

# LLMPot: Automated LLM-based Industrial Protocol and Physical Process Emulation for ICS Honeypots

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## ABSTRACT

Industrial Control Systems (ICS) are extensively used in critical infrastructures ensuring efficient, reliable, and continuous operations. However, their increasing connectivity and addition of advanced features make them vulnerable to cyber threats, potentially leading to severe disruptions in essential services. In this context, honeypots play a vital role by acting as decoy targets within ICS networks, or on the Internet, helping to detect, log, analyze, and develop mitigations for ICS-specific cyber threats. Deploying ICS honeypots, however, is challenging due to the necessity of accurately replicating industrial protocols and device characteristics, a crucial requirement for effectively mimicking the unique operational behavior of different industrial systems. Moreover, this challenge is compounded by the significant manual effort required in also mimicking the control logic the PLC would execute, in order to capture attacker traffic aiming to disrupt critical infrastructure operations. In this paper, we propose LLMPot, a novel approach for designing honeypots in ICS networks harnessing the potency of Large Language Models (LLMs). LLMPot aims to automate and optimize the creation of realistic honeypots with vendor-agnostic configurations, and for any control logic, aiming to eliminate the manual effort and specialized knowledge traditionally required in this domain. We conducted extensive experiments focusing on a wide array of parameters, demonstrating that our LLM-based approach can effectively create honeypot devices implementing different industrial protocols and diverse control logic.

## KEYWORDS

ICS Honeypots, LLM, Protocol Emulation

## 1 INTRODUCTION

Industrial Control Systems (ICS), including programmable logic controllers (PLCs), are essential for managing operations of industrial processes across various sectors, like power generation and distribution, water treatment facilities, and manufacturing plants, among others. The industrial landscape has been going through a rapid transformation, with contemporary deployed ICS devices gaining increased connectivity, support enhanced programmability, and offer advanced features such as encrypted connections and

on-device web servers. Essentially, this merges the Operational Technology (OT) with the Information Technology (IT) space.

Due to the critical nature of the infrastructure they manage, ICS are increasingly targeted by cyber attacks. And given the increased connectivity of ICS devices as well as the much larger attack surface due to the numerous features offered by modern ICS, attackers can find many entry points to these systems. Notable incidents include the Stuxnet [26] worm that targeted Iranian nuclear facilities, causing physical damage to centrifuges and the Ukraine power grid attack [30] powered by the BlackEnergy [24] malware, leading to widespread electricity outages. The implications of such attacks are severe, ranging from economic losses and environmental damage to risks to human life and national security, highlighting the crucial need for robust cybersecurity measures in these systems.

A honeypot serves as a security mechanism specifically designed in a controlled and isolated environment to improve cyber security posture of ICS devices [13, 33, 36, 47]. The objective of honeypots is to mimic the functionalities of real ICS devices so convincingly that they attract and redirect malicious activities away from legitimate devices. This allows security professionals to monitor and analyze the intercepted network traffic, offering insights into attacker methods and improving the security of critical infrastructures. Therefore, the primary challenge lies in developing a honeypot that closely mimics the behavior and responses of ICS devices with such precision that it becomes indistinguishable from the actual devices, ensuring the honeypot's effectiveness as a security decoy.

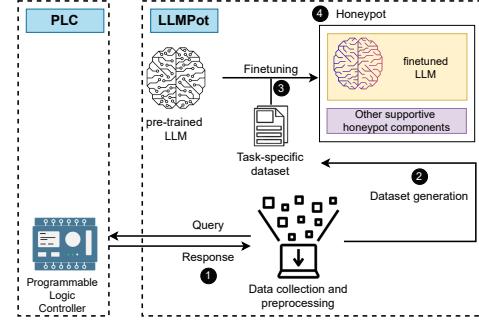
Existing ICS honeypot frameworks primarily focus on emulating industrial protocols, which requires extensive knowledge and implementation capabilities of the associated network communication protocols. Notably, many protocols are proprietary and vendor-specific, making their documentation rarely available to the public. A crucial metric of honeypot effectiveness is its level of interactivity. As defined in HoneyPLC [29], *low-interactive honeypots* typically offer services mainly developed using basic scripts and finite state machines. As a result, attackers may not be able to carry out their attack phases fully or may even recognize that they are interacting with a decoy system. In contrast, *high-interactive honeypots* are designed to mimic nearly all, or a substantial portion, of the services the real device provides, making them virtually indistinguishable.

While useful for specific purposes, low-interactive honeypots [9, 12, 23, 25, 38, 48] have inherent limitations to emulate the full spectrum of services that real devices offer, making them more susceptible to being identified by potential attackers [29]. High-interactive honeypots [8, 14, 15, 28, 29, 43, 51], aim to offer a more comprehensive emulation of industrial devices by supporting physical processes to varying extents. However, their capabilities tend to be restricted to specific scenarios (e.g., water treatment processes by Antonioli et al. [8]) and lack the flexibility to modify or extend the emulated control logic [15, 28]. They rely on existing frameworks for protocol emulation [9, 23], which provide only a limited set of functionalities. Additionally, some high-interactive honeypots do not implement physical process emulation [14, 29, 43, 51]. Hence, despite their advanced level of interaction, even high-interactive honeypots face limitations in their emulation scope. Such limitations highlight a fundamental challenge in existing honeypot development: Achieving a balance between specificity in emulation and the ability to adapt. For a honeypot framework to be truly effective, it must not only convincingly emulate specific industrial protocols and processes, but also adapt to various operational scenarios without requiring manual intervention. This adaptability remains a major obstacle for low- and high-interactive honeypots.

To effectively address the adaptability challenges of existing ICS honeypot frameworks, it is essential to develop an automated system capable of emulating industrial protocols and control logic of ICS devices. Current emulation strategies, which rely on static scripting or fully-fledged applications [29], often fail to cover all possible scenarios, eventually leading to replies that may not fully reflect to real-world responses. These methods also require deep understanding of industrial protocols and significant manual effort to accurately model physical processes that are often unique to each scenario. Thus, the essence of the issue is the need for an automated module capable of generating responses to protocol-specific requests, aligning with expected physical interactions controlled by the ICS device's control logic. This requires a careful interpretation of incoming requests to provide valid and accurate responses.

The desired functionality of such an automated module is to generate a sequence of responses for protocol-specific queries. The requirement for sequential responses points to the use of machine learning models tailored for processing sequential data. Long Short-Term Memory (LSTM) [21] and Transformers [50] are particularly effective in this context, with Transformers being favored for their ability to handle long-term dependencies. The recent emergence of Large Language Models (LLMs) such as GPT-4 [7] and LLaMA [46], which use Transformers architecture, represents a significant advancement in sequential data generation. Their ability to generate precise, context-specific responses makes them ideal candidates for the development of an automated module generating structured network packets that emulate ICS protocols and physical processes.

Therefore, in this paper, we introduce LLMPot, an LLM-based approach for protocol and physical process emulation, leveraging pre-trained LLMs. To the best of our knowledge, this is the first work where pre-trained LLMs are used to emulate ICS protocols and physical processes or control logic installed in PLCs. The use of pre-trained LLMs offers two advantages: First, it significantly reduces resource consumption and accelerates development timelines, thanks to these models' pre-existing training on broad datasets,



**Figure 1: High-level diagram of LLMPot.** The aim of LLMPot is to be able to “copy” an industrial protocol and process running on a PLC port and “paste” it to an LLM: 1. A client that automatically probes the PLC and captures responses. 2. Captured traffic forms a training dataset. 3. Finetuning of the LLM using the dataset. 4. Generated LLM-based Honeypot with supportive components.

eliminating the need for costly and time-intensive training from scratch. Second, these pre-trained LLMs can be efficiently finetuned with a relatively small and domain-specific dataset, enhancing their ability to generate specialized and accurate responses.

As Figure 1 shows, our methodology enables “**copying**” of an industrial protocol running on a PLC port (example, “Modbus:502”) and “**pasting**” to an LLM, which we call LLMPot. After LLMPot has been successfully trained, it can be deployed either as a single instance or in multiple copies with potentially different IPs to capture more attacker traffic. The PLC device is only used during the offline phase to build the honeypot and is not needed during the honeypot deployment. The main **contributions** of LLMPot can be summarized as follows:

- It proposes a novel automated ICS network traffic dataset generation approach for emulating industrial network protocols using LLMs. The approach is flexible and supports the emulation of various protocols, demonstrating its effectiveness in generalizability compared to the state-of-the-art.
- It extends the dataset generation using a weighted approach to explore effective strategies for emulating physical processes or control logic installed in PLCs.
- It proposes three metrics for evaluating the performance of LLMs in honeypot development: *Byte-to-byte Comparison Accuracy* (BCA), *Response Validity Accuracy* (RVA), and *Response Validity Accuracy - Epsilon* (RVA- $\epsilon$ ).
- It proposes a framework for developing ICS Honeypots from PLC devices using the LLM-based emulation of network protocols and physical processes along with other supportive honeypot components. The code will be made publicly available.

## 2 BACKGROUND

### 2.1 ICS Devices and Communication Protocols

A key component in ICS networks is the PLC, a compact industrial computer programmed to perform logical operations based on inputs from sensors, relays, switches, and others to control actuators, valves, and more. Prominent PLC vendors include Allen-Bradley,

Modbus Communication								
Modbus Application Protocol (MBAP) Header				Protocol Data Unit (PDU)				
Transaction ID	Protocol ID	Length	Unit ID	Function	Data			
a 00 01	00 00	00 06	00	03	00 01	00 01		
b 00 01	00 00	00 05	00	03	02	00 00		

S7 Communication - Query								
Header				Parameter				
Protocol ID	ROSCTR	Redundancy ID	(PDU) Reference	Parameter length	Data length	Function	Item count	Items
c 32	01	00 00	01 00	00 0e	00 00	04	01	12 0a..

S7 Communication - Response								
Header				Parameter				
Protocol ID	ROSCTR	Redundancy ID	(PDU) Reference	Parameter length	Data length	Error class/ code	Function	Data
d 32	03	00 00	01 00	00 02	00 04	00 00	04	01 05 ...

**Figure 2: Modbus and S7Comm packet structure attributes with an example of a query and respective response.**

Siemens, WAGO, and ABB. ICS communication protocols like Modbus [31], S7Comm [49], EtherCAT [18], and Profinet [37] have been developed to enable reliable and efficient data exchange within these PLCs to monitor physical processes across various sectors.

Figure 2 depicts the frame formats for two different industrial communication protocols: Modbus and S7Comm. It shows a Modbus query frame **a** and response **b**, as well as an S7Comm query frame **c** and response **d**. The standard Modbus protocol is wrapped in a TCP/IP layer, enabling communications over Ethernet networks. Modbus query and response frames contain a Modbus Application Protocol (MBAP) header and a Protocol Data Unit (PDU). In contrast, S7comm frames generally include a header, a parameter, and a data field. Headers in both protocols are crucial for correlating queries with responses by matching several identifiers (e.g., Transaction ID, Protocol ID, etc.) and verifying frame length. A key element in both protocols is the function code in the PDU or parameter section, which dictates the command or operation a client requests to the server. The data fields, which depend on the function code, detail the variables involved and their count. In both protocols, the data is represented as a series of digital and analog input/output; therefore, both protocols support functions for reading and writing to these data types. Also, the packets are typically represented in hexadecimal format.

## 2.2 ICS Honeypots and Related Work

ICS honeypots are specialized cybersecurity tools designed to mimic ICS environments and devices to detect, attract, and analyze potential malicious activities targeting industrial systems. These honeypots are categorized as either *low-interactive* or *high-interactive*, based on their realism and interaction levels. Low-interactive honeypots, which simulate essential limited services, are cost-effective and relatively easy to deploy. Examples include Honeyd [38], which mimics the network stack to emulate the behavior of several operating systems, deceiving network scanning and fingerprinting tools. It is also capable of creating arbitrary virtual routing topologies. Additionally, it can evade network scanning attempts with a fake fingerprint by generating the network packets needed for the corresponding scanning attempts. CryPLH [12] uses a Python script to mimic S7Comm protocol and a version of the Simple Network Management Protocol (SNMP) to replicate a very specific

Siemens PLC's functionality. SHaPe [25] supports the IEC 61850 standard by utilizing Dionaea, a deprecated work with no online resources. Gspot [48] simulates the external behavior and command responses of the gas-tank-monitoring systems that monitor fuel levels remotely to observe potential attacks, without emulating any ICS communication protocol. Conpot [23] proposes a framework that emulates several industrial protocols, such as Modbus, S7Comm, and EtherNet/IP [40]. MiniCPS [9] offers a palette of physical processes that other honeypots can use on demand. However, the simplicity and limited functionality of these honeypots often lead the attackers to quickly identify them as decoys [29].

On the other hand, high-interactive honeypots provide a more complex and authentic environment that simulates real operating systems and their services, making them ideal for detailed data collection on attackers' methodologies. Key examples of high-interactive honeypots include DiPot [14], which is a distributed system that uses Conpot [23] to simulate industrial protocols like Modbus, S7Comm, BACnet, SNMP, ipmi, Guardian\_Ast, and Kamstrup. S7commTrace [51] claims superiority over Conpot [23] by extending S7Comm protocol with additional function codes. HoneyPLC [29] enhances functionality by simulating the storage of ladder logic on PLCs and supports out-of-the-box PLCs Siemens S7-300, Allen-Bradley MicroLogix 1100, ABB PM554-TP-ETH PLCs, etc. NeuralPot [43] employs a Generative Adversarial Network [20] and Auto-Encoders [22] to learn the behavior of the ICS device and dynamically generate Modbus traffic. However, these systems lack the essential aspect of ensuring high fidelity by emulating a physical process. Antonioli et al. [8] addressed this by designing a virtual high-interactive honeypot that mimics a water treatment process. However, developing a testbed that accurately simulates real-world conditions or integrates various technologies is challenging and highly complex. On top of that, building testbeds is costly and requires regular maintenance and technical support to keep the testbed operational, which involves an ongoing effort. HoneyPhy [28] focuses on creating realistic cyber-physical system (CPS) simulations using the Distributed Network Protocol (DNP3) protocol [16]. However, this work relies on constructing a white box model, which requires detailed knowledge of the ICS device. ICSPot [15] is built on top of HoneyPLC [29], focusing on emulating network communications and physical-layer interactions using Industrial Hacking Simulator [27]. It utilizes a simplified simulation of water treatment process provided by MiniCPS [9]. However, this work only supports a single predetermined physical process.

Table 1 illustrates a qualitative comparison of the aforementioned state-of-the-art honeypots with our proposed LLMPot. Honeyd [38], Conpot [23], and MiniCPS [9] are mostly used as frameworks to build honeypots on top, providing services and functionality other honeypots can leverage from. Whereas CryPLH [12], SHaPe [25], DiPot [14], S7commTrace [51], HoneyPLC [29], and NeuralPot [43] focus mainly on providing ICS network services and out-of-the-box PLC functionality, but generally lack in implementing physical interactivity. In the context of emulation, several works emulate only a single protocol, marked as *S* in the table. While among all these works, Conpot [23], DiPot [14], HoneyPLC [29], and ICSPot [15] emulate multiple industrial communication protocols, marked as *M*. Many of the frameworks include logging features that capture crucial data on cyber-attackers, such as IP addresses, query details,

**Table 1: Comparison of different honeypots in the literature.**

Honeypot	Interactivity	PLC Extensibility	Emulation		Logging
			Protocol	Physics	
Honeyd [38]	low	●	-	-	✓
CryPLH [12]	low	○	S	-	✗
SHaPe [25]	low	●	S	-	✓
Gaspot [48]	low	○	-	Pre	✓
Conpot [23]	low	●	M	-	✓
MiniCPS [9]	low	●	S	Pre	✓
DiPot [14]	high	●	M	-	✓
S7commTrace [51]	high	●	S	-	✓
HoneyPLC [29]	high	●	M	-	✓
NeuralPot [43]	high	○	S	-	✓
Antonioli et al. [8]	high	○	S	Pre	✓
HoneyPhy [28]	high	○	S	Pre	✗
ICSpot [15]	high	●	M	Pre	✓
LLMPot (this work)	high	●	M	Any	✓

●: Extendable to cover any PLC device, ○: Limited coverage, ○: No coverage, S: Limited to cover only single protocol, M: Covers multiple protocols, Pre: Limited to cover a pre-defined set of processes, Any: Covers any process as it is learned from the PLC, - (dash): Not supported.

and timestamps. Such data is crucial for analyzing attack techniques and developing defensive strategies that enhance security. HoneyPLC [29] and ICSpot [15] utilize a profiler for their honeypot setup to acquire device-specific parameters to disguise as a real PLC device, whereas all other related works rely on the manual edition of these parameters in a device-specific configuration file. Therefore, the PLC Extensibility<sup>1</sup> depicted in Table 1 shows ● (full coverage) for HoneyPLC and ICSpot, whereas most of the other related works are marked as ○ (limited coverage) or ○ (no coverage at all). Despite the advanced features of HoneyPLC and ICSpot, HoneyPLC does not support interactive emulation of physical processes for attackers, and ICSpot is restricted to only a pre-defined number of physical processes. In this work, we propose LLMPot to provide a versatile and extensible framework for generating a high-interactive honeypot using LLMs. This framework is designed to effectively emulate multiple protocols and any physical processes running on various PLC devices while also logging data on cyber attackers attempting to infiltrate the honeypot.

### 3 LLMPOT OVERVIEW

#### 3.1 Research Questions

Using an LLM to emulate industrial protocols and physical processes involves intricate tasks. For industrial protocols, it is essential to accurately capture and replicate the complex interactions between devices. Likewise, for physical processes, accurately modeling variable changes is critical. These efforts require careful data preparation for the model training, which presents various research questions in achieving realism and maintaining accuracy:

<sup>1</sup>As defined in [29], it allows effective PLC simulation of different models and vendors.

- **RQ1: Protocol Emulation Challenge:** Can an LLM emulate the behavior of an ICS protocol with its wide range of functions and values? Can it provide realism by incorporating exception handling? Can the dataset generation be extended to other protocols and dynamically configured to adapt to different parameters and circumstances?
- **RQ2: Process Emulation Challenge:** Can an LLM learn to emulate the control logic of industrial physical processes and accurately capture the states of the variables? What is the limit of complexity for control logic that this framework can handle without failing?
- **RQ3: Honeypot Efficiency:** Can the honeypot reflect the PLC device’s authentic characteristics upon scanning and disguise itself as a realistic device? Can the honeypot deceive network reconnaissance tools?

#### 3.2 LLM Evaluation Metrics

The primary objective of LLMPot is to leverage LLMs for developing ICS honeypots that not only attract and analyze potential cyber threats but also significantly improve honeypot realism and effectiveness through advanced language processing. A key element of these honeypots is their interactivity, which relies on their ability to respond accurately to requests with appropriate data. To assess LLMPot’s ability to respond appropriately, we define three different metrics:

##### Definition 3.1

###### Byte-to-byte Comparison Accuracy (BCA)

A byte-to-byte comparison of the expected response with the response generated from the finetuned LLM. The total accuracy is a percentage of the exact correct responses over the total requests sent.

The BCA metric measures whether the LLM can produce the exact response the PLC would produce for the same request, tested byte-by-byte. While BCA is a straightforward way to assess LLM’s accuracy, sometimes the bytes may not match for various reasons, for example, the physical process returns a different integer value, while the response packets themselves otherwise are perfectly valid. Therefore, to measure the ability of the LLM to respond with valid packets, we need to define a new metric, RVA.

##### Definition 3.2

###### Response Validity Accuracy (RVA)

A custom **validator** that checks if a produced response from the LLM is an expected network packet (see Figure 2) in terms of specific fields of the protocol, like *transaction id* or *function code*, but ignores the actual value of the analog or digital inputs/outputs and only validates if they are within the protocol defined range.

It should be explicitly noted that RVA is not simply packet validity (i.e., the packet produced is a valid protocol packet) but checks individual fields for validity, e.g., *transaction id* and/or *function code*. Merely producing a valid network packet that is meaningless can

be easily detected as a honeypot. Obviously, RVA will be equal to or greater than BCA.

Typically, attackers check if they are receiving a valid response and rarely further analyze the data fields of the response to understand whether the underlying physical process produces expected responses. For sophisticated attackers who would check the data fields for physical process responses, BCA needs to be maximized, as RVA maximization may not be sufficient. However, since the expected responses are based on the underlying process that could include noise and disturbances, they can potentially differ by some amount  $\epsilon$ . This variation can still mislead the attacker into thinking a real process is being controlled. Therefore, we introduce a new metric  $\text{RVA}-\epsilon$  to capture this  $\epsilon$  difference.

### Definition 3.3

#### Response Validity Accuracy - Epsilon (RVA- $\epsilon$ )

$\text{RVA}-\epsilon$  expands the RVA metric by also checking the actual value of analog or digital inputs/outputs. If the value is within  $\pm\epsilon$  of the actual value, the response is considered accurate.

Following Definition 3.3, it can be inferred that  $\text{RVA}_0 = \text{BCA}$  and  $\text{RVA}_\infty = \text{RVA}$ . Also,  $\text{BCA} \leq \text{RVA}-\epsilon \leq \text{RVA}$ .

### 3.3 Base LLM

Generally, LLMs excel in generative tasks, primarily through a tokenizer, which converts incoming text into tokens that can then be used to formulate the response. In the context of network protocols, effective tokenization would require a deep understanding of each protocol, considering the structured layers of packets, each with its unique fields and parameters. Thus, creating a universal tokenizer capable of handling multiple protocols poses significant challenges. We essentially need a machine learning model that would not need tokenization to understand the network packet and produce responses.

The ByT5 model, developed by Google, introduces a novel approach to natural language processing by operating at the byte level, diverging from traditional token-based architectures [52]. By processing text as a sequence of UTF-8 encoded bytes, ByT5 can handle a diverse range of languages and special characters without relying on a predefined vocabulary. This byte-level processing enables the model to manage inputs and outputs simply as byte sequences. Given this capability, if we consider only a specific ICS network protocol layer within the entire TCP packet stack, we can input just this segment to the ByT5 model and receive a response without needing to tokenize the packet. This method highlights the clear advantages of choosing the ByT5 model as the base LLM for LLMPot, as it eliminates the need for tokenization. In LLMPot, a hexadecimal representation of the request packet is fed into the ByT5 model, which returns the response in the same format.

### 3.4 Dataset Generation Process

The efficacy of finetuning LLMs for specific tasks heavily relies on the quality of the dataset used. A key factor in dataset generation is ensuring diversity across various scenarios relevant to the task. This diversity prevents model bias and enhances its ability to generalize

across different conditions, leading to more robust performance. Figure 3 illustrates a flow diagram of the dataset generation process adopted by LLMPot, which begins with a configuration file for the industrial protocol (step ①). This file includes various attributes and constraints that are unique to the specific protocol used by the target PLC device which the LLM aims to “copy”.

**3.4.1 Protocol Client Initialization.** The parameters specified in the configuration file are crucial for constructing a customized/user-specific PLC client that effectively replicates ICS interactions (see protocol client module in Figure 3). These settings ensure that the protocol client meets specific user requirements and adheres to protocol standards. Figure 3 presents an example of a JSON configuration file used as an input during dataset generation, which includes various client/server configuration attributes. The *protocol* attribute specifies the industrial protocol used, such as “modbus”. The range of *function* codes specifies permissible actions within the protocol, as each function supports a specific operation that allows the protocol server to perform a task. Each function corresponds to a single or multiple read/write commands to a specific data type, where data types are categorized as either digital or analog inputs. For example, the packet sample in Figure 2, ② shows the function code as “03”, which is decoded to read analog data from a specific address in Modbus, while the function code “04” in Figure 2, ③ is decoded to read the data address from a specific data block area in s7Comm. The range of data *values* specifies the valid data points for each input and output, guaranteeing that the operations are within an expected scope and preventing incorrect data values. The permissible set of data values that can be read from or written to the PLC device is crucial for ensuring that the created dataset accurately reflects realistic and applicable data scenarios. The maximum range of valid *addresses* determines the maximum possible accessible areas within the PLC memory for the protocol. The range of valid addresses is identified by how many elements or components are needed to be active, based on the user’s requirements. Once the active components are identified, they are mapped to their corresponding addresses in the PLC’s address space. This mapping allows direct access to relevant data, preventing unauthorized access. To generate the configuration file, a user needs to have an understanding of different fields in the target protocol, which serve as attributes in the configuration file.

**3.4.2 PLC Probing.** After the initialization, the protocol client establishes a connection to the target PLC device, allowing interaction through various request-response commands (step ②). Subsequently, an extensive network interaction traffic between the protocol client and the PLC is captured using a tool like Unix *tcpdump* [45] (step ③). Capturing this traffic allows for collecting real-life PLC interactions, enhancing the diversity and realism of the communication data. The captured network traffic is stored in a packet capture (PCAP) file. This file is sent as input to a parser (step ④) to extract useful information.

**3.4.3 PCAP Parser.** The parser is specifically designed to convert the raw binary data from the PCAP file into hexadecimal byte strings, which are essential for analyzing network traffic. The parser then aligns responses with their corresponding requests to ensure the correct interactive sequences. This aligned data is saved in a

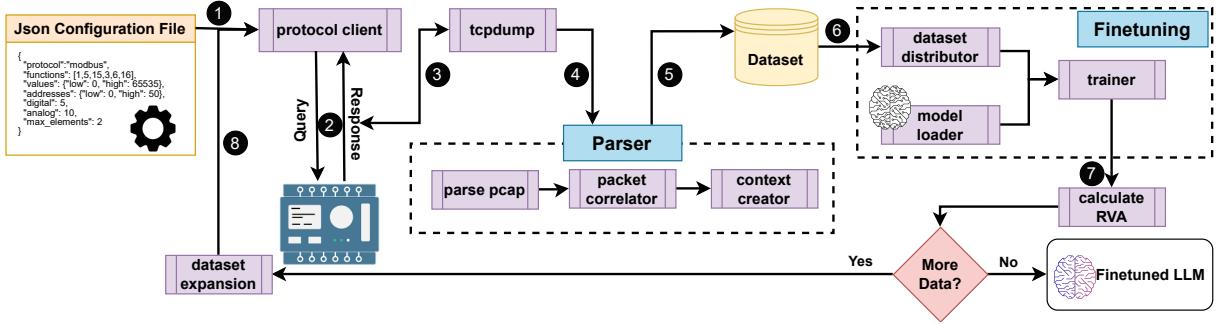


Figure 3: Dataset generation and LLM finetuning process used in LLMPot.

source_text					
Query 1	:	Response 1		Query 2	:
0001000000600040000002	:	0001000000700040400003fb0		0002000000600030000002	
<b>target_text</b>					
Response 2					
000200000070003040000000					

Figure 4: Sample output of context creator with context length 1.

CSV format (step ⑤), where each entry is structured into columns: **source\_text** for requests and **target\_text** for responses. To prepare the data for machine learning applications, it is randomly shuffled and divided into distinct sets for training, testing, and validation.

**3.4.4 Context-Sensitive Dataset Generation.** For protocol emulation, historical data is not needed in the dataset. The dataset provides correct functionality effectively with individual requests and their corresponding responses since each pair is independent. However, emulating physical processes is more intricate. In this scenario, the response to a request might be affected by changes from previous interactions. Thus, datasets aimed at emulating physical processes must include contextual information to reflect the dynamic and interconnected nature of these events accurately. The PCAP parser includes an additional pre-processing step that organizes data into a specific format to differentiate between sessions and build a structured contextual dataset. Figure 4 illustrates an example where the context length is one. The input sample, labeled as **source\_text**, contains a session of a request (query 1) and a response (response 1), separated by a colon ":". This session is followed by another session, separated by a pipe "|". For this example, with a context length of one, the next session contains only the next request (query 2). A colon is also added at the end to ensure the model is trained to produce the corresponding response. The response to query 2 (response 2) is stored separately in the **target\_text**. This structured dataset helps in finetuning the LLM to produce context-aware responses and adjust to new queries based on past interactions. For a longer context, the input format extends to include more query-response pairs before introducing a new query. For example, with a context length of two, the input includes two consecutive query-response pairs followed by a third query.

### 3.5 LLM Finetuning Process

LLMPot utilizes the PyTorch Lightning framework [4] to facilitate a structured method for model training, including efficient dataset

management, validation during training, and post-training testing cycles. This framework has been adapted to finetune a pre-trained ByT5 model (e.g., google/byt5-small), which we use as our base LLM. Performance of the finetuned LLM is measured explicitly as how accurately the model produces replies to specific requests (see Definition 3.1, Definition 3.2, and Definition 3.3).

**3.5.1 Model Finetuning.** Figure 3 presents a flow diagram of the LLM finetuning process adopted in this framework. The process begins with the dataset distributor module, which inputs the generated dataset from Section 3.4 into the trainer module (step ⑥). Simultaneously, the trainer module loads the pre-trained base LLM and initiates the finetuning phase. The trainer module performs a test cycle at the end of each training epoch, enabling continuous evaluation against a test dataset to monitor the actual model performance. The finetuning phase is terminated if there is no improvement in validation loss after a set number of consecutive epochs. This early termination helps prevent overfitting and optimize the model's generalization to new, unseen data. Two critical hyperparameters for ByT5 model finetuning are **source\_max\_token\_len** and **target\_max\_token\_len**. The former limits the number of bytes in the input sequence provided to the model, and the latter sets the maximum length of the output sequence generated by the model as a response during inference. The values for these hyperparameters are derived from the PCAP Parser, based on the network packet lengths of requests and responses.

**3.5.2 Iterative Dataset Sizing.** It is crucial to determine an appropriate dataset size for LLM finetuning. A dataset that is too small may not fully capture the complexity of the task, leading to underfitting. In contrast, an excessively large dataset can lead to overfitting and unnecessary computational expenses. Therefore, as discussed in Section 3.5.1, the finetuning process begins with a small dataset size. The finetuned model is then evaluated using the RVA- $\epsilon$  metric (step ⑦) outlined in Section 3.2. The dataset size is then incrementally doubled through a dataset expansion module requesting additional data from the protocol client (step ⑧). The model is further finetuned with each increase in dataset size. This iterative process continues until no further improvements in the RVA- $\epsilon$  metric are observed across multiple consecutive iterations over different dataset sizes. This approach provides a controlled and systematic exploration of the relationship between dataset size and model performance, identifying a point of diminishing returns where additional data no longer contributes to better model performance.

The framework returns the finetuned LLM that effectively emulates the target PLC device.

## 4 LLMPOT INDUSTRIAL NETWORK PROTOCOL EMULATION

We first aim to train an LLM that can accurately respond to network packets from a PLC device supporting a specific network protocol.

### 4.1 Method to Generate Representative Dataset

The approach builds on the dataset generation method described in Section 3.4. The implementation of the *protocol client* shown in Figure 3 is described in Algorithm 1. Most protocols typically support the reading or writing of multiple values with a single command. This algorithm manages the *m\_elem* parameter, which must be set to an integer signifying the maximum number of read/write requests using only one command specified by the protocol. The parameters *addr\_low* and *addr\_high* represent the range of analog or digital variables involved, subject to the constraints of the chosen protocol. The permissible values for these variables may be user-defined or set to the maximum the protocol allows.

Algorithm 1 describes the *boundaries* method for reducing the dataset size needed to cover the entire address and value space supported by a protocol by selecting only the minimum, maximum, and one randomly chosen intermediate value for each sample request. The method starts with the *execute* function [line: 7], which probes the PLC with read and write commands. The total list of commands is coordinated by the “functions” attribute in the configuration file, as outlined in Section 3.4. The initial loop [line: 8] iterates through values from one to *m\_elem*, setting up the subsequent loops and operations. The second loop [line: 11] iterates over values derived from the *triplet* function [line: 31], demonstrating that valid responses lie between the lowest and highest values. To further add a layer of realism, this method includes requests that trigger erroneous responses (i.e., exceptions). Exceptions can occur when a request is made using an inactive address outside the valid range. This approach allows the dataset to reflect typical operational data and include scenarios that simulate potential error conditions. Before the final loop [line: 13], the *combs* function [line: 21] is called to produce all possible data combinations based on the given range of possible values and the number of elements to accommodate.

The *Combs* function [line: 21] starts by calling the *triplet* function to obtain a set of three numbers. These numbers are then used to compute the Cartesian product of the specified number of elements [line: 23], which is later used in the request commands that include multiple inputs. In this way, we cover all possible combinations of values for the number of elements. The resulting values are formatted into triplets for use in the *execute* function. The *Triplet* [line:31] function generates three specific values: the lowest, the highest minus the provided elements, and a random number in between, which forms the basis of *boundaries* method. The *execute* function then sends requests to a PLC or simulator and is called repeatedly to align with the dataset size in the configuration file.

After executing Algorithm 1, we obtain a dataset that describes a protocol in a non-exhaustive manner. By employing the *boundaries* method, we significantly reduce the dataset size compared to what would be required using an exhaustive approach from a

---

#### Algorithm 1 LLMPot Protocol Emulation using *boundaries*

---

**Require:**

```

1: read, write: abstract functions specific to the network protocol.
2: m_elem: the number of elements up to which to read or write using
   only one command.
3: addr_low, addr_high: the range of addresses available according to
   the protocol running on the PLC.
4: max_addr: max address supported by PLC-protocol combination.
5: val_low, val_high: the range of values that the PLC is configured to
   reply with normal responses.
6:
7: function EXECUTE
8:   for elem in range(1, m_elem) do
9:     bounds  $\leftarrow$  TRIPLET(addr_low, addr_high, m_elem)
10:    e_bounds  $\leftarrow$  TRIPLET(addr_high + 1, max_addr, m_elem)
11:    for addr in [bounds, e_bounds] do
12:      combinations  $\leftarrow$  COMBS(val_low, val_high, elem)
13:      for data in combinations do
14:        WRITE(address, data)
15:        READ(address, elem)
16:      end for
17:    end for
18:  end for
19: end function
20:
21: function COMBS(low, high, elem)
22:   bounds  $\leftarrow$  TRIPLET(low, high, 0)
23:   combs  $\leftarrow$  CARTESIAN_PRODUCT(bounds, elem + 1)
24:   result  $\leftarrow$  empty dictionary
25:   for comb, index in combs do
26:     result[index]  $\leftarrow$  comb
27:   end for
28:   return result
29: end function
30:
31: function TRIPLET(low, high, elem)
32:   return [low, RAND(low + 1, high - elem - 1), high - elem]
33: end function

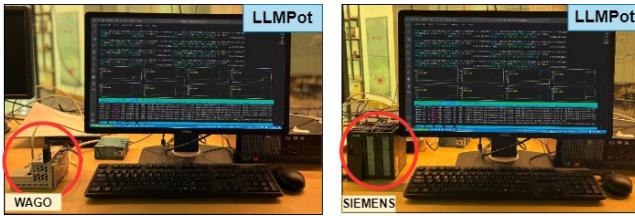
```

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scale of billions to just a few thousand. For instance, in the case of Modbus protocol, an exhaustive approach would need  $65536^2$  different requests to cover all registers and their potential values for just one type of command (e.g., read or write). Although larger datasets typically enhance model performance, they also demand significant resources for training. Boundaries method allows us to reduce the dataset size while preserving accuracy. Required sample size for fine-tuning the LLM is discussed in the following section.

### 4.2 Finetuning base LLM

We evaluated LLMPot on WAGO and SIEMENS PLC devices (see Figure 5), which use Modbus and S7comm protocols, respectively, to demonstrate LLMPot’s generalizability in emulating different protocols. Our exploration starts by generating several datasets following Algorithm 1, aiming to identify the optimal dataset size for the best performance of the LLM. Table 2 presents various combinations of dataset size used in our experiments for dataset generation. The minimum size of the finetuning dataset is determined based on the minimum number of samples generated in one iteration by



**Figure 5:** The PLCs used in our experiments, WAGO:Modbus [6] (left) and SIEMENS:S7comm [5] (right), being copied by LLMPot.

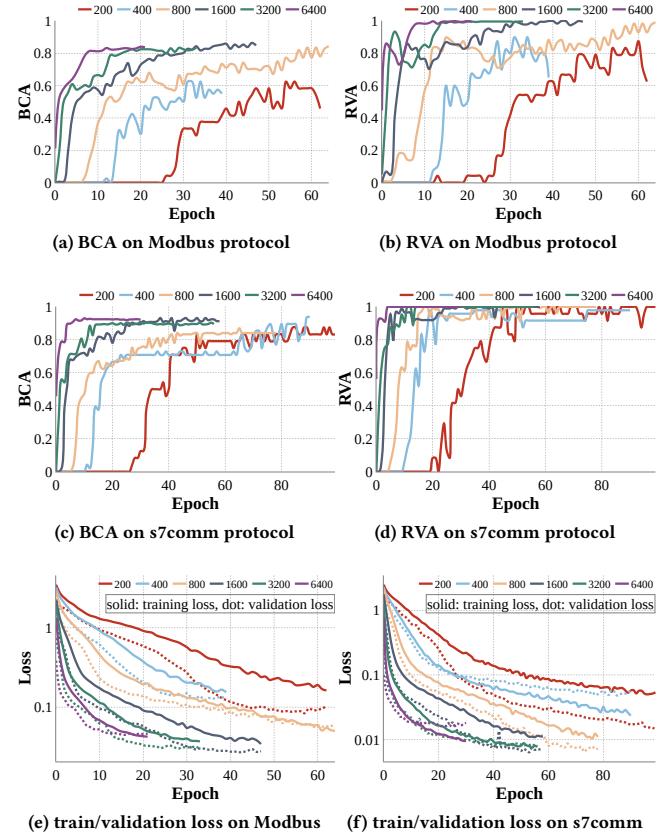
**Table 2:** Datasets used to finetune and test the finetuned byt5-small model with the corresponding PLC configuration.

Characteristic	Finetuning (80%-10%-10%) (Train-Validation-Test)	Emulation		Generalization		
		d1	d2	g1	g2	
Sizes	200, 400, 800 1600, 3200, 6400	1600		1600		
Functions	1-5-15-3-6-16					
Digital (d)	40	10000	100	5000		
Analog (a)	40	10000	100	5000		

Algorithm 1, which is 144 samples, irrespective of the protocol<sup>2</sup>. Therefore, we set the minimum meaningful sample size to 200 and continue to double the dataset size until no further improvement is observed in our results, as discussed in Section 3.5. Our evaluation focuses on a specific set of read and write commands that handle both analog and digital inputs/outputs for the protocol emulation<sup>3</sup>. Users define these commands in the configuration file to meet their specific needs. For this evaluation, we cover a subset of functions denoted by their particular numerical codes (e.g., digital read/write: 1, 5, 15, and analog read/write: 3, 6, 16). For instance, as shown in Figure (2, ❶), the function code “03” translates to the hexadecimal code for reading analog data. A finetuned LLM using these function codes will respond with an invalid packet if it encounters a function not specified in the configuration file. The specific operations associated with each function code can be found in Modbus or S7comm documentation. Industrial protocols offer a wide range of addresses to manage analog and digital read/write operations. Typically, industrial processes do not utilize the full range of available addresses, instead assigning a specific, predetermined number of variables to certain addresses. The configuration file specifies the count of valid analog and digital inputs and outputs. We experimented with various numbers of permissible inputs and outputs across the allowable range for both Modbus and s7comm protocols, with values ranging from lower (e.g., 40, 100) to higher (e.g., 5000, 10000). This was done to demonstrate the efficiency of protocol emulation across both small and large sets of addressable inputs and outputs within these protocols. For finetuning, we randomly select 40 valid analog

<sup>2</sup>The number of samples is determined by the *max\_elements* attribute specified in the configuration file. This attribute defines the number of elements to read or write using only one command, which is independent of the protocol used. The number of samples of 144 is generated by Algorithm 1 using *max\_elements*, regardless of any other parameters used in the algorithm.

<sup>3</sup>We focused on read and write commands as our final goal is to emulate physical processes that involve these commands.

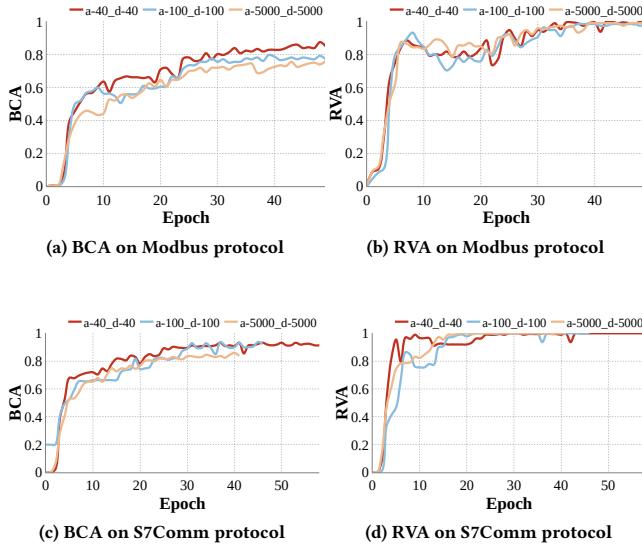


**Figure 6:** The BCA and RVA per epoch of the byt5-small model when using different dataset sizes and protocols to finetune. A patience value of 10 epochs was used to stop the finetuning in case the validation loss was not improving, thus the different ending epochs for each dataset size.

and digital inputs and outputs. We consider two distinct emulation datasets: **d1**, having the same PLC configurations as the finetuning datasets, and **d2**, which utilized different configurations, both comprising 1,600 samples<sup>4</sup>. While **d1** includes 40 valid inputs and outputs, **d2** contains 10,000. Additionally, we demonstrate LLMPot’s generalization capabilities with two more datasets, **g1** and **g2**, each with 1600 samples but differing in the number of active addresses for digital and analog inputs and outputs in the PLC setups. While **g1** includes 100 valid inputs and outputs, **g2** contains 5,000.

During the finetuning phase, we evaluate the LLM’s performance using the BCA and RVA metrics at the end of each epoch, using 10% of the finetuning dataset. This assessment helps determine how many epochs are necessary for the model to reach its maximum performance, given the dataset size. Figure 6 presents the BCA, RVA and train/validation losses for both protocols for different

<sup>4</sup>We determined through experimentation that the smallest dataset size that yields the best performance is 1600 samples. Increasing the dataset size beyond this point does not further improve results.



**Figure 7:** The BCA and RVA per epoch of the byt5-small model when using different configurations of analog and digital inputs/outputs.

dataset sizes. We can observe that the RVA improves more rapidly and achieves higher values as the dataset size increases.

For smaller datasets, overfitting is evident as depicted by the validation loss surpassing the training loss (Figure 6e and Figure 6f). Additionally, losses for these smaller datasets remain relatively high, indicating inadequate finetuning. The results conclude that the LLM can effectively learn and respond to network protocols, providing responses with high RVA that verifies that the responses are valid network packets. Additionally, the saturation of the model’s performance with increasing dataset size supports the effectiveness of using the *boundaries* method to create a smaller finetuning dataset rather than adopting an exhaustive approach for dataset generation.

We consider a finetuning dataset of 1600 samples along with  $\mathbf{g}_1$  and  $\mathbf{g}_2$  to demonstrate the generalizability of LLMPot across varying numbers of active addresses for digital and analog inputs and outputs in PLC setups. Figure 7a and Figure 7c presents the BCA and Figure 7b and Figure 7d presents the RVA metrics for different combinations of analog and digital inputs and outputs for both Modbus and S7comm protocols. We can observe that all plots share similar characteristics with almost identical final values. Figure 7a and Figure 7c show that the BCA values over the training epochs converge closely, highlighting the stochastic nature of LLM training. Figure 7b and Figure 7d present similar outcomes but with slightly improved metrics due to the characteristics of the RVA metric. The results conclude that regardless of the PLC configuration in terms of address availability for digital and analog inputs and outputs, the model’s performance remains consistent when the same dataset size is used for finetuning.

Table 3 provides a high-level request/response set for different PLC configurations. The request column has some indicative commands with specific addresses, which are corner cases permissible from the protocol for input and outputs. The response column consists of  $\mathbf{d}_1$ ,  $\mathbf{d}_2$ , and model sub-columns. These sub-columns

**Table 3:** Example request-response set for the different emulation scenarios, the model’s responses and the validation using both BCA and RVA.

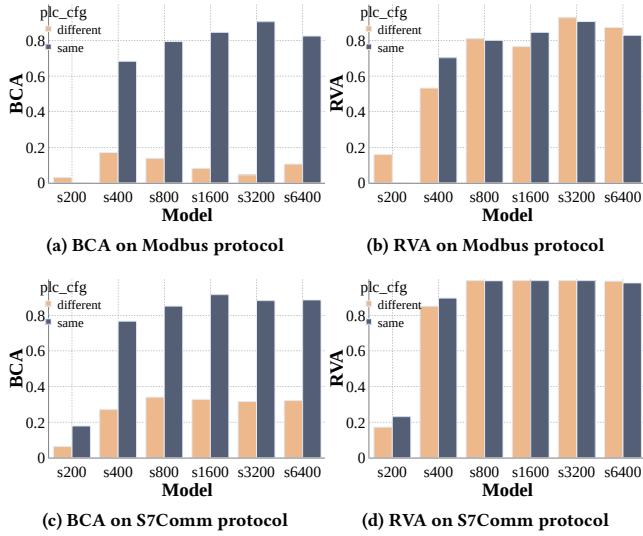
Request	Response			BCA		RVA	
	$\mathbf{d}_1$	$\mathbf{d}_2$	Model	$\mathbf{d}_1$	$\mathbf{d}_2$	$\mathbf{d}_1$	$\mathbf{d}_2$
read(addr=41)	exc	val	<b>exc</b>	✓	✗	✓	✓
read(addr=41)	exc	val	<b>val</b>	✗	✓	✗	✗
read(addr=10001)	exc	exc	<b>exc</b>	✓	✓	✓	✓
read(addr=10001)	exc	exc	<b>val</b>	✗	✗	✗	✗
read(addr=35)	val	val	<b>exe</b>	✗	✗	✗	✗
read(addr=35)	val	val	<b>val</b>	✓	✓	✓	✓

contain the response values for the two emulation datasets and the possible responses the model (trained using the finetuning dataset) can potentially provide. Replies in bold mean a correct response and striked-out ones mean an unexpected or erroneous response. Next columns mark if the reply of the model is correct (✓) or wrong (✗) given different types of validation, BCA and RVA. As an example, in the second line of Table 3, given the request to read address 41, the  $\mathbf{d}_1$  dataset has an exception reply since the valid address range was up to 40, while dataset  $\mathbf{d}_2$  includes a reply with a value of this address because the valid range is up to 10,000. Considering that we use  $\mathbf{d}_1$  as a dataset for the validator, BCA will mark this as a wrong answer but correct if we use  $\mathbf{d}_2$ . It is worth mentioning here that BCA is just the exact match of the model’s reply against the one in the dataset. For RVA, in both cases, the reply is wrong, because the validator checks, given the requested address what should have been the correct reply, considering the PLC configuration that was used to train the model. Finally, we analyze the emulation datasets for different finetuning dataset sizes on both Modbus and S7Comm protocols and demonstrate the results in Figure 8a and Figure 8c for BCA and Figure 8b and Figure 8d for RVA. The most important outcome of the emulation is depicted in Figure 8a and Figure 8c, where the BCA is pretty low for different PLC configurations. In contrast, the RVA is high since the validator incorporates logic that compares against the PLC configuration used when training the model. Essentially, the model “copied” the PLC with a specific configuration and behaves in the same manner and not in a random way in terms of responses.

Overall, these results provide strong evidence related to Research Question (RQ1) in Section 3.1, proving that LLMPot effectively emulates the behavior of industrial network communication protocols with high realism. The results provided from both protocols, Modbus and S7Comm, prove LLMPot’s generalizability to other ICS protocols, utilizing the proposed dataset generation method.

## 5 LLMPOT PHYSICAL PROCESS EMULATION

In an ICS framework, control logic reflects the real-time interaction between devices and components involved in a physical process. Fundamental elements of a physical process are mathematical functions. Exhibiting the LLM’s ability to understand and replicate these functions is crucial for accurately mimicking physical processes.

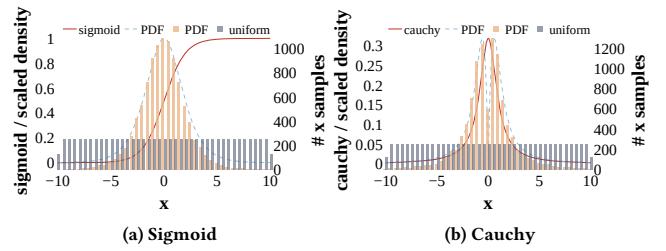


**Figure 8: Best BCA and RVA of the byt5-small model when using different dataset sizes to finetune for same and different configuration compared to the one used to finetune the model for generating the test dataset.**

## 5.1 Exploration of LLMs Learning Math

To verify ByT5 model’s ability to learn various mathematical functions, we utilized the Open Source Community for Automation Technology (OSCAT) library [3], as it provides a wide range of functionalities that can be used for industrial automation projects. This library was accessed using the CODESYS [1] platform running on a WAGO PFC200 PLC (shown in Figure 5). The mathematical functions included in this study were classified into discrete methods, involving conditional statements (signum function “*sgn*”), and continuous methods, subdivided into exponential (exponential base 10 “*expo10*” and hyperbolic cosine “*cosh*”), and bounded (“*sigmoid*” and “*cauchy*”) categories.

When trying to “copy” the behavior of a PLC, it may not be possible to know apriori the mathematical function it uses. A practical approach would be to sample the PLC’s responses across a range of uniformly spaced  $x$ -values to create a dataset. This dataset can then be used to train an LLM to approximate the PLC’s function. However, uniform sampling may not effectively capture regions where the function changes more rapidly. By focusing on the regions where the function’s slope varies significantly, we can optimize our sampling strategy for generating a dataset representing the function’s characteristics more accurately. The optimized dataset helps estimate a probability density function (PDF), highlighting areas where denser sampling is required to capture the function’s rapid changes accurately. For example, flat regions of a function might be well represented by just a few points, whereas more complex curves could require many more, ideally an infinite number. This concept is illustrated with *sigmoid* and *cauchy* functions, as shown in Figure 9. In the figure, a histogram illustrates the distribution of sampled points along the  $x$ -axis, with yellow representing points



**Figure 9: Visual examples of the sampling method to sigmoid and cauchy functions. Plotted are the corresponding functions along with the derivative and  $x$  axis bins.**

---

**Algorithm 2** Algorithm to generate a weighted distribution of  $x$ -axis points for the math function explored.

---

**Require:**

```

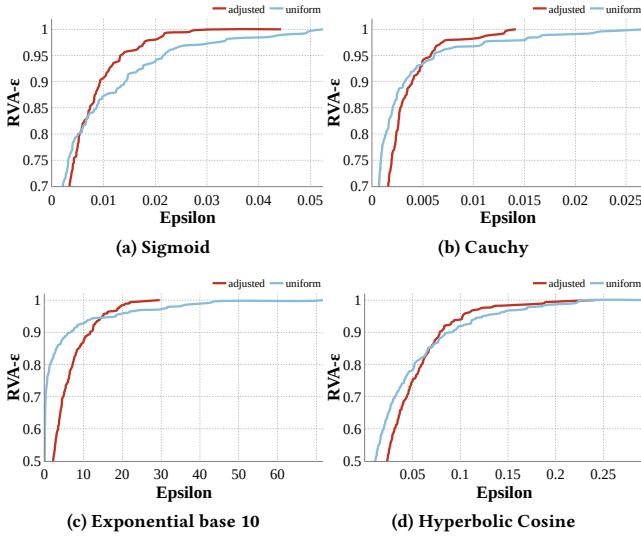
1: mix_ratio: parameter that dictates the weighting between the uniform
   and derivative-based probability density in the mixed PDF.
2: power: parameter between (0, 1] that softens high values of the df.
3: df: derivative of the math function studies, returns a set of  $x$ ,  $y$ .
4: ct: function that returns the cumulative integral of  $y$  along  $x$ .
5: inverse_cdf: function that returns values of  $x$  corresponding to the
   cumulative density values using interpolator.
6:
7: function X_AXIS_VALUES_DISTRIBUTED(x_values)
8:   samples  $\leftarrow$  LEN(x_values)
9:   dv  $\leftarrow$  DF(x_values, samples)
10:  dv  $\leftarrow$  POWER(dv, power)
11:  diff  $\leftarrow$  dv[0] - dv[1]
12:  pdf  $\leftarrow$   $\frac{dv}{\text{sum}(dv \cdot diff)}$ 
13:  uni  $\leftarrow$  ONES(samples) / samples
14:  adj_pdf  $\leftarrow$   $(1 - mix\_ratio) \cdot dv + mix\_ratio \cdot uni$ 
15:  adj_pdf  $\leftarrow$   $\frac{adj\_pdf}{\text{sum}(adj\_pdf \cdot diff)}$ 
16:  cdf  $\leftarrow$  CT(adj_pdf, x_values)
17:  cdf  $\leftarrow$  cdf / cdf[-1]
18:  uni  $\leftarrow$  RANDOM(samples)
19:  inv_cdf  $\leftarrow$  INTERP_1D(cdf, x_values, ‘linear’)
20:  x  $\leftarrow$  inv_cdf(uni)
21:  x  $\leftarrow$  SORT(x)
22:  return x
23: end function

```

---

sampled using the PDF mentioned above and grey indicating a discrete uniform distribution. We can observe that the PDF sampling is denser in areas where the functions change rapidly with  $x$  and sparser where the function values are more stable. Algorithm 2 outlines the strategy for generating this weighted dataset. The main idea is to create a distribution of points on the  $x$ -axis that best represents the  $y$ -axis values of a mathematical function.

Algorithm 2 requires uniformly distributed points as a base for sampling along the  $x$ -axis to facilitate the application of the Inverse Transform Sampling (ITS) method [41]. The *power* requirement softens the derivative values in regions of rapid change. The *mix\_ratio* requirement allows points from the uniform distribution to be mixed with those chosen by the PDF. This strategy increases the selection of points in areas where the function tends to be flat.



**Figure 10: RVA- $\epsilon$  for math functions.** In red is the metric value when using the distribution produced by Algorithm 2 and cyan is the result of using the uniform discrete distribution.

The rest of the requirements are helper functions to support the algorithm’s functionality. Algorithm 2 starts by calculating the derivative of the target function [line: 9]<sup>5</sup>, which is then raised to a selected *power* between zero and one to soften its values. The derivative is normalized [line: 12] using the difference between two uniformly distributed points [line: 11], resulting in a PDF. To avoid zeros when the function flattens and ensure a comprehensive exploration of the input space, a mixed PDF is constructed by combining the uniformly distributed PDF with the derivative-based PDF, controlled by the *mix\_ratio* [line: 14]. This ratio adjusts the contribution of each PDF to the mix, focusing on critical regions while covering the entire range. The resulting adjusted PDF is normalized [line: 15] by dividing it by the sum of the product of the mixed PDF and the interval between successive  $x$ -values [line: 11], ensuring the area under the curve equals one and forms a valid probability distribution. To derive the adjusted  $x$ -axis data points from the adjusted PDF, we first calculate the cumulative distribution function (CDF) by integrating the PDF across uniformly distributed  $x$ -values using the trapezoidal rule [line: 16] [11]. This step forms the basis for generating the inverse CDF through linear interpolation [line: 19], using the initial distribution of  $x$ -values. The inverse CDF then interacts with a uniformly distributed set of values to produce the adjusted  $x$ -axis data points, which are subsequently sorted [line: 21] for the sake of clarity in our analyses.

The output of Algorithm 2 is used in an iterative loop to probe the PLC with the sampled  $x$ -axis values to generate necessary packets for model finetuning. This loop is much simpler than the one used in for protocol emulation in Section 4. It consists of a write followed by a read on the corresponding analog input and output for each sample collected by the algorithm. The collected values are controlled by the range that communication protocols (e.g.,

<sup>5</sup>The derivative is estimated numerically based on the responses from a PLC for an unknown function.

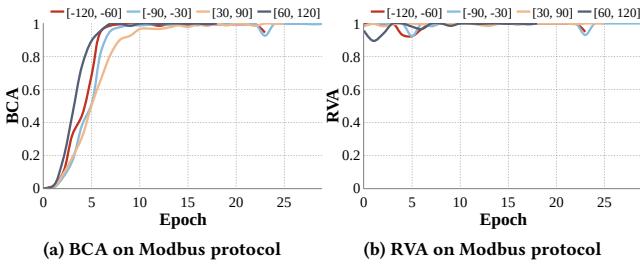
Modbus, s7Comm, etc) can support. The data collection amount follows the same method discussed in Section 4.

**Results.** The results obtained from experimenting with the capability of the LLM model to emulate math functions can be seen in Figure 10. The  $x$ -axis and  $y$ -axis depict the epsilon value and the cumulative RVA- $\epsilon$ , respectively. Starting with Figure 10a for *sigmoid* and Figure 10b for *cauchy*, Algorithm 2 manages to create an advantage over the uniform sampling method by increasing RVA- $\epsilon$  metric faster and providing full accuracy in smaller epsilon. This effect is seen to be bigger in exponential functions, like *expo10* in Figure 10c and *cosh* in Figure 10d. For these functions, the standard deviation is significantly smaller for the adjusted distribution, 5.1 for *expo10* and 0.036 for *cosh*, while it is 8.23 and 0.045 respectively when using uniform distribution. This is depicted by the fact that RVA- $\epsilon$  curve reaches its maximum sooner. On the other hand, the *sgn* outputs -1, 0, or 1 depending on whether the input is negative, zero, or positive respectively. Due to the simplicity of the conditional nature of the function, the derivative that is used to calculate PDF will always be zero. This allows LLMPot to quickly capture the pattern and emulate the function accordingly with BCA and RVA of 100%.

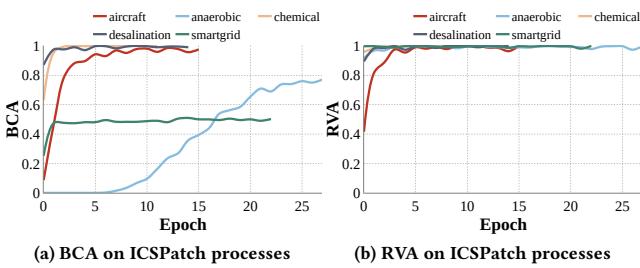
## 5.2 LLM-based Emulation of Physical Processes

Building on the results from the previous analysis, we extend our exploration to evaluate the LLM’s capabilities in emulating various control logics. We apply this analysis to five industrial processes outlined in ICSPatch [39]: *Aircraft Flight Control*, *Anaerobic Digestion Reactor*, *Chemical Plant*, *Desalination Plant*, and *Smart Grid*. These systems were accessed through CODESYS on a WAGO PFC200 PLC, with Modbus as the communication protocol.

The dataset generation process for control logic processes is similar to Algorithm 1 and involves two key functions: *valid\_function* and *exception\_function*. The *valid\_function* queries the PLC device with read and write commands within a permissible address range specified in the PLC’s memory map. This function iterates through all possible elements [line: 8] specified by the process to dictate the number of elements in the read/write commands. If the element count exceeds one, it employs multiple read or write commands accordingly. The process continues with iterations over the digital inputs, followed by the analog inputs in the control logic. The values for the write commands to these inputs are derived from evenly distributed values within a given interval, which was initially random but later adjusted incrementally to confirm consistent model performance across different intervals, as illustrated in Figure 11. Furthermore, the *exception\_function* queries the PLC with commands that target addresses beyond the valid scope using the *boundaries* method [line: 21] to generate all possible data combinations. This function is crucial for capturing exception codes from the PLC. It also iterates through every element defined in the process and creates addresses outside the valid range, as done in [line: 10], where it considers the lowest, highest, and a randomly chosen intermediate address. These functions are executed repetitively according to the dataset size outlined in the configuration file detailed in Section 3.4.



**Figure 11:** The BCA and RVA per epoch of byt5-small model when using different probe value ranges for the same physical process.



**Figure 12:** The BCA and RVA per epoch of byt5-small model emulating ICSPatch processes.

**Results.** The results obtained from experimenting with the capability of the ByT5-small model to emulate control logic processes from the ICSPatch [39] case study can be seen in Figure 12. The results of BCA and RVA shown in Figure 12a and Figure 12b, respectively, prove the ability of LLMPot to capture the states of the variables across multiple processes. However, it can be noted that the emulation for specific processes, anaerobic and smart grid, inherent some complex functionality and large input and output numbers, which require additional ablation studies to improve the dataset generation to accurately capture the variables' states. Overall, the findings of this section address the Research Question (RQ2) in Section 3.1, demonstrating that LLMPot effectively captures and emulates the control logic of industrial physical processes.

## 6 HONEYBOT DEVELOPMENT AND ANALYSIS

### 6.1 Honeybot Setup

LLMPot uses Nmap [34] and wget [19] to automatically gather essential parameters such as MAC addresses and operating systems from the target PLC device. We emulate the honeybot's TCP/IP stack using Honeyd [38], configuring it with the appropriate Nmap fingerprint and integrating real services via Docker containers [17]. These containers host both the website and the protocol emulation. The system operates on an Ubuntu 22.04 desktop setup with Honeyd and Docker, and the LLM runs on an RTX-3090 Ti. Network traffic is managed by a router that directs specific traffic to the host machine or the virtual hosts managed by Honeyd. Traffic on ports 502, 80, and 443 are routed to the host machine, where HAProxy [2] then redirects web traffic to ensure secure communication, directing HTTP to HTTPS and handling port-specific traffic.



**Figure 13: Geolocation of Honeybot Interaction**

The PLC website replication involves manually downloading the web server files. A Python Flask application mimics the site's functionality, including a REST API, to provide dynamic web content [35]. We manually generate the web server's SSL certificate using the OpenSSL tool [44]. For data logging and analysis, we employ MongoDB [32] with the Beanie ODM [10] for robust data management. The system logs detailed information about each interaction, such as IP addresses and the timing of requests and responses. It also captures login credentials attempted during brute force attacks and records incoming and outgoing Modbus server traffic.

### 6.2 Interaction Analysis and Resilience to Reconnaissance Tools

We exposed the developed honeybot to the internet to monitor network activities. Over one month, the honeybot recorded 753 connection attempts from unique IP addresses. Figure 13 indicates that most of these attempts originated in the United States (423 interactions). Germany and Great Britain (55 attempts each) are the second most common sources of interactions.

To evaluate the effectiveness of the honeybot in emulating real network devices, it was tested using various network reconnaissance tools. Nmap testing revealed that the honeybot effectively camouflages as a legitimate device; for instance, Nmap shows confidence of 95% for WAGO's operating system, PLC, while LLMPot obtained an 87% confidence rating. Further testing was done using Shodan [42], which evaluates devices based on characteristics such as the number of open ports and specific network configurations to determine if a device is potentially a honeybot. Our deployed honeybot was successfully detected as an industrial control system.

### 6.3 Real-time Responsiveness

The LLM response needs to be generated in a time comparable to the real PLC response time. Indeed, using a RTX-3090 Ti, LLMPot produces a valid response in 180ms, comparable to 40ms of the real PLC. The small difference between the two is masked by the much longer delays of the full stack network communication.

## 7 DISCUSSION AND LIMITATIONS

**ByT5 Architecture and Resources:** LLMPot uses the ByT5-small model from the ByT5 series, which includes various sizes to balance computational complexity and the capacity to handle complex patterns. The sizes range from ByT5-small with 300M parameters to ByT5-XXL with 12.9B parameters. Although ByT5-base with 528M performed similarly to ByT5-small in our tests, we opted for ByT5-small due to its lower computational demands. Larger

ByT5 models are also compatible with LLMPot for users with more computational resources.

**Finetuning an LLM to Emulate Multiple Protocols:** LLMPot uses distinct models to emulate Modbus and S7Comm protocols. Our initial experiments with a unified LLM that emulates both protocols have shown promising results. In future research, we plan to explore the integration of multiple protocols into a single LLM.

**Emulating Unbounded Functions:** Another challenge encountered in exploring mathematical functions is related to the exponential functions, which typically grow indefinitely. This characteristic poses significant difficulties in predicting accurate results, especially as function values become excessively large. However, in physical processes, variables are naturally constrained and do not extend infinitely. Findings from Section 5.1 demonstrate the effectiveness of LLMPot in emulating bounded functions.

**Protocol Configuration File:** LLMPot depends on a configuration file that includes data fields that are specific to various industrial protocols. This can be potentially automated in future work. However, this is a one-time effort per industrial protocol, and the number of industrial protocols is not very large.

## 8 CONCLUSION

The LLMPot framework is, to the best of our knowledge, the first approach to use LLMs to emulate ICS network protocols and physical processes. It provides a novel platform that researchers can use to mimic network protocols, mathematical equations, and physical processes. This platform can also be used to create a real honeypot. LLMPot demonstrates the LLMs potential and capabilities in industrial protocol emulation, real-time interaction, and physical process capturing. LLMs can inherently understand and emulate industrial protocols, such as Modbus, S7Comm, etc. They can generate and handle, in real-time, low-level network communications and emulate protocol-specific behaviors, through mimicking the dynamics of a physical process.

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