M_i,C_j), and given as:

$$\forall M_i, C_j \in P(V_k) \wedge (ts(M_i) < ts(C_j)) : \quad C_j \hookleftarrow C_i \tag{2}$$

ts is a timestamp. This control dependency indicates that any alteration of device j considers the state of i before it is done.
Control-time Δ is the time interval between two dependent commands. Bridge computes Δ as;

$$\forall C_i, C_j \in P(V_k) \;\; s.t. \;\; i \neq j : \quad \Delta(i,j) := ABS(ts(C_i) - ts(C_j)) \tag{3}$$

where *ABS* means absolute value.
A *burst* B is a continuous execution of commands for the same device, without interruption. Control-Burst μ is the difference in *burst size* between two adjacent bursts. Bridge computes μ for a current burst B_C and previous burst B_P of C_i, such that ts(B_P) < ts(B_C), as follows:

$$(\forall B_{C_i}, B_{P_i} \in P(V_k) : \quad \mu_j := |B_{C_i}| - |B_{P_i}| \tag{4}$$

Control Frequency F is the number of specific control commands of C_i in $P(V_k)$, computed as:

$$\forall C_i \in P(V_k) \quad F(i) := |C_i| \tag{5}$$

3.3 Calibration-Agnostic Measurements

We explain how BRIDGE aggregates the statistical behavior of control time, control-burst, and control-frequency using a relative dependency (R_D) modeling to derive process constraints for attack detection regardless of the setpoint calibration of the process task.

3.3.1 Formulation of Relative Dependency. To formulate R_D, BRIDGE applies a statistical measure of dispersion called the coefficient of variation (C_V) [36, 37]. C_V measures the ratio of standard deviation to the mean to compare *degrees of variation* from one data series to another, even if their means are drastically different. BRIDGE leverages this C_V property to model dependencies among dependent devices involved in physical task, whereby the *inter-ratio* of work between devices is the same regardless of the calibrated amount of work [14, 90, 91]. R_D enables BRIDGE to be setpoint-agnostic in detecting attacks. That is, BRIDGE does not analyze statistical values in absolute terms, (e.g., "time-interval of $70k$ scan cycles is too short"). Rather, it analyzes the inter-dependent variations, or what ensures devices are always working in harmony regardless of the amount of setpoint which can increase/decrease the task duration. Further, devices can have more than one dependency relationship. To adjust for these loose dependency instances, BRIDGE measures 2 properties; the degree of dependency or ϵ, and degree of dominance or λ to *adjust* calculated statistical dependency value bounds. Specifically, ϵ of a control command dependence ($c_i \longleftrightarrow c_j$) measures *how dependent* a control command c_j is to c_i, based on the ratio of their occurrence ($c_i \longleftrightarrow c_j$) to other j's control dependencies. λ of a control burst size of commands C_i measures how *common* or *rare* (i.e., a ratio) a specific control burst size is to other burst sizes.

In deriving control-time dependency, let $P(V_k) := \{C_i, C_{i+1}...C_n\}$ be the sequence of process-control commands induced by event k in event set V. $\epsilon_{i-1,i}$ is the degree of ($c_{i-1} \longleftrightarrow c_i$) dependency. j is all instances of time-intervals between subsequent commands for $\Delta_{(i-1,i)}$ of ($c_{i-1} \longleftrightarrow c_i$) in $P(V_k)$. $Deviation(j)$ and $Mean(j)$ are the standard deviation and mean of j. BRIDGE derives $R_{D\Delta}$ as:

$$R_{D\Delta}(i-1,i) = \frac{Deviation(j) + \epsilon_{(i-1,i)}}{Mean(j)} \tag{6}$$

In deriving control-burst dependency, let λ_i be the λ of C_i in $P(V_k)$. BRIDGE derives $R_{D\mu}$ as follows:

$$R_{D\mu}(i) = \frac{Deviation(j) + \lambda_{(i)}}{Mean(j)} \tag{7}$$

In deriving control-frequency dependency, let $|C_i \in P(V_k)|$ be the no. of all instances of command C_i in $P(V_k)$. It derives R_{DF} as:

$$R_{DF}(i) = \frac{|C_i \in P(V_k)|}{|P(V_k)|} \tag{8}$$

3.4 Anomalous Process-Constraints Violation

For each event k in V, the R_D model outputs three maps (i) event-to-control time (ii) events-to-control burst, and (iii) event-to-control frequency scores. Event-to-control time map is $V_{k(i,j)} \mapsto R_{D\Delta(i,j)}$, where $R_{D\Delta(i,j)}$ is the legitimate time-interval semantic dependency in terms of control time of dependent control command pair (C_i, C_j). Event-to-control burst map is $V_{k(i)} \mapsto R_{D\mu(i)}$, where $R_{D\mu(i)}$ is the legitimate frequency semantic dependency in terms of control burst of the control command C_i. Events-to-control frequency ratios map is given as $V_{k(i)} \mapsto R_{DF(i)}$, where $R_{DF(i)}$ is the frequency semantic dependency in terms of control frequency ratio of C_i.

Malicious Control Execution. On observing C_i, BRIDGE compute the *observed* control time metric $\Delta_{OBSERVED}$:

$$\Delta_{OBSERVED}(C_{i-1}, C_i) := \frac{ABS(ts(C_{i-1}) - ts(C_i))}{Mean(ts(C_{i-1}) - ts(C_i))} \tag{9}$$

($C_{i-1} \longleftrightarrow C_i$). ts indicates timestamp. C_i is anomalous if $\Delta_{OBSERVED}$ *deviates* the legitimate control time behavior $R_{D\Delta(C_{i-1,i})}$ mapped to by $V_{k(i,i-1)}$. BRIDGE will compute the observed control burst metric $\mu_{OBSERVED}$ as follows:

$$\mu_{OBSERVED}(C_i) := \frac{|B_{C_i}| - |B_{P_i}|}{Mean(B_{C_i}, B_{P_i})} \tag{10}$$

C_i is anomalous if $\mu_{OBSERVED}$ *deviates* from legitimate control burst behavior $R_{D\mu(C_i)}$ mapped to by $V_{k(i)}$. BRIDGE computes the observed frequency ratio $F_{OBSERVED}$ as:

$$F_{OBSERVED}(C_i) := \frac{|C_i|}{|P(V_k)|} \tag{11}$$

C_i is anomalous if the frequency ratio F_{C_i} *deviates* the legitimate control-frequency behavior $R_{DF(C_i)}$.

3.5 Domain Knowledge PINNs For Robust Learning of Industrial Process Behaviors

PINNs lie at the intersection of neural networks and physical modeling. Network networks loss functions to make robust predictions by learning to find optimal parameters to minimize the value of the loss function [38]. PINNs use partial derivative equations (PDE) to help the model learn from the intrinsic physical properties of the data at hand. This makes PINNs robust even in partial or noisy data due to the physics-based loss function which provides strong regularization terms that help prevent overfitting [38, 39]. BRIDGE develops a physics-informed learning architecture tailored to learn and correlate behaviors in industrial processes and SCADA. First, it designs a PINN to capture the inertial dynamism of industrial processes via a domain knowledge-based PDE loss function. This limits the space of admissible solutions and facilitates the learning algorithm to converge better and generalize well. BRIDGE then implements the PINN/PDE in a Transformer-based AE to instantiate multiple Attention processes for each process input sequence within an ITB. This enables the PINN to capture the periodicity of process and to timely correlate with the SCADA side.

3.5.1 Embedding Inertial Properties of Processes. An AE is a neural network M which consists of an encoder $En(x)$ that compress an input sequence of symbols $x = (x_1, ..., x_n)$ into an encoding $z = (z_1, ..., z_n)$, and a decoder $De(e)$, which reconstructs x from a given z to an output sequence of $y = (y_1, ..., y_n)$. When trained with the objective $De(En(x)) = x$, an AE learns to summarize the distribution of $x \in X$ where $X \in \mathbb{R}^n$. AEs can detect anomalous sequences when trained on a benign distribution because M will fail to reconstruct the features of x [32, 92]. To detect an anomaly, given an input reconstruction $M(x) = \tilde{x}$, we calculate the mean-square error (MSE) and check if the output is above a threshold, as follows:

$$MSE(x, \tilde{a}) = \frac{1}{m} \sum (x^i - \tilde{x}^i)^2 \tag{12}$$

BRIDGE make use of a variational AE, which comprises a generative and latent loss. The generative loss penalizes the model for having differences between the input to the model and the output from the model. We set our generative loss as the MSE loss (or L2-loss).

The latent loss compares the learned distribution of input data in the latent layer to that of a Gaussian/Normal distribution. We used the Kullback-Leibler (KL) divergence loss as our latent loss. Then, to embed the inertial properties of processes into our model, we develop and introduce a third term in our loss function based on knowledge of actuating systems under inertia [33–35] as follows:

$$\sin\left(\frac{dV}{dt}\right)\cdot\omega-\cos\left(\frac{d^2X}{dt^2}\right)=0 \tag{13}$$

where X is a vector of the process' numerical features (e.g., the level of the tank), V is a vector of the rate of change (with respect to time) of these features, and ω is a scaler of their inertia delay. The sin and cosines trigonometric functions capture their angular phase shifts. The goal of the PDE is to minimize the angular displacement (i.e., bring it to 0) in processes with inertia. To explain, without inertia, the second-order derivative of the angular positions of X (or acceleration) should be equal to the first-order derivative of V. That is, ω is the displacement. In order to incorporate the equation into our neural network, we extracted the first term of the equation from the reconstruction of the input data given by the model and the second term directly from the input data. Following this, we set our PINN loss function to be the mean squared difference between the first and second terms. This way, the network can learn parameters that minimize the difference between the two terms.

3.5.2 Attention Mechanism for Process Periodicity. Bridge uses the attention mechanism [40, 89] to prioritize important causal relationships in actuators and sensor values in the ITB-sized input time series. In AEs, each step in reconstructing the input is auto-regressive, i.e., previously generated symbols are used as input when generating the next. To mitigate this sequential bottleneck, Bridge uses the Transformer multi-head attention architecture [89] to encode and decode each input in parallel. Each encode-decode pass finds a unique attention filter for the same input sequence. Bridge uses an attention function to compute a *rank* for each input in the sequence by applying the softmax function [89]. For each process, Bridge computes the rank on a set of simultaneous queries in the matrix of actuator/sensor vectors, Q, comprised of K and V matrices of their keys and values, as follows:

$$rank(Q,K,V)=SoftMax(\frac{QK^T}{\sqrt{d_k}}) \tag{14}$$

We detail our implementation approach in the appendix in Fig. 13.

4 EVALUATION

We evaluate Bridge's ability to (i) detect and correlate Scada and process attacks, and (ii) outperform existing works in detection.

4.0.1 Implementation and Dataset. We used public real-world Scada and process data from 11 diverse industrial scenarios in water treatment, manufacturing, and shipping plants.[3] Unlike other datasets like SWAT [93] (which only has process data), this data has execution traces of real Scada hosts during the process operations. We trained Bridge's PINN on a NVIDIA GeForce RTX 2080 Ti GPU (~300 lines of Python code), which outputs a model of an avg. side of 3-4 MB per process in training time of 1-4 mins per epoch. Each

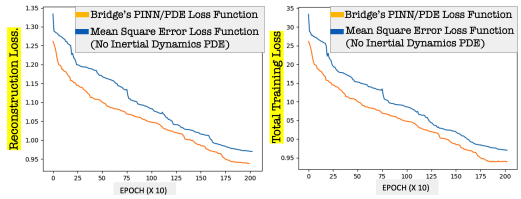


Figure 7: Performance of Bridge's PINN vs. current loss functions for learning process behavior: As shown, our PDE loss functions based on Inertial Process Dynamics performed significantly better

of the process data in the dataset comprises about 4-7 days of continuous process runs. Bridge's Scada side comprises of ~240 lines of python code. Both the Scada side and process detection (~ lines of python code) runs in an Intel(R) Xeon(R) CPU E5-1620 v2 @ 3.70GHz (4 cores). Our implementation is provided online[4].

4.1 Modeling and Analysis Results

Table 2 presents results from Bridge's analysis, at both the Scada and process aspects. We highlight important details. Columns 5, 6, and 7 show the key actuators for each process task. In column 4 totals for "States", we see that Bridge analyzed a total of 338 distinct process-control traces out of the 346 that were induced by the OPC event states (97.7% relevant behavior coverage). It missed 8 (column 4 totals for "Verify"). This is due to parsing errors when matching PLC/process device names to Scada OPC tags. We verified this via manual checking of the dataset. In the totals of columns 8 and 9 (i.e., CMD, Nodes/Edges), we see that the 338 traces generated 526 process constraints, 128 of which are from unique device pairs (i.e., total no. of Edges). This shows Bridge's robust ability to derive process constraints from process-control executions. Columns 10, 11, and 12 are the statistical relative R_D aggregates of the control-time, control-frequency, and control-burst constraint values. The Scada side analysis took $\tilde{8}$ mins for each process, which is reasonable, based on the scenario sizes (column 3). The last 4 columns show the PINN training results. Bridge attained avg. of training precision and recall above the 85% mark. Further, the loss curves in Fig. 7 shows that Bridge's PINN performs significantly better than MSE loss functions. The total training loss curve for different ITB runs shows that our model not only has lower training loss but also converges faster than a generic AE. This shows that Bridge's PINN is robust. This is also the case in the reconstruction loss (left figure).

4.2 Adaptive Attacks and Detection Results

From the public attack dataset [1], we draw 50 attacks from five categories of past incidents as shown in Table 3, which also explains their attack TTP. Each category has 10 attack instances as follows: (*I*) Stuxnet-category ($T831$), (*II*) Industroyer-category ($T855$), (*III*) Oldsmar-category ($T836$), (*IV*) Triton-category ($T801$), (*V*) System crash-category ($T816$). Cat. I-IV attacks target specific actuators or parameters across all processes. They also used a stealthy approach [14, 17–19] to perturb processes. Specifically, for numeric parameters, they steadily increment the process value by a fraction

[3] https://github.com/lordmoses/SCAPHY

[4] https://anonymous.4open.science/r/bridge/

Table 2: Showing BRIDGE's analysis results per process based on public dataset of diverse real-world industrial processes.

Industrial Processes	Diverse Domains	OPC Events (Per Process)		SCADA Process-Control Dependency Analysis					Process Constraints (Statistical Averages)			Analysis Time (mins)	Process Behavior (PINN Training using PDE)			
				Process Task and Relevant Actuators			Proc Graph									
		Scenario FileSize	States/ Verify	Description	Task ID	Key Actuator	CMDs	Nodes/ Edges	$R_{D\Delta}$	$R_{D\mu}$	R_{DF}		Inertia/ Seq Size	Seq Size	Precision /Recall	F1
Chemical Dosing	Water Treatm	11.5K	10/0	level control	2.1	holding tank	24	4/6	0.47	0.125	0.105	7.6	4.5/5	5	85/70	77
		11.5K	14/2	dosing	2.2	dose valve	22	5/9	0.419	0.111	0.344	7.5	4.5	5	94/87	90
Auto warehouse	Manufacture	29K	20/0	pallet alignment	3.2	Axes X,Z	26	6 /4	0.41	0.133	0.088	12.4	5.1	5	95/93	94
		29K	36/1	throughput	3.2	entry conveyor	32	7/5	0.42	0.167	0.034	12.9	5.1	6	77/83	80
Assembler	Manufacture	9.5K	28/0	product haul	4.1	clamp lid/base	22	5/9	0.24	0.71	0.048	7.7	5.7	6	71/73	72
		9.5K	11/1	load balancing	4.2	conveyor2	17	4/3	0.686	0.14	0.05	9.3	5.1	6	88/93	90
Elevator	Manufacture	11K	13/0	prod safety	11.1	conveyor1-3	25	6/6	0.198	0.195	0.51	12.0	7.4	7	92/85	88
		11K	12/0	throughput	11.2	entry conveyor	14	8/5	0.318	0.119	0.691	6.1	7.4	7	89/77	83
Queue processor	Manufacture	9K	12/0	spacing	7.1	buffer conveyor	17	4/5	0.091	0.089	0.441	4.7	6.4	6	82/90	86
		9K	29/0	throughput	7.2	entry conveyor	32	8/4	0.358	0.678	0.224	12.1	6.4	6	88/95	91
HVAC	A/C	6K	18/0	heat setpoint	6.1	room temp	9	4/5	0.219	0.053	0.09	11.6	11.8	13	79/92	85
		6K	17/1	heat flow	6.2	vent	23	5/5	0.178	0.410	0.065	10.2	11.8	13	88/83	85
Palletizer	Shipping	7.8K	21/1	load alignment	5.1	push clamp	33	9/4	0.289	0.845	0.717	14.6	4.1	4	80/88	84
		7.8K	29/0	prod protection	5.2	entry conveyor	36	6/7	0.091	0.459	0.455	5.8	4.1	8	71/79	75
Converge station	Shipping	6.2K	11/1	path throughput	7.1	load/unload	32	7/5	0.421	0.616	0.321	9.5	5.1	6	86/93	89
		6.2K	19/0	alt throughput	7.2	transfer	23	9/8	0.51	0.18	0.085	11.4	5.1	6	88/93	90
Production line	Manufacture	8.5K	21/1	alignment	4.1	control arm	22	8/6	0.267	0.371	0.571	11.3	12.1	12	84/99	91
		8.5K	11/0	throughput	8.2	conveyors	25	5/5	0.211	0.098	0.0510	9.9	12.1	12	66/94	78
Sort station	Shipping	9K	16/0	sort accuracy	9.1	unloader	22	8/7	0.4	0.335	0.118	15.1	5.5	6	92/93	92
		9K	16/0	throughput	9.2	conveyor	17	9/5	0.107	0.291	0.0821	10.6	5.5	6	97/70	89
Separator	Shipping	4.9K	18/0	accuracy	10.1	pusher1-2	26	11/8	0.132	0.439	0.264	12.0	7.6	8	89/73	81
		4.9K	15/0	throughput	10.2	conveyors	27	8 /7	0.414	0.193	0.072	9.6	7.6	8	86/86	80

of the current value at each step. For Boolean parameters, the attacks repeatedly toggled them at a slow pace. Cat V attacks (System crash-category) exploit device-specific targets [94].

4.2.1 Attack Explanation and False Alarms. For Cat. I-IV, 10 attacks were injected in 5 processes, 2 each. For Cat. V, 4 of the 10 attacks are launched against processes. The remaining 6 use real-world exploit code from ICSSPLOIT [94]. For example, as shown, exploits of I/O corruption were used do shut down devices. However, because these are *noisy* attacks, they triggered high variance anomalies, especially the control-burst $R_{D\mu}$ which is sensitive to chatty behaviors. In contrast, control-time behavior $R_{D\Delta}$ detected mostly semantic attacks (Cat I-IV). Overall, process anomalies were more rampant than SCADA. However, since they are applied as a filter for SCADA attack, it did not affect BRIDGE results. Although BRIDGE detected all 3 process-constraints violations in R_D, $R_{D\mu}$, and R_{DF} in many combinations of targets, which also had FPs. However, in some cases, they were discarded since no process effects were seen. Via manual checking, we found that this FP was due to a SCADA anomaly flagged around the same time a process error/noise exist on the system. To mitigate this rare phenomenon, BRIDGE can use the process evolution by discarding process anomalies that started *before* the flagged SCADA anomaly. This is because they could not have been caused by SCADA (i.e., the effect cannot happen before the cause) On average, BRIDGE's time-to-detect is about 7-9 seconds (last column), which is practical for near-real time detection.

4.2.2 Discussions and Lesson Learned. We discuss how BRIDGE was impacted by the diverse physical processes used. We observe that processes with more actual devices than parameters (such as PID) are less prone to semantic attacks. Control parameters are typically set once during SCADA operation, hence having fewer dependencies than actual devices. This is depicted in the no. of generated commands (column 9 of Table 2). As a real-world example, in the HVAC scenario (which uses soft parameters for A/C control), although 18 states were used to induce SCADA, only 9 commands were executed, compared to a more physical system such as Queue Processor, which although generated fewer states, revealed more SCADA commands and dependencies. However, processes with more actual devices are more prone to shutdown attacks (*T*0816) than the parameter-based ones. We found that soft parameters allow more automation than mechanical devices. These lessons can inform building secure processes (e.g., resilient to attack).

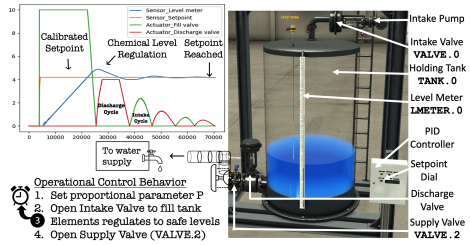


Figure 8: Chemical dosing process constraints violated by Attacker

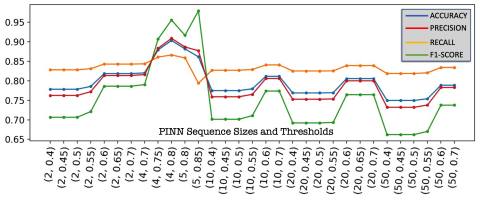


Figure 9: PINN performance for diff sequences sizes. Inertia-informed sizes (4,5 for chemical dosing) performed better overall

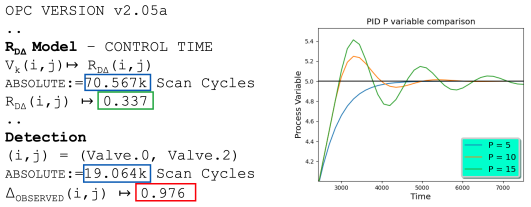
4.3 Case Study 1: Real-World Process Attack

We analyze the 2021 Oldsmar attack, which altered process parameters to dump excess chemicals into the water higher than the calibrated setpoint, while using normal SCADA tools/system calls.

4.3.1 Chemical Dosing Operation and Injected Attack. Chemical dosing involves two processes: *Level control* (LV) and *Dosing*. Fig. 8

Table 3: Attacks Detection Results. Attacks TTPs were generated by recent work based on MITRE/ICSSPLOIT Frameworks [94–96]

Attack Category	Total Attacks	TTP ID	Attack Description/ TTP Goal	Attacked Process (IDs in Table 2) (2 attack injected per process ID)	Process-Control Violations (Totals) C-TIME	C-BURST	C-FREQ	Process Anomalies (Totals)	Correlated Attacks	TP	FP	Detect Time (sec)
I. Stuxnet Cat.	10	T831	CTRL Manipulation/Impact Control	2.1, 10.2, 6.2, 9.1, 3.2	3	7	8	21	12	12	0	10.2
II. Industroyer	10	T855	Unauthorised CMD/Crash Process	1.1, 8.2, 11.1, 7.1, 2.2		8	5	19	10	9	1	7.8
III. Oldsmar Cat.	10	T836	Modify Parameter/Impact Contr	4.1, 7.2, 10.1, 8.2, 11.2	17	11		35	24	24	0	5.4
IV. Triton Cat.	10	T801	Corrupt State	7.1, 6.2, 8.1, 5.1, 4.2	8	2	13	27	22	22	0	9.4
		T816	Device shutdown/Inhibit Resp fxn	7.1, 9.1, 2, 7.2		1		4	1	1	0	5.4
		SPLOIT1.1	stop Controller/Siemens Simatic-1200	ICSA-11-186-01(Unprotected Port)	1	1	1	1	1	1	0	7.4
V. System-Crash Cat (High Variance) Attacks	10	SPLOIT1.2	remote Code execution/QNX SDP 660	CVE-2006-062(Buffer Overflow)	1		1	1	1	1	0	9.2
		SPLOIT1.3	remote Device halt/Schneider Quantum	ICSA-13-077-01(I/O corruption)	1		1	1	1	1	0	6.7
		SPLOIT1.4	Crash RTOS service/QNX INETDd	CVE-2013-2687(Buffer Overflow)		1	1	1	1	1	0	7.4
		SPLOIT1.5	RPC Device Crash/WindRiver VXWorks	CVE-2015-7599(Integer Overflow)		1	1	1	1	1	0	12.6
		SPLOIT1.6	denial of service/Siemens S7-300/400	CVE-2016-9158(Input Validation)	1	1	1	1	1	1	0	7.2



(a) Output Results based on our adapted Oldsmar Example **(b) Effect of different $P's$ to reach S_V**

Figure 10: Depicted output for our running example attack, and the effect of different $P's$ to reach the calibrated setpoint

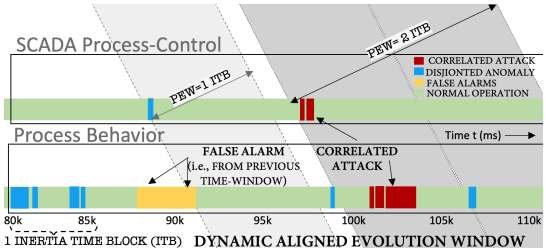


Figure 11: Example anomaly correlation of our running example

shows the HMI and main devices involved. LV regulates chemical in a holding tank, *Tank.0*, based on S_V. When S_V is reached, *Dosing* opens the *Supply Valve*, *Valve.2* to let the chemical into the water supply. Level control is based on a physical domain *Proportional Integral Derivative* (*PID*) logic. Because S_V cannot be reached in one shot, *PID* performs several "intake" and "discharge" cycles, (Fig. 8) whereby an Intake Pump *Pump.0* and *Intake Valve Valve.0* fills chemical into *Tank.0*, and a Discharge Valve *Valve.1* remove excesses, until S_V is achieved, shown in Fig. 8. A PID parameter $P.0$, controls how aggressively the intake and discharge cycles are driven. E.g., a high $P.0$ pumps an *initial* excessive volume into *Tank.0*. Fig. 10b shows how different $P.0$ values affect how S_V is reached. S_V is set in the PLC hardware dial, so cannot be altered via Scada. To perform the attack, the attacker set $P.0$ to a high value, set *Valve.0* to open, and then, opened *Valve.2*. Although this execution sequence is normal, the control time between opening the *Intake Valve* and *Supply Valve* is less than the operational time for LV to regulate the volume. This caused the initially filled excessive volume due to P to be dumped into the water supply.

4.3.2 Evading Existing Techniques. The Scaphy work noted that it could not detect the Scada attack since benign system calls/HMI were used, which evades its signature approach [1]. On the process side, Scaphy flagged when the process went over the S_V. However, we see that the attacker can stay just below the S_V, but over time causes the same damages. Invariant misclassified the high P value as an attack, which is a false alarm. Note that although the very high P value seems anomalous, by itself, it is benign because with time, LV will regulate excessive volumes to safe levels. In addition, the attacker could incrementally perturb P to be just below Invariant's threshold, while still achieving the attack. In this case, since all other actuator sequences will be normal, Invariant will miss the attack.

4.3.3 Bridge Analysis. Bridge derives the chemical dosing inertia via the de-energizing time of *Pump.0* and *Valve.0*, which took about 4.7 sec before the tank stops filling. Based on this, the ITB is 5. Fig. 9 shows the PINN performance of the with different sizes. As shown, several thresholds on sequence size 5 achieved the best results, which supports our hypothesis. The attack was injected around the 97-98th sec as shown in Fig. 11. It blends with normal operation by listening for the same events as Scada, which is *Valve.0.Open*.

4.3.4 Correlation and Detection. In Scada, Bridge detected an anomalous *control-time* dependency between *Valve.0* and *Valve.2*. The output derivations are shown in Fig. 10a. Bridge then waited for the inertia time of 4.7 sec before analyzing its process output. Steady-state was reached in one inertia time block (that is, only one inertia time block was added to the process evolution window). Bridge flagged an anomaly around the 101th sec. Since both anomalies exist on the correlated scada-physics time window, alarm is raised as an actual attack. Fig. 11 shows several isolated anomalies of the process (in blue). We captured a rare occasion around the 90th sec when false alarms arose in both Scada and Physics. However, Bridge filters it as a false alarm since the process anomaly permeated from the previous window (88th sec). As such, the process anomaly may not have not come from Scada (i.e., the effect cannot happen before the cause). The chemical dosing operation was induced by event V_k :=*Valve.0.Open*, via a read (tag.Valve.0) API call. Bridge detected calls that opened the Intake Valve as write (tag.Valve.0) (which begins the filling) and the Supply Valve opening as write (tag.Valve.2). That is, $(i, j) = (Valve.0, Valve.2)$. Bridge then computes the *observed* time-interval for the dependent commands on i, j as $\Delta_{OBSERVED}(i, j) := 0.976$, which deviates from the established $R_{D\Delta(i,j)} \mapsto 0.337$, hence anomalous. Note that the absolute time-interval of 70k and 19k scan cycles shown in Fig. 10a

Table 4: This is to show BRIDGE's Resiliency to configuration changes using randomly and uniformly generated setpoint S_V for the Chemical Dosing scenario. We show (1) BRIDGE's R_D Dispersion based on $(i, j) = (Valve.0, Valve.2)$ and $(i) = P.0$ and (2) Detection Results

	Max S_V Config	Min S_V Config	R_D Average / R_D Dispersion			BRIDGE Detection Resilience				
			$R_{D\Delta(i,j)}$	$R_{D\mu(i)}$	$R_{DF(i)}$	Total	Detected	Missed	TP%	FN%
Normal Calibration	2.35	2.35	0. 0.092/-	0.092/-	0.25/-	1	1	0	100	0
Random Calibration Changes	4.6	1.7	0.187/0.303	0.118/0.3744	0.25/0.443	53	51	2	96.2%	3.8
Uniform Calibration Changes	10.0	1.0	0.293/0.427	0.156/0.418	0.25/0.593	53	48	5	90.6%	9.4

Table 5: Comparison BRIDGE with Existing Approaches

Reference Work	Approach	Attack/ Benign	Semantics Correlated	Time Correlated	Detection Results		
					TP	FP	FN
SCAPHY [1]	SCADA + Process	120/ 268	0 (0%) (disjointed)	71(75%) (with maps)	94 78.3%	15 13.7%	26 21.6%
INVARIANT Rules [16]	Process Invariant	120/ 268	- N/A	- N/A	89 74.2	17 16%	31 25.8%
BRIDGE	SCADA + Process	120/ 268	119 (100%) (false=1)	119 (100%) (Avg. ITB=3)	118 98.3%	1 0.8%	2 1.6%

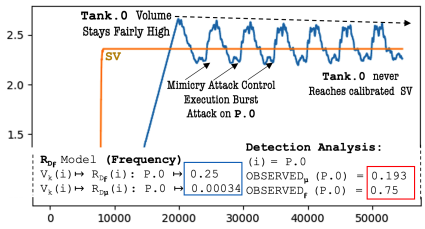


Figure 12: An Evasive Mimicry Oldsmar Attack: Can evaded $R_{D\Delta}$, but violates $R_{D\mu}$ R_{DF} behaviors, allowing BRIDGE to detect it

is to illustrate time interval in absolute terms. However, BRIDGE computes relative dependency measure (i.e., R_D = 0.337). BRIDGE's alert to operators contains the affected devices (e.g., the *Supply Valve* and *Intake Valve* tags). This helps them better understand the attack and inform threat remediation at both SCADA and physical.

4.4 Case Study 2: Real-World Mimicry Attack

We used an advanced Oldsmar attack that mimics BRIDGE's timing R_D dependency behavior to evade BRIDGE and achieve its attack. This attack obeys the expected control-time between *Valve.0* and *Valve.2* by carefully incrementing parameter $P.0$ every few scan cycles, such that as the process gets close S_V, process-control (based on P) still pumps excessive intake chemical. The attack uses the same semantic logic as process-control to monitor the difference between $L.Meter.0$ to S_V to calculate how much to increment P to keep $Tank.0$ high enough until BRIDGE's control-time is satisfied. To explain this semantic attack, recall that *PID* process-control logic uses $P.0$ to compute how aggressively to fill the tank at every process (i.e., intake and discharge) cycle, which is about 9k scan cycles based on Fig. 8. Given that *Level control* takes 70k scan cycles to achieve S_V, there's room to manipulate P to still poison the water. The attack commands kept $Tank.0$ high enough as shown in Fig. 12, and when BRIDGE's expected R_D is reached, it opened the dosing valve *Valve.2* achieving the same attack goal. However, BRIDGE detected the attack based on control-burst $R_{D\mu}$ and control-frequency R_{DF} behaviors, shown in Fig. 12. The attack incremented $P.0$ a total of 18 times out of 24 total commands leading to an anomalous *control frequency ratio* of 0.75 compared to R_{DF} =0.25. Further, the injection bursts of 2,3,2,3,2,3,3 led to a control burst behavior of 0.193 compared to $R_{D\mu}$=0.00004 (i.e., $C_{P.0}$ almost always have burst of 1). These SCADA anomalies were validated by process in the same time window, but may evade isolated sensor analysis.

4.5 Case Study 3: Process Calibration Changes

We draw experiment data to evaluate BRIDGE resilience to S_V changes. Recall that BRIDGE's R_D model is designed to work for different calibrated S_V. In this experiment, we answer 2 questions (i) how much does BRIDGE's R_D *disperse* when derived from varying S_V of the same CPS scenario, and (ii) how many attacks are *missed* due to new S_V. We chose the chemical dosing scenario for this experiment because it provides many S_V decimals, from which we generated 53 S_V calibrations. Table 4 details our results. For (i), columns 4-6 show the average output of $R_{D\Delta}$, R_{DF}, and $R_{D\mu}$, which are very close to their original derivation. To mathematically reason about their *dispersion*, we compute their standard deviation (SD). As shown, the low SDs indicate very low dispersion, showing that BRIDGE's R_D is very resilient to S_V changes. For (ii) columns 5-8 show BRIDGE detection performance in new S_V configs, with high 96.2% and 90.6% TP for *randomly* and *uniformly* generated S_V changes. We found that slightly higher FN in uniformly generated changes is due to boundary limits rarely seen in the plant. We found that we can tune this behavior using BRIDGE's degree of dependence and dominance (ϵ and λ), which are designed to tune dependencies that rarely occur.

4.6 Comparing Against Existing Work

We compare BRIDGE with current approaches as shown in Table 5, which are INVARIANT [16] and SCAPHY [1]. INVARIANT mined invariant rules from predicates generated in sensor traces. These rules must be satisfied between the predicates and actuator states otherwise the states are deemed anomalous. SCAPHY detects attacks in both SCADA and processes. It learns system call signatures unique to SCADA phases and created process signatures from observing disruptive physical impact. To compare BRIDGE against these works, we used the public dataset in [1]. SCAPHY's implementation is online. For INVARIANT, we used an open-source tool [97] to first build a network graph of each process' FBD/STL, and then generate rules from the time-series of sensor/actuator states that satisfy them.

4.6.1 Results. We draw experiments from the dataset whose behaviors are observable from both SCADA and process traces, totaling 120 attacks and 268 benign instances. For the detection threshold, we used normalized average values based on the 75% percentile.

Table 5 shows the results. Overall, Bridge achieved a 98.3% detection accuracy with 0.8% FP, compared to 78.3% detection and 13.7% FP of Scaphy, which had the second-best result. Bridge correlated all its detected attacks in both semantics and time (columns 4 and 5), with an average process evolution window of 3 ITBs for each process. Although Scaphy had 0% semantic correlation due to it's inherent design flaw, when we provide it with our ITB evolution mappings, it correlated 75% of its detected attacks in time (column 5). Scaphy missed many attacks due to it's use of known signatures. Further, its use of "outside setpoint" process anomaly signature caused false alarms. Invariant detected 89 attacks, i.e., 74.2% true positives (TP) with 17 FPs (16%). The high FP is due to flagged sensor deviations that are part of normal behaviors but misclassified by rules. For example, recall in Oldsmar, a high $P.0$ by itself is a benign behavior, but only malicious during the transition to the dosing task. In addition, rules constructed by invariants can be incomplete based on the training data [63]. Further, since Invariant is a process-only technique, it did not perform correlation with the Scada side, which impeded it's detection results.

4.6.2 Sensor Invariant Rules vs. Process-Control Constraints. We drew a general experiment to compare Bridge's process (dependency) constraints (i.e., how devices depend on each other to achieve a task) with invariant rules (i.e., properties that should hold in sensor readings). To draw up this experiment from the public data, we injected random perturbations in a normal process and Scada data of the water treatment scenario, similar to what was done in the [16] work. Results are shown in Table 6. For our evaluation metric, we derived a *Noise-Ratio* score by dividing the FP with the total dependency or rules generated. Overall, constraints from process-control had better results with low Noise-Ratio (15.1,9.6,12.5) compared to (41.4,30.6,41.3) of invariant rules. Intuitively, invariant rules may have *hard* predicates which semantic attacks can still satisfy while causing disruption [63]. For example,Invariant assumes that every update of actuator states is due to critical predicates. [63, 98] showed that such rules may be spurious or incomplete. In contrast, process-control behavior is *task-driven*, hence deviations from them have a high chance of violating intrinsic constraints.

4.7 Limitations and Discussions

4.7.1 Manual Effort Required. Due to the namespace difference between Scada OPC tags and process PLC/device names, we had to manually inspect the PLC FBD/STL files (i.e., shows how devices are connected) of each process to match process-side device names with the Scada side. However, in some scenarios, the namespace was similar (e.g., "VALVE.1" vs. "VAL-1"), which enabled us to use a semi-automated regular expression matching script. This manual activity took us under an hour to match device names in each process. However, it is only to be performed once per scenario.

4.7.2 Physical Changes. Since Bridge relies on physical dependencies, adding new devices will break its process constraints. Since Bridge is mostly automated, new dependencies can be re-learned.

4.7.3 Correlation Overhead. When Scada attacks are flagged, Bridge must wait for at least 1 ITB to check for the process effect. Although inertia helps to prevent instant damages, depending on the sensitivity, damages may occur before operators can respond.

Table 6: Sensor Invariant Rules vs. Process-Control Constraints

	Physical Actuator States Perturbed					Results			
	Fill Valve		Discharge Valve						
Approach	Level (volts)	Flow (cm/s^2)	Level (volts)	Flow (cm/s^2)	No. Of Trials	DEPS/ RULES	FN	FP	Noise Ratio
Invariants	|@5	0.984	@5	-0.975	100	41	11	17	41.4%
	|@1	0.1962	@1	-0.184	100	62	8	19	30.6%
Rules	|@10	1.968	@10	-2.025	100	29	12	12	41.3%
	|@5	0.984	@5	-0.975	100	33	7	5	15.1%
Process	|@1	0.1962	@1	-0.184	100	52	2	5	9.6%
Constraints	|@10	1.968	@10	-2.025	100	24	10	3	12.5%

While this limitation applies to all process anomaly tools, we can explore early warning signs. Bridge detects attacks around 8s on avg., which is useful for near real-time detection (Section 4).

5 RELATED WORK

Unlike in IT, industrial processes are governed by physics laws, whose normal behavior can be learned to detect attacks [14, 15, 62, 63, 90]. In the wild, cyber-attacks originate from infected Scada hosts, which can inject stealthy process changes, but overtime leads to damages. Process anomaly techniques [14, 15, 58–63, 76] such as Invariant and Tabor [13, 16] can detect process (sensor) changes but cannot identify the Scada cause, hence have false alerts due to noise/faults [43]. Host anomaly tools such as Orpheus and Lee [20, 21] can detect abnormal system calls, but can't know if it caused adverse process effects, which also causes false alarms. To counter false alarms, Scaphy [1] combined Scada and process anomaly data, but limited by both signature-based detection and false alarms because Scada execution does not map to process dynamics nor evolve at similar time-scales (i.e., semantic/time gap). Bridge uses domain knowledge in Scada process-control and process-tailored PINNs to bridge their unique semantic and time gap, which reduce false positives and improve attack understanding.

PLC Man-in-the-Middle (MITM) attacks such as Harvey [99] can present false sensor data to Scada. [69, 70] proposed MITM mitigation such as using separate sensor channels channels and physics knowledge. [88] uses non-PLC diode gateways to avoid MITM. VetPLC and TSV [22, 72] can detect PLC logic alteration, but not suited for Scada attack which can alter PLC I/Os at runtime without touching its logic. Traffic analysis [43–45, 49, 78–80, 80, 82–85] are promising for abnormal traffic such as scans, but evaded by modern attacks which are semantic-based [100]. Reinforcement and Deep Learning [55–57, 77] uses game theory to learn attack behaviors but requires known attacks and expert reward function, which may limit its diverse use in ICS. Bridge *generalizes* attacks by detecting anomalies that *violates* intrinsic dependencies in Scada and process operation.

6 CONCLUSION

Bridge is a domain knowledge-based correlation of Scada and industrial process behaviors that bridges their unique semantic and time evolution differences in detection ICS process attack. This reduces false alarms and improves attack understanding. Bridge achieved high accuracy and outperformed existing work.

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7 APPENDIX

7.1 More Details On Bridge's Attention Design Implementation

An attention function can be described as mapping a query and a set of key-value pairs to an output, where the query, keys, values, and output are all vectors [89]. The output is computed as a weighted sum of the values, where the weight assigned to each value is computed by a *compatibility* function of the query with the corresponding key (shown in Fig. 13). Bridge uses the scaled dot-product attention developed in [89], whose input consist of queries and keys of dimension d_k, and values of dimension d_v. In Bridge, the query, key, and value matrices are simply copies of the input sequences, as shown in Fig. 13. Each is passed through different linear layers (layers with no activation), simply to map the input to the output and reduce dimensions and computational cost. The results of the query and key after being passed through the input layer are first multiplied (using dot product), scaled by dividing each by the square root of d_k, and then passed through the *softmax* function. The output is called the *attention filter*. The attention filter is multiplied by the value matrix to obtain the weights on the values. The attention filter allows us to identify the important time series, i.e., actuator input and sensor outputs that have the most causal relationship. Bridge uses the attention function to compute a *rank* for each input in the sequence by applying the softmax function. In practice, Bridge compute the attention function on a set of queries simultaneously in the matrix Q. K and V are matrices of the keys and values.

$$Rank(Q, K, V) = SoftMax(\frac{QK^T}{\sqrt{d_k}}) \tag{15}$$

PhysicsRank is Bridge's attention function that ranks actuator sensor vectors with the most Physics causal relationship.

Parallelizing Attention. Bridge uses multiple attention heads (depicted in Fig. 13 to identify useful attention filters for the input sequence, as well as compute the *PhysicsRank* in parallel. That is, instead of performing a single *PhysicsRank* function with d dimensional keys, values, and queries, they can be projected h times (where h is the Inertia-informed sequence size) to different learned d_k, d_q and d_v dimensions, respectively. The attention function, *PhysicsRank*, can now be performed on each of these projected versions of queries, keys, and values, to yield output values in dv dimension. Bridge then concatenates the results of the multiplication with each attention filter and then applies the linear layer to reduce (shrink down) the dimensions, and output the final values as shown in Fig. 13.

Internally, Bridge implements the architecture of stacked self-attention and fully connected layers. The encoder and decoder process their input x using a stack of identical layers equal to the ITB, each having two sub-layers, $Sublayer(x)$. The first is a multi-head self-attention mechanism and the second is a fully connected feed-forward network. Bridge uses a residual connection followed by normalization around each sub-layers. We detail our implementation approach in the appendix in Fig. 13. The output of each sublayer in Bridge is given below. Note that $Sublayer(x)$ is

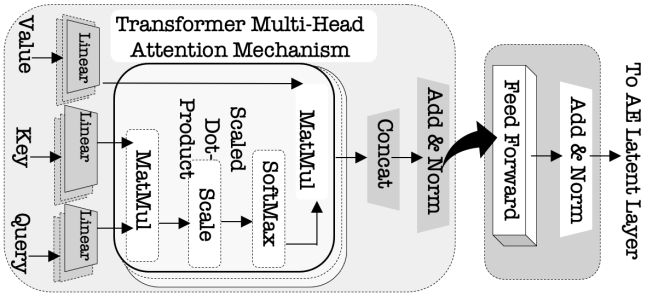


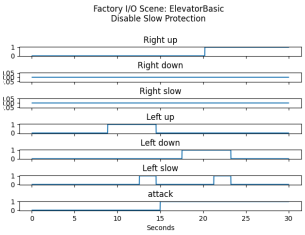
Figure 13: Bridge's multi-head attention encoder and decoder to rank important Physics relationships and remove bottleneck of AEs

the function implemented by the sub-layer.

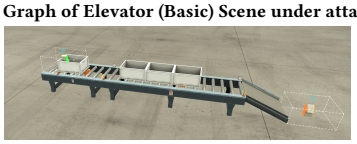
$$output(x) = LayerNorm(x + Sublayer(x)) \tag{16}$$

By using attention to prioritize causally-related actuator/sensor vectors within the ITB time window, Bridge captures the periodic nature of a process in its learning algorithm.

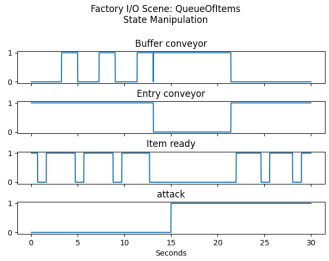
(a) HMI for Elevator (Basic) Scene



(b) Graph of Elevator (Basic) Scene under attack

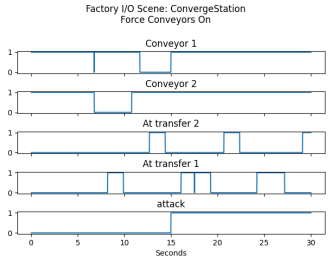


(c) HMI for Queue Processor Scene

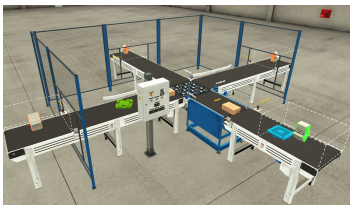


(d) Graph of Queue of Items Scene under attack

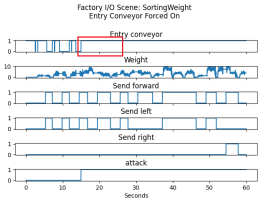
(e) HMI for Converge Station Scene



(f) Graph of Converge Station's tags while under attack

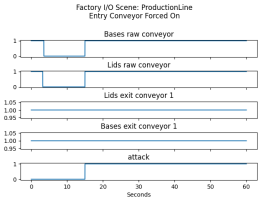


(g) HMI for Sort By Weight Scene

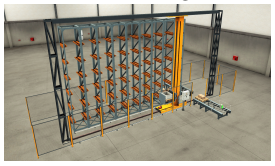


(h) Graph of Sort By Weight's tags while under attack

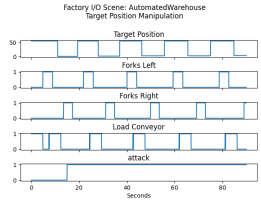
(i) HMI for Production Line Scene



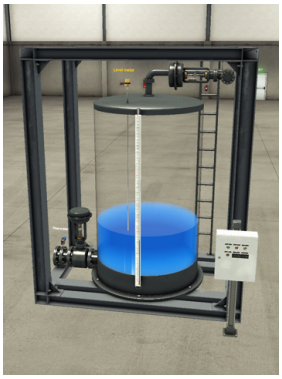
(j) Graph of Production Line's tags while under attack



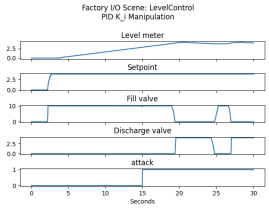
(k) HMI for Automated Warehouse Scene



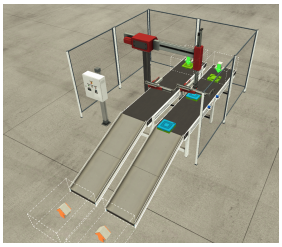
(l) Graph of Automated Warehouse's tags while under attack



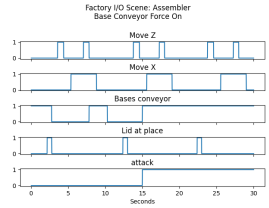
(m) HMI for Chemical Dosing Scene



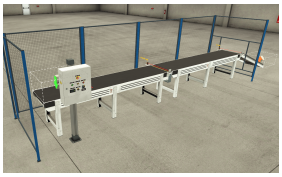
(n) Graph of Level Control's tags while under attack



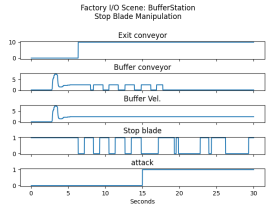
(o) HMI for Assembler Scene



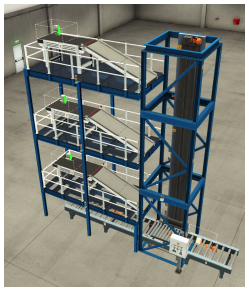
(p) Graph of Assembler's tags while under attack



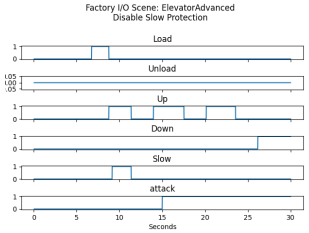
(q) HMI for Buffer Station Scene



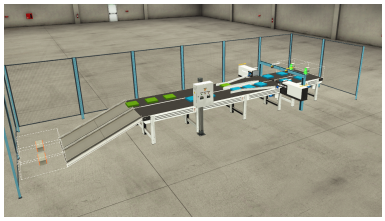
(r) Graph of Buffer Station's tags while under attack



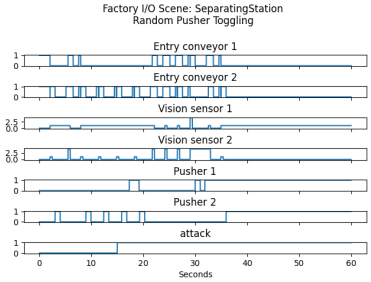
(a) HMI for Elevator (Advanced) Scene



(b) Graph of Elevator (Advanced) under attack

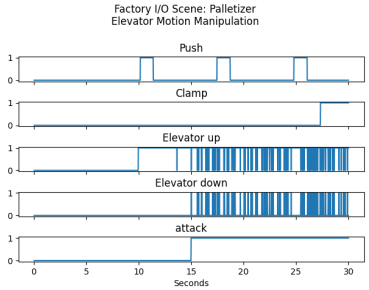


(c) HMI for Separating Station Scene

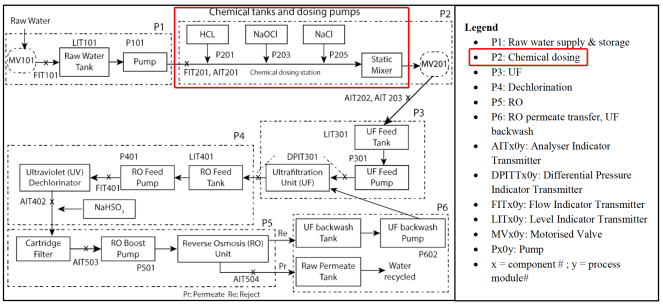


(d) Graph of Separating Station's tags while under attack

(e) HMI for Palletizer Scene



(f) Graph of Palletizer's tags while under attack



(a) Complete water treatment plant based on [93, 101]: The chemical dosing operation was attacked in the Oldsmar water poisoning attack