Tuning energy consumption strategies in the railway domain: a model-based approach

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Abstract. Cautious usage of energy resources is gaining great attention nowadays, both from environmental and economical point of view. Therefore, studies devoted to analyze and predict energy consumption in a variety of application sectors are becoming increasingly important, especially in combination with other non-functional properties, such as reliability, safety and availability.
This paper focuses on energy consumption strategies in the railway sector, addressing in particular rail road switches through which trains are guided from one track to another. Given the criticality of their task, the temperature of these devices needs to be kept above certain levels to assure their correct functioning. By applying a stochastic model-based approach, we analyse a family of energy consumption strategies based on thresholds to trigger the activation/deactivation of energy supply. The goal is to offer an assessment framework through which appropriate tuning of threshold-based energy supply solutions can be achieved, so to select the most appropriate one, resulting in a good compromise between energy consumption and reliability level.

1 Introduction

Nowadays studies devoted to analyze and predict energy consumption in a variety of application sectors are receiving increasing importance, both from environmental and economical point of view. When the application domain is a dependability-critical one, such as the transportation sector, energy saving needs to be considered in conjunction with other properties requested to the system, including reliability, safety and availability. Therefore, the interplay of energy consumption and dependability-related measures needs to be analysed. This is a rather new research activity. Dependability analysis has been pursued for a long time, while energy consumption evaluation is becoming rather popular only in recent years. However, the research effort in these topics have been mainly conducted in isolation and not in combination, as addressed in this paper.

A research line by the authors in this direction has been developed over the last year [4] [3], by applying a stochastic model-based approach to evaluate energy consumption strategies in the railway sector, addressing in particular rail road switches through which trains are guided from one track to another. Such switches are critical components in the railway domain, since reliability of the railway transportation system highly depends on their correct operation, in absence of which potentially catastrophic consequences may be generated. Low temperature, especially during winter, can put in danger their correct operation. To deal with this problem, nowadays heaters are used so that the temperature of the rail road switches can be kept above freezing.

The referred previous studies developed a modeling and analysis framework suited to analyze a variety of policies for heating rail road switches, to assess the degree of their ability to optimise the energy consumption and at the same time to ensure reliability. In line with such previous studies and resorting to the same modelling framework, this paper provides as original contribution the analysis of a family of energy consumption strategies tailored to rail road switch heaters, based on thresholds to trigger the activation/deactivation of energy supply. In particular, we consider an *adaptive* strategy which changes the behaviour of the policy of energy-saving based on the environment temperature, and a *static policy* which does not.

We show how the adaptive strategy improves the reliability indicators, by saving 25% of supplied energy while guaranteeing acceptable reliability levels. The goal is to offer an assessment framework through which appropriate tuning of threshold-based energy supply solutions can be achieved, so to select the most appropriate one, resulting in a good compromise between energy consumption and reliability level. A prioritized approach has been considered, where the heaters are categorized according to their importance inside the analysed railway station. Note that a failure of the heating system is accounted for by other components of the railway system, namely interlocking mechanisms which guarantee safety; however we do not include them in our analysis.

Structure of the paper Stochastic model-based analysis is introduced in Section 2. We present the models of the rail road switch heating system in Section 3, which are then instantiated to a real scenario in Section 4. The results of our experiments are discussed in Section 5, while related work and conclusions are in Sections 6 and Section 7, respectively.

2 Stochastic Model-based Analysis

For evaluating the selected case study, a stochastic model-based approach has been adopted [6, 12]. Indeed, stochastic phenomena are involved in our analysis, namely the failure occurrence and weather forecast. Stochastic model-based methods are useful to support the development of systems, in all the phases of their life cycle.

In the early design phases they provide indications in several directions, leading to better efficiency in time and resources in the development phase. Typically, starting from the properties and the requirements that the system under development must satisfy, which can be both non-functional properties such as dependability and performability, a model of the system under analysis is built, to represent its behaviour. The developed model can be exploited to: i) highlight problems in the design of the system, such as criticality of the system components with respect to stated requirements; ii) compare different alternatives for the same system, and select the one that better suits the requirements; iii) conduct sensitivity analysis to varying system parameters, to find the best tuning in accordance with system relevant criteria. In this work, model-based analysis is applied to obtain support in tuning the parameters of the considered heating strategy.

When the design phase is completed, a model allows predicting the overall behaviour of the system, fostering an analysis for the fulfilment of constraints in the design phase and the acceptance cases.

For an already existing system, an a-posteriori analysis of properties such as dependability or performance is useful in order to improve the system in its future releases.

Moreover, with a model-based analysis it is possible to predict future behaviours to plan the maintenance and the upgrading of the system [19].

Stochastic Activity Network

In the literature a vast number of stochastic modelling techniques and methods have been proposed [2, 18, 1, 5, 10]. SAN [18] is a formalism widely used for performance, dependability and performability evaluation of complex systems, given its high expressiveness and the powerful tools for modelling and evaluating them [9]. The SAN formalism is a variant of Stochastic Petri Nets [5], and has similarities with Generalised Stochastic Petri Nets [2].

Möbius [9] is a multi-formalism multi-solver tool that can be used for defining and solving SAN models. Möbius supports various formalisms and different analytical and simulative solvers, and can be used for studying the reliability, availability, and performability of systems. It follows a modular modelling approach, where atomic models are building blocks that can be composed with proper operators *Rep* and *Join* to generate a composed model.

3 Description of the Model

The considered case study is a rail road switch heating system. A rail road switch is a mechanism enabling trains to be guided from one track to another. It works with a pair of linked tapering rails, known as points. These points can be moved laterally into different positions, in order to direct a train into the straight path or the diverging path. Such switches are therefore critical components in the railway domain, since reliability of the railway transportation system highly depends on their correct operation.

During winter, snow and ice can prevent the switches from working properly, hence heaters are used so that the temperature of the rail road switches can be kept above freezing. Different policies may be adopted to power the heaters (by electricity), as for example to heat a selection of switches for a given amount of time or to heat all the switches together.

Stochastic model

We briefly outline the models of the system of (remotely controlled) rail road switch heaters, which will be used for evaluating energy and reliability indicators. A more detailed description of the proposed models can be found in [3]. We will consider an on-off policy for heating the switches, with parametric thresholds representing the temperatures triggering the activation/deactivation of the heating. We will also consider a

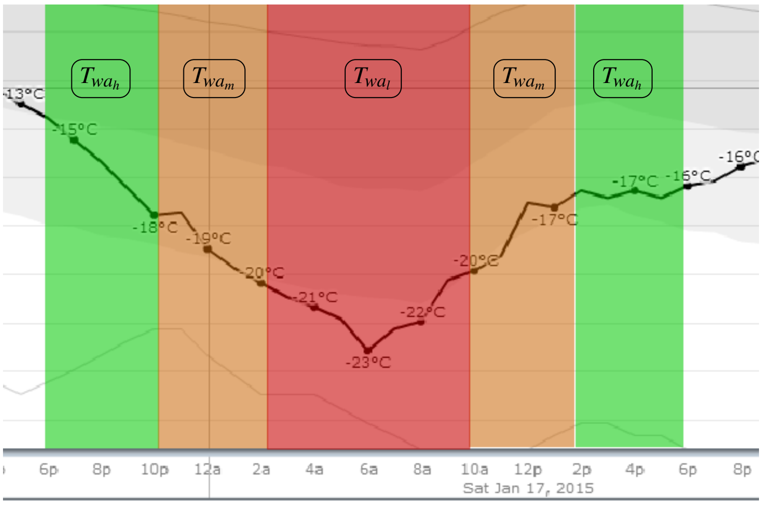


Fig. 1: The temperatures for coldest winter nights in the city Montreal, retrieved from [22]. Different areas represent different warning threshold levels.

prioritized approach. Indeed, in a railway station there are tracks which are less important than others, and it is important to distinguish between those switches that must be primarily heated and those that may be heated later on. The switches whose temperature cannot be kept above the freezing threshold may experience a failure.

The two main logical components describing the system are the *heater* and the *central coordinator*. The network of heaters is realised by replicating the heater component. The central coordinator manages the activation/deactivation of each heater. We discuss these two main components.

- *Heater*: we have based the policy employed for activating and deactivating the heating on two threshold temperatures:
  - *warning threshold* (T_{wa}): this temperature represents the lower temperature that the track should not trespass. If the temperature is lower than T_{wa}, then the risk of ice or snow can lead to a failure of the rail road switch and therefore the heating system needs to be activated;
  - *working threshold* (T_{wo}): this is the working temperature of the heating system. Once this temperature is reached, the heating system can be safely turned off in order to avoid an excessive waste of energy.

  In [3] we have considered *fixed values* of T_{wa} and T_{wo}. Here we will consider a *fine-grained* warning threshold, which is *flexible* and adapts to the different temperatures during the day, which corresponds to different hours. Indeed, as shown in Figure 1, we have partitioned the day in three intervals. In the analysis, we assume that during a day the *higher* temperatures are from $2pm$ to $10pm$, the *medium* temperatures are from $10pm$ to $2am$ and from $10am$ to $2pm$, while the *lower* temperatures are from $2am$ to $10am$. Of course, different intervals can be accommodated in the developed model. Accordingly we will adopt *three warning thresholds*:

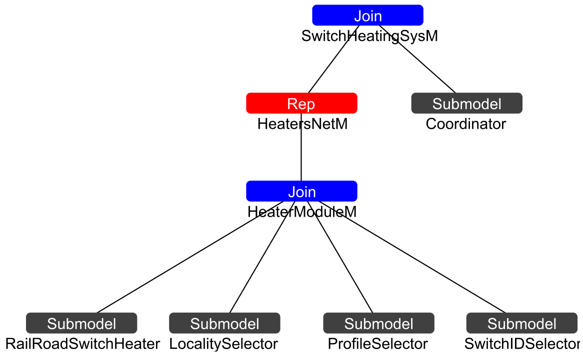


Fig. 2: The composed model.

T_{wa_h},T_{wa_m} and T_{wa_l}, which will be used during respectively the higher, the medium and the lower temperatures of the day. In Section 5 we will show how the flexible warning threshold improves the reliability and energy consumption of the system. In the following, if not stated otherwise, T_{wa} will refer to the tuple (T_{wa_h};T_{wa_m};T_{wa_l}), also called *flexible* warning threshold.

– *Coordinator*: the coordinator collects the requests of activation from the pending heaters, and it manages the energy supply according to a prioritized FIFO order, i.e. the first heater which asks to be turned on will be the first to be activated. The percentage of heaters that can be turned on at the same time is called NH_{max}. This value represents the maximum amount of energy deliverable by the system, and cannot be exceeded. If there is no energy available, each request will be enqueued in the queue of pending heaters.

The overall model is obtained by the composition of the atomic models, using the *Join* and *Rep* operators of the Möbius tool, as shown in Figure 2. Basically, with the *Join* operator different models are linked by sharing some places, called *shared places*, through which they interact. The *Rep* operator generates several instances of the same model, which can be uniquely identified using a tailored SAN model ($SwitchIDSelector$ in our case).

The atomic model $Coordinator$ represents the central coordinator. The submodel $HeatherModuleM$ corresponds to an instance of a single heater module, obtained by the composition, using the join operator, of the four atomic SAN models $ProfileSelector$, $LocalitySelector$, $SwitchIDSelector$ and $RailRoadSwitchHeater$, which share different parameters concerning a single rail road switch heater. The submodel $HeatersNetM$, obtained by replicating *numRep* times the model $HeatherModuleM$, models the network of heaters, where the parameter *numRep* identifies the number of devices composing the network. Finally, the model $SwitchHeatingSysM$, obtained using the join operator, represents the overall system. Indeed, all the submodels share the same coordinator.

The SAN model $RailRoadSwitchHeater$ models an instance of a rail road switch heater. It is used for evaluating the energy consumption and the probability of failure of the modelled heater. Indeed, according to the heating policy, once the system temperature goes below a pre-defined warning threshold (T_{wa}), the heating needs to be activated, otherwise the associated switch fails. Then, once the temperature rises and reaches the working threshold (T_{wo}), the heating system can be safely turned off. If the temperature goes below 0°C then the switch may experience a failure, according to an exponential distribution where the rate is based on the internal temperature of the switches. This SAN model has been modified as follows: the input and output gates that are responsible for turning on and off the heater are updated with two functions that select the proper T_{wa} according to the current time. The heater sub-net interacts with the Coordinator SAN model through places shared among all the replicas of the heater model and the Coordinator model.

The physical behaviour concerning the increment and decrement of the temperature of the rail road track, respectively when the heater is turned on or off, is modelled by a differential equation representing the balance of energy, see [3] for more details. Assuming that the values of the temperature of the surrounding area T_e and the previous internal temperature T are known, the updated internal temperature T after time t is computed by solving the following differential equation:

$$mc\frac{\partial T}{\partial t} = -uA(T - T_e) + \dot{Q}$$

where u is the coefficient of convective exchange; c, the heat capacity of iron; A, the surface area exposed to the external temperature; m, the mass of the iron bar; $\dot{Q}$, the power used when the heater is turned on, if the heater is turned off this value will be zero.

4 Scenarios and Settings

The scenarios and settings that we have considered for our analysis are described in the following, where we have used real world data for guaranteeing that our evaluation is realistic. Indeed, we have considered an average medium-size railway station of a northern city [8], with cold winter days. The instantiation of the physical model is based on real devices data [7].

The chosen railway station is composed of 41 switches that we have divided into three different classes of priority depending on the criticality of the service offered by the switches. In the considered case study, we have 23 high priority switches, 6 medium priority switches and 12 low priority switches [3].

Concerning the weather data, we have used environment temperatures based on those of mid-January 2015 in the city of Montreal [22]. The temperatures for the considered days are displayed in Figure 1, where we emphasize the partitioning of the day into three portions corresponding to T_{wa_h}, T_{wa_m} and T_{wa_l}. In our experiments, the environment temperatures are selected according to a uniform distribution.

The setting of parameters representing the best compromise between energy consumption and reliability in [3] is $T_{wa} = 7°\text{C}, T_{wo} = 8°\text{C}$ and for high priority switches $NH_{max} = 50\%$, while for medium and low priority switches $NH_{max} = 75\%$. By comparing the above values with the results of the experiments we have conducted, we will show that by adopting a fine-grained warning threshold an improvement in the overall reliability of the system and its energy consumption can be obtained.

We will analyse two different strategies of deactivation of the heating system, by considering a fixed value of:

1. $T_{wa}-T_{wo}$, that is a fixed gap between T_{wa} and T_{wo}. For different values of T_{wa_h}, T_{wa_m} and T_{wa_l} the value of T_{wo} will change accordingly. For example, for a fixed value of $T_{wa}-T_{wo}=$ 1°C, if $T_{wa}=(7;8;9)$ then $T_{wo}=(8;9;10)$;
2. T_{wo}, hence for different values of T_{wa_h},T_{wa_m} and T_{wa_l} we will obtain different gaps between T_{wa} and T_{wo}.

In all the experiments we have performed, we only have considered an amount of energy that suffices for charging contemporary 50% of all the switches in the network, i.e. $NH_{max} = 50\%$. Indeed, for $NH_{max} = 75\%$ we have shown in [3] that a higher level of reliability is obtained, which is not the case for $NH_{max} = 50\%$. Conversely, by adopting $NH_{max} = 25\%$ the energy consumption is too low to guarantee acceptable reliability levels. In the following analysis we will show that the supplied energy can be reduced to $NH_{max} = 50\%$ while guaranteeing levels of reliability similar to $NH_{max} = 75\%$ for the low priority switches. This is important because we are able to save 25% of supplied energy per time. The values for T_{wa_h},T_{wa_m} and T_{wa_l} range from 6°C to 10°C, with an increment of 0.25°C. For item 1, in our experiments we considered $T_{wa}-T_{wo}=$ 1°C, which is the optimal value according to [3]; while for item 2 the values of T_{wo} range from 8°C to 10°C, with an increment of 0.25°C.

In all the considered evaluations, we assume that at starting time the system is in a safe condition, that is the internal temperature of all switches is equal to its working temperature. This assumption is useful for avoiding instantaneous failure.

We have considered all the combinations of those parameters, and in the following we will discuss the evidence of our experiments, emphasizing the most significant results.

Measures of Interest

We borrow the two considered measures of interest from [3]. The first concerns the energy consumption while the second addresses reliability.

1 $CE(t,l)$: the time (in hours) a heater is activated in the time interval $[t,t+l]$. This measure is defined by accumulating the time that each replica of the SAN model *RailRoadSwitchHeater* spends in the marking m, where m represents the heating phase. Hence $CE(t,l)$ is the amount of time (expressed in hours) that a heater is active. By multiplying $CE(t,l)$ for the power consumed (kilowatt per hour) it is possible to derive the energy consumed by the system;
2 $PFAIL(t,l)$: the probability that at least a switch fails (becomes frozen) within time $t+l$, given that at time t is not failed. This measure is defined as the probability that within time $t+l$ the switch has failed.

We remark that reliability is computed as the probability that no failure occurs in the interval of time under analysis [20], that is $1-PFAIL(t,l)$. Note that the measures of interest are priority-wise.

5 Discussion of Results

We now describe the results of the evaluations we have performed in order to compare the two strategies of energy saving based on a fixed and a flexible warning threshold. We have plotted the outcome of our results in different graphs, to show how the measures of interest are affected by the relevant parameters.

Concerning the fixed value of $T_{wa} - T_{wo} = 1°C$, in Figure 3 we compare a fixed T_{wa} with a flexible T_{wa}, focussing on values of T_{wa} through which the best results are obtained. Note that the values on the x axis concern both flexible and fixed T_{wa}, and their order is immaterial. The probability of failure is analysed in Figure 3b and Figure 3a, the energy consumption in Figure 3d and Figure 3c, with medium priority in Figure 3c and Figure 3a and low priority in Figure 3d and Figure 3b. The high priority switches are not displayed because their probability of failure is neglectable.

In Figure 4 and Figure 5 we evaluate the measures of interest with "bad" values of T_{wa} considering all the priority classes, to better understand how the different values of T_{wa_h},T_{wa_m} and T_{wa_l} affect the reliability of the switches with different priorities. The probability of failure is analysed in Figure 4a and Figure 5a while the energy consumption is in Figure 4b and Figure 5b.

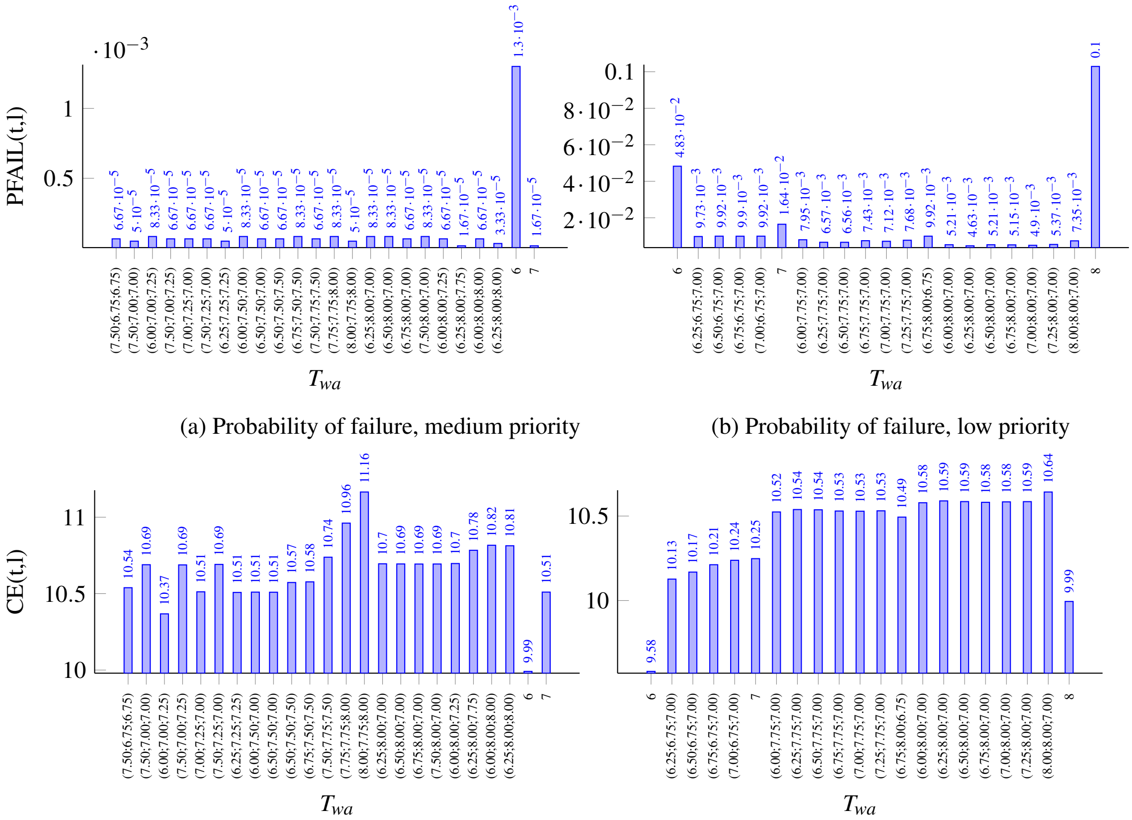
The case of fixed T_{wo} is displayed in Figure 6, where we focus on the probability of failure at varying T_{wa} and T_{wo}.

Fixed gap between thresholds. We will analyse $PFAIL(t,l)$ and $CE(t,l)$, observing that in general $CE(t,l)$ is affected by $PFAIL(t,l)$, i.e. if a heater fails then it will no longer consume energy.

Improving the reliability. Concerning medium priority switches, in Figure 3a for $T_{wa} = 6°C$ and $T_{wa} = 7°C$ the values of $PFAIL(t,l)$ are respectively 0.0013 and $1.667e-05$. By adopting a flexible T_{wa} we do not have neither an improvement nor a deterioration of the optimal value of $PFAIL(t,l)$, while we slightly reduce $CE(t,l)$ with $T_{wa} = (6.00; 7.00; 7.25)$, as shown in Figure 3c.

The results for the low priority switches are more interesting. In this case, as shown in Figure 3b, with fixed T_{wa} the lower value of $PFAIL(t,l)$ is 0.0164 (for $T_{wa} = 7$). Remarkably, by considering the flexible $T_{wa} = (6.25; 8.00; 7.00)$, we reduce $PFAIL(t,l)$ of one order of magnitude, i.e. $PFAIL(t,l) = 0.004625$. Moreover, we register an improvement in $PFAIL(t,l)$ by also considering the other values of T_{wa} closer to the optimum. In Figure 3d we observe that the energy consumption $CE(t,l)$ is affected marginally, which is due to the reduced probability of failure.

An explanation of these results follows. We note that the values of T_{wa_h},T_{wa_m} and T_{wa_l} are correlated with the different priorities. Indeed, since our experiments start at $6pm$ and the high priority switches are the first to be activated, they are mostly affected by T_{wa_h}, that is the warning threshold adopted from $6pm$ to $10pm$. In Figure 3b (low priority switches) we note that by increasing T_{wa_h}, $PFAIL(t,l)$ is affected marginally; this is because those are not the coldest hours of the day. Conversely, with higher values of T_{wa_m}, $PFAIL(t,l)$ decreases. This is because the heaters are approaching the coldest hours of the day, and it is important to raise to a higher level of temperature for getting



(a) Probability of failure, medium priority

(b) Probability of failure, low priority

(c) Consumed energy, medium priority

(d) Consumed energy, low priority

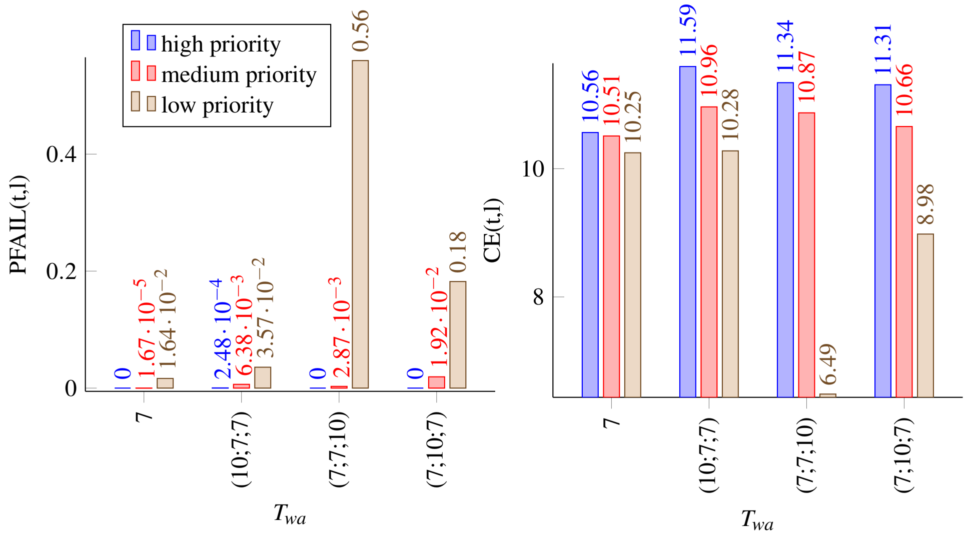
Fig. 3: The measures of interest of the heaters with fixed $T_{wo} - T_{wa} = 1$°C and optimal values of T_{wa}

prepared to the minimum temperatures. In the coldest hours T_{wa_l} is adopted, and the optimal value corresponds to the one with fixed T_{wa}, i.e. 7°C. This is because T_{wa_l} is the threshold which mostly affects $PFAIL(t,l)$, as explained below.

Impact of T_{wa_l} *on the reliability.* In Figure 4 we emphasise the impact of T_{wa_h},T_{wa_m} and T_{wa_l} in $PFAIL(t,l)$ and $CE(t,l)$, considering all the priorities. This is done by analysing the warning thresholds $(10;7;7)$°C, $(7;10;7)$°C and $(7;7;10)$°C. Indeed, from the previous analysis we know that 7°C is a "good" value while 10°C is a "bad" value.

In Figure 4a we note that, starting from the fixed T_{wa}=7°C, the worst value of $PFAIL(t,l)$ for the high priority switches is T_{wa}= $(10;7;7)$°C, that is $PFAIL(t,l)$= $2.40e-04$. In this case an increment in the energy consumed is also registered, as shown in Figure 4b, even though $PFAIL(t,l)$ has increased too.

For the medium priority switches, with T_{wa}= $(7;10;7)$°C we obtain $PFAIL(t,l)$= $1.92e-2$, while $CE(t,l)$ is marginally affected.



(a) The probability of failure

(b) The consumed energy

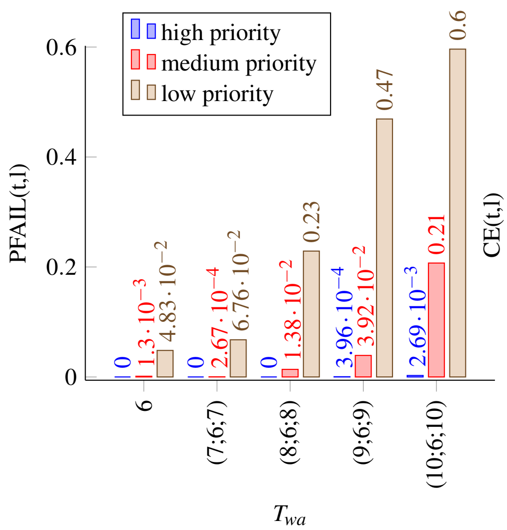
Fig. 4: The measures of interest for different priorities with fixed $T_{wo} - T_{wa} = 1°$C, with fixed $T_{wa} = 7°$C and "bad" values for respectively $T_{wa(h)}, T_{wa(l)}$ and $T_{wa(m)}$

For the low priority switches, with T_{wa}= $(7;7;10)°$C we obtain $PFAIL(t,l)$= 0.56 as the worst value, which is unacceptable. In this case, $CE(t,l)$ is highly affected, since almost half of the heaters with low priority have failed.

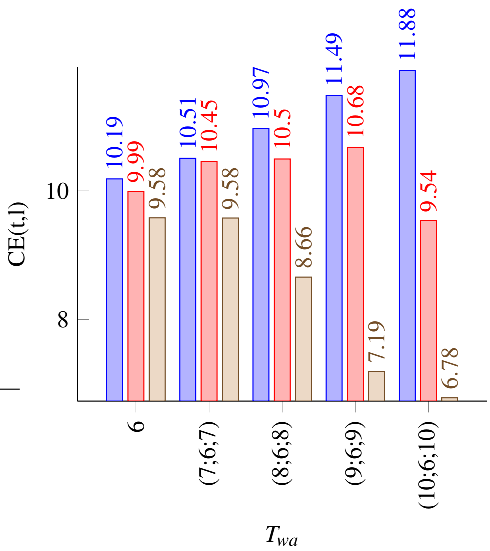
Hence, Figure 4 has shown that the worst case scenario is T_{wa}=$(7;7;10)°$C. This means that $PFAIL(t,l)$ for low priority switches is the one which is mostly affected by the corresponding T_{wa_l}. Intuitively, the coldest hours are the most critical for the reliability of the system, and the low priority switches are the most failure-prone.

Worst scenario for medium priority switches. From the experiments we have conducted, we observed that by adopting particular values of the flexible T_{wa}, an important increment in $PFAIL(t,l)$ for the medium priority switches is registered, which was not evaluated in the previous experiments. We discuss this phenomenon in Figure 5, in order to better understand the behaviour of the system. We considered $PFAIL(t,l)$ and $CE(t,l)$ for an increasing difference of T_{wa_m} from both T_{wa_h} and T_{wa_l}, that is $(7;6;7)°$C, $(8;6;8)°$C, $(9;6;9)°$C and $(10;6;10)°$C.

While in Figure 4a for the medium priority switches with T_{wa}=$(7;10;7)°$C we obtained the worst value of $PFAIL(t,l)$ (i.e. $PFAIL(t,l)$= $1.92e-2$), in Figure 5a with T_{wa}=$(10;6;10)°$C we obtain $PFAIL(t,l)$= 0.21, which is surprisingly higher than the previous values, and represents the worst reliability value of our analysis for all priorities. We note that this result is not generated by the higher value of T_{wa_h}, for example for T_{wa}= $(10;6;6)°$C, we have $PFAIL(t,l)$= $1.74E-02$ for the medium priority switches. On the converse, the higher value of T_{wa_l} highly affects $PFAIL(t,l)$,



(a) The probability of failure



(b) The consumed energy

Fig. 5: The measures of interest for different priorities with fixed $T_{wo} - T_{wa} = 1°$C, with increasing difference between T_{wa_m} and T_{wa_h},T_{wa_l}

as explained above, and for example for T_{wa}= $(6;6;10)°$C we obtain $PFAIL(t,l)$= $1.39E-01$ for the medium priority switches; while for T_{wa}=$(10;10;6)°$C, we have $PFAIL(t,l)$= $5.33E-04$.

We explain this phenomenon as follows: with T_{wa_h}= 10°C, the high priority switches jeopardize all the energy for reaching a higher temperature, then during T_{wa_m}= 6°C the medium priority switches are heated, but their temperature does not rise to a sufficient level. Finally, with T_{wa_l}= 10°C, all the energy is once again jeopardized by the high priority switches, thus leaving the medium and low priority switches with a low temperature and no energy, so maximising their probability of failure.

Fixed working threshold. We analyse the second strategy presented in Section 4, that is a fixed value of T_{wo}. We only focus on the low priorities switches, and the values of $PFAIL(t,l)$ for varying values of the fixed T_{wo} are shown in Figure 6. When T_{wo}= 8°C we observe the lower values for $PFAIL(t,l)$, in particular for T_{wa}= $(6.50;7.75;7.00)°$C, we obtain $PFAIL(t,l)$= 0.0056, which is the best reliability level of this strategy. By adopting higher values of fixed T_{wo}, we observe in Figure 6 that $PFAIL(t,l)$ gradually increases.

Comparisons. We compare the two strategies described in Section 4, focussing on the low priority switches. We note that in the fixed T_{wo} strategy, when T_{wo}= 8°C we have approximatively $T_{wa}-T_{wo}$= 1°C, that is the two strategies are similar. This is also the

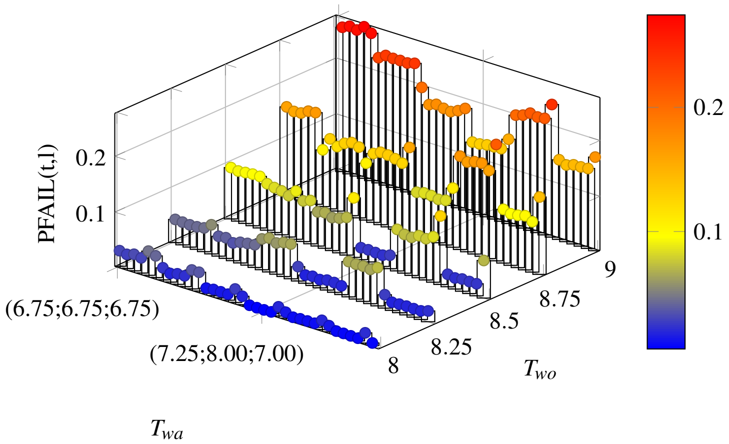


Fig. 6: The probability of failure of the low priority heaters with fixed values of T_{wo}

optimal value for the fixed T_{wo}, that is $PFAIL(t,l)$= 0.0056. A similar value is obtained for the case of fixed T_{wa} - T_{wo}, that is $PFAIL(t,l)$= 0.0046. However, the strategy of maintaining a fixed gap between T_{wa} and T_{wo} has shown to be more reliable also for other combinations of T_{wa_h},T_{wa_m} and T_{wa_l}.

Summary of results. Concluding, we have shown that by adopting a flexible warning threshold, which adapts to the different temperatures during the day, we improve the overall reliability of the system. Remarkably, the probability of failure for the low priority switches has reduced of one order of magnitude, so passing from 0.0164 with fixed T_{wa} to 0.0046 with a flexible T_{wa}. Hence, the overall energy supplied to the system can be reduced from NH_{max}= 75% to NH_{max}= 50% while guaranteeing similar reliability levels. Moreover, by comparing the two strategies of energy management, we have obtained better results with a fixed gap between T_{wo} and T_{wa}, while considering a fixed T_{wo} we observed a deterioration in the reliability of the system.

Experiments performance Simulation-based evaluations have been performed using the Möbius tool [9], considering from a minimum of 1000 batches to a maximum of 10000 batches. The measures of interest were estimated within an interval of confidence of 0.95 using simulations. For computing the results of $PFAIL(t,l)$ and $CE(t,l)$, considering all three levels of priorities and the set-up of parameters discussed in Section 4 we have performed 1500 experiments (only a portion of the overall results has been discussed in this paper) with an average time of 30 seconds per experiment. It has been used a machine with CPU Intel Core i5-4570 at 3.20 GHZ with 8 GB of RAM, running 64-bit Windows 10.

6 Related work

In the literature there are several works that analyse and optimise the energy consumption in several application domains using formal approaches, even though they do not analyse rail road switch heating systems. We recall some of them in the following. Services negotiation of energy and reliability requirements is the selected case study in [21], where an energy provider, an energy consumer and a mediator try to find an agreement on the amount of energy delivered, its reliability and price. Their reliability and energy requirements are given parameters that are negotiated between the parties; instead in our approach we are interested in computing their optimal values at the varying of prescribed parametric policies.

In [16] Generalized Stochastic Petri Nets [2] are used to solve the dynamic power management problem for systems with complex behaviour. Dynamic power management addresses reduction of power dissipation in embedded systems with a selective shut-off or slow-down of system components that are idle or underutilized. In our case complex behaviours are modelled with SAN models, which are a generalization of Generalised Stochastic Petri Nets. We also consider a policy of switching on/off the heater when a given temperature threshold is reached.

The dynamic power management problem is interpreted as a hybrid automaton control problem and integrated stochastic control in [13], where Hybrid automata mixed both a discrete state, representing the power mode of the system, and a continuous one, representing the consumed power. Two strategies are compared: on demand wake-up of a component (that was previously turned off) and pre-emptive wake-up. The former provides better results for the conservation of energy and prevention of latency. It would be interesting to implement in our work a power adjustment mechanism.

The survivability of a smart house is analysed in [14], that is the probability that a house with locally generated energy (photovoltaic) and a battery storage can continuously be powered in case of a grid failure. Hybrid Petri Nets [10] are used for modelling this scenario. The authors consider a randomly chosen probability of failure and fixed thresholds, while in our case the probability of failure is derived from the model and we consider flexible thresholds. The trade-off between energy saving and reliability is studied in [23], by managing frequencies and voltage of the delivered energy. In our approach the energy consumption is managed by changing the power consumed by the system.

Concerning the analysis and optimization of a railway station using formal techniques, in [11] Stochastic Activity Networks are used to improve timetable and delay minimization of the traffic in a station. In [15] an Automatic Train Supervision is designed that prevents the occurrence of deadlocks. It would be interesting to integrate such studies with the possible failure of switches studied here, in order to analyse how a failure in a switch impacts on possible delays of trains, and deadlocks.

7 Conclusion and Future Work

The paper addressed analysis for a rail road switch heating system through a model-based approach, using Stochastic Activity Networks and the Möbius tool [9]. In previous work [4, 3], a SAN modelling framework has been developed to represent (i) the behaviour of the physical system and (ii) the strategies of energy management of the switch heaters. Building on that, a study devoted to explore the tuning of such heating strategies has been carried out here. In particular, we have studied the sensitivity of energy consumption and reliability indicators at varying the thresholds temperatures adopted by the heating strategies. To make the analysis more realistic, the adaptation of thresholds to different time intervals characterized by different temperatures during the day has been performed.

We have considered a realistic scenario for our case study. The data concerning the layout of the railway station were taken from a real case [8], and the data for the temperatures in extremely cold conditions were retrieved from [22]. The physical model for the heater has been instantiated by taking values available at [7] [17].

The results have shown that by adopting thresholds that adapt to different temperatures during the day, we have improved the overall reliability of the system, especially for the low priority switch heaters. It is then possible to safely save almost 25% of the overall energy supplied to the system.

An interesting direction for extending this study would be considering different layouts of railway stations. Indeed, in this analysis only a fixed percentage of higher, medium and low level priority switches have been evaluated. Even though these values represent a "standard" layout for a middle-size railway station, it would be valuable to study how the reliability and energy consumption indicators are affected by different distributions of priorities, and how to tune the thresholds accordingly.

References

1. Alur, R., Dill, D.L.: A theory of timed automata. Theoretical Computer Science 126(2), 183 – 235 (1994)
2. Balbo, G.: Introduction to generalized stochastic petri nets. In: Bernardo, M., Hillston, J. (eds.) Formal Methods for Performance Evaluation, LNCS, vol. 4486, pp. 83–131. Springer Berlin Heidelberg (2007)
3. Basile, D., Chiaradonna, S., Giandomenico, F.D., Gnesi, S.: A stochastic model-based approach to analyse reliable energy-saving rail road switch heating systems. Journal of Rail Transport Planning and Management pp. – (2016), http://www.sciencedirect.com/science/article/pii/S2210970616300051
4. Basile, D., Chiaradonna, S., Giandomenico, F.D., Gnesi, S., Mazzanti, F.: Stochastic model-based analysis of energy consumption in a rail road switch heating system. In: Software Engineering for Resilient Systems - 7th International Workshop, SERENE 2015, Paris, France, September 7-8, 2015. Proceedings. pp. 82–98 (2015), http://dx.doi.org/10.1007/978-3-319-23129-7_7
5. Bause, F., Kritzinger, P.S.: Stochastic petri nets: An introduction to the theory. SIGMETRICS Perform. Eval. Rev. 26(2), 2–3 (Aug 1998)
6. Bernardi, S., Merseguer, J., Petriu, D.C.: Model-Driven Dependability Assessment of Software Systems. Springer (2013)
7. Brodowski, D., Komosa, K.: A railroad switch and a method of melting snow and ice in railroad switches (2013), https://data.epo.org/publication-server/rest/v1.0/publication-dates/20131225/patents/EP2677079NWA1/document.html
8. https://en.wikipedia.org/wiki/Carlisle_railway_station
9. Clark, G., Courtney, T., Daly, D., Deavours, D., Derisavi, S., Doyle, J.M., Sanders, W.H., Webster, P.: The möbius modeling tool. In: Proceedings of the 9th International Workshop on Petri Nets and Performance Models. pp. 241–250 (2001)
10. David, R., Alla, H.: On hybrid petri nets. Discrete Event Dynamic Systems 11(1-2), 9–40 (Jan 2001)

11. Di Giandomenico, F., Fantechi, A., Gnesi, S., Itria, M.L.: Stochastic model-based analysis of way operation to support traffic planning. In: Gorbenko, A., Romanovsky, A., Kharchenko, V.S. (eds.) Software Engineering for Resilient Systems, 5th International Workshop, SERENE 2013. Proceedings. LNCS, vol. 8166, pp. 184–198. Springer (2013)
12. Diab, Hassan B.; Zomaya, A.Y.: Dependable computing systems: paradigms, performance issues and applications. John Wiley & Sons (2005)
13. Erbes, T., Shukla, S.K., Kachroo, P.: Stochastic learning feedback hybrid automata for dynamic power management in embedded systems. In: SMCia/05, IEEE Mid-Summer Workshop on Soft Computing in Industrial Applications, June 2005 (2005)
14. Ghasemieh, H., Haverkort, B.R., Jongerden, M.R., Remke, A.: Energy resilience modelling for smart houses. In: 45th Annual IEEE/IFIP International Conference on Dependable Systems and Networks, DSN 2015. pp. 275–286. IEEE (2015)
15. Mazzanti, F., Spagnolo, G.O., Longa, S.D., Ferrari, A.: Deadlock avoidance in train scheduling: A model checking approach. In: Lang, F., Flammini, F. (eds.) Formal Methods for Industrial Critical Systems - 19th International Conference, FMICS 2014. Proceedings. LNCS, vol. 8718, pp. 109–123. Springer (2014)
16. Qiu, Q., Wu, Q., Pedram, M.: Dynamic power management of complex systems using generalized stochastic petri nets. In: DAC. pp. 352–356 (2000)
17. `http://www.railsco.com/~electric_switch_heater_controls.htm`, (accessed on June 2016)
18. Sanders, W.H., Meyer, J.F.: Stochastic activity networks: Formal definitions and concepts. In: Brinksma, E., Hermanns, H., Katoen, J. (eds.) Lectures on Formal Methods and Performance Analysis, First EEF/Euro Summer School on Trends in Computer Science 2000, Revised Lectures. LNCS, vol. 2090, pp. 315–343. Springer (2000)
19. Front matter. In: Karlin, H.M.T. (ed.) An Introduction to Stochastic Modeling (Revised Edition), pp. iii –. Academic Press, revised edition edn. (1994), `http://www.sciencedirect.com/science/article/pii/B978012684885450001X`
20. Trivedi, K.S.: Probability & statistics with reliability, queuing and computer science applications. John Wiley & Sons (2008)
21. Čaušević, A., Seceleanu, C., Pettersson, P.: Distributed energy management case study: A formal approach to analyzing utility functions. In: Margaria, T., Steffen, B. (eds.) Leveraging Applications of Formal Methods, Verification and Validation. Specialized Techniques and Applications, Lecture Notes in Computer Science, vol. 8803, pp. 74–87. Springer Berlin Heidelberg (2014)
22. `https://weatherspark.com/#!graphs;ws=27985`, (accessed on March 2016)
23. Zhu, D., Melhem, R., Mossè, D.: The effects of energy management on reliability in real-time embedded systems. In: Computer Aided Design, 2004. ICCAD-2004. IEEE/ACM International Conference on. pp. 35–40 (Nov 2004)