A Digital Twin Setup for Safety-aware Optimization of a Cyber-physical System

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Abstract: Digital twin technology offers a sophisticated and flexible methodology to design high fidelity models of cyber-physical systems for simulation, optimization, formal verification and validation purposes. This has made such a technology a nascent process being currently adopted in many industries. This paper introduces a digital twin setup for safety-aware performance optimization of a cyber-physical system (*Energy Buck converter* EBC). This is achieved by designing a high fidelity digital twin model of the Buck converter through synchronization of the model with the physical system, namely calibration. The behavior model is originally built in MATLAB to identify potential runtime optimization patterns using a genetic algorithm. Such a model is translated to a Uppaal model to perform formal verification of the safety properties. The behavior patterns from optimization are provided as inputs to the verification engine for approval, where only valid and feasible patterns are pushed into the actual control loop of EBC. The proposed setup has led to maintain the system safety while optimizing the performance and reducing the output errors.

1 INTRODUCTION

Due to the increasing energy demand and the underlying need to reduce CO2 emissions, different international authorities have dictated many regulations and policies about high energy efficiency for different application domains (Asdrubali and Desideri, 2019; Yu et al., 2011; Labandeira et al., 2020; Eyring et al., 2005). To comply with such requirements, the manufacturers of electrical equipments seek sophisticated and optimal control strategies to operate such equipment with high performance following the deployment environments (Teng et al., 2021; Wei et al., 2019; Rodrigues et al., 2018; Frangopoulos, 2018; Letafat et al., 2020).

To investigate the operation performance and optimize the equipment control, flexible methodologies that enable low cost design of high fidelity models and high confidence analysis of the functional and non-functional properties have been studied in the literature (Teng et al., 2021; Suslov, K. et al., 2019; Wu et al., 2020; García-Gusano et al., 2017; Domke, 2012; Boudjadar et al., 2014a). However, two challenges have emerged: 1) it is not trivial to design high fidelity digital models of complex systems (Austin et al., 2020); 2) designing a model to analyze different nature properties (safety, performance, responsiveness) can be misleading due to merging different modeling profiles is overly conservative (Rodrigues et al., 2018; Boudjadar et al., 2015).

A digital twin (DT) is a model replica of a physical system, known also as physical twin (PT), (Fitzgerald et al., 2019). To ensure high fidelity of a digital twin model to its physical twin, a calibration process can be conducted (Wang et al., 2020a). In fact calibration amounts at synchronizing inputs, outputs and actions triggering of DT to that of PT and converge the DT output values to that of PT. Thus, potential behavior exploration, optimization, testing and verification can be conducted on DT rather than PT.

To perform sophisticated verification with high guarantee, one needs to either describe the DT models in a formal specification language or use a domain specific modeling language that can be translated to a formal specification for verification purposes. The former option is not well suitable for industry as it is expensive and not engineer-friendly. The later option is much feasible given the cheap modeling cost however the challenging aspect is that performance related features are usually abstracted through translation to prevent state space explosion of the formal verification process (Clarke et al., 2012).

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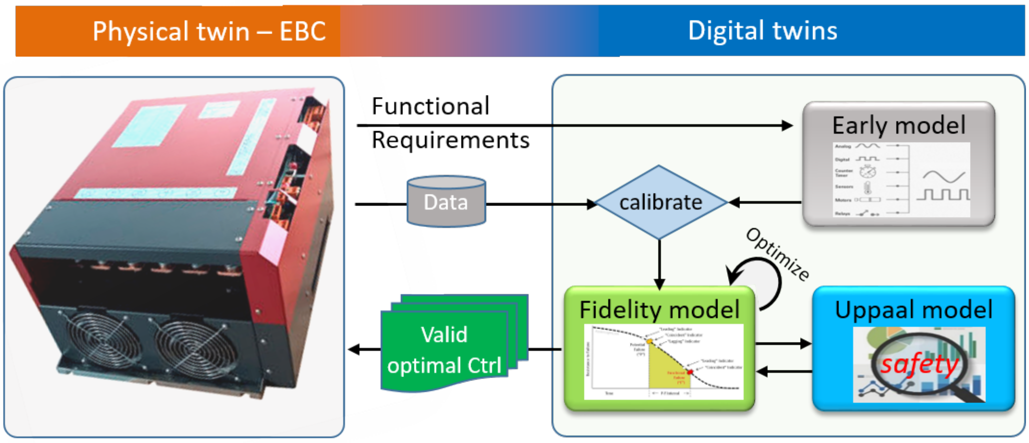

Figure 1: Proposed methodology.

The safety and energy efficiency of CPS for electric applications have been thoroughly explored in the state of the art (Bizon, 2018; Odeim et al., 2015; Banaei et al., 2021; Banaei et al., 2020; Rafiei et al., 2021) such as road vehicles (Andari et al., 2018), buses (Peng et al., 2017) and trams (Zhang et al., 2017), however only few attempts consider both metrics together when designing controllers for safety-critical applications (Banerjee et al., 2012). Making safety as the driving property in the design of safety-critical systems may lead to expensive operation cost and inefficient utilization of the energy resources (Wang et al., 2020b).

This paper introduces a methodology for safe and energy-efficient control optimization of the EBC cyber-physical system. The methodology combines model-based design and data-driven engineering. Our controller focuses on finding a compromise between safety, performance and response time (frequency) to operate the switch of EBC so that the energy efficiency is improved as high as the safety and response time permit. Runtime control decisions are calculated with respect to the actual system state such as components temperature (safety), output voltage deviation (error) and EBC frequency (constraint). Matlab models are used for calibration and optimization purposes, whereas a translation to Uppaal is carried out to perform formal validation of the optimization sequences using model checking.

The overall proposed methodology is depicted in Figure 1. The rest of the paper is organized as follows: Section 2 presents the EBC system architecture and early model of the EBC operation and temperature dynamics. Section 3 describes the calibration of early model to a high fidelity model and the optimization process. Section 4 presents our formal specification and verification using Uppaal. Section 5 cites relevant related work. Finally, Section 6 concludes the paper.

2 EBC SYSTEM MODELING

This section presents the Matlab models of EBC, default controller to operate EBC and the calibration process. The energy Buck converter we consider is a high voltage DC-DC converter operating with a capacity of 200W and a maximum frequency of 50KHz. EBC is a step-down converter that decreases the voltage of its input, from a supply for example, to its output. EBC can experience output error where the actual output voltage deviates from the expected output voltage. A constraint about EBC fault tolerance is that the output voltage value deviates at most with 2 volts from the requested output voltage.

The higher the positive deviation is the larger energy waste will be. Meanwhile, the larger negative deviation is, the higher the risk will be to damage external load connected to EBC.

2.1 Modeling of Buck Converter

The model of EBC is made in Matlab/Simulink due to the availability of the instantiable PowerLib library [1] to model the different hardware and electronic components, however the behavior logic is mathematically modeled and integrated into Matlab. EBC model

[1] https://se.mathworks.com/products/simscape-electrical.html

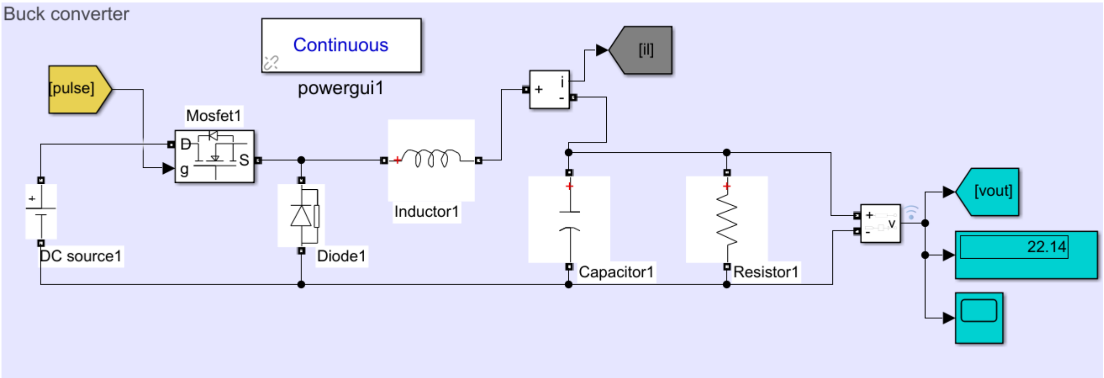

Figure 2: Buck converter hardware.

consists of different components where the Mosfet switch is the master piece (Beck, 2020a). EBC output interface has two ports: expected reference voltage V_{ref} (24v in our case) and actual output voltage V_{out} (it is 22.14 in Figure 2).

In fact, the switch is the gate to pass on the current (`On` state) or not (`Off` state). The switch operation is controlled by a pulse signal decided by a PID controller (Haq and G, 2016), i.e. when to pass on current from the source to the output through the other components of EBC. In simple words, the default PID controller measures the actual error, as the difference between expected and actual output voltages, and decides to open/close the switch to rectify such an error.

In order to operate safe, the temperature of the integrated circuits of EBC must not exceed 150° C (Beck, 2020a). The temperature depends mainly on the switch operation (frequency to transit between states `On` and `Off`) and the internal resistance leading to power loss. The power loss $\Delta_P(t)$ of EBC can be calculated at any time point t as follows:

$$\Delta_P(t) = (1-\eta) * P_{in} \tag{1}$$

Where η is a heat efficiency factor related to the EBC size and material, and P_{in} is the input power. One can see that P_{in} is not time dependent as it is always constant. Since P_{in} is effective only when the switch state alternates to `On`, reducing the switching frequency will reduce the power loss in the converter (Beck, 2020a). However, this may lead to lower the output voltage. Thus, a tuning of the switch frequency needs to be made with respect to both power loss and output voltage deviation. The thermal performance R of EBC at a given time point t is calculated according to equation (2).

$$R(t) = \frac{\mathcal{T}(t) - \mathcal{T}_A(t)}{(1-\eta) * P_{in}} \tag{2}$$

Where $\mathcal{T}(t)$ is the EBC temperature at time point t and $\mathcal{T}_A(t)$ is the ambient temperature at time point t. Accordingly, the internal temperature of EBC can be calculated as follows:

$$\mathcal{T}(t) = \mathcal{T}_A(t) + R(t) * \Delta_P(t) \tag{3}$$

In fact one can reduce actual temperature by reducing the power loss which is dependent on the the switch frequency through manipulation of P_{in}. In a similar way, the output voltage V_{out} of EBC can be calculated as follows:

$$V_{out}(t) = V_{in} * D(t) \tag{4}$$

Where V_{in} is the constant input voltage (110v) and $D(t)$ is the converter duty cycle factor related to $\Delta_P(t)$. Thus, output error is calculated by:

$$Error(t) = V_{ref} - V_{out}(t) \tag{5}$$

According to the output voltage of our early stage model, for an expected output value $V_{ref} = 24v$ the actual output voltage varies from 19.5 to 37 if we ignore the model initialization phase.

It is clear that the maximum error ($Error(t)$=24-37) of our model is too high and not acceptable. Moreover, the temperature calculated by our DT model is far from the actual EBC temperature. Thus, in Section 2.2 we calibrate the behavior of our DT model to that of the PT device.

2.2 EBC Model Calibration

The calibration goal is to establish an accurate synchronization between the physical system (PT) and the early DT model. This leads to creating a high fidelity DT model of EDC through updating some of the state calculation functions of the early DT model so that the internal states of PT and the final DT model match. Through synchronization analysis of PT and DT, achieved using Matlab simulations displayed as signals on an oscilloscope, we noticed the following:

- DT actions are not synchronized with the actions of PT. Thus, we calibrated the actions durations in DT following how long the executions of such actions take in PT. This enables us to time our DT model and maintain synchronization between DT and PT behaviors.
- The temperature calculated by DT converges to that in PT only if the EBC is idling or just started the operation. After being in operation for longer than 37s, DT temperature is considerably lower than that in PT. This is in fact due to the temperature calculation (Eq. (3)) does not consider the most recent temperature of EBC and only refers to the ambient temperature. Thus, we have updated the calculation of temperature dynamics of the digital twin model as follows, by which DT and PT temperatures align in most of the cases:

  $$\mathcal{T}(t) = \mathcal{T}(t-\delta) + \mathcal{T}_A(t) + R(t) * \Delta_P(t) \quad (6)$$

  and δ=36s.

Thanks to synchronization of DT actions through calibration, the error calculation (Eq. (5)) has drastically decreased and converged to the actual error in PT. However, although the error is immensely reduced, it is still higher than the tolerance threshold which is *2v*. Given that the calibrated DT model exposes a high fidelity to PT, in the next section we will conduct an optimization of the controller using the calibrated DT model in order to improve the EBC performance and reduce error. The control patterns resulting from DT optimization will first be approved against safety, frequency and error tolerance requirements using Uppaal verification engine.

3 OPTIMIZATION OF EBC OPERATION

Given that power loss of EBC during operation is proportional to its temperature (Beck, 2020b), the optimization goal then is to make EBC working with the lowest possible temperature while satisfying the requirements for maximum error tolerance and frequency (response time).

Optimizing the performance of a cyber-physical system can lead to degrading other safety and reliability metrics (Teng et al., 2021; Boudjadar and Khooban, 2021) given that the system parameters can be conflicting. As an example, the optimization process can speed up the switch operation to minimize the output voltage error which can result in heating up the device beyond safety threshold. Thus, a tradeoff between the different performance and safety parameters must be carefully established and maintained during runtime.

The optimization task has been achieved using a genetic algorithm where the objective function is the minimization of the output voltage error. The overall requirements for the EDC operation are: *a*) Maximum error of output voltage cannot go above 2; *b*) EBC control switch has to be operable at maximum 50kHz; c) EBC temperature must not exceed 150° C.

The optimization process workflow is depicted in Figure 3. Following the optimization process outputs (parameters *P*, *I* and *D*), for the configurations satisfying PID feasibility requirements, the PID controller calculates the system actuations through which error, temperature and response time are assessed accordingly. The error result is then compared to the current best (minimal) where a new iteration of the optimization algorithm can be triggered if the newly obtained error does not outperform the actual minimum. To prevent running the optimization algorithm endlessly in case the the iterations do not converge to a better output value, we bound the number of iterations to 20. In fact, we have empirically identified that 20 iterations will always lead to the system optimum no matter of the input configuration.

Algorithm 1: Optimization algorithm.

```
function DEF RUNSIMULATION(X, DRAWPLOT=FALSE)(:)
    P = X[0]
    I = X[1]
    D = X[2]
    eng.set_param simlP', 'value',Str(P), nargout=0)
    eng.set_param simiI', Value',Str(I), nargout=0)
    eng.set_param( simlD', value',str(D), nargout=0);
    eng.sim 'Simulationssim1.slx')
    result = eng.workspace['errors']
    vOut = eng.workspace['vout']
    avg = 0.0
    for res in result do:
        avg = avg + abs(np. float32(res))
        avgError = avgresult.size[0]
    end for
    if drawPlot then:
        print("Smulation:") Plot(out) print("Parameters: ",P,I,D)
        print("AvgError:",avgError)
        return avgError
    end if
end function
```

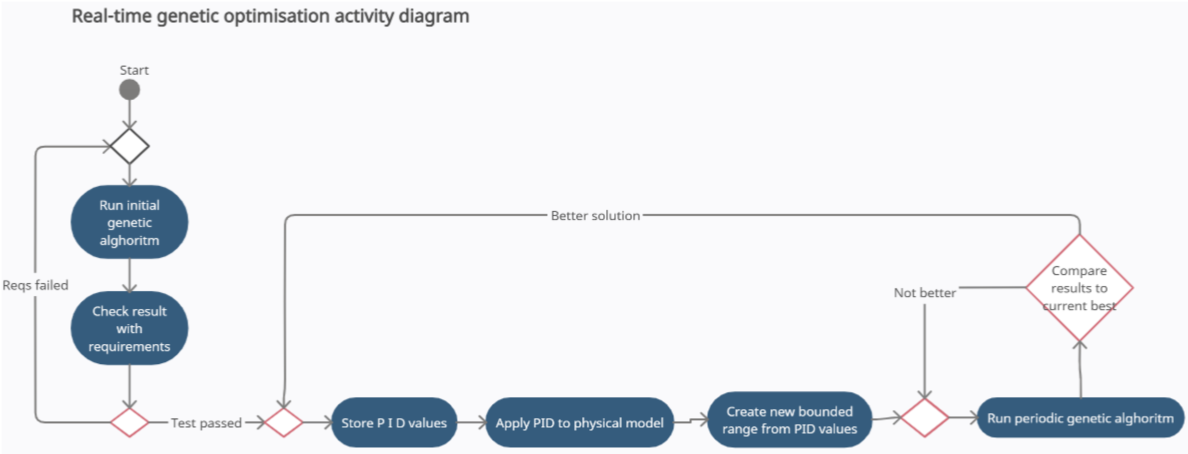

Figure 3: Optimization diagram.

A sketch of the optimization algorithm is depicted in Algorithm 1 where the parameters of the genetic algorithm are as follows:

$$\begin{cases} population\ size = 20 \\ iterations = 20 \\ mutation\ probability = 0.1 \\ elite\ ratio = 0.01 \\ crossover\ probability = 0.5 \end{cases}$$

Figure 4 illustrates the outputs of the optimization algorithm for 20 iterations. One can see that the first iteration reduces the error to be below 2v which is the maximum tolerance value. This is very practical for the solution to be implemented in real-time so that one iteration of the optimization process is sufficient to tune the control parameters of EDC.

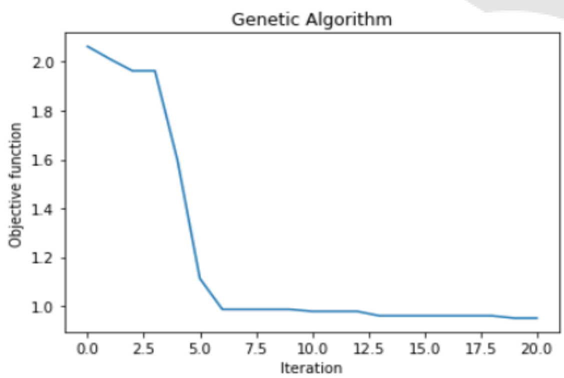

Figure 4: Output error following the optimization iterations.

Our mission now is to secure that the system configurations obtained through optimization will not violate, immediately or potentially leading to a future state, EBC safety and operation requirements. To such an end, in the next section, we will translate the high fidelity model of EDC from Matlab to Uppaal in order to perform formal verification of the safety and operation requirements following the input parameters calculated by the optimization function so that only the optimization configurations satisfying the requirements will be candidates to integration in the controller of the physical twin.

4 FORMAL VERIFICATION AND VALIDATION

This section describes the verification model and process.

Verification Model. We have built a verification model, using Uppaal timed automata (Boudjadar et al., 2014b), to implement the theory introduced in Section 2. Globally, the verification model of the EBC system is formed by a set of processes, each of which specifies the behavior of one EBC component, synchronizing through different events and shared variables. Besides, a process simulating the optimization function is integrated into the set of behavior processes to map the optimization outputs to the input parameters of Uppaal model.

Namely, a process P_i is a timed automaton given by $\langle V_i, L_i, l_i^0, I_i, \rightarrow_i \rangle$, over a set of global variables V and channels C shared with other processes, where:

- V, V_i are set of global and local variables, including discrete and continuous variables (clocks).
- L_i is the set of locations whereas l_i^0 is the initial location.
- $I_i : L_i \mapsto pred(V \cup V_i)$ is the invariant relation.
- $\rightarrow_i \subseteq L_i \times pred(V \cup V_i) \times (C! \cup C? \cup \{\tau\}) \times \mathcal{U} \times L_i$ is the transition relation.

$pred()$ is a predicate defining the syntax of guards and comparison constructs over clocks and variables in Uppaal (Bodeveix et al., 2011). τ is an internal (silent) event and $\mathcal{U} : V \cup V_i \mapsto \mathcal{R}$ is the update to local and global variables.

Transitions between the different locations of each process can be driven by either events such as `Req`, `On`, `Off` or time durations. Semantically, a process state is given by the actual location of the corresponding Uppaal template and a valuation of the different variables.

Given that Uppaal transitions are instantaneous and the stays happen only at locations, we calculate the state update upon leaving a location by calling a function with the duration spent at that location as a parameter. Since Uppaal clocks are continuous, to be able to pass the time on as a parameter we designed a time discretizer automaton. This is in fact implemented via a clock variable which is reset almost at each transition. In iterative way, the clock value clk is compared to an integer to find the interval $[t, t+1]$ such that $clk > t$ and $clk < t+1$.

At the corresponding transitions, the EBC control process calculates the different safety attributes (error, temperature, duration between two switch events) according to the equations presented in Section 2 and following the stay durations at the relevant locations.

The switch control process schedules the ON operations following the actual energy convert status and the output error. We define an energy supply request $R = \langle e, d \rangle$ to be the energy supply rate e and the time duration d for which the supply holds (Boudjadar and Khooban, 2021).

Requirements Specification. In order to perform formal verification and validation of EBC safety following the optimization process, we formalized the aforementioned requirements (temperature, max error, frequency) as safety properties using CTL logic as follows:

$$S_1 \doteq \forall[]\ Temp \leq Max\_Temp;$$
$$S_2 \doteq \forall[]\ Freq \leq Max\_Freq$$
$$S_3 \doteq \forall[]\ Error \leq Max\_Error;$$

Each safety property S_i is examined individually as a query to the Uppaal symbolic model checker. So that for each input configuration from the optimization, we run 3 verification processes in an automated way as described below.

Verification and Validation. The verification of S_1, S_2 and S_3 for each optimization output is done using a script to trigger Uppaal verification on the same models with optimization configurations as parameters. The verification outcomes of the EBC case study show an alignment between the number of optimization iterations and the number of configurations satisfying the safety requirements. In fact, the higher the iterations number is the higher number the optimization configurations satisfying safety requirements will be. The reason could be that the optimization converges towards values that prevent the frequency momentum to escalate rapidly to which the temperature increase is proportional.

Cost and Scalability Challenges. Running the verification process for each of the parameter configurations obtained by the optimization process is a tedious operation that is expensive and time consuming. This leads the verification process to be behind the optimization operation most of the time, thus optimization results cannot be adopted upon arrival which is not profitable from a performance engineering point of view. A future work would be to optimize the verification process by identifying the boundaries of feasible parameter values so that only candidates having a high likelihood to be safe will be subject to verification. This can be achieved using a machine learning (ML) process to calculate the boundaries dynamically together with a feedback loop from the verification process to ML.

5 RELATED WORK

Ensuring high performance and safety properties of cyber-physical systems (CPS) is a challenging task given the spatio-temporal dynamics of the underlying physical environment (Banerjee et al., 2012). Safety validation and energy performance optimization of cyber-physical systems, using digital twins, have been studied in the literature for different applications (Wang et al., 2021; Bizon, 2018; Bizon, 2017; Herr et al., 2017; Herr et al., 2014; Boudjadar and Khooban, 2021). However, only few attempts focused on coupling the optimization with formal verification to secure high performance while maintaining the underlying safety requirements (van Biert et al., 2016).

The authors of (Wang et al., 2021) proposed a digital twin setup for network energy optimization and safety analysis of Unmanned Aerial vehicles (UAV). They used a energy-based weighted clustering algorithm (EWCA) to optimize the life of the overall communication network and enhance its availability by minimizing the energy consumption. However, the safety analysis is conducted in a statistical way (probability-based) making room for misleading decisions given that no absolute guarantee can be delivered about when an optimization is safe.

The authors of (Bizon, 2017; Bizon, 2018) introduced a controller for electric hybrid vehicle power systems. The control algorithm is coupled with an optimization process to find the efficient injection rate so that minimizing the gap and energy waste between the supply and the load demand. However, making the performance as the only driving optimization factor may jeopardize the system safety.

The authors of (Herr et al., 2017; Herr et al., 2014) propose an optimization process for multi-stack energy supply system to improve the reliability and lifetime of individual electric units. A unit is chosen to supply the energy load if the cost related to its activity is the cheapest possible, this will contribute most likely to escalate the temperature of the cheap resource units and thus violates safety.

The authors of (He et al., 2019) present a digital twin setup to integrate process monitoring, diagnosis and enable automated calibration of system models. An optimization approach has been proposed to enhance the control stability and safety under apparatus faults.

Our paper differs from the aforementioned references by using Matlab as a domain-specific setup to model EBC, calculate and optimize the performance metrics while using Uppaal as a powerful verification engine to deliver absolute guarantee about the safety properties following the optimization. However, our approach might be much expensive and less automated compared to the work in (He et al., 2019).

6 CONCLUSION

This paper presented a digital twin setup for model-based optimization, verification and validation of a cyber-physical system (EBC).

An early stage digital twin model has been designed in Matlab. Besides, a data-driven engineering approach has been used to calibrate the early stage model where the outputs of the physical system (actions, values, time points) are used to synchronize and tune the digital twin model. Optimization and safety verification have been conducted on the resulting high fidelity model. The optimization consists in identifying candidate control configurations that lead to a better performance and smaller output errors. To maintain safety requirements, we have translated the Matlab model to Uppaal timed automata for formal verification. We coupled the optimization with the verification so that only safe optimal configurations will be integrated into the physical system control loop.

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