Towards Parameter-Independent Fault Detection Using Qualitative Simulation

Ankita Das*, Roxane Koitz-Hristov, Franz Wotawa

Institute of Software Engineering and Artificial Intelligence,
Graz University of Technology, Inffeldgasse 16b/2, A-8010 Graz, Austria
{ankita.das,rkoitz-hristov,wotawa}@tugraz.at

Abstract

Monitoring and diagnosis of cyber-physical systems typically rely on either quantitative simulation models with system-specific parameters or large amounts of training data. However, both approaches often struggle to generalize across systems that share the same physical structure but differ in configuration or operating conditions. To address this limitation, we previously proposed a fault detection framework based on Qualitative Simulation (QSIM) that avoids instance-specific parameterization.

In this paper, we empirically evaluate the proposed approach on a set of systems from several domains. Across these case studies, we investigate various faults and analyze the ability of our technique to detect deviations from nominal behavior. These initial results suggest that QSIM-based diagnosis is a promising but model-sensitive direction for parameter-independent fault detection, particularly when faults produce clear qualitative deviations from nominal behavior.

1 Introduction

Fault detection and diagnosis (FDD) is essential in order to ensure the availability and reliability of cyber-physical systems (CPS) to prevent equipment damage, system shutdowns, unnecessary operational costs, and potentially safety critical scenarios. However, developing monitoring solutions that remain robust across various installations featuring different configurations and operation environments continues to be a challenge [Dowdeswell *et al.*, 2020]. Let us consider the building domain; smart buildings featuring identical architectural designs may exhibit different thermal dynamics due to seasonal changes, degradation over time, or differing occupancy patterns [Genkin and McArthur, 2022]. Conventional monitoring solutions, such as quantitative simulation or machine learning approaches, often struggle with this variance. For example, temperature and humidity changes can affect a building's thermal resistance, which may cause rigid quantitative models that rely on precise parameterization to produce inaccurate results [Venkatasubramanian *et al.*, 2003; Katipamula and Brambley, 2005]. Data-driven approaches face a similar challenge. Because buildings are unique, models trained for a specific building often generalize poorly on others [Lu *et al.*, 2019]. While transfer learning has been explored to mitigate this issue, its effectiveness across heterogeneous buildings remains limited [Genkin and McArthur, 2022; Dou and Zhang, 2025].

This lack of generalization extends to the basic components of a smart building. Let us consider a standard RC circuit as depicted in Figure 1, which is a fundamental building block in many sensors and control units. A quantitative model tuned to monitor a circuit with a resistance of $R = 10\Omega$ and capacitance of $C = 0.001F$ may no longer remain accurate when applied to an otherwise identical circuit with $R = 15\Omega$. However, the underlying causal physics remain unchanged: the circuit still obeys Kirchhoff's laws and the relation $i = C \cdot \frac{dv_C}{dt}$, independent of the specific parameter values. Qualitative reasoning naturally captures this invariance and provides an abstraction for precise numerical parameters while focusing on the underlying structure and behavior of the system [Forbus, 1984; Kuipers, 1989a].

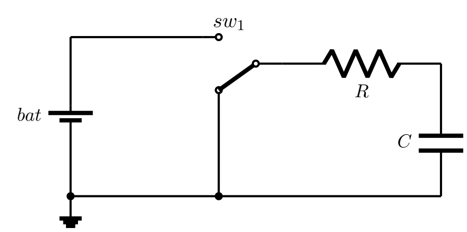

Figure 1: Simple RC circuit consisting of a resistor R, a capacitor C, and a switch sw_1, and a battery bat.

In previous work [Das *et al.*, 2025], we introduce a fault detection approach using Qualitative Simulation (QSIM) [Kuipers, 1986], in particular ASP-QSIM [Wiley *et al.*, 2013], to monitor CPS. We model the system under diagnosis using qualitative constraints encompassing the nominal system behavior. Faults are detected by comparing the conformance of the qualitative behaviors generated by the simulation with the abstracted system observations. While our previous work established the theoretical framework, its abil-

*Authors are listed in alphabetical order.

ity to generalize across parameter shifts has not yet been systematically evaluated. In this paper, we address this gap by conducting an empirical study of QSIM-based fault detection in CPS under parametric variance. We demonstrate that our QSIM framework is capable of detecting faults across diverse parameterizations without any modification to the underlying qualitative model.

The remainder of the paper is structured as follows. Section 2 covers related work, while in the subsequent section we discuss the fundamental theoretical background of our work. Section 4 describes our evaluation setup, benchmarks and results. Afterward, we conclude the paper and elaborate on future work.

2 Related Work

Qualitative reasoning is a well-established approach for modeling and analyzing physical systems without requiring precise numerical values, thereby enabling reasoning about dynamic system behavior under incomplete knowledge [Travé-Massuyès and Milne, 1995]. Early approaches include qualitative physics based on constraint relations [De Kleer and Brown, 1984], Qualitative Process Theory (QPT) for modeling system behavior in terms of interacting processes [Forbus, 1984; Bredeweg *et al.*, 2009], and QSIM, which generates possible system behaviors from qualitative differential equations (QDEs) [Kuipers, 1986; Kuipers, 1989b]. One important application area of qualitative reasoning is the monitoring and diagnosis of dynamic systems. An early approach is MIMIC [Dvorak and Kuipers, 1991], which combines qualitative simulation, behavioral tracking and model-based diagnosis (MBD) [Reiter, 1987; de Kleer and Williams, 1987]. MIMIC utilizes qualitative and semi-quantitative simulation to generate a hypothesis space of possible behaviors. This predicted behavior is compared to the observed system behaviors over time. Diagnosis is performed through a hypothesize-and-match cycle in which observations evoke fault hypotheses. Qualitative simulation is then used to generate the predicted behavior of each hypothesized fault. If the predictions of a fault model match further observations a possible abnormality has been identified. Rinner and Kuipers (1999) extended the framework to enable the monitoring of dynamic systems that exhibit both discrete mode changes and continuous evolution. However, MIMIC assumes that all possible fault models are explicitly represented and simulated a priori. Approaches by Lackinger and Nejdl [Lackinger and Nejdl, 1991], Leitch et al. [Leitch *et al.*, 1993], and Subhramanian and Mooney [Subhramanian and Mooney, 1994] used qualitative simulation to generate behavioral predictions and identify fault hypotheses explaining inconsistencies between predicted and observed behavior. These approaches additionally emphasized synchronous tracking, temporal consistency, and behavioral verification over evolving qualitative state sequences.

In contrast to existing qualitative simulation approaches to monitoring and diagnosis, we perform fault detection based on a conformance relation over sets of behaviors generated by qualitative simulation [Das *et al.*, 2025]: faults are detected when the observed system evolution cannot be explained by any nominal behavior. This is realized by comparing a qualitative abstraction of the observation trace against the predicted behaviors using a conformance relation inspired by Aichernig et al. [2009], who used conformance in the context of test case generation. More generally, conformance-based approaches compare observed traces against behaviors permitted by a model or specification and have been studied in the context of cyber-physical and hybrid systems [Mohaqeqi *et al.*, 2014].

3 Preliminaries

In this section, we outline the fundamental concepts that form the basis of our approach. We first provide a brief overview of qualitative simulation using QSIM before putting it into practice within the ASP-QSIM framework. Finally, we describe how qualitative simulation can be used for fault detection in combination with conformance checking.

3.1 Qualitative Simulation (QSIM)

Qualitative simulation is a reasoning technique used to predict possible responses of dynamic systems when precise quantitative data is unavailable. System variables are described by qualitative magnitudes (e.g., positive, negative, or zero) and qualitative directions of change (e.g., increasing, decreasing, or stable) [Forbus, 1984]. One influential framework for qualitative reasoning is QSIM [Kuipers, 1986]. QSIM represents system dynamics using QDEs, which describe relationships between system variables and their derivatives in symbolic form. These equations capture the structure of the physical system while abstracting away from precise numerical values.

Definition 1 (Qualitative Differential Equation)**.** *[Kuipers, 1989b] A qualitative differential equation (QDE) is a tuple*

$$\mathcal{Q} = \langle V, Q, C, T \rangle,$$

where V is a finite set of system variables, Q assigns to each variable in V a quantity space consisting of qualitative landmarks and intervals, C is a set of qualitative constraints relating the variables, and T is a set of transition rules specifying how qualitative states may evolve over time.

Given a set of QDEs and an initial qualitative state, QSIM generates the set of admissible qualitative behaviors. Each behavior is a sequence of states such that every successor state is consistent with the constraints and transition rules of the QDEs.

3.2 ASP-QSIM

ASP-QSIM [Wiley *et al.*, 2014; Wiley, 2017] is a declarative framework for qualitative simulation based on Answer Set Programming (ASP). Within this logic programming framework, QSIM is represented as qualitative constraints, QDEs, and transition rules.

To illustrate how qualitative models are encoded and simulated in ASP-QSIM, let us consider the simple RC circuit in Figure 1. The circuit consists of a resistor, a capacitor, and a switch controlling the charging and discharging process. The system is described by a set of qualitative variables V, including the battery voltage ($battery\_v$), switch position ($switch\_pos$), operating mode ($mode$), capacitor voltage ($cap\_voltage$), its derivative ($dcap\_voltage$), current ($current$) and resistor voltage ($res\_voltage$).

Each variable is assigned a quantity space defined by qualitative landmarks or symbolic values, such as $\{zero, half, full\}$ for capacitor voltage and $\{zero, half, max\}$ for current and resistor voltage. Adjacency relations define admissible qualitative transitions between neighboring regions. In this study, landmarks are fixed per benchmark. In order to represent rising and falling trends, the derivative of the capacitor voltage is modeled using both positive and negative landmarks. In addition, the $switch\_pos$ and $mode$ are modeled as control variables, which determine the active operating regime of the circuit. While qualitative variables evolve continuously between qualitative landmarks over time, control variables govern structural changes in the model by activating different sets of constraints.

The qualitative dynamics of the system are captured using constraints and rules encoded in ASP-QSIM. Core constraints describe relationships that always hold. Examples include the constant battery voltage and the derivative relation $deriv(cap\_voltage, dcap\_voltage)$. Additional constraints model proportional relationships, e.g., $mplus(res\_voltage, current)$, reflecting that the resistor voltage follows the current.

To model different operating regimes, ASP-QSIM employs rule-based constraints with preconditions. In charging mode ($mode = charge$ and $switch\_pos = pos2$), constraints such as $sum(res\_voltage, cap\_voltage, battery\_v)$ are active. In discharging mode ($mode = discharge$ and $switch\_pos = pos1$), different constraints become active reflecting the absence of the battery in the circuit loop. This enables ASP-QSIM to capture both charging and discharging behaviors within a unified qualitative model.

The initial qualitative state of the RC circuit is defined by `init()` facts. In the discharging case, the switch is initialized to *pos1* and the capacitor voltage is set to *full*, indicating a fully charged capacitor that releases energy through the resistor. In contrast, in the charging scenario, the switch is initialized to *pos2* indicating an initially empty capacitor that is charged by the battery and the capacitor voltage is set to *zero*. Therefore, the `init()` facts set the operating regime from which the qualitative simulation starts.

The desired state of the simulation is defined by `goal()` facts. In the discharge scenario, the goal is for the capacitor's voltage and current to go close to *zero*, which indicates that the capacitor is entirely depleted. The goal of the charging scenario is for the capacitor voltage to reach *full* and the current to reach *zero*, both of which signify the completion of the charging procedure. Thus, the `goal()` facts specify the qualitative end state that ASP-QSIM aims to reach from the chosen initialization.

3.3 Fault Detection with QSIM

QSIM generates all possible qualitatively consistent behaviors of a system based on its qualitative model [Kuipers, 1986]. These behaviors capture the different ways in which the system can evolve over time under the given qualitative constraints including inherent ambiguities due to abstraction. Each behavior is represented as a sequence of qualitative states, where each state assigns a qualitative magnitude (*qmag*) and direction of change (*qdir*) to all system variables.

Our fault detection approach [Das *et al.*, 2025] is based on comparing the observed system behavior with the set of behaviors predicted by the qualitative model. Intuitively, the model defines the space of all admissible system evolutions under nominal conditions and a fault is detected when the observed behavior cannot be explained by any of these admissible trajectories. The observed data obtained from simulation traces or sensor measurements is first abstracted into a qualitative representation by mapping numerical values to qualitative magnitudes using predefined landmarks. Values are assigned either to landmarks or to intervals between adjacent landmarks. To capture transitions between sampled time points, we introduce a small number of intermediate steps via linear interpolation. Furthermore, we abstract away the direction of change and focus only on qualitative magnitudes as they provide more robust indicators under noise and measurement uncertainty. Consecutive states with identical qualitative values are removed, yielding a compact (minimal) representation of the observed behavior.

Let B_{nom} denote the set of qualitative behaviors generated from the model and B_{obs} the qualitative behavior derived from observations. The system is considered nominal if there exists $b \in B_{\text{nom}}$ such that $B_{\text{obs}} \cong b$, where $\cong$ denotes qualitative conformance between behaviors. In practice, we adopt a bounded notion of conformance [Das *et al.*, 2025], where only a finite prefix of length m is considered. Thus, the system is considered conformant if the first m qualitatively distinct states of B_{obs} match those of at least one behavior $b \in B_{\text{nom}}$; otherwise, a fault is detected indicating that the observed behavior deviates from all admissible model behaviors. Those inconsistencies can arise from violations of qualitative constraints, unexpected changes in qualitative magnitudes, or missing state transitions.

Consider again the RC-circuit benchmark, whose quantitative simulation behavior is shown in Figure 2. The measured variables, such as capacitor voltage, resistor voltage, and current, are abstracted into qualitative magnitudes using the predefined landmarks and the intermediate refinement step. This abstraction yields the observed qualitative behavior B_{obs}, represented as a sequence of qualitative states and encoded as ASP integrity constraints. ASP-QSIM generates the set of admissible nominal behaviors B_{nom} from the qualitative model. Conformance is then checked by comparing B_{obs} against B_{nom}. Figure 3 illustrates one admissible qualitative charging trace of the RC-circuit benchmark, while Figure 4 shows one admissible qualitative discharge trace.

4 Evaluation

The objective of this evaluation is to assess the effectiveness of qualitative simulation and conformance checking for parameter-independent fault detection across different CPSs. More specifically, we examine whether qualitative models capture system behavior with sufficient fidelity to enable reliable fault detection without requiring precise numerical parameter values.

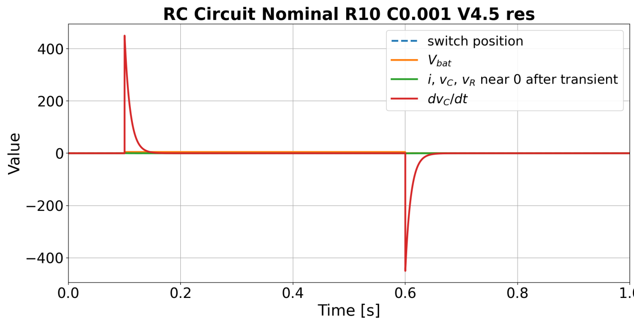

Figure 2: Quantitative simulation of the nominal RC circuit (with $R = 10\,\Omega, C = 0.001\,\mathrm{F}$ and $V_{bat} = 4.5\,\mathrm{V}$) showing the charging and discharging dynamics over time. Plotted signals include capacitor voltage (v_C), resistor voltage (v_R), current (i), applied battery voltage (V_{bat}), switch position, and the capacitor-voltage derivative dv_C/dt. The switch transitions to the battery-connected position at $t = 0.1s$, initiating capacitor charging, and returns to the discharge position at $t = 0.6s$, initiating capacitor discharge.

To this end, we conduct experiments on multiple benchmark systems from different domains and evaluate the ability of the proposed approach to detect deviations between observed behavior and the set of behaviors generated by the qualitative model through conformance checking. Since parameter independence is a core goal of this work, both fault detection and conformance checking are evaluated across multiple parameterizations of each benchmark. The evaluation thus assesses not only the applicability of the approach across different domains and system types but also the robustness and reusability of a single qualitative model under parameter variation.

4.1 Benchmarks

We evaluate our approach on a set of benchmark systems from different physical domains, including electrical, mechanical, fluid, and thermal systems:

- **Electrical:** The electrical benchmarks consist of a DC e-motor model, represented by a resistor and an inductor connected to a voltage source via a switch, and a standard RC circuit capturing charging and discharging behavior (see Figure 1).
- **Mechanical:** As a mechanical benchmark, we consider the qualitative spring–mass–damper formulation of Coghill et al. [2008], in which a mass is connected to a fixed support through a spring and a viscous damper operating in parallel and is subject to an external force, yielding damped oscillatory dynamics.
- **Fluid:** For the fluid domain, we use the classical bathtub model, which captures accumulation and flow dynamics through the interaction of inflow, outflow, and water level [Kuipers, 1986; Forbus, 1984]. The system consists of a reservoir with controlled inflow and gravity-driven outflow through a drain. Our benchmark instance was adapted from the ASP-QSIM implementation released by Wiley et al. [2014]. [1]
- **Thermal:** We consider a benchmark heating system for the thermal domain that includes a heating element, a thermal volume, and a thermostat-based controller [Wotawa *et al.*, 2021]. The system regulates the internal temperature by turning the heater on and off based on the difference between the current temperature and a desired temperature. The dynamics are controlled by heat input from the heater, heat loss to the environment, and the resulting temperature evolution, resulting in a first-order thermal process.

[1] https://github.com/timothy-wiley/aspqsim

To obtain quantitative data for evaluating our fault detection approach, we generate simulation traces using Modelica [Fritzson, 1998] for both nominal and faulty system variants for each benchmark system. The injected faults represent common physical failure mechanisms that cause deviations from the expected system dynamics. For the electrical benchmarks, we consider switching anomalies that alter the operating mode as well as parameter changes corresponding to short and open circuit conditions. In the mechanical spring–mass–damper system, actuator faults and variations in physical parameters such as mass, damping coefficient, and spring stiffness are introduced to represent realistic defects. For the fluid benchmark, i.e, the bathtub, we consider faults affecting the inflow and outflow behavior, including blockages, leaks, and altered flow relations. In the thermal benchmark, faults include heater degradation, complete heater failure, switching anomalies, and external disturbances such as increased heat loss. Let us again consider the RC circuit. For this benchmark, we considered the following faults:

- **F1:** *Resistor short circuit:* The resistor offers negligible resistance, leading to excessive current flow.
- **F2:** *Resistor open circuit:* The circuit is interrupted, preventing current flow.
- **F3:** *Capacitor broken:* The capacitor cannot sustain its voltage dynamics.
- **F4:** *Switch stuck open:* The circuit remains permanently disconnected.
- **F5:** *Intermittent switch:* Irregular switching causes unstable behavior.
- **F6:** *Battery fault:* Deviations in supply voltage lead to abnormal circuit behavior.

In addition to physical faults, we introduce synthetic sensor faults into the generated time-series data to model measurement errors. These faults include:

1. *Stuck*: the signal remains constant after a fault onset.
2. *Drift*: a bias accumulates gradually over time.
3. *Spike*: isolated outliers in the signal.
4. *Missing_nan*: temporary signal dropouts.

For the RC circuit, we take into account the following sensor-level perturbations in addition to physical faults:

- **S1:** *Missing data* ($\mathrm{v_C}$)*:* Temporary dropouts in the capacitor voltage signal.
- **S2:** *Drift* (i)*:* Gradual bias affecting the current measurement.

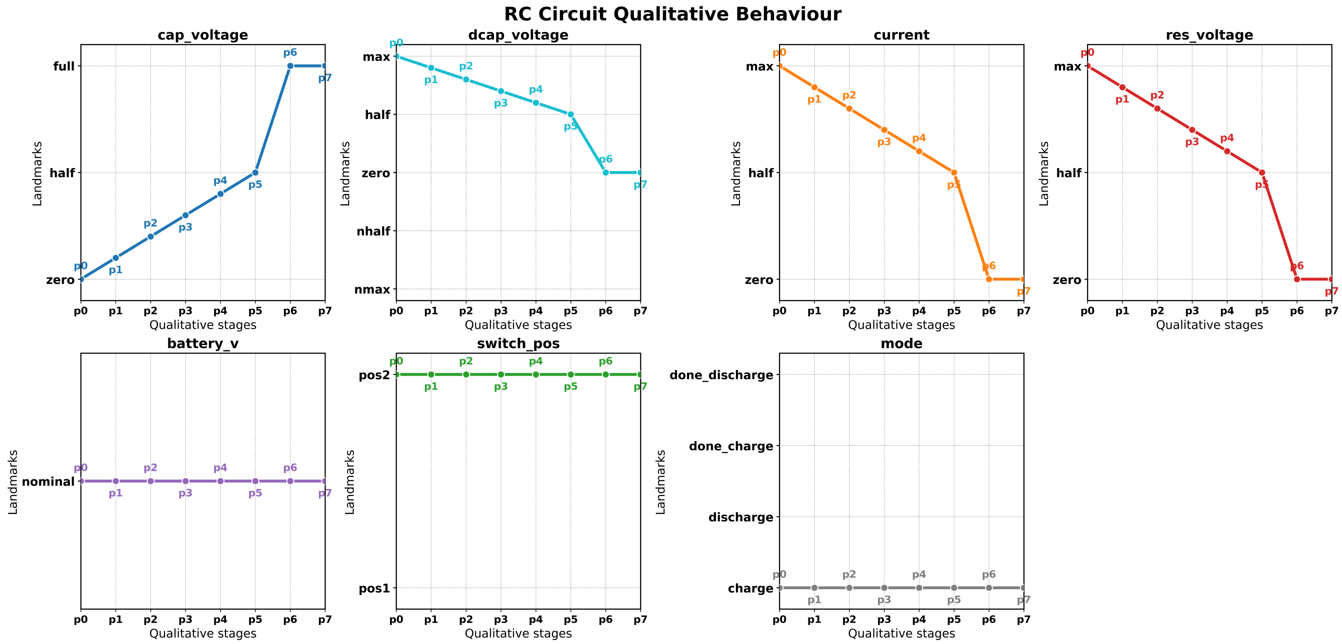

Figure 3: Qualitative behavior of the RC circuit showing the charging dynamics

- **S3:** *Missing data* (i)*:* Intervals of unavailable current measurements.
- **S4:** *Spike* (i)*:* Isolated outliers in the current signal.

To capture various operating situations, parameter modifications are added for all the benchmarks for the nominal and fault models. For the RC circuit benchmark, we vary the resistor, capacitor, and battery parameters. The resistor parameter ($R \in \{9, 10, 11\}\,\Omega$) determines the resistance to current flow and directly influences the charging and discharging rate of the capacitor. The capacitance ($C \in \{0.0008, 0.001, 0.0012\}\,\mathrm{F}$) defines the storage capacity of the capacitor and affects how quickly the capacitor voltage changes over time. The battery voltage ($V_{bat} \in \{4.0, 4.5, 5.0\}\,\mathrm{V}$) acts as the energy source driving the circuit and determines the maximum capacitor voltage reached during charging.

By varying these parameters across nominal and faulty model variants, we generate traces under different electrical conditions while preserving the structural dynamics of the system. Figure 5 shows the quantitative simulation behavior of the RC circuit under fault F3 (capacitor broken) with a specific parameter set, namely $R = 10\,\Omega, C = 0.001\,\mathrm{F}$ and $V_{bat} = 4.5\,\mathrm{V}$, while Table 1 contains the considered parameter ranges for each benchmark.

4.2 Experimental Setup

Each benchmark is associated with a qualitative model as defined in Section 3. These models are implemented using ASP-QSIM. We build upon the abstraction and conformance framework introduced in our previous work [Das *et al.*, 2025].

For each benchmark, the quantitative time-series data generated from Modelica simulations [Fritzson, 1998] is first down-sampled at a fixed rate and transformed into a qualitative representation. Each benchmark is evaluated under multiple parameter settings, where only the numerical parameter values (e.g., resistance, capacitance, inflow rate, or thermal resistance) vary while the qualitative model structure and its landmark definitions remain fixed. This ensures that both nominal and faulty simulation runs are abstracted into the same qualitative state space allowing behavioral deviations to be attributed to parameter variations or injected faults rather than changes in the model itself.

We use a single benchmark-specific abstraction specification implemented in the same JSON configuration file across all evaluated parameter settings for each benchmark. This file defines the qualitative variables, landmarks, and interval boundaries used to map quantitative traces into qualitative states. Hence, while the simulated numeric trajectories vary with the parameter values, the qualitative abstraction itself remains unchanged throughout the evaluation. This design is intentional as the objective is to assess whether the same qualitative model and abstraction can support conformance checking and fault detection across different parameterizations without retuning the abstraction for each run.

In other words, labels such as *zero*, *half*, and *full* are not redefined separately for each parameter setting; instead the same benchmark-specific qualitative partition is used throughout the evaluation. Values sufficiently close to a landmark are assigned directly to that landmark while values between adjacent landmarks are mapped to the corresponding interval. This abstraction allows continuous system behavior to be represented symbolically while preserving the relevant structural changes in the trajectory. To capture transitions that may occur between two sampled points, we introduce a single intermediate step ($n = 1$) by linearly interpolating

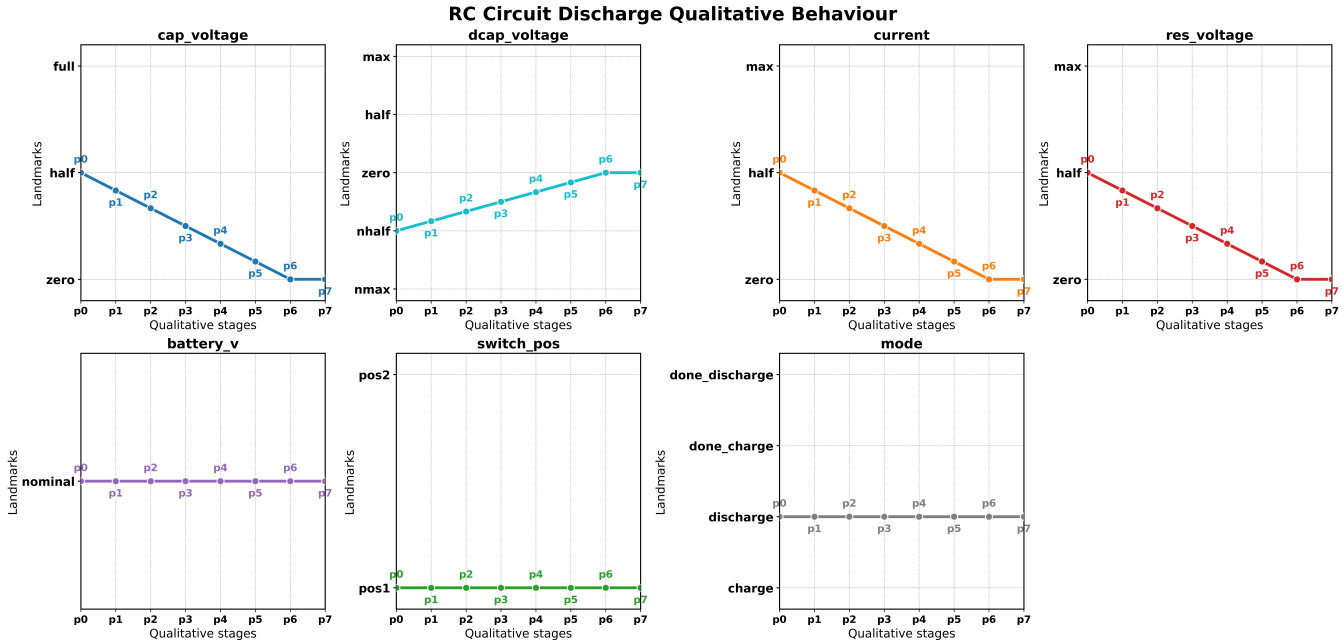

Figure 4: Qualitative behavior of the RC circuit showing the discharging dynamics.

Table 1: Benchmark parameter ranges and conformance results between the qualitative models and the corresponding nominal quantitative simulation behaviors.

Benchmark	**Parameter**	**Range**	**Result**
RC Circuit	R resistance C capacitance V_{bat} voltage	$\{9, 10, 11\}$ $\{0.0008, 0.001, 0.0012\}$ $\{4.0, 4.5, 5.0\}$	✓
DC e-Motor	R resistance L inductance V_{bat} voltage	$\{1.8, 2.0, 2.2\}$ $\{0.04, 0.05, 0.06\}$ $\{10, 11, 12\}$	✗
Spring–Mass–Damper	k spring constant c damping coefficient $x(0)$ initial position $\dot{x}(0)$ initial velocity	$\{0.5, 1.0, 2.0\}$ $\{0.3, 1.0, 3.0\}$ $\{-0.5, 0, 0.5\}$ $\{-0.5, 0, 0.5\}$	✓
Bathtub	q_{in} inflow A_d drain area $V(0)$ initial volume	$\{0.04, 0.08, 0.12\}$ $\{0.002, 0.005, 0.010\}$ $\{0.10, 0.20, 0.40\}$	✓
Heating system	q_{in} heater Power A_d thermal resistance $V(0)$ target temperature	$\{8, 10, 12\}$ $\{4, 5, 6\}$ $\{24, 25, 26\}$	✗

between consecutive measurements. This prevents qualitative state changes, such as crossing a landmark, from being missed due to coarse sampling.

After abstraction, the resulting qualitative trace is reduced by removing consecutive states that are qualitatively identical, retaining only behaviorally distinct transitions. This reduction decreases redundancy and improves the efficiency of the subsequent conformance check. The reduced qualitative trace is translated into ASP integrity constraints of the form $\leftarrow\ not\ holds(p(t), var, qmag, \_).$, which enforce that observed qualitative states appear in admissible trajectories.These constraints enforce that the observed qualitative states must appear in every admissible trajectory generated by the simulation model. Conformance is checked by combining the observed qualitative trace with the corresponding qualitative model in ASP-QSIM and executing the reasoning process using the underlying ASP solver. If at least one admissible trajectory satisfies all imposed constraints, the observed behavior conforms to the nominal model. Otherwise, the absence of a consistent solution indicates a behavioral deviation

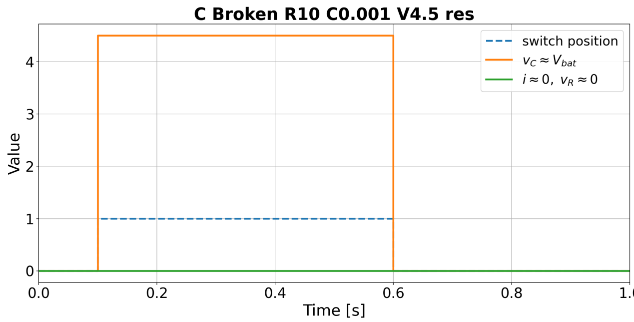

Figure 5: Quantitative simulation behavior of the RC circuit under fault F3 (capacitor broken). The capacitor voltage (v_C) follows the applied battery voltage (V_{bat}), while the current (i) and resistor voltage (v_R) remain approximately zero due to the open-circuit fault.

and therefore a potential fault. The conformance check is executed for every benchmark and all considered parameterizations against the corresponding nominal qualitative behavior, allowing faults to be detected under varying operating conditions.

The evaluation is performed in two stages. First, we assess whether the nominal quantitative simulation traces conform to the behaviors generated by the corresponding (nominal) qualitative model. Only if this nominal conformance can be established, we proceed with fault detection by evaluating whether faulty quantitative traces violate the qualitative conformance relation.

4.3 Results and Discussion

In this section, we first discuss the conformance results and analyze the possible reasons why two of our qualitative models do not conform to their respective nominal quantitative model. Second, we analyze the fault detection results on the remaining benchmarks.

Conformance Results

Table 1 summarizes the conformance results across all benchmarks. For the nominal scenarios of the RC circuit, bathtub system, and spring-mass-damper model the observed behaviors conform to at least one qualitative behavior generated by the model. This confirms that the qualitative models accurately capture the expected system dynamics. For the DC motor and the heating system we were not able to establish conformance between the qualitative model and the simulation.

Regarding the conformance result of the DC motor, the hybrid nature of the DC motor benchmark led to a failure to conform: the switch position is a discrete control variable while current and voltages are continuous variables. The quantitative trace contains both abrupt switching events and continuous motor dynamics but these were abstracted together into a single qualitative trace and checked against one qualitative scenario. This creates a mismatch in representation since discontinuous mode changes and continuous state evolution are forced into one uniform qualitative interpretation. As a result, the abstraction becomes inconsistent around switching instants where rapid changes in system mode coincide with continuous transient responses in the electrical variables. These inconsistencies lead to conflicting state constraints causing the ASP-QSIM conformance check to become unsatisfiable.

During the conformance analysis of the heating circuit benchmark, non-conformance was observed between the quantitative simulation traces and the qualitative simulation model. This mismatch remained even after improving the quantitative-to-qualitative abstraction by selecting more suitable trace segments and refining the mapping from quantitative values to qualitative landmarks. A likely reason for this failure to conform lies in the qualitative simulation model itself, in particular in the encoding of the thermal balance relation. In the heating circuit, the temperature derivative is determined by the difference between heat input and heat loss, i.e., $\dot{T}_{int} = q_{in} - q_{out}$. To model this, qualitative subtraction in the form of $X = -Y$, we added additional constraints to the ASP-QSIM implementation. However, this formulation did not appear to be sufficient for representing the heating balance relation adequately. We therefore reformulated the relation using `sum` constraints in the equivalent form $q_{in} = \dot{T}_{int} + q_{out}$. Even with this reformulation, exact conformance was still not achieved. A possible reason is that the correspondence mapping used for the `sum` constraints did not capture the benchmark behavior accurately enough, especially during transient switching phases. We therefore assume that a more direct qualitative subtraction relation of the form $Z = X - Y$, which is currently not supported in the ASP-QSIM implementation, may be necessary for modeling this type of thermal balance more faithfully.

Fault Detection Results

We evaluated the QSIM framework on all fault scenarios listed in Table 2 under varying parameterizations. Note that we only consider the benchmarks where the qualitative model conforms to the nominal system behavior. In case, we cannot establish this conformance, we cannot use the qualitative simulation for fault detection.

The results indicate that the framework generalizes well under parametric variation and is able to detect faults consistently without requiring any modification to the underlying qualitative model. Besides physical component faults, we also considered sensor-related faults allowing us to assess the robustness of the qualitative model across different fault types. The results demonstrate that even in the presence of these observation-level interruptions conformity checking is still beneficial. In particular, *drift* and *stuck* flaws, which are recognized as abnormal behaviors create systematic fluctuations in qualitative magnitudes and derivative trends. Even though they are typically isolated, *spike* faults create short lived violations in the qualitative state sequence. *Missing-value* defects (NaN intervals) reduce the quantity of visible information but interpolation and subsequent qualitative abstraction allow the framework to detect deviations when missing segments affect important transitions between landmarks. Overall, these results show that the approach is not only effective for detecting structural and parametric faults but also robust to observation level imperfections making it suitable for realistic settings with noisy or incomplete sensor data. In

Table 2: Fault-detection results for the conforming benchmarks. Physical faults (F) are Modelica fault models, while sensor-level perturbations (S) are injected during post-processing. The reported detection results hold for all parameter values considered.

Benchmark	ID	Scenario	Detected
Bathtub	F1	Low overflow threshold	✓
	F2	Extra drain leak	✓
	F3	Partial drain blockage	✓
	F4	Full drain blockage	✓
	S1	Outflow stuck	✓
	S2	Outflow drift	✓
	S3	Level spike	✓
	S4	Inflow drift	✓
Spring–Mass –Damper	F1	Weak damper	✓
	F2	Stiff damper	✓
	F3	Actuator stuck at zero	✓
	F4	Low actuator gain	✓
	F5	Broken spring	✓
	F6	Coulomb friction	✓
	S1	Force gain low	✓
	S2	Force stuck	✓
	S3	Force gain zero	✓
RC Circuit	F1	Resistor short	✓
	F2	Resistor open	✓
	F3	Capacitor broken	✓
	F4	Switch stuck open	✓
	F5	Intermittent switch	✓
	F6	Battery degraded	✓
	S1	Capacitor voltage missing	✓
	S2	Current drift	✓
	S3	Current missing	✓
	S4	Current spike	✓

the RC circuit benchmark, sensor faults affecting the current and capacitor-voltage signals produced deviations consistent with the expected qualitative behavior further confirming the sensitivity of the model to observation level anomalies.

5 Conclusion

In this paper, we present a QSIM-based framework for fault detection in dynamic systems using behavioral conformance checking. Our approach relies on ASP-QSIM to generate admissible nominal behaviors of the system and detects faults by determining whether the observed trajectories conform to any of the predicted behaviors.

We evaluated this approach across electrical, thermal, fluid, and mechanical systems to demonstrate that qualitative conformance checking can successfully detect a broad range of faults. The experiments further showed that a single qualitative model can support monitoring across varying parameterizations without modifications to the model itself, but only to the procedure that abstracts the quantitative into qualitative ones.

At the same time, the results highlight an important challenge in qualitative reasoning, i.e., deriving a suitable qualitative model that captures the behavior of the system under consideration. In particular, from our five benchmark sets we investigated, two qualitative models did not conform to their respective nominal system behavior. This, however, is the foundation of our fault detection method.Qualitative abstraction improves robustness to parameter variation but may miss subtle faults that remain within the same qualitative regions despite quantitative deviations.

In future work, thus, we plan on further evaluating our approach and plan on investigating larger, real-world CPS to determine whether our technique scales. Additionally, we plan on using qualitative simulation models of faults, similar to previous work (e.g., MIMIC [Dvorak and Kuipers, 1991]), to not only detect abnormal behavior, but also identify faults. Currently, we work on determining whether we can leverage qualitative simulation models and conformance checking for weak supervision of machine learning approaches to mitigate the cold-start problem.

Acknowledgments

The work presented in this paper has been supported by the FFG project Artificial Intelligence for Smart Diagnosis in Building Automation (ALFA) under grant 914932. Ankita Das is supported by the Christian-Doppler Forschungsgesellschaft (CDG) project AI-based Diagnosis for Energy Transition and the Circular Economy (AID4ETCE).
The following AI-based tools were used for language editing and polishing: ChatGPT 5.2, Google Gemini 3, and DeepL Write.

References

[Aichernig *et al.*, 2009] Bernhard K. Aichernig, Harald Brandl, and Franz Wotawa. Conformance testing of hybrid systems with qualitative reasoning models. *Electronic Notes in Theoretical Computer Science*, 253(2):53–69, 2009.

[Bredeweg *et al.*, 2009] Bert Bredeweg, Floris Linnebank, Anders Bouwer, and Jochem Liem. Garp3 — workbench for qualitative modelling and simulation. *Ecological Informatics*, 4(5):263–281, 2009. Special Issue: Qualitative models of ecological systems.

[Coghill *et al.*, 2008] George M. Coghill, Ashwin Srinivasan, and Ross D. King. Qualitative system identification from imperfect data. *Journal of Artificial Intelligence Research*, 32:825–877, 2008.

[Das *et al.*, 2025] Ankita Das, Roxane Koitz-Hristov, and Franz Wotawa. Using qualitative simulation models for monitoring and diagnosis. In Marcos Quiñones-Grueiro, Gautam Biswas, and Ingo Pill, editors, *36th International Conference on Principles of Diagnosis and Resilient Systems, DX 2025, Nashville, TN, USA, September 22-24, 2025*, volume 136 of *OASIcs*, pages 4:1–4:14. Schloss Dagstuhl - Leibniz-Zentrum für Informatik, 2025.

[De Kleer and Brown, 1984] Johan De Kleer and John Seely Brown. A qualitative physics based on confluences. *Artificial Intelligence*, 24(1):7–83, 1984.

[de Kleer and Williams, 1987] Johan de Kleer and Brian C. Williams. Diagnosing multiple faults. *Artificial Intelligence*, 32(1):97–130, 1987.

[Dou and Zhang, 2025] Hongwen Dou and Kun Zhang. Transfer learning for cross-building forecasting of building energy and indoor air temperature in model predictive control applications. *Journal of Building Engineering*, 111:113341, 2025.

[Dowdeswell *et al.*, 2020] Barry Dowdeswell, Roopak Sinha, and Stephen G. MacDonell. Finding faults: A scoping study of fault diagnostics for industrial cyber–physical systems. *Journal of Systems and Software*, 168:110638, 2020.

[Dvorak and Kuipers, 1991] Daniel Dvorak and Benjamin Kuipers. Process monitoring and diagnosis: a model-based approach. *IEEE expert*, 6(3):67–74, 1991.

[Forbus, 1984] Kenneth D. Forbus. Qualitative process theory. *Artificial Intelligence*, 24(1-3):85–168, dec 1984.

[Fritzson, 1998] Peter Fritzson. Modelica - a language for equation-based physical modeling and high performance simulation. In *Proceedings of the 4th International Workshop on Applied Parallel Computing, Large Scale Scientific and Industrial Problems*, PARA '98, pages 149–160, London, UK, UK, 1998. Springer-Verlag.

[Genkin and McArthur, 2022] Mikhail Genkin and J. J. McArthur. Using reinforcement learning with transfer learning to overcome smart building cold start. In *International Conference on Computational Science and Computational Intelligence, CSCI 2022, Las Vegas, NV, USA, December 14-16, 2022*, pages 713–718. IEEE, 2022.

[Katipamula and Brambley, 2005] Srinivas Katipamula and Michael R. Brambley. Review article: Methods for fault detection, diagnostics, and prognostics for building systems—a review, part i. *HVAC&R Research*, 11(1):3–25, 2005.

[Kuipers, 1986] Benjamin J. Kuipers. Qualitative simulation. *Artificial Intelligence*, 29(3):289–338, 1986.

[Kuipers, 1989a] Benjamin Kuipers. Qualitative reasoning: Modeling and simulation with incomplete knowledge. *Automatica*, 25(4):571–585, July 1989.

[Kuipers, 1989b] Benjamin Kuipers. Qualitative reasoning: Modeling and simulation with incomplete knowledge. *Automatica*, 25(4):571–585, 1989.

[Lackinger and Nejdl, 1991] Franz Lackinger and Wolfgang Nejdl. Integrating model-based monitoring and diagnosis of complex dynamic systems. In John Mylopoulos and Raymond Reiter, editors, *Proceedings of the 12th International Joint Conference on Artificial Intelligence. Sydney, Australia, August 24-30*, pages 1123–1128. Morgan Kaufmann, 1991.

[Leitch *et al.*, 1993] Roy Leitch, Qiang Shen, George Coghill, Mike Chantler, and Andrew Slater. Qualitative model based diagnosis of a continuous process. In George Rzevski, John Pastor, and Richard A. Adey, editors, *Applications of Artificial Intelligence in Engineering*, volume 2, pages 291–309. Computational Mechanics Publications, 1993.

[Lu *et al.*, 2019] Jie Lu, Anjin Liu, Fan Dong, Feng Gu, João Gama, and Guangquan Zhang. Learning under concept drift: A review. *IEEE Transactions on Knowledge and Data Engineering*, 31(12):2346–2363, 2019.

[Mohaqeqi *et al.*, 2014] Morteza Mohaqeqi, Mohammad Reza Mousavi, and Walid Taha. Conformance testing of cyber-physical systems: A comparative study. In *The 14th International Workshop on Automated Verification of Critical Systems, University of Twente, Enschede, Netherlands, 24–26th September, 2014*. European Association of Software Science and Technology, 2014.

[Reiter, 1987] Raymond Reiter. A theory of diagnosis from first principles. *Artificial Intelligence*, 32(1):57–95, 1987.

[Rinner and Kuipers, 1999] Bernhard Rinner and Benjamin Kuipers. Monitoring piecewise continuous behaviors by refining semi-quantitative trackers. In *Sixteenth International Joint Conference on Artificial Intelligence (IJCAI-99)*, volume 16, pages 1080–1086. LAWRENCE ERLBAUM ASSOCIATES LTD, 1999.

[Subhramanian and Mooney, 1994] Siddharth Subhramanian and Raymond J. Mooney. Multiple fault-diagnosis using general qualitative models with fault modes. In *Working Papers of the 5th International Workshop on Principles of Diagnosis*, pages 321–325, New Paltz, NY, Oct 1994.

[Travé-Massuyès and Milne, 1995] Louise Travé-Massuyès and Robert Milne. Application oriented qualitative reasoning. *The Knowledge Engineering Review*, 10(2):181–204, 1995.

[Venkatasubramanian *et al.*, 2003] Venkat Venkatasubramanian, Raghunathan Rengaswamy, Kewen Yin, and Surya N. Kavuri. A review of process fault detection and diagnosis: Part i: Quantitative model-based methods. *Computers & Chemical Engineering*, 27(3):293–311, 2003.

[Wiley *et al.*, 2013] T. Wiley, C. Sammut, and I. Bratko. Planning with qualitative models for robotic domains. In *Advances in Cognitive Systems (Poster Collection), Second Annual Conference*, pages 251–266, 2013.

[Wiley *et al.*, 2014] Timothy Wiley, Claude Sammut, and Ivan Bratko. Qualitative simulation with answer set programming. In *European Conference on Artificial Intelligence (ECAI)*, May 2014.

[Wiley, 2017] Timothy Colin Wiley. *A planning and learning hierarchy for the online acquisition of robot behaviors*. PhD thesis, University of New South Wales, Sydney, Australia, 2017.

[Wotawa *et al.*, 2021] Franz Wotawa, Oliver Tazl, and David Kaufmann. Automated diagnosis of cyber-physical systems. In Hamido Fujita, Ali Selamat, Jerry Chun-Wei Lin, and Moonis Ali, editors, *Advances and Trends in Artificial Intelligence. From Theory to Practice*, pages 441–452, Cham, 2021. Springer International Publishing.