

# The Slow and The Furious? Performance Antipattern Detection in Cyber-Physical Systems

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## Abstract

Cyber-Physical Systems (CPSs) have gained traction in recent years. A major non-functional quality of CPS is performance, since it affects both usability and security. This critical quality attribute depends on the specialized hardware, simulation engines, and environmental factors that characterize the system under analysis. While a large body of research exists on performance issues in general, studies focusing on performance-related issues for CPSs are scarce. The goal of this paper is to build a taxonomy of performance issues in CPSs. To this aim, we present two empirical studies aimed at categorizing common performance issues (Study I) and helping developers detect them (Study II). In the first study, we examined commit messages and code changes in the history of 14 GitHub-hosted open-source CPS projects to identify commits that report and fix self-admitted performance issues. We manually analyzed 2699 commits, labeled them, and grouped the reported performance issues into antipatterns. We detected instances of three previously reported Software Performance Antipatterns (SPAs) for CPSs. Importantly, we also identified new SPAs for CPSs not described earlier in the literature. Furthermore, most performance issues identified in this study fall into two new antipattern categories: Hard Coded Fine Tuning (399 of 646) and Magical Waiting Number (150 of 646). In the second study, we introduce static analysis techniques for automatically detecting these two new antipatterns; we implemented them in a tool called **AP-Spotter**. We analyzed 9 open-source CPS projects not utilized to build the SPAs taxonomy to benchmark **AP-Spotter**. Our results show that **AP-Spotter** achieves 59.49% precision in detecting the antipatterns.

*Keywords:* Software Performance Antipatterns, Cyber-Physical Systems, Antipattern Detection, Software Maintenance, Empirical Software Engineering, Static Analysis

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## 1. Introduction

The term CPSs was first coined at the 2006 National Workshop on Cyber-Physical Systems by Gill [1]. As described by Lee and Seshia [2], a CPS is an integration of computation with physical processes whose behavior is defined by both cyber and physical parts of the system. Examples of CPSs are medical devices [3], automation of industrial manufacturing systems [4], air traffic control and aircraft avionics systems [5], smart cars [6, 7, 8], and unmanned vehicles [9, 10].

In recent years, CPSs became of interest across many industries [11, 12]. The increased adoption of CPSs increases the urgency to tackle CPSs-specific challenges [13]. A key challenge when working with CPSs is that it is difficult to consider the parts in isolation due to the tight interactions [14]. As with other real-time systems, CPSs have a limited time to react to their environment [15]. For example, a self-driving car needs to react fast if suddenly a deer wanders on the road. The performance of the system is a big factor in how well it could respond.

One of the standard methods for achieving high software performance is to use a catalog of Software Performance Antipatterns (SPAs) [16, 17]. This catalog documents the common performance problems in the software architecture and design of systems. The description of these antipatterns helps detect bad design/coding choices that influence performance. A previous study empirically showed that SPAs are beneficial while providing reusable solutions applicable in various domains [18]. Moreover, identifying SPAs helps design and inform refactoring actions, which ensure that the performance antipatterns can be removed from the project's architecture or designs [19, 20]. Recent studies identified various performance antipatterns that are widespread in *classical* software (i.e., not related to CPSs) [17, 16, 21, 22]. In the context of CPSs, Smith [23] started a CPS-specific SPA catalog in 2020. This catalog describes nine performance antipatterns, three of which are CPS specific, and six are also applicable to generic software. Although the antipatterns introduced in Smith's study facilitate the recognition and refactoring of CPS performance-related issues and show the relevance of performance antipatterns in an industrial context, their work has two main limitations. First, the proposed catalog was formulated based on the author's

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experience, rather than empirically collecting and analyzing data from existing and diverse CPSs. Second, their study did not assess how common and widespread these antipatterns are.

The aim of this paper is twofold: (1) building an extensive taxonomy (or catalog) of performance antipatterns in CPSs based on empirical data and evidence collected from heterogeneous open-source systems; (2) helping developers detect the most common and widespread antipatterns. Therefore, this paper presents two studies that cover both the classification (**Study I**) and the detection (**Study II**) of performance-related antipatterns in CPS.

**Study I** aims to identify, classify, and categorize performance issues into a *taxonomy*. Therefore, we investigate the following research questions

**RQ1:** *Which CPS-specific performance antipatterns can we identify in open-source CPSs?*

**RQ2:** *How prevalent are CPS-specific performance antipatterns in open-source CPS projects?*

To answer these two research questions, we analyzed the code history of 14 open-source CPS projects publicly available on GitHub and used in prior studies related to CPSs [24]. We examined commits that reported and fixed self-admitted performance issues by analyzing (1) commit messages, (2) code and project documentation, and (3) code changes. Self-admitted issues are identified based on performance-specific keywords (e.g., *run-time*, *memory*) using a tool that we implemented and coined **PyRock**. This resulted in 1059 candidate commits to validate manually. Through manual analysis, we identified 530 (81.11%) commits discussing one or more performance-related issues. We further expanded the keywords by using textual analysis methods [25] and topic modelling [26], [27]. This resulted in 1640 additional commits, of which 163 commits (9.37%) contained one or more self-admitted performance-related issues. In total, we manually analyzed 2699 commits, labeled them, and grouped the reported performance issues in common categories (or antipatterns).

In this final set of 2699 commits, we found eight instances of Smith’s [23] CPS-specific antipatterns. Interestingly, we identified six potential new CPS-specific performance antipatterns with 638 instances in total. As this is exploratory research, we decided that for them to be confirmed as antipattern, they needed to occur in more than two projects. Following this criterion, we confirmed four antipatterns:

- *Magical Waiting Number*. (9 projects, 150 instances) Lack of proper waiting time, the potential of being often manually changed due to adding support for slower/faster hardware platforms.
- *Hard Coded Fine Tuning*. (6 projects, 399 instances) Variables that are closely related to hardware support, which keeps being changed throughout the project’s history.

- *Fixed Communication Rate*. (5 projects, 66 instances) Frequent changes are made to the communication rate of the hardware modules, as the minimum latency is hard-coded (the same for all platforms in all situations) instead of dynamically.
- *Rounded Numbers*. (5 projects, 10 instances) Mathematical errors made due to type usage for situations requiring high accuracy.

**Study II** aims at helping developers identify and detecting the two most frequently occurring new antipatterns (*Magical Waiting Number* and *Hard Coded Fine Tuning*). To this aim, we present and assess a novel tool, named **AP-Spotter**, that detects these antipatterns based on static analysis methods. The benefit of using a static analysis technique is that it is fast, compared to dynamic analysis, so it can give timely feedback to the developer. We implemented this technique with the **AP-Spotter** tool. Therefore, we formulated the following research question:

**RQ3:** *How precise can our approach detect performance antipatterns?*

To answer this research question, we ran **AP-Spotter** against a benchmark of 9 additional open-source CPS projects not utilized to build the new SPAs taxonomy (i.e., not considered in Study I). We manually validated the instances detected by **AP-Spotter** and reached a precision of 62.02% for *Magical Waiting Number*, and 58.98% for *Hard Coded Fine Tuning*.

**Paper Structure** The remainder of the paper is structured as follows: Section 2 provides background and related work. Section 3 is the repository mining study on Performance Antipatterns. Section 4 discusses the new potential antipatterns from our study. In Section 5, we explore automatically detecting CPS antipatterns and evaluate our approach empirically in our second study. Further, Section 6 discusses the threats to the validity of our studies. And finally, Section 7 presents our conclusion.

## 2. Background and Related Work

In this section, we give a brief overview of research relevant to our studies.

### 2.1. Software Performance Antipatterns

The concept of design patterns for software was introduced in 1994 by Gamma et al. [28], as a schematic to follow for designing software components or subsystems. Software antipatterns stand opposite to design patterns, in that they describe patterns to be avoided because of potential issues in the software’s security, performance, stability, or maintainability [29, 30].

The specific subcategory of antipatterns in which we conduct our study is called Software Performance Antipatterns (SPAs). SPAs focus on common patterns in software

architecture and design, which lead to performance issues in the system [17].

These antipatterns have been introduced by Smith and Williams [17] and were later extended for pipe-and-filter architectures [21] and concurrent programs [22]. Various studies have contributed towards defining SPAs for other application domains (e.g., databases [31]), and provided solutions to tackle them [32].

## 2.2. Known SPAs for CPSs

To the best of our knowledge there is only one prior study that has identified SPAs specific to CPSs, this study was conducted by Smith [23]. In particular, Smith’s [23] recent study carried out a preliminary investigation into Performance Antipatterns for CPS. She identified three new SPAs specific to CPS and also recognized six other SPAs specific to CPS. Based on industrial experience in the field, Smith [23] introduced three new SPAs specific to CPS and also recognized six other SPAs specific to CPS. These antipatterns are described in Table 1.

Despite the undisputable contribution by Smith [23], the study did not provide any empirical data to support the findings. Therefore, our goal is to shed light on the prevalence of SPAs in CPSs by performing an empirical study on a large set of CPSs, eventually extending the existing SPAs taxonomy.

## 2.3. From Automatic Detection of Performance Issues to CPS Performance Antipatterns (CPS-PAs)

Performance issues in a system can i.a., negatively impact its security [34, 35] and usability [36]. Therefore, detecting performance problems has been of interest among researchers [37], from researching Machine Learning methods for performance prediction [38] to the creation of several tools to aid in detecting performance issues earlier on. Some of the available tools are: i) **PerformanceHat** [39] (*This tool aids to bring awareness to development choices and its impact on performance.*) and ii) **Toddler** [40] (*An automated oracle to detect redundant and inefficient use of loops, causing unnecessary performance degradation.*). Applying performance models for analysis is a popular research area, examples of different approaches in this field are: i) detecting performance regression using the system’s history [41], and ii) the interactions between configurations options towards performance [37]. Research into the different modelling options also resulted in the creation of PUMA [42], a tool architecture aiming to bridge the different available design- and performance-tools. In another work, Pinciroli and Trubiani investigate how architectural patterns in cyber-physical systems can influence different performance metrics, e.g., the system response time [43]. Their approach relies on stochastic performance models and enables software architects to quantitatively evaluate architectural patterns in terms of performance.

As manually detecting antipatterns is tedious, time-consuming, and requires expert developers [44] [45], automatic detection of antipatterns has also become a popular

research topic. Multiple approaches have been proposed in the literature to identify generic performance antipatterns, such as approaches based on first-order logic representation [46], decision trees [47], multivariate analysis [48], and load testing [49]. Examples of tools that have been created to automatically detect antipatterns are: i) **DECOR** [50] (*Detects antipatterns such as The Spaghetti Code and The Blob antipatterns*) and ii) **PMD** [51, 52] (*A static code analyzer that can be used to detect Code Duplication and the Leak Collection antipattern*).

To the best of our knowledge, a recent article by Pinciroli et al. [53] is the only study that focused on detecting CPS-PAs. The authors modeled the performance antipatterns for CPSs that have been introduced by Smith [23], by utilizing queuing networks. Then, their tool monitors the components’ states dynamically to identify the performance antipatterns in the CPS’s operation.

While their focus is on dynamically identifying performance antipatterns, we approach this detection with static analysis and rely on the project’s historical development. Dynamic analysis can have the benefit of getting a rich insight into the antipatterns impact on the system’s performance. For the static analysis method, the code does not need to be run, therefore it can provide faster feedback to the CPS developers [54].

## 3. Study I — Commit-Message Based Search for Performance Antipatterns

In our first study, we aim (1) to empirically establish how widespread the antipatterns from the existing catalog created by Smith [23] are, and (2) to potentially identify any previously undocumented antipatterns across open-source CPS projects.

Our investigation is steered by the following two research questions:

**RQ1:** *Which CPS-specific performance antipatterns can we identify in open-source CPSs?*

**RQ2:** *How prevalent are CPS-specific performance antipatterns in open-source CPS projects?*

This section is structured as follows: first, we discuss the projects selected for this study (Section 3.1), followed by a description of how we searched for performance issues (Section 3.2), the analysis (Section 3.3), and results (Section 3.4). We discuss the results from this study in Section 4.

### 3.1. Subjects

To derive a taxonomy of antipatterns in CPS projects, we selected a set of 14 open-source CPS projects hosted on GitHub. We selected these projects based on the following criteria:

- **Relevance:** the project must be related to a CPS domain, such as robotics, drones, or automotive.

Table 1: Existing catalog of SPAs for CPSs by Smith [23].

| Name                                  | Type         | Description  |
|---------------------------------------|--------------|--|
| Are We There Yet?                     | CPS-specific | Over-checking whether an event occurred. This problem usually stems from a polling procedure in CPS with small checking intervals, compared to the frequency of event occurrences. This Performance Antipatterns leads to overusing system resources.  |
| Is Everything OK?                     | CPS-specific | constantly checking the status of the system (e.g., storage space, battery usage). This performance issue happens when the status checker threads and processes are triggered too often.   |
| Where Was I?                          | CPS-specific | Processes that lost information about the system’s state, such as a system restart. It can also happen if too much time (i.e., more than 1 minute) is given to processes that keep the user waiting. This type of antipattern leads to execution overheads to perform required calculations to drive the CPS back to the desired status. |
| Unnecessary Processing                | Generic      | Heavy and unnecessary processes are executed in critical scenarios [22]. To tackle this antipattern, the execution of processes whose outputs are not required in critical scenarios should be postponed.  |
| How Many Times Do I Have to Tell You? | Generic      | Invoking a method many times in scenarios in which the CPS could call the method only once and store and reuse the returned outputs for the following processes. To address this antipattern, redundant calls should be removed.   |
| More is Less                          | Generic      | A CPS has access to too many resources that negatively impact the system’s overall performance [23]. Adding too many resources (such as threads and processes) may lead to extra overheads for tasks like scheduling and context switching   |
| The Ramp                              | Generic      | The performance and efficiency of the CPS are exponentially reduced as the processing time linearly increases [21]. This type of performance issue can occur in CPS for various reasons, such as changes in the environment or processing a large amount of historical information [23].   |
| Museum Check-room                     | Generic      | A CPS uses a simple First Come First Serve (FCFS) queue to manage resource allocation to processes [33]. This can lead to performance issues in cases where this resource management system needs to handle too many processes. To resolve it, CPS developers should implement priority queuing.   |
| Falling Dominoes                      | Generic      | A failure of a module leads to more failures in other modules [23]. Since CPSs includes many small interacting hardware pieces with various software modules, this common antipattern can also occur in a CPS. Developers must ensure that modules are as isolated as possible to prevent this antipattern from occurring.               |

- *Activity*: the project must have a minimum of 50 commits as we have to identify self-admitted performance issues. This lower limit was chosen to be inclusive of less active projects while excluding projects that did not use GitHub to track and resolve issues.
- *Popularity*: a selection of popular and less popular projects must be made; We selected the two most popular projects in the CPS domain, i.e., the projects with the most stars and forks; nine relatively popular projects; and an additional four projects with less than 100 stars, as we are interested in antipatterns that arise independently of the maturity of a project. From the most and least popular projects, one project with a high star rating and one with a high fork rating was selected. For the less popular project, we selected two additional projects as this category of projects were shown to have a low number of commits. The other eight projects are selected to range between the least and most popular

projects.

- *Programming language*: the project must be written in C, C++, Java, JavaScript, or Python. While C, C++ are the most common programming languages for CPS [24], we also consider other programming languages to increase the generalizability of our results. Therefore, the resulting selection of projects must be a diverse selection of programming languages used.

This resulted in 14 projects, which are described in Table 2. Notice that the projects written in C, C++, and Python have also been used in a prior study [24] aimed at characterizing CPSs according to the type of functional bugs/issues they contain. Our selection comprises projects with various maturity levels: PX4-Autopilot and Vacuum Robot Mark II have the highest and lowest contributions, with 35,537 and 54 commits to the main branch, respectively. Furthermore, these projects reflect different applications of CPS, such as software for controlling drones,

vacuum cleaners, or small robot kits. Table 2 also indicates the number of stars and forks for each of the CPS projects. The most popular projects in this dataset are Johnny-Five with 12.4K stars and PX4-Autopilot with 4.8K stars. This diversity in projects aims to ensure that we find antipatterns not specific to one CPS domain, a programming language, or the maturity projects.

### 3.2. Analysing Self-admitted Performance Issues

To build our taxonomy of antipatterns, we manually analyzed and classified self-admitted performance issues, i.e., issues related to performance aspects (e.g., memory usage) that are mentioned by the developers in the commit messages, or source code changes and comments. Our main methodology is, therefore, based on manual analysis of structured (source code) and unstructured (commit messages) data, which we manually classified into categories of antipatterns.

There are two ways to build a taxonomy [55]: (1) *top down* (also called *enumerative*), where the categories are predefined, or (2) *bottom up* (or *faceted*), where the categories are created by analyzing the data. Since we have a pre-existing catalog by Smith [32], we used a hybrid approach: for every commit we analyzed, we checked if it matched any of the categories in Smith’s taxonomy; in case of no match, we marked them and later clustered them into new categories.

As reported in Table 2, there are 52,318 commits in total to analyze across all projects. Since manually analyzing all commits in our dataset would be infeasible, we combined (1) keywords search, (2) information retrieval, and (3) topic modeling techniques to extract a subset of commits that are likely to contain performance-related issues. This “candidate” list of commits was then manually analyzed for validation (to check for their relevance) and classification (for the creation of the taxonomy).

The next subsections detail the steps of our methodology as well as the semi-automated tools we employed to identify the relevant commits.

#### 3.2.1. Initial Keyword Selection

We relied on a keyword search to extract the list of candidate commits for the manual analysis. That is, we manually selected a set of keywords likely to be used in performance-related issues, and we searched for commits containing at least one of these keywords. We created an initial set of keywords based on the authors’ experience. Further, we expanded the list of keywords by including keywords from the literature related to embedded systems and performance, i.e., [32, 17]. We then manually analyzed a sample set of commits and added any keywords we also deemed relevant. Table 3 reports the resulting list of 22 keywords. These keywords were also validated with domain experts from the H2020 COSMOS project [56].

#### 3.2.2. Keyword Set Expansion with Information Retrieval and Topic Modeling

To ensure we gathered all performance-related commits from each project, we applied both Information Retrieval (IR) and Topic Modeling (TM) techniques to expand our initial keyword set.

**Data preprocessing.** For each project, we downloaded all commit messages and code changes. Then, we pre-process these artifacts by tokenizing the commit message, removing stop words, and stemming. First, *tokenization* aims to extract words in the text and remove non-relevant characters, such as punctuation marks, special characters, and numbers [27]. As commit messages can contain code snippets, we split compound names (i.e., identifiers) into tokens using *camel case* and *snake case* splitting [57]. For example, the method name `get.data` will be split into the two tokens `get` and `data`.

We further applied *stop-word list* and *function* to remove words that do not contribute to the semantic content of the analyzed text [58, 59]. The former is a list of generic words (i.e., prepositions, articles, auxiliary verbs, and adverbs) that are commonly found in any text, thus, not providing any useful information. Our stop-list includes the standard list for the English language [59], plus a list of words that are specific to the programming languages (i.e., reserved keywords like `class` in Java). The stop-word function instead removes words that are too short [58], i.e., that contain less than three characters.

Finally, we applied *stemming* algorithms to reduce the words to their root form. To this aim, we used the Porter stemming algorithm [60].

**Topic modeling.** To better understand the context in which the keywords are also used, we also applied topic modeling [61] [27], specifically Latent Dirichlet Allocation (LDA), to each project separately. Figure 1 depicts the overall process. Given a software project A ①, we apply LDA ② on all commit messages after the pre-processing steps described above.

LDA requires setting three hyperparameters, namely  $\alpha$ ,  $\beta$ , and the number of topics  $k$  [61]. For this study, we performed unsupervised hyper-parameter tuning using genetic algorithms based on the silhouette coefficient, as suggested by literature [26, 27]. The resulting parameter values are as follows:  $k = 20$ ,  $\alpha = 0.5$ , and  $\beta = 0.2$ . To address the probabilistic nature of LDA, we ran Gibb’s iterative process 10 times with different random seeds [27]. Therefore, the topics obtained are the average across the repetitions. The topic modeling returned a list of 20 topics per project, each containing 20 words ③ that are statistically related to one another according to LDA.

Using this methodology, we could quickly analyze each project’s topics and words that might be of interest for further analysis. We reviewed each word ④ and identified words that are related to performance issues. These words were then added to the list of keywords for the next step of the methodology.

| Project Name         | Language   | Nr. of commits | Stars | Forks | Domain        |
|----------------------|------------|----------------|-------|-------|---------------|
| PX4-Autopilot        | C++        | 35,537         | 4.8K  | 11.3K | Automotive    |
| Andruino-esp32       | C          | 1747           | 8.5k  | 5.4k  | Arduino       |
| Grbl                 | C          | 699            | 3.2k  | 1.4k  | Arduino       |
| DroneKit Android     | Java       | 5,810          | 211   | 217   | Drones        |
| Node AR Drone        | JavaScript | 281            | 1.7K  | 446   | Drones        |
| Android App Manager  | Java       | 231            | 10    | 12    | Robotics      |
| Cylon                | JavaScript | 1,323          | 3.8K  | 367   | Robotics      |
| Johnny Five          | JavaScript | 3,355          | 12.4K | 1.8K  | Robotics      |
| Robonomics-JS        | JavaScript | 68             | 13    | 8     | Robotics      |
| Robonomics-Contracts | JavaScript | 502            | 78    | 31    | Robotics      |
| Vacuum Robot Mark II | Java/C++   | 54             | 28    | 3     | Wheeled Robot |
| TurtleBot            | C++        | 1,142          | 236   | 280   | Wheeled Robot |
| TurtleBot 3          | Python     | 526            | 770   | 637   | Wheeled Robot |
| Valetudo             | JavaScript | 1,043          | 2.5K  | 258   | Wheeled Robot |

Table 2: Projects selected for Study I

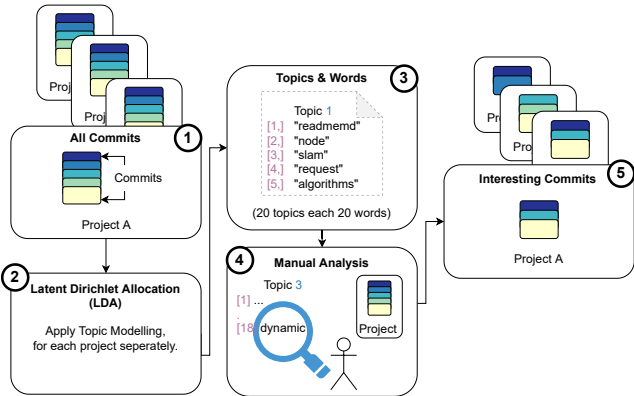


Figure 1: Topic-Modelling process

While we started with an initial set of 22 keywords, this procedure led us to add 28 additional keywords after applying stemming. This means that keywords like “time” will be used to represent all words (in the commit messages) with the same root, such as “timing”, “timed”, “timer”, and so on.

For the sake of brevity, we do not report the full list of keywords in this paper. However, interested readers can find the list of keywords in our online appendix [62].

### 3.2.3. Extraction of Candidate Commits

The keywords from the previous steps have then been used to extract commits that should be manually analyzed. To this aim, we created the tool PyRock. It mines the history of a Git project and returns all commits whose message contains one of the targeted keywords. Figure 2 visualizes the tool’s architectural design.

PyRock requires two input parameters: (1) the repositories list and (2) the local/remote flag. The former is a list of repositories on which we want to perform the automated code history analysis. The latter parameter indicates whether the repositories are available locally or PyRock needs to fetch them remotely. For the local mode,

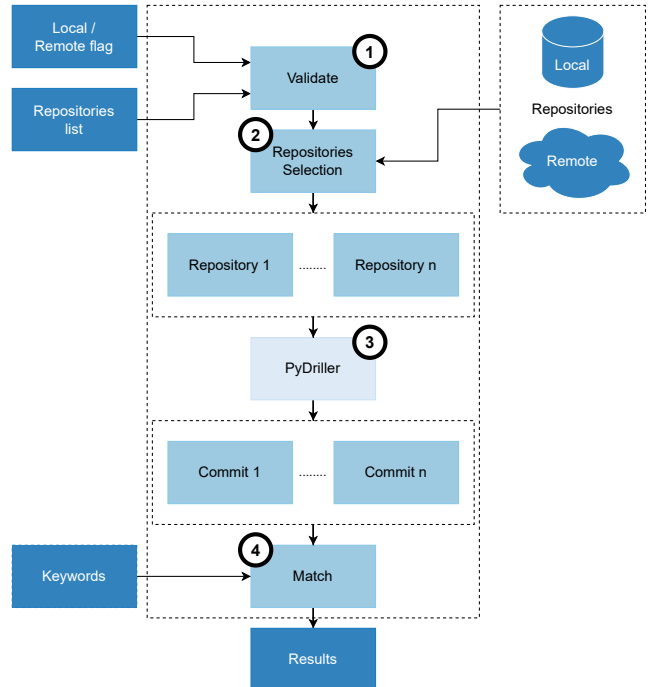


Figure 2: PyRock Architecture

the user also needs to provide the directory in which the local repositories are stored.

These user inputs are first validated by PyRock’s Validate module (see ① in Figure 2). This module checks that the user has indicated which mode (local/remote) to run and which repositories to analyze. In local mode, PyRock will only check locally stored repositories; in remote mode, PyRock will only check remotely located repositories. Further, it is possible to run PyRock with one or a full list of repositories.

After verification, PyRock selects each repository with the Repositories Selection module, see ② in Figure 2, for initiating the next step. In local mode, this module validates the input data and checks whether the given

| Keywords  | Explanation   |
|---|---|
| performance, runtime  | As the focus of the research is performance, the keywords ‘performance’ and ‘runtime’ link directly to any commit that is related to this area. |
| slow, slower, slowing, fast, faster, increase, decrease   | These adjectives are used to indicate a change in the commit in the described way. This could indicate a performance improvement or decrease.   |
| memory, memory-heap, memory-leak, memory leak, bottleneck, overhead, deadlock, live-lock, infinite, speed, impasse, hang, stuck | These keywords are chosen based on previous experience, books regarding performance, and found during the analysis phase.                       |

Table 3: Keywords in our initial steps along with their description

repositories’ location contains the projects presented in the repository list. In remote mode, it checks whether the repositories’ remote addresses are reachable.

To mine the history of the repositories (③ in Figure 2), PyRock utilizes PyDriller [63], a commonly used open-source Python framework for mining Git repositories. PyRock passes the information to PyDriller regarding each repository one at a time.

In the next step, the commit messages returned by PyDriller are passed through the Match module, see ④ in Figure 2. This module utilizes a keyword file containing a list of keywords that could indicate a potential performance antipattern and formed using IR and TM as described in Section 3.2.2. See Table 3 for the keywords used in this analysis. This module considers any commit message containing at least one of the performance-related keywords as a candidate commit for further analysis. Finally, this module stores and returns the list of collected candidate commits, which are then considered for manual validation.

### 3.3. Manual Analysis

As a result of the previous steps, we obtained a list of 2699 commits potentially related to self-admitted performance issues. Out of these, 1059 commits are related to the keywords in our initial set (see Section 3.2.1). In contrast, the remaining 1640 commits are related to the keywords found by applying information retrieval and topic modeling techniques (see Section 3.2.2).

Two authors of this paper manually analyzed these commits independently following an open coding procedure. The authors followed a rigorous procedure to ensure the quality of the analysis, handling potential conflicts and disagreements. In particular, each validator separately read and analyzed each commit by reading the commit message. If a commit was unclear, the validators further analyzed the code changes, the associated issues, pull requests, and documentation when needed. This allowed us to: (1) identify and remove false positives, (2) check eventual matches with the existing catalog by Smith [17], and (3) identify self-admitted performance issues that do not belong to any of the existing CPS antipatterns.

Therefore, our manual analysis process required to follow seven steps as described below:

1. Check the **commit message** for the developer’s explanation of what has been done.
2. **Code changes** in the commit. Can we find any of Smith’s [23] CPS antipatterns? Do we see other potential antipatterns?
3. Check if the commit is mentioned in any **issue or pull request**, to understand if the changes are linked to any other changes.
4. In case it is relevant, **read comments and notes** mentioned in the issues and pull requests. What were the design considerations discussed in the comments? More information received regarding the original issue?
5. Read the **documentation** of the changed classes to obtain more information regarding the developers’ design considerations potentially.
6. Analyze the **final version** of the file in the main branch to check if the CPS developers modify/revert the changes in the commit under analysis. This can reveal if the changes were accepted or if other issues were found with the proposed solution.
7. In case it is relevant, read the documentation regarding the **software and hardware architecture** of the projects under analysis. To understand the reasoning for changes to the design due to added hardware support.

To further increase the reliability of our analysis, 38% of the commits were cross-reviewed by two external validators (students) that are not authors of this paper. The overall agreement among the validators was 93.88%. In case of disagreements, the validators discussed the reasons for the disagreement and reached a consensus on whether the commit should be considered a performance issue or not and whether it fits in the existing taxonomy or not. In total, the manual analysis took 904 hours, including the cross-review process and disagreement resolution.

The complete list of commits analyzed and the results of the manual analysis are available in our GitHub project <sup>1</sup>.

<sup>1</sup>[https://github.com/ciselab/CPS\\_repo\\_mining](https://github.com/ciselab/CPS_repo_mining)

| Project              | # Analyzed Commits | False Positives      | ①<br>Are We There Yet<br>Is Everything OK<br>Where Was I | ②<br>Unnecessary Processing<br>How Many Times Do I Have to Tell You?<br>More is Less<br>The Ramp<br>Museum Checkroom<br>Falling Dominoes | ③<br>Excessively Flexible Storage<br>For-If<br>Extraneous Fetching<br>Unbuffered streams<br>Big-load<br>Hard Coding<br>Bottleneck<br>Code Duplication | ④<br>Deadlock<br>Recreate Objects<br>Not Deallocating | ⑤<br>Performance Issues To Further Analyze | Total number of Performance Issues |            |
|----------------------|--------------------|----------------------|--|--|---|---|--|------------------------------------|------------|
| Android App Manager  | 7                  | 6 (85.71%)           | - - 1  | - - - - -  | - - - - -   | - - - - -   | 1  | 2                                  |            |
| Arduino-esp32        | 140                | 114 (81.42%)         | - - 1  | 2 - - - -  | - - - - -   | - - - - -   | 15   | 29                                 |            |
| Cylon                | 21                 | 21 (100.00%)         | - - -  | - - - - -  | - - - - -   | - - - - -   | 0  | 0                                  |            |
| DroneKit Android     | 99                 | 88 (88.89%)          | - - -  | 1 - - - -  | 1 - - 1 1   | - - - - 1   | 6  | 11                                 |            |
| Grbl                 | 217                | 199 (91.71%)         | - - -  | 1 - - - -  | - - - - -   | - - - - -   | 26   | 27                                 |            |
| Johnny Five          | 147                | 131 (89.12%)         | - - -  | - - - - -  | 2 - - - -   | - - - - -   | 12   | 14                                 |            |
| Node AR Drone        | 48                 | 47 (100.00%)         | - - -  | - - - - -  | - - - - -   | - - - - -   | 2  | 2                                  |            |
| PX4-Autopilot        | 1869               | 1297 (69.40%)        | 1 3 1  | 12 1 - - -   | 2 - - 1 -   | 55 1 2  | 5  | 18                                 |            |
| Robonomics-Contracts | 7                  | 7 (100.00%)          | - - -  | - - - - -  | - - - - -   | - - - - -   | 0  | 0                                  |            |
| Robonomics-JS        | 0                  | 0 (0.00%)            | - - -  | - - - - -  | - - - - -   | - - - - -   | 0  | 0                                  |            |
| Turtlebot            | 24                 | 20 (83.33%)          | - 1 -  | - - - - -  | - - 1 - -   | 1 - - - -   | 1  | 4                                  |            |
| Turtlebot 3          | 27                 | 10 (37.04%)          | - - -  | - - - - -  | - - - - -   | - - - - -   | 21   | 21                                 |            |
| Vacuum Robot Mark II | 2                  | 2 (100.00%)          | - - -  | - - - - -  | - - - - -   | - - - - -   | 0  | 0                                  |            |
| Valetudo             | 91                 | 84 (92.31%)          | - - -  | - 1 - - 1  | - 1 - - -   | - - - - -   | 3  | 7                                  |            |
| <b>Total</b>         | <b>2699</b>        | <b>2026 (75.06%)</b> | <b>1 4 3</b>   | <b>16 2 0 0 0 1</b>  | <b>5 1 1 2 1</b>  | <b>58 1 2</b>   | <b>6 2 26</b>                              | <b>638</b>                         | <b>770</b> |

Table 4: Number of manually analyzed commits and their classification in false positives (commits not related to performance issues) and true positives. The latter are classified based on the existing performance antipattern catalogs. The column *Performance Issues To Further Analyze* denotes the performance issues that do not match any of the existing antipatterns.

### 3.4. Results

Table 4 reports the results of our manual analysis for the 2699 commits that are potentially related to performance issues. It reports (1) the number of false positives (e.g., commits not actually related to performance issues), (2) commits related to performance issues that are further categorized based on the existing catalogs. In particular, we clustered the manually-validated (true positives) performance issues based on whether they are related to the antipatterns in the existing catalog by Smith [32] (columns marked with ①), generic performance antipatterns that occur in both traditional software and CPS as suggested by Smith (columns marked with ②), generic antipatterns reported in the literature for traditional software only (columns marked with ③), generic performance issues (columns marked with ④), and performance issues that do not match any of the existing antipatterns ⑤.

As we can observe, the number of false positives (i.e., commits not related to actual performance issues) is quite high, being 75.06% on average. This result was expected since some keywords (e.g., *increase*) can be used in the commit message for different purposes, such as increas-

ing the number of features or increasing the waiting time for concurrency issues. However, we have kept ambiguous keywords in the search query to avoid missing relevant commits.

First and foremost, we can observe that performance issues are widely-common in the analyzed projects. Only four out of 14 analyzed projects do not have any performance issues. The project with the highest number of performance issues is PX4-Autopilot, with 653 performance issues out of 1869 analyzed commits. Note that this project has the largest code history among all projects in our study. Nevertheless, instances of performance issues can be found in the other nine projects as well.

**Finding 1.** Self-admitted performance issues are widely-common in 71% of analyzed projects. Their frequency of occurrence in these projects ranges from 2 up to 653.

With regard to the antipatterns, we could find instances of antipatterns by Smith in the selected projects. However, they are not the most common, representing only 8 out of 770 performance issues identified in our manual analysis. Generic performance issues (e.g., not specific to CPS)



cover in total 124 of the 770 performance issues. Finally, 638 performance issues (97.70%) are not covered by any of the existing catalogs within CPS and traditional software.

**Finding 2.** The existing catalog of antipatterns for CPS by Smith [32] characterizes only 8 out of 770 performance issues identified in our manual analysis.

CPS projects are often characterized by other performance issues that are not specific to CPS projects and that occur in more traditional software projects. The most common generic performance issues are related to unnecessary processing, memory, and network usage. However, they characterize only 16.10% of the total number of performance issues.

**Finding 3.** 97.70% of the identified self-admitted performance issues are not covered by any of the existing catalogs within CPS and traditional software.

#### 4. Extending the taxonomy of CPS antipatterns

Given the large percentage of performance issues that do not match existing antipatterns, we manually analyzed these instances in order to identify common patterns and characteristics. To this aim, two authors (hereafter referred to as *annotators*) of this paper manually analyzed the 689 performance issues that remained **unclassified** after the first manual analysis (see Section 3.3). Each *annotator* manually analyzed each of the 638 performance issues by inspecting (1) the commit message, (2) the code changes, and (3) the documentation of the source software project (if available). The *annotators* were asked to identify the main reason/cause for the performance issue and to provide a short description of the antipatterns and the reason why it was identified. At the end of this procedure, the two *annotators* compared their results, discussed the differences and agreed on a final classification.

The resulting classification is reported in Table 5. The table also includes the occurrence of each category across all projects in our study. In reporting our results, we distinguish between performance issues and performance antipatterns based on the number of projects in which their instances occur. We consider reoccurring performance issue patterns confirmed as an antipattern if they are found in more than two projects. This is critical to discriminate between issues specific to a single project (project-specific) from issues that can occur in CPS systems in general (common anti-patterns). Instead, performance issues that have a negative effect on the system but occur in only one project are not considered a confirmed antipattern. Further studies are needed to confirm whether these project-specific issues might be common in other CPS systems or not.

In the remaining parts of this section, we discuss six identified performance issues: *Magical Waiting Number*, *Hard Coded Fine Tuning*, *Fixed Communication Rate*, *Bad*

| Project              | Hard Coded Fine Tuning | Magical Waiting Number | Fixed Communication Rate | Rounding Errors | Bad Noise Handling | Delayed Sync With Physical Events | Total |
|----------------------|------------------------|------------------------|--------------------------|-----------------|--------------------|-----------------------------------|-------|
| Android App Manager  | -                      | 1                      | -                        | -               | -                  | -                                 | 1     |
| Arduino-esp32        | 8                      | 5                      | 1                        | 1               | -                  | -                                 | 15    |
| Cylon                | -                      | -                      | -                        | -               | -                  | -                                 | 0     |
| DroneKit Android     | 2                      | 1                      | 1                        | 2               | -                  | -                                 | 6     |
| Grbl                 | 14                     | 9                      | 1                        | 2               | -                  | -                                 | 26    |
| Johnny Five          | 4                      | 6                      | -                        | 1               | 1                  | -                                 | 12    |
| Node AR Drone        | -                      | 2                      | -                        | -               | -                  | -                                 | 2     |
| PX4-Autopilot        | 363                    | 122                    | 51                       | 4               | 10                 | 1                                 | 551   |
| Robonomics-Contracts | -                      | -                      | -                        | -               | -                  | -                                 | 0     |
| Robonomics-JS        | -                      | -                      | -                        | -               | -                  | -                                 | 0     |
| Turtlebot            | -                      | -                      | -                        | -               | -                  | 1                                 | 1     |
| Turtlebot 3          | 8                      | 1                      | 12                       | -               | -                  | -                                 | 21    |
| Vacuum Robot Mark II | -                      | -                      | -                        | -               | -                  | -                                 | 0     |
| Valetudo             | -                      | 3                      | -                        | -               | -                  | -                                 | 3     |
| <b>Total</b>         | 399                    | 150                    | 66                       | 10              | 11                 | 2                                 | 638   |

Table 5: Number of instances of Potential new CPS-PA from the manually analyzed commits.

*Noise Handling*, *Rounding Errors*, and *Delayed Sync with Physical Events*. We discuss each of these identified performance issues by providing (1) an explanation of the potential antipattern, (2) providing an example found in the Git history of one of the projects in our dataset, (3) discussing whether such an issue can be considered an antipattern, and (4) proposing a solution to mitigate the issue.

##### 4.1. Magical Waiting Number

This SPA refers to the lack of a proper waiting time in the CPS when interacting with hardware. When the CPS sends a request or invokes a module in the hardware, it needs to correctly estimate the time it takes for the hardware to finish the task and, if applicable, return the response. We detected many scenarios in our analysis in which the CPS developers either (i) mistakenly did not consider adding a waiting time when sending a request to hardware, or (ii) put a hard-coded incorrect global value for the time it expected the hardware devices to respond.

**Example** As an example, a reported issue in the Valetudo project <sup>2</sup> exposes a bug in which sending a request to the Viomi robot vacuum cleaner <sup>3</sup> to change the time

<sup>2</sup><https://github.com/Hypfer/Valetudo/issues/799>

<sup>3</sup><https://www.viomi.com>

zone, takes the entire connection between the robot and the controller down. The root cause of this performance bug is the little timeout considered by the CPS to complete the setting time zone task. According to the discussions about this bug in the Valetudo repository <sup>4</sup>, this task can take about 10 seconds. Hence, as presented in Listing 1, this bug is fixed by increasing the timeout to 12000 milliseconds.

```

1  this.sendCommand("get_prop", ["timezone"],
2    {timeout: 12000}).then((res) => {
3    if (res.length > 0) {
4      const timezone = res[0];
5      if (timezone !== 0) {
6        // Set timezone to UTC
7        this.sendCommand("set_timezone",
8          [0],
9          {timeout: 12000}).then(_ => {
10         Logger.info(
11           "Viomi timezone adjusted to UTC
12         ");
13       });
14     }
15   });

```

Listing 1: Solution implemented

Figure 3 shows a visualization of this potential antipattern. Here two different hardware targets are shown, each with a different amount of time needed to complete their calculations. If only one waiting time is manually set, no matter what type of hardware is used, a waiting time of 10 seconds will be used for both of them.

From this example in Figure 3, when used in combination with hardware that could have handled a one-second waiting time, there is a nine seconds unnecessary delay. This could slow down the system in multiple ways, for example: the information from the hardware arrives slower than it could, resulting in other processes waiting for this information before continuing. As another example, a thread could be blocked, waiting for this information for an unnecessary duration. Depending on how often this information from the hardware is required, the system’s performance will be more heavily influenced.

**Is it a performance antipattern?** As presented in Table 5, we have detected Magical Waiting Number instances in 150 commits that we have manually analyzed in this study. These commits are from nine different projects: PX4-Autopilot, Valetudo, Johnny Five, Node AR Drone, Grbl, Arduino-esp32, Android App Manager, DroneKit Android, and Turtlebot 3. The projects are developed in four different programming languages and used for various applications (e.g., controlling drones, vacuum cleaners, or robotic programming). Hence, given that this kind of bad coding practice is frequently found in various projects in our analysis, we consider Magical Waiting Number as a new CPS-Performance Antipattern (PA).

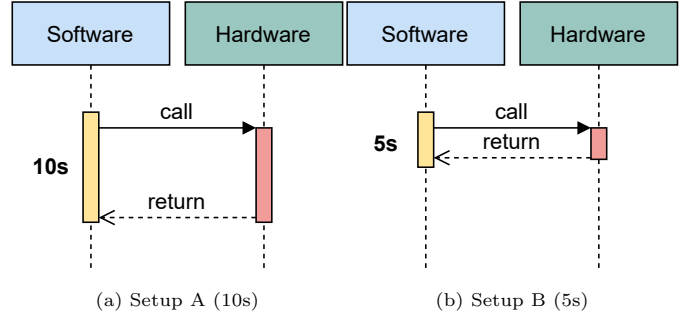


Figure 3: Magical Waiting Number, visualization of two hardware targets with different durations needed to complete calculations.

**Proposed solution(s)** The refactoring solution should aim to assign the waiting times dynamically according to the target hardware module.

#### 4.2. Hard Coded Fine Tuning

This potential antipattern occurs when a setting or value is manually tweaked to improve the CPSs performance. In these cases, the result of the software performance is verified by seeing the end result of the change, rather than a calculated or documented reason. Making a potential performance improvement with such a method can be a slow process, as an adjustment to the same value is done over multiple commits. We observed this antipattern based on the comments in the connected issues and assumed from the changes made to the same variable with the time/date of the changes.

**Example** In PX4-Autopilot, we detected two linked commits <sup>56</sup> where multiple stack sizes are reduced to free up some memory. However, one of the software modules in this CPS (sdlog) needed that amount of memory. There is no test to ensure the resources required by sdlog are upheld, and thereby the build process did not fail after this memory reduction, the developers noticed the performance issue after implementation. These changes show that they are tweaking the settings manually to see the results to free up some memory.

**Is it a performance antipattern?** As the examples show, manual adjustments do not prove that these values are the most optimal setting for the system. The process of manual adjustments does indicate that an adjustment could positively impact the performance of the CPS. Outside of the area of CPS, a similar phenomenon could be adjustments of stack size. The reason we consider this antipattern as CPS specific, is the core challenge with CPSs: their real-time response in a real environment. Every time new hardware is added to the system, the hardcoded values need to be fine-tuned to include the new hardware. With an increasing range of hardware, the system needs

<sup>4</sup><https://github.com/Hypfer/Valetudo/pull/806>

<sup>5</sup><https://github.com/PX4/PX4-Autopilot/commit/ab63a77edf78a198117757a1d5e2dbe34cde1263>

<sup>6</sup><https://github.com/PX4/PX4-Autopilot/commit/edd2715f84532f6c4c748cc97f0fe8a2982aa885>

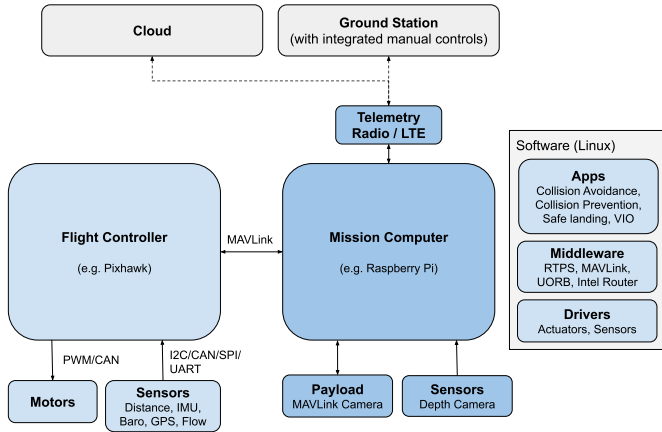


Figure 4: High-level overview of hardware and software modules for a typical PX4 Autopilot system. This figure is taken from the project’s guide page<sup>7</sup>

to support, the constant adjustments could become more difficult to manage.

As reported in Table 5, we detected 399 commits in our manual analysis that strive to set the most optimum setting for the CPS. Given these findings, we consider the Hard Coded Fine Tuning as a new CPS-PA.

**Proposed solution(s)** The refactoring solution should aim to identify the values that have been tuned for each hardware argument, before the subsequent releases. And adjust these values such that they are easily adjustable based on the build target. Avoid having to use the slowest setting for the list of supported targets.

#### 4.3. Fixed Communication Rate

Many CPS projects contain multiple hardware modules working synchronously together. These hardware modules need to communicate with the minimum latency to make sure that the CPS performs as expected. As an example, Figure 4 presents the general hardware and software architecture for PX4-Autopilot (one of the CPS projects in our analysis). This CPS provides a framework to control different vehicles automatically or manually. This system contains a hardware module for controlling the flights and, in general, movements (Flight Controller), and another hardware element for providing advanced features, such as collision prevention and object avoidance (Mission Computer in Figure 4). Also, these two main modules communicate with various other small hardware devices, such as sensors, cameras, and actuators. In these projects, the CPS developers should make sure that this communication happens with the minimum latency to ensure the performance and efficiency of the CPS. However, setting an excessively high communication rate leads to a higher usage rate of resources (for instance, higher energy consumption), which is especially unfavorable for devices with limited energy resources (e.g., drones, robots, and smart vacuum cleaners).

In our analysis, we detected cases where CPS developers set a fixed communication rate between these devices and modules. In some other cases, they set a limit for these communication rates. As we have seen, for example, in a commit from PX4-Autopilot<sup>8</sup>. Later, these developers find scenarios where low communication rates negatively affect the system’s performance.

**Example** In the DroneKit Android project architecture, Android devices need to communicate with drones for controlling purposes. In this project, the CPS developers set a default communication rate between the Android device and the drone. However, they noticed that this default rate is not enough when the user enters the tuning screen. Hence, in one of the commits<sup>9</sup>, they implemented a dynamic procedure to increase the communication rate when a user opens the tuning screen and returns the rate back to default when they close it.

**Is it a performance antipattern?** As is shown in Table 5, we detected 66 commits in our manual analysis that strives to tackle the fixed communication rate. We identified this performance issue in five projects: (i) DroneKit Android (implemented in Java), which provides a framework for developing applications for Android devices to control drones, (ii) PX4 Autopilot (implemented in C++) that enables the automated and manual control of moving devices such as multi-copters, small airplanes, airships, balloons, rovers, boats, and even small submarines, (iii) Arduino-esp32, Arduino ESP32 core (implemented in C), (iv) Grbl, Parallel-port-based motion control for CNC milling (also implemented in C), and (v) Turtlebot 3, a wheeled robot written in Python and C++. Given these observations, we consider the Fixed Communication Rate as a new CPS-PA.

**Proposed solution(s)** The refactoring action should aim to ensure that the communication rates between hardware components adapt during the operation of CPSs according to the need for communication between the components. Though, when considering this proposed refactoring, the CPU and thereby power consumption can possibly be affected. It would be interesting for future work to investigate the impact of implementing the proposed solution.

#### 4.4. Rounding Errors

In some scenarios, CPSs contains software modules that perform calculations related to the physical events (e.g., the exact angle of a robotic arm or the location of a drone) in the project. These calculations should have the highest precision for more accuracy and reliability to prevent any threat to the safety of different processes in

<sup>7</sup>[https://docs.px4.io/master/en/concept/px4\\_systems\\_architecture.html](https://docs.px4.io/master/en/concept/px4_systems_architecture.html)

<sup>8</sup><https://github.com/PX4/PX4-Autopilot/commit/81a4df0953e738041d9fdc2b2eb353a635f3003b>

<sup>9</sup><https://github.com/dronekit/dronekit-android/commit/2c9d9bc08147b0952eba4b6ef28701641a99bb21>

the CPS. For instance, one of the known mathematical calculation errors that can endanger the precision of the calculations is a rounding error in which one of the numbers is altered to a type with fewer decimals [64, 65].

**Examples** In our analysis, we found eight commits in which CPS developers changed the number types in these calculations to increase the calculation precision and prevent rounding errors. As an example, a commit in DroneKit Android <sup>10</sup> changes the types of numbers related to the latitude, longitude, and altitude of the drone from float to double. The message of this commit also indicates that this change is applied to increase the precision of these numbers. At first sight, this bad practice leads to functional issues. For instance, in this example, the miscalculation of the drone’s latitude, longitude, and altitude leads to problems in how the CPS functions. However, it can also — indirectly — negatively impact the performance of the CPS. For example, a miscalculation in detecting the proper coordination for the landing of drones can trigger other correcting processes (e.g., recalculating the right coordinate or recalculating other metrics for landing in the new location), which are energy and time-consuming.

**Is it a performance antipattern?** As presented in Table 5, we identified ten instances of Rounding Errors in our manual analysis. These instances are detected in five projects, two of which are for controlling various types of drones: DroneKit Android and PX4 Autopilot (implemented in C++ and Java). We also found Rounding Errors in Arduino-esp32, Grbl, and Johnny Five (the first two are implemented in C and the last one in JavaScript). As with these three projects, we think that this type of antipattern can be found in any CPS containing mathematical calculations for physical values (e.g., robotics and self-driving cars). For example, depending on the compiler and hardware used, there is a difference in precision and range for using a float [66]. Some systems compensate for the functional errors with correction actions; these are pure overhead and cause performance issues or potentially crash the system. Given these findings, we consider Rounding Errors as a new CPS-PA.

**Proposed solution(s)** Assure that the types of variables do not introduce rounding errors for the values passed to the hardware-related methods. For example, review all number types (e.g., int, double, and floats) used in hardware-related code to verify that the appropriate precision is used.

#### 4.5. Delayed Sync with Physical Events

This issue refers to scenarios in which the CPS does not notify running software processes and threads when an unexpected physical event occurs. We detect two cases in our analysis that expose this performance issue.

<sup>10</sup><https://github.com/dronekit/dronekit-android/commit/e29a5fde6f5c871ce956ffe6659e8b34f3d8a5b2>

**Examples** We detected this performance issue in TurtleBot and the PX4-Autopilot project. TurtleBot is a personal multi-functional robot kit with different input and output ports, including a USB port for connecting it to other controlling devices. In the detected issue, the driver node for communicating via this USB port is not notified and is stopped if the USB connection is disconnected. In this scenario, if the user plugs in another device, the driver node considers the new device as the previous one. This issue is fixed in one of the commits we manually analyzed in this study <sup>11</sup>. This commit assures that the driver node fast-fails when the USB device is disconnected. This change also ensures that the driver node does not mistakenly detect and re-associate with a newly plugged-in USB device as the previous USB device.

**Is it a performance antipattern?** Since we identified two instances of this issue in our analysis (see Table 5), we cannot confirm if this performance issue commonly occurs in CPSs. Hence, for now, we do not consider Delayed Sync with Physical Events as an antipattern.

#### 4.6. Bad Noise Handling

Several hardware devices contain sensors that require software-based noise-handling techniques to collect accurate data, as the input collected from these devices can be noisy. However, in some situations, the noise-handling techniques are not efficient, with entails that the CPS needs to collect more data to increase the accuracy, but this also leads to an increase in I/O resource consumption. Similar to the previous section, we detected this performance issue in only two projects. There were a total of ten instances found across these two projects.

**Examples** We detected this performance issue in PX4-Autopilot and the Johnny Five project. The Johnny Five project is a JavaScript robotics programming framework working with various hardware. This project handles the noises by selecting the median value collected from sensors. However, by looking at the changes in the code history of this project <sup>12</sup>, we noticed that the implemented median calculation was not efficient enough. One of the commits <sup>13</sup> in this project improves the noise handling procedure with a faster and more stable technique.

**Is it a performance antipattern?** Similarly to the previous performance issue, the Bad Noise Handling is detected in only two projects in our analysis. Therefore, we currently cannot confirm that this performance issue is common enough to be considered an antipattern.

#### 4.7. Revisiting RQ1 and RQ2

Summarizing the discussion of each identified CPS-PA and results, we noted the occurrence of four previously

<sup>11</sup><https://github.com/turtlebot/turtlebot/commit/f2d46b705722b61948313e3f2ec167dcaeeb3359>

<sup>12</sup><https://github.com/rwaldron/johnny-five/pull/138>

<sup>13</sup><https://github.com/rwaldron/johnny-five/commit/d3541a70d7767e52fb9aa67b32d9f32669abf45f>

undescribed CPS-PAs and three from Smith [23] (RQ1). Of these CPS-PAs, the Hard Coded Fine Tuning antipattern is the most prevalent with 63.03% of the total number of CPS-PA occurrences, followed by the Magical Waiting Number antipattern with 23.70%. A short overview of the detected CPS-PA is shown in Table 6 (RQ2).

| Antipattern              | Occurrence | of total CPS-PA occurrences |
|--------------------------|------------|-----------------------------|
| Hard Coded Fine Tuning   | 399        | 63.03 %                     |
| Magical Waiting Number   | 150        | 23.70 %                     |
| Fixed Communication Rate | 66         | 10.43 %                     |
| Rounding Errors          | 10         | 1.58 %                      |
| Is Everything OK         | 4          | 0.63 %                      |
| Where Was I              | 3          | 0.47 %                      |
| Are We There Yet         | 1          | 0.16 %                      |
| Total                    | 633        |                             |

Table 6: Order of CPS-PAs occurrences detected in our study.

## 5. Study II - Automated Detection of the new CPS Antipatterns

As we have seen in previous studies [17, 30], antipatterns can negatively impact a system’s performance and stability. Informing the developer of existing antipatterns in their system gives them the ability to resolve the issues [19, 20], and therefore possibly improve the software’s code quality [67], performance [18], and stability [32].

In this section, we propose a novel approach to statically detect the two most frequently occurring CPS-PA from our Study I (see Section 3), in particular, the *Magical Waiting Number* and *Hard-Coded Fine Tuning* antipatterns. We focus on these two antipatterns since they represent the large majority (71.30%) of the instances of performance issues we have identified in Study I (see Table 4 and Table 5) and CPS-PA occurrences (86.73%).

To detect these two antipatterns, we rely on static analysis rather than dynamic analysis as done by Pinciroli et al. [53]. Our choice is due to the fact that static analysis is faster since it does not require re-running the code on the hardware or in a simulated environment, nor the test cases, which are usually very expensive to run [6, 68]. Furthermore, it does not require to re-build old releases of the CPS systems, which can be very challenging due to obsolete hardware, dependencies, and libraries [69, 70]. However, static analysis has limitations as it requires manually validating the raised warnings and removing false alarms [71].

In this section, we first describe our approach for detecting Magical Waiting Number and Hard Coded Fine Tuning (Section 5.1), and then we evaluate against a benchmark (Section 5.2) of nine open-source CPS projects not considered in Study I.

### 5.1. Our Approach: APSpotter

We have implemented two detection strategies for the Magical Waiting Number and Hard Coded Fine Tuning patterns in our tool, **APSpotter**. Details of these strategies are in the following subsections (Section 5.1.1 and Section 5.1.2). Our tool employs rule-based static analysis techniques to detect performance issues in CPSs. In contrast to dynamic detection approaches, static analysis techniques do not require high computational effort to monitor the application during execution. See Figure 5 for the software architecture of our tool.

**APSpotter** runs over a project (refer to ① and ③ in Figure 5) in search of one specific antipattern (②) at a time. It analyzes the project directory and selects the source code files (such as C++ classes) that are of interest for the specific antipattern under analysis. For instance, for the Magical Waiting Number antipattern, **APSpotter** selects the files that contain the `wait()` method or similar method/function calls for hardware-software communication and multiprocessing (step ④). Since we are interested in antipatterns at the source code level, **APSpotter** skips modules related to Git, Azure, Docker files, documentation, web pages, Gradle usage, tests, test data, examples, and templates. After this selection process, **APSpotter** creates an Abstract Syntax Tree (AST) using ANTLR4 [72] ⑤. Then, it analyzes the structure of the AST in search of the antipattern (⑥-⑦) for which it was run. Our tool is publicly available on GitHub <sup>14</sup>.

The parser used in this tool is specifically for C++ projects, but there are parsers available for other languages. This tool has been designed to process an Abstract Syntax Tree (AST) resulting from any parser; thereby making it possible to be extended to other languages for future research.

#### 5.1.1. Detecting Magical Waiting Number

As described in Section 4.1, the Magical Waiting Number antipattern occurs when two events happen: (1) a software component sends a request to hardware, and (2) the software waits for a fixed amount of time or does not wait at all to read the response from the hardware.

To detect this antipattern, we first identify source code files that import drivers for the hardware; hereafter, we refer to these files as *candidate files*. We then check whether these two events described above occur using specific rules (regular expressions). An overview of the method for detecting this antipattern is presented in Figure 6. This procedure contains three phases and is repeated for each

<sup>14</sup>[https://github.com/ciselab/CPS\\_SPA\\_Detection\\_Tool](https://github.com/ciselab/CPS_SPA_Detection_Tool)

candidate file. The first phase involves identifying the requests sent to hardware, in which the detector analyzes each file to determine if it has any direct request to hardware. In the second phase, our detector identifies waiting commands after sending the request, i.e., statically identifying waiting commands such as sleep or timeout methods. Finally, our detector analyzes the code history of the CPS to determine whether the waiting time was both hard-coded and manually changed in prior commits.

**Identifying the requests sent to hardware (Phase 1 in Figure 6)** As the first step, the detector checks if it can find at least one request to the hardware in the given candidate file (condition ① in Figure 6). The command used for sending the request to hardware varies depending on the language and the project. For instance, PX4-Autopilot, a well-known open-source CPS for controlling drones, is implemented in C++ and uses SerialLib<sup>15</sup> for serial communication between modules, or MAVLink<sup>16</sup> to communicate with MAVLink-based vehicles<sup>17</sup>. We designed regular expressions based on the documentation of these libraries to find the send requests in a given source code file; in case of a regex match, the file is considered as a *candidate file* to further check for the presence of the Magical Waiting Number antipattern.

Suppose the detector cannot find any hardware request. In that case, it assumes that it is not possible to find the Magical Waiting Number in this file, stops the process, and continues with the next source code file in the project repository. However, if it finds at least one request, it enters the second phase of the detection procedure.

**Identifying the waiting commands after the request (Phase 2 in Figure 6)** The second phase starts by searching for the waiting command after the request to hardware (condition ② in Figure 6). If it cannot find any waiting command, it checks if the system uses any method of detecting the request sent previously has been finalized before requesting the results (condition ③ in Figure 6). If it finds no method, the detector identifies the request command as a Magical Waiting Number. In contrast, the detector assumes that it is not an antipattern if no usage can be found. If the detector manages to find any waiting command in condition ②, it checks the numeric value used as the amount of time that the system needs to wait for the request sent to the hardware (condition ④ in Figure 6). If a fixed hard-coded value is used, the detector enters Phase 3. However, if a variable is used to set the waiting time, it continues Phase 2 by finding the closest statement that assigns a value to this variable. Then, it checks whether the assigned value is hard-coded (condition ⑤ in Figure 6). If the variable is assigned dynamically, the detector decides that this pattern is not a Magical Waiting Number antipattern. However, if the value is assigned a hard-coded fixed value, the detection

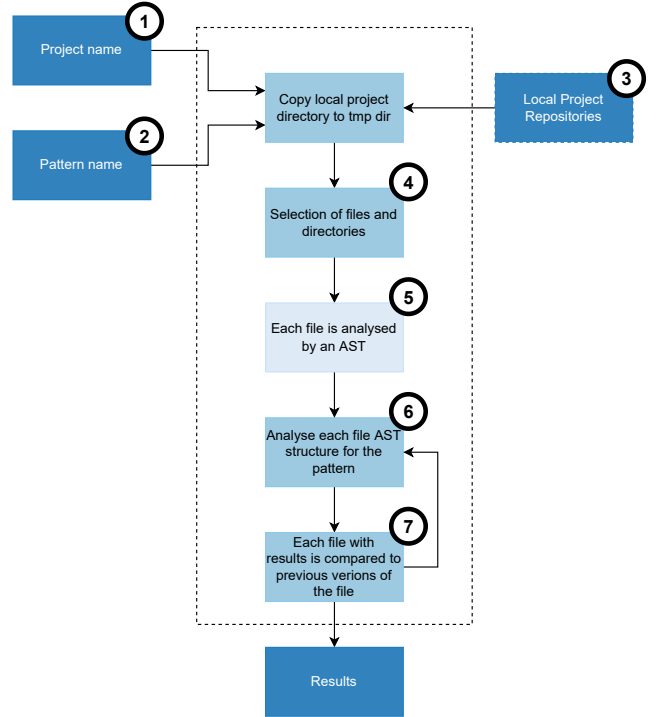


Figure 5: AP-Spotter

process enters Phase 3.

**Analyze the code history (Phase 3 in Figure 6)** If the code under analysis is still a potential antipattern (AP) according to Phase 2, we start the last phase. The first condition happens when a hard-coded fixed value is directly passed as the waiting time to the wait method (true branch of condition ④ in Figure 6). The second condition regards variables that are assigned to a hard-coded value and passed as the waiting time (true branch of condition ⑤ in Figure 6). In both cases, the detector checks if the hard-coded value used as the waiting time is changed in the code history (condition ⑥ in Figure 6). If this hard-coded value is changed, it shows that developers had to change the waiting time because they either detected a physical event or a specific hardware module that the previous waiting time was not suitable. Hence, the detector considers it as the Magical Waiting Number antipattern. However, if the hard-coded value is not changed in the code history, we cannot be sure if there is any scenario in which the current hard-coded value does not work, and thereby the detector does not consider it as an antipattern.

### 5.1.2. Detecting Hard Coded Fine Tuning

Detecting this performance antipattern in CPSs requires (1) identifying the method calls that pass any numeric values to hardware (e.g., requests, property setters, etc.); (2) checking whether the passed numeric arguments are hard-coded in the code; and (3) checking if the hard-coded value used for these arguments is changed in the project's code history. This antipattern can occur in any file; thus, we first need to identify the interesting code files

<sup>15</sup> <https://github.com/imabot2/seriallib>

<sup>16</sup> <https://mavlink.io/en/>

<sup>17</sup> <https://microsoft.github.io/AirSim/mavlinkcom/>

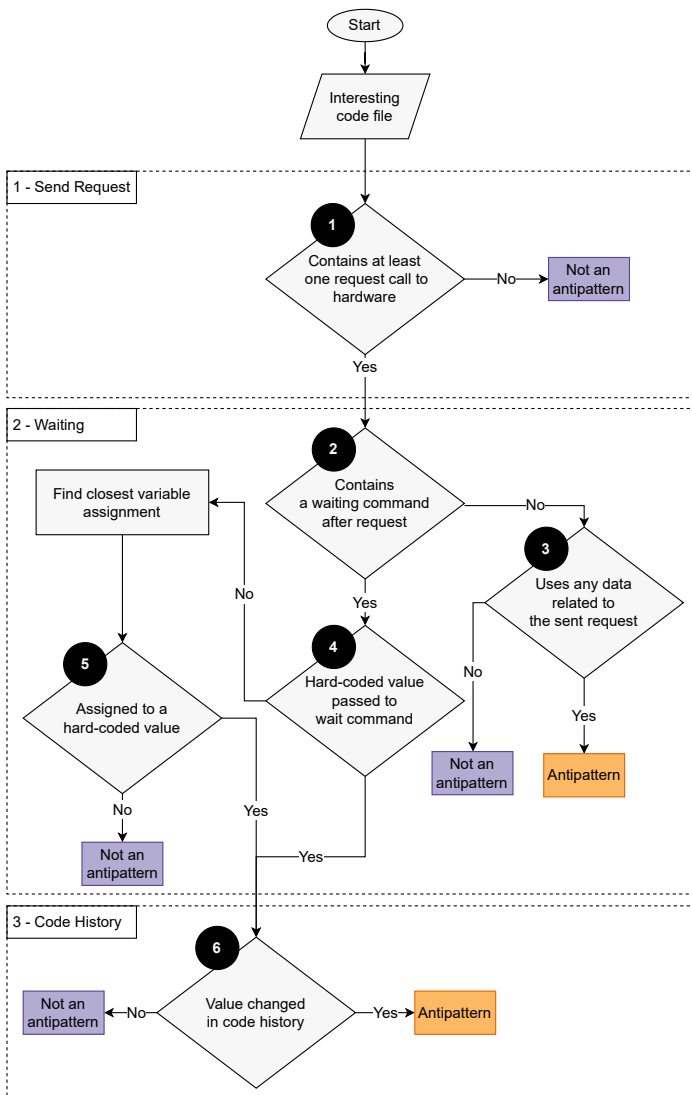


Figure 6: General overview for detecting the Magical Waiting Number antipattern in CPS.

(same as the files used in Section 4.2).

Figure 7 illustrates the detection procedure for the Hard Coded Fine Tuning antipattern. Similar to the detection procedure for Magical Waiting Number, this detection method has three phases that can be applied to each interesting code file. The first phase identifies hardware-related methods, i.e., any request or method call passing numeric values to hardware modules. The second phase analyzes input arguments, where the detector analyzes each of the numeric input arguments to hardware-related method calls and detects the ones which are assigned from a hard-coded value. Finally, Phase 3 analyzes the code history to check whether the hard-coded values are modified in the CPS's

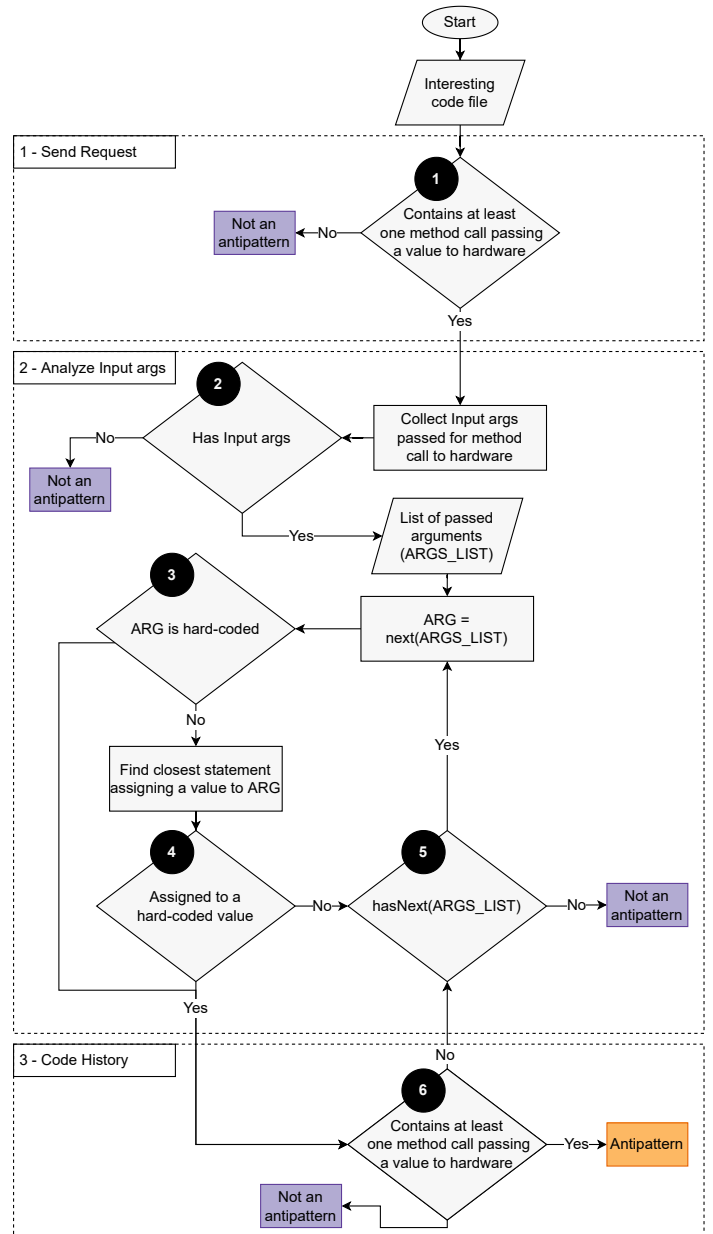


Figure 7: General overview for detecting the Hard Coded Fine Tuning antipattern in CPS.

code history.

**Identify hardware-related methods calls (Phase 1 in Figure 7)** In the first step, the detector examines each of the lines of code in the interesting files to detect any hardware-related method calls (e.g., requests sent to hardware modules or method calls that set a value in the property of hardware, etc.). This step is represented by condition ① in Figure 7. Similar to detecting requests to hardware modules for the Magical Waiting Number antipattern, if the detector knows the library used for communication between software and hardware, or one hardware module and another hardware component, it can easily detect hardware-related methods, as it just needs to scan for the particular methods. If the file under analysis does not

contain any hardware-related method calls, the detector assumes that it cannot find any Hard Coded Fine Tuning antipattern in this file and continues the detection process with the following interesting files. However, if the file invokes at least one hardware-related method, the detection procedure for this file enters Phase 2.

#### Analyze input arguments (Phase 2 in Figure 7)

For each of the numeric input arguments passed to the hardware-related method call that is detected in Phase 1, the detector inspects if the passed argument is a hard-coded value (condition ③ in Figure 7). If this value is hard-coded, the detector enters Phase 3. If the value passed as an argument of the hardware-related method is a variable, the detector finds the closest statement in the code that assigns a value to the variable. If this assigned value is hard-coded (true branch of condition ④ in Figure 7), the detector enters Phase 3. If assigned dynamically (false branch of condition ④ in Figure 7), the detector assumes that this case is not a Hard Coded Fine Tuning antipattern.

**Code history analysis (Phase 3 in Figure 7)** This section is similar to the procedure explained for the Magical Waiting Number AP. We examine the code history of the CPS to collect all the modifications to the hard-coded values, which are passed to the hardware-related method calls and requests (condition ⑥ in Figure 7). These hard-coded values can be passed directly to the hardware-related method call or assigned to variables that are passed later to these methods. If the values are changed, it indicates that developers found scenarios in which the hard-coded value was not suitable (hence a Hard Coded Fine Tuning antipattern is detected). If it was not changed, we cannot be sure if this value is not suitable for all the possible scenarios in the operation of the CPS.

## 5.2. Empirical Evaluation

In this section, we evaluate the precision of the **AP-Spotter** tool in detecting the Magical Waiting Number and Hard Coded Fine Tuning antipatterns. Therefore, our second study is guided by our third research question:

**RQ3:** *How precise can our approach detect performance antipatterns?*

### 5.2.1. Benchmark

To assess our tool, we have selected a set of 9 CPS projects that were not previously used in Study I. This is because we want to avoid any positive bias towards the projects we have manually analyzed to identify the new antipatterns. In particular, we selected 9 projects, whose statistics are summarized in Table 7. These projects differ in their sizes (number of commits, stars, and forks) and application domains. All projects are developed in **C++** (a constraint of our tool), are open-source, and are publicly available on GitHub.

It is also worth noticing that six of these projects (i.e., *Arduino*, *Arduino-IR Remote*, *ArduinoJson*, *Carla*, *RFID*,

and *Ardupilot*), have been used in a prior study aimed at classifying functional bugs in CPS [24]. These projects have a high activity level and are well maintained, these projects are known by the research community as interesting projects to select when investigating code quality of CPS systems.

Three additional projects are added to the list for analysis, i) *AirSim*, ii) *CoppeliaSimLib*, and iii) *ArduMower*. *AirSim* is a simulation platform by Microsoft and used for AI research and experimentation [73], including assessing reinforcement learning methods [74] and testing [75]. *CoppeliaSimLib* is a library part of Coppelia Robotics [76], its robotics simulation is i.a., of interest due to its physics engines support [77] and known in the robotics community. *ArduMower* is an open-source robotic project of interest in the DIY community. This project has a lower popularity and number of commits compared to some of the other projects selected. These projects have been selected for their industrial usage, DIY community, machine learning components, or popularity by researchers in their domain.

### 5.2.2. Study Setup

To answer RQ3, we ran **AP-Spotter** on each project and collected the files for which our tool indicates the presence of an antipattern (hereafter called *warnings*). To assess the detection precision, we manually validated the raised warnings considering (1) all commits (title, message, and code changes) related to the file and statements for which the warning is raised, (2) the project documentation, and (3) GitHub issues and pull-requests. This allowed us to gain more information about the nature and rationale for the applied changes.

To assess the final precision of the tool we calculated the weighted average. This is done as follows:

$$Precision = \frac{(A * ATP\%) + (B * BTP\%)...}{TW} \quad (1)$$

Where ‘A’ is the number of warnings for Project A and ‘ATP%’ is its percentage of true positives. ‘TW’ is the total number of warnings in all the projects.

The total number of warnings of each project is taken into consideration, as with a higher number of warnings the “True positives” calculation would be more accurate. For example, for the “Arduino-IRremote” project in Table 8 the percentage of true positives is 100%, but the number of warnings is only 1. Therefore we take this into lower consideration than “Ardupilot” with a true positives percentage of 50.70% with 71 warnings. This calculation is done for each antipattern separately to know the tool’s precision for that antipattern. For the tool’s total precision, we combined both the Magical Waiting Number and the Hard Coded Fine Tuning results.

### 5.2.3. Results

The total number of warnings that **AP-Spotter** raised for each project is reported in Table 8. In short, **AP-Spotter**



| Project Name     | Language | Nr. of commits | Stars | Forks | Domain        |
|------------------|----------|----------------|-------|-------|---------------|
| AirSim           | C++      | 3,523          | 13.2k | 3.8k  | Automotive    |
| Carla            | C++      | 5,439          | 7.8k  | 2.4k  | Automotive    |
| Arduino          | C++      | 4,236          | 14.1k | 12.5k | Arduino       |
| Arduino-IRremote | C++      | 684            | 3.6K  | 1.6k  | Arduino       |
| ArduinoJson      | C++      | 1,553          | 5.7k  | 1k    | Arduino       |
| RFID             | C++      | 512            | 2.3k  | 1.3k  | Arduino       |
| Ardupilot        | C++      | 53,400         | 7.4k  | 12.8k | Drone         |
| CoppeliaSimLib   | C++      | 375            | 57    | 28    | Robotics      |
| Ardumower        | C++      | 1,579          | 207   | 126   | Wheeled Robot |

Table 7: Projects used with the Detection Tool AP-Spotter

| Projects         | Total files in project | Hard Coded Fine Tuning |                    |             |                    | Magical Waiting Number |                   |             |                    |
|------------------|------------------------|------------------------|--------------------|-------------|--------------------|------------------------|-------------------|-------------|--------------------|
|                  |                        | # Files with warnings  | TP Files           | # Instances | TP Instances       | # Files with warnings  | TP Files          | # Instances | TP Instances       |
| AirSim           | 1450                   | 0                      | -                  | -           | -                  | 7                      | 3 (42.86%)        | 7           | 3 (42.86%)         |
| Carla            | 1289                   | 0                      | -                  | -           | -                  | 0                      | -                 | -           | -                  |
| Arduino          | 1310                   | 6                      | 5 (83.33%)         | 9           | 8 (88.89%)         | 0                      | -                 | -           | -                  |
| Arduino-IRremote | 122                    | 1                      | 1 (100.00%)        | 1           | 1 (100.00%)        | 0                      | -                 | -           | -                  |
| ArduinoJson      | 461                    | 0                      | -                  | -           | -                  | 0                      | -                 | -           | -                  |
| Ardumower        | 3350                   | 4                      | 3 (75.00%)         | 8           | 5 (62.50%)         | 0                      | -                 | -           | -                  |
| Ardupilot        | 4515                   | 59                     | 26 (44.07%)        | 71          | 36 (50.70%)        | 5                      | 3 (60.00%)        | 6           | 4 (66.67%)         |
| CoppeliaSimLib   | 1289                   | 0                      | -                  | -           | -                  | 4                      | 3 (75.00%)        | 4           | 3 (75.00%)         |
| RFID             | 68                     | 0                      | -                  | -           | -                  | 0                      | -                 | -           | -                  |
| <b>Total</b>     | <b>13854</b>           | <b>70</b>              | <b>35 (53.93%)</b> | <b>89</b>   | <b>50 (58.98%)</b> | <b>16</b>              | <b>9 (59.29%)</b> | <b>17</b>   | <b>10 (62.02%)</b> |

Table 8: Projects analysed with AP-Spotter and the number of antipattern occurrences found.

detects the Magical Waiting Number antipattern in 3 projects, and the Hard Coded Fine Tuning antipattern in 4 projects.

For each project, the number of files containing warnings and the number of instances across these files are shown. In a number of files, multiple instances of the antipattern were detected. For example, in the Arduino project the antipattern Hard Coded Fine Tuning is found in 6 files, with a total of 9 antipattern instances. We manually validated these findings to verify how many of these warnings were true positives.

Taking into consideration the Weighted average of each antipattern detection, the weighted total tool precision is 59.49%. Examples of detected Hard Coded Fine Tuning antipattern instances are: i) changes to the target’s speed after test results<sup>18</sup> and ii) re-tuning of the gyro sensitivity

<sup>18</sup><https://github.com/ArduPilot/ardupilot/commit/dd392f8c0a74fa0ff603ae5283792cd335fcdfcb>

based on user-provided logs<sup>19</sup>. These stood out as their reasoning, as described in the commit message, clearly relates to tweaking done after received feedback. Either by the community or by test results. In the latter instance, it is unclear which stage of testing was meant by the developer.

Further, examples from the detected Magical Waiting Number antipattern instances are: i) a hard-coded sleep duration, with no explanation regarding the chosen value, after started listening to Gazebo topics<sup>20</sup> and ii) relates to the support for multiple peripherals in the Software in the Loop (SITL)<sup>21</sup>. A code snippet from this last example

<sup>19</sup><https://github.com/ArduPilot/ardupilot/commit/53c4b163ce61a8d58651cb07e54bcfa0bbbd44>

<sup>20</sup><https://github.com/microsoft/AirSim/blob/main/GazeboDrone/src/main.cpp>

<sup>21</sup>[https://github.com/ArduPilot/ardupilot/blob/09a0d8d0c0ff060f1ea9d85d6923bf70c1b15f8f/libraries/AP\\_HAL\\_SITL/SITL\\_Periph\\_State.cpp](https://github.com/ArduPilot/ardupilot/blob/09a0d8d0c0ff060f1ea9d85d6923bf70c1b15f8f/libraries/AP_HAL_SITL/SITL_Periph_State.cpp)

can be seen in Listing 2.

```
30 void SITL_State::wait_clock(uint64_t
    wait_time_usec) {
31 while (AP_HAL::native_micros64() <
    wait_time_usec) {
32     usleep(1000);
33 }
34 }
```

Listing 2: ArduPilot SITL code-snippet.

This code snippet shows the possibility to use a waiting function, for which the duration can be given in microseconds. Though this function seems to support the possibility to request any duration in microseconds, the waiting method always goes in steps of 1000 microseconds. This is not clearly described in the code or documentation.

#### 5.2.4. Discussion and Revisiting RQ3

In this section, we discuss the results of our empirical evaluation.

From our results, we can see that it is possible to automatically detect the Hard Coded Fine Tuning (58.98%) and Magical Waiting Number (62.02%) antipatterns, with a total tool precision of 59.49% (**RQ3**). Though we also see a relatively high number of false positives. Reviewing the results to investigate these false positives, shows that two main challenges are causing these problems: 1) issues with building the AST, and 2) the definition of these antipatterns require them to be closely related to the hardware.

For the first point, regarding the AST, the **AP-Spotter** tool uses an existing library to generate the AST. An incorrectly generated AST will result in the **AP-Spotter** tool analyzing the information based on an incorrect AST, resulting in a possible false positive. This could be due to an issue in the library, or an edge case that the library does not take into consideration (yet). For future research, we plan to re-review these cases and provide assistance, in the form of pull requests and issue creation, to the further development of the library.

The second point is related to the definition of these CPS-PAs. They require to be closely related to hardware interaction with the rest of the system. In our automatic detection approach, we describe that detecting a hardware-related call is necessary, see Figure 6 and Figure 7. As this in itself is a difficult challenge that requires insight into each project and the libraries used, a more generic detection method will need to be investigated in the future. For the **AP-Spotter** tool, a generic approach was decided, which requires a preselection of interesting modules to be made before running the **AP-Spotter** tool. This could result in both possible false negatives and false positives. As we do not have a catalog of antipatterns existing in the selected projects, we cannot verify how many false positives are occurring.

## 6. Threats to Validity

In this section, we review the threats to the validity of our studies separated by category.

To ensure the replicability of our studies, we provide the data collected during analysis and the tools created at [https://github.com/ciselab/CPS\\_repo\\_mining](https://github.com/ciselab/CPS_repo_mining) for our first study, and [https://github.com/ciselab/CPS\\_SPA\\_Detection\\_Tool](https://github.com/ciselab/CPS_SPA_Detection_Tool) for our second study. We also include README.md files in these replication packages as a guide on how to replicate our studies.

### 6.1. Internal Validity

To select possible interesting commits for the first study, we selected commits based on performance-related keywords. This is to find developer-admitted performance issues and analyze these commits in search for possible antipatterns. This method relies heavily on the chosen keywords. To mitigate possible author bias in selected keywords, we extended our set of selected commits by applying Topic Modeling to the non-selected commits and adding relevant resulting commits to our data set. Further, these keywords were validated by domain experts from the H2020 COSMOS project [56]. There is still a risk of interesting commits being missed due to how the developers write their commit messages. In future research, we want to analyze the projects for Performance Antipatterns and review the keywords used in their commit messages.

For the second study, we manually validated each result of the Automatic Detection Tool **AP-Spotter**. This method of validating the results would only confirm true and false positives. Potential false negatives that we are not aware of can still occur. This would be overcome by having a benchmark project where all antipattern in a system are known. As far as we are aware, such a benchmark does not yet exist. In future research, we will create such a benchmark for a small system.

### 6.2. Conclusion Validity

For the first study, we selected 14 projects. Extending the pool of projects could potentially change the number of occurrences of each antipattern and possibly confirm other potential antipatterns. We mitigated this by having a broad and diverse selection of projects, but for future research, it would be of interest to keep an eye on possible occurrences of the potential antipatterns as described in this paper.

For the second study, we analyzed 9 projects, which differ from those used in the first study. Only 3 projects showed warnings for Magical Waiting Number and 4 projects for Hard Coded Fine Tuning. Selecting a larger set of projects would give us a more accurate estimate of the tool's precision.

### 6.3. External Validity

In the first study, we did not consider the age and current activity level of each project. There is a possibility that the developers of older projects were not aware of the existence of the SPA. Thereby, these antipatterns could be more prevalent in older projects. The developers of the newer projects, on the other hand, could have been aware of the existence of these SPAs at the design stage of the project. And thereby these SPAs would not be occurring as often.

For the second study, the detection tool **AP-Spotter** analyses the current state of the project and the history of the file when detecting potential antipatterns. As such, it could be that at some point in time antipatterns were present in the system, but were resolved before the version that we analyzed. These antipatterns are not part of our analysis.

## 7. Conclusion

Since the coinage of the term CPS in 2006 by Gill [1], CPSs have increasingly become more part of our daily lives [35, 12, 11], from smart cars [6] to medical devices [3]. This paper researches the occurrences of CPS Performance Antipatterns in Open-Source projects on GitHub, further, it presents an approach to detect the two most frequently occurring CPS-PA. The goal of this paper is to aid developers in performance-demanding CPS projects and increasing awareness of existing CPS-PAs.

We conducted two studies in this paper; first, we analyzed multiple open-source CPS projects to catalog the frequency of known CPS-specific antipatterns and search for unknown ones. In our second study, we proposed an automatic detection approach for the two most frequently occurring antipatterns, and we evaluated our approach against a set of different open-source CPS projects.

As we have seen from our results, we detected the following antipatterns in the open-source projects that we considered: i) Hard Coded Fine Tuning, ii) Magical Waiting Number, iii) Fixed Communication Rate, iv) Rounding Errors, v) Is Everything OK, vi) Where Was I, and vii) Are We There Yet (**RQ1**). The most frequently occurring antipatterns are: i) Hard Coded Fine Tuning (399 out of 646 occurrences), and ii) Magical Waiting Number (150 out of 646 occurrences) (**RQ2**). Further, our automatic detection approach showed a precision of 62.02% for Magical Waiting Number and 58.98% for the Hard Coded Fine Tuning antipattern. The main challenges for automatic detection of these antipatterns are i) building the AST, and ii) detecting a hardware connection in the modules (**RQ3**).

We hope that the **AP-Spotter** tool can be a starting point for practitioners and researchers to be used, extended, and adjusted for the continuing effort of improving the overall performance and code quality of CPSs.

This paper makes the following contributions:

- **PyRock**: an open-Source mining repository tool to find commits that are related to self-admitted performance issues based on the commit message.
- A data set of 2699 potentially performance-related commits from 14 Open-Source projects.
- A catalog/taxonomy of new CPS-PAs identified through manual classification and analysis of self-admitted performance issues.
- An approach for automatically detecting the two most frequent occurring antipatterns, namely Magical Waiting Number and Hard Coded Fine Tuning.
- **AP-Spotter**: An implementation of our proposed CPS-PAs detection approach.

Replication packages for both studies are available openly on GitHub<sup>22 23</sup>. These replication packages contain the data collected during the analysis and source code of the tools introduced in this paper.

For future work, we want to conduct surveys and interviews with the CPS developers to better understand why we see such a high number of occurrences for each type of antipattern. Further, we would like to see if an automatic detection tool for these antipatterns would be helpful to the developers.

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<sup>22</sup>[https://github.com/ciselab/CPS\\_repo\\_mining](https://github.com/ciselab/CPS_repo_mining)

<sup>23</sup>[https://github.com/ciselab/CPS\\_SPA\\_Detection\\_Tool](https://github.com/ciselab/CPS_SPA_Detection_Tool)

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