Increasing Energy Saving with Service-based Process Adaptation

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Abstract: The aim to reduce the energy consumption in data centres is usually analyzed in the literature from a facility and hardware standpoint. For instance, innovative cooling systems and less power hungry CPUs have been developed to save as much more energy as possible. The goal of this paper is to move the standpoint to the application level by proposing an approach, driven by a goal-based model and a Complex Event Processing (CEP) engine, that enables the adaptation of the business processes execution. As several adaptation strategies can be available to reduce the energy consumption, the selection of the most suitable adaptation strategy is often the most critical step as it should be done timely and correctly: adaptation has to occur as soon as a critical point is reached (i.e., reactive approach) or, even before it occurs (i.e., proactive approach). Finally, the adaptation actions must also consider the influence on the performance of the system that should not be violated.

1 INTRODUCTION

The adoption of the PUE (Power Usage Effectiveness) to measure how much energy a data centre consumes to run facilities instead of the IT equipments, has affected the methods proposed in the literature. Indeed, most of the proposed work are focused on the reduction of the power consumed by the cooling systems, or by the optimization of the IT equipments. On the contrary, less attention has been paid to the optimization of the applications running in the data centres. With this work, we want to focus on this aspect leveraging on the an adaptive system that detect anomalies in energy consumption and react by moving the application to a greener state.

The design and implementation of systems able to adapt their own behavior with respect to new and unforeseen requirements, or to deal and solve problems that involve the underlying hardware and software, are some of the most challenging and interesting research questions in the computer science nowadays. As also discussed in the Autonomic Computing manifesto (Kephart and Chess, 2003), only with a deep knowledge of the system that we would like to adapt, the adaptation is possible. This knowledge concerns the components of the system and how they are organized, along with the values of indicators that are able to capture the performance of the system.

According to the MAPE (Monitor - Analyze - Plan - Execute) cycle, a monitoring infrastructure that continuously collects information about the status of the system is required. The analysis of the gathered data leads the system to better identify any malfunctionings and which are the possible adaptations to eliminate them. Finally, the most suitable adaptation action has to be selected and enacted. In case of service-based processes, KPIs (Key Performance Indicators) can be used as a way to evaluate a process in terms of a set of metrics capturing the most relevant aspects of the process performance. Among these metrics, energy saving is gaining more importance. For this reason, we introduce the concept of GPIs (Green Performance Indicators) as a way to monitor the greenness of the process.

The monitoring system should be able to compute these indicators through the data previously collected. Actual problems are how their current values can be used to assess the correctness of the process execution, how it is possible to react to a critical situation and, finally, if it is also possible to anticipate the adaptation predicting the next values of KPIs and GPIs.

This paper presents a methodology for energy efficiency in a service-based process context, with the aim of reducing the impact of the process execution as much as possible via a set of techniques combined together. The proposed approach is composed of three main elements: (i) a goal-based model used to specify which are the KPIs and GPIs that must be fulfilled

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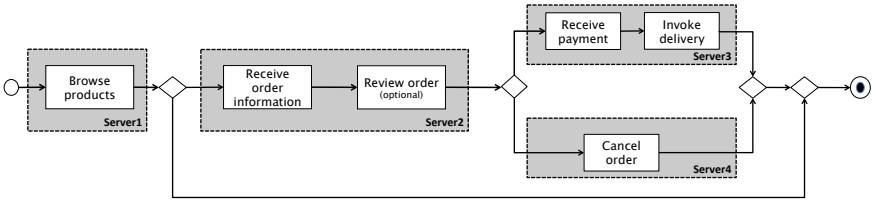


Figure 1: e-Commerce sample process.

and, if this is not possible, the actions that might be performed to adapt the execution; (ii) a prediction system used to anticipate possible violations of the indicators; and (iii) an architecture that includes a CEP (Complex Event Processing) engine (Luckham, 2001) and combines it with the other elements in order to detect both the occurring and the predicted violations and to produce a ranked list of the adaptation actions that could solve the problem.

Our approach has been validated for a service-based process running on a testbed where a monitoring system exists. The validation shows how the system is able to detect anomalies in terms of energy consumption. Moreover, the system is able to support the selection of the proper adaptation action that will reduce the energy consumption of the running process without affecting the performance parameters, as the response time. Finally, the proposed approach is also useful for collecting information to further improve improve the initial goal-based diagram.

The paper is organized as follows. Section 2 introduces a running example used along the paper to better describe our approach. Section 3 describes the details of the approach and, in particular, the adopted goal-based model and the data prediction techniques. The CEP-based architecture, that combines these elements, is described in Section 4. A validation of the approach is the goal of Section 5. After a comparison of the work with the state of the art in Section 6, the paper concludes with a discussion about possible future extensions in Section 7.

2 RUNNING EXAMPLE

To better understand and provide a validation of our approach, we use an e-commerce example, inspired by the TPC-C (Raab et al., 2001) benchmark, where services are invoked during the execution of a process for buying a good. Figure 1 shows the structure of the process and a possible deployment of the services on a data center (we assume that the orchestrator is running on another server, i.e., *Server0* not included in the figure). It is worth noting, as it will be also discussed during the validation, that an alternative "centralized" deployment is possible: in such a scenario all the services are executed on the *Server1*.

For this case study, Table 1 reports some of the relevant indicators and the metrics to calculate them. These ones concern both with typical performance dimensions (e.g., response time) and with green-aware indicators (e.g., application green performance). To compute these indicators, we assume that a proper monitoring infrastructure is available.

The goal of our approach is to monitor these predefined KPIs and GPIs and to properly adapt the application deployment in order to satisfy all the goals agreed with the users. The achievement of this objective requires the mediation between two perspectives that often clash. On the one side, the satisfaction of performance indicators, as the response time, demands more and more resources. On the other side, the increasing of resources usage raises the energy consumed; so that the green-aware indicators could be not satisfied.

3 PROPOSED APPROACH

3.1 Goals and Adaptation

The goal-based model proposed by (Asnar et al., 2011) has been adapted to represent what we need to monitor, the occurrences that could affect our observations, and to exploit the characteristics of adaptivity of the process. This model encompasses three conceptual structures that are organized in three corresponding layers, named respectively Asset, Event and Treatment layer:

- *Goals* (depicted as ovals) are strategic interests that actors intend to achieve for generating values;
- *Events* (depicted as pentagons) are uncertain circumstances, typically out of the control of actors, which can have an impact, positive or negative, on the fulfillment of goals;
- *Treatments* (depicted as hexagons) are sequences of actions used to achieve goals or to treat events.

Figure 2 shows an application of the model for our running case study: (i) Goals represent a set of de-

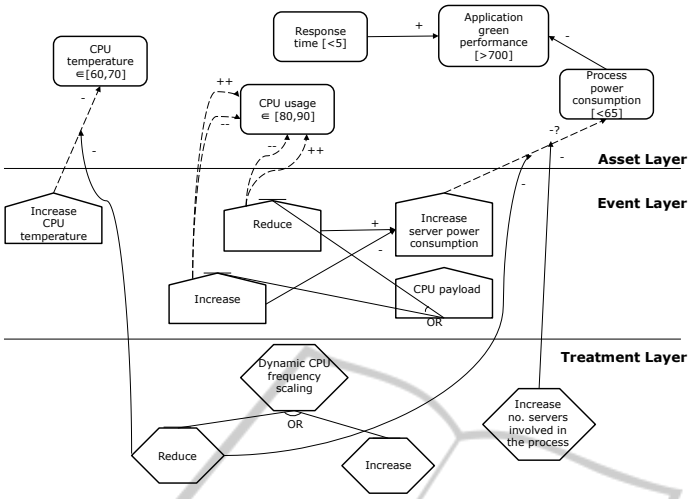


Figure 2: Goal-based model.

Table 1: KPIs and GPIs calculation.

Indicator	Threshold	Metric
CPU temperature	$\in [60,70]$	$temperature(^{\circ}C)$
CPU usage	$\in [80,90]$	$CPU usage\,(\%)$
Process power consumption	< 65	$\sum_{server_i}(power_i(W))$
Application green performance	> 700	$\#transactions/kWh$
Response time	< 5	$\sum(task\,response\,time(s))$

fined constraints on the KPIs and GPIs of the system; (ii) Events embody possible situations that could affect the integrity of KPIs or GPIs constraints and any other context that requires the enactment of an adaptation action; finally, (iii) Treatments symbolize the available repair actions.

An added value of the adopted goal-based model is the possibility to define relationships among goals. This means that an indicator may depend on other correlated indicators. In order to react to the violation of an indicator, it is possible to take actions influencing the correlated indicators and, consequently, indirectly improve the considered indicator. Indicators' thresholds have to be defined at accurately. It is also possible to describe how events affect the goals.

It is worth noting that, in order to ensure a proactive adaptation, the defined events are determined in terms of value trends that can have positive or negative impacts on the goal. A non-trivial task is to figure out which trends are occurring and when the values are considered so critical to require a treatment. The goal of the prediction, as described in the next section, is twofold. On the one side, the time series analysis (a necessary preliminary stage for the prediction itself) is able to identify and to model the trends of the monitored data. On the other side, the prediction is capable of anticipating the achievement of critical values, so that an adaptation action can be activated before the indicator violation occurs.

3.2 Data Prediction

In general, a series is defined as a sequence of several observations of a phenomenon with respect to a qualitative nature. If this feature is time, the series is called historical or, commonly, time series.

Given the phenomenon Y, any observations collected at time t is represented by the notation Y_t. So, formally, $Y = [Y_t : 1 \leq t \leq L]$ where L is the total number of observations gathered.

The classical approach for time series analysis provides a model that describes any observation as:

$$Y_t = f(t) + u_t$$

in which the value of the observation at time t is the result of the composition between a deterministic component $f(t)$, called systematic part, and a sequence of random variables u_t, named stochastic part.

It is worth noting that, before any kind of analysis, time series data need to be examined in order to make some adjustments and replace outliers. These adjustments are necessary when discontinuity and effects due to the different duration of time intervals affect the series. Figure 3 shows the effect of an outlier

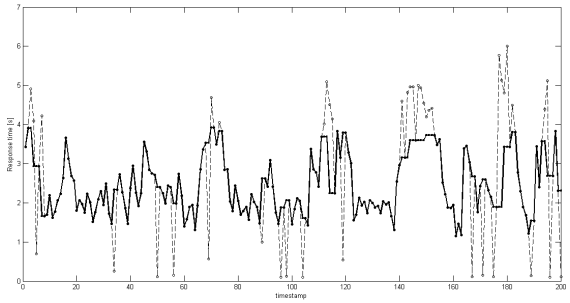


Figure 3: Outlier elimination samples.

elimination procedure on a generic time series.

In this paper, time series analysis is used to predict the values of a KPI, or a GPI. That means using a model to anticipate the future behavior of the observed variable, based on its past values. Indeed, the sooner we can figure out a possible violation of an indicator, the sooner we can react and possibly avoid that such a violation occurs. In particular, considering our running example, we noticed that several outliers arise. As a consequence, and in order to obtain a reliable prediction, such outliers need to be deleted.

Models for time series can have many forms and represent different stochastic processes. AutoRegressive (*AR*) models, Integrated (*I*) models and Moving Average (*MA*) models are some of the most popular way to theoretically define a time series. Combinations of them produce well known AutoRegressive Moving Average (*ARMA*) and AutoRegressive Integrated Moving Average (*ARIMA*) models.

In our case, we use autoregressive model to represent time series data. The notation $AR(p)$ indicates a p-order autoregressive model which is defined as:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \phi_p y_{t-p} + \eta_t$$

where $\phi_1, \phi_2, ..., \phi_p$ are the parameters of the model which act for the linear regression coefficient of the random variable y_t, compared to its past values, and η_t is white noise.

The most common manner to identify a model is through its transfer function $W(z)$. Called $u(t)$ the function that describes the input values in terms of time and $y(t)$ the function that represents the output, knowing that any autoregressive and moving average model provides an output that is a linear combination of previous values of both the input and the output, $y(t)$ is obtained by (1):

$$y(t) + \alpha_1 y(t-1) + ... + \alpha_p y(t-p) = \beta_0 u(t) + 1 \\ + \beta_1 u(t-1) + ... + \beta_q u(t-q) \quad (1)$$

Applying the Discrete Fourier Transformation, (1) can be rewritten introducing lag operator z, which has the aim to delay or to anticipate a value:

$$\begin{aligned} y(t) &= \frac{\beta_0 + z^{-1}\beta_1 + ... + z^{-q}\beta_q}{1 + z^{-1}\alpha_1 + ... + z^{-p}\alpha_p} \cdot u(t) = \\ &= \frac{C(z)}{A(z)} \cdot u(t) = W(z) \cdot u(t) \end{aligned} \quad (2)$$

$W(z)$ is called transfer function and, in order to compute a reliable prediction, we assume it is already in the *canonical spectral factor* form, as required by the time series analysis theory.

Starting from (2), we can get the one-step ahead predictor transfer function[1]:

$$\hat{y}(t+1 \mid t) = \frac{z \cdot (C(z) - A(z))}{C(z)} \cdot y(t) \quad (3)$$

So, in order to estimate the future value of the series, we need to calculate the difference between the numerator $C(z)$ and the denominator $A(z)$ of the autoregressive model transfer function, multiply this with the lag operator z and then divided by $C(z)$.

Regarding multi-step ahead prediction, the r-step-ahead predictor transfer function $\hat{W}_r(z)$ is the result of the method of Polynomial Long Division between $C(z)$ and $A(z)$, applied r times (Cheng et al., 2006).

The prediction accuracy always depends on the value of an error indicator. In case of $ARMA(p,q)$ model, the Final Prediction Error (FPE) is used as a statistical measure of goodness-of-fit. The same indicator can be also used in case of an $AR(p)$ model, as any autoregressive model is equal to an *ARMA* model where $q = 0$. The Final Prediction Error (FPE) is given by:

$$FPE_n = \frac{(L + (p+1))}{(L - (p+1))} \cdot \sigma_p^2$$

where σ_p^2 is the variance of model residuals, L is the length of the time series, and p is the number of estimated parameters in the model. The variance of model residuals is calculated iteratively by:

$$\sigma_p^2 = \sigma_{p-1}^2 (1 - (\hat{\phi}_p \cdot p)^2)$$

in which $\hat{\phi_0}^2 = 0$ and $\sigma_0^2 = \frac{1}{L}\sum_{t=1}^{L}(Y_t - \overline{Y})^2$ is the variance of the time series.

Several candidate models can be calculated using different criteria, but only the one with the lowest FPE value is selected as the best-fit model.

[1]Due to the limited number of pages, in this paper we omitted the complete procedure to obtain the predictor. For more details, we suggest to read (Hamilton, 1994)

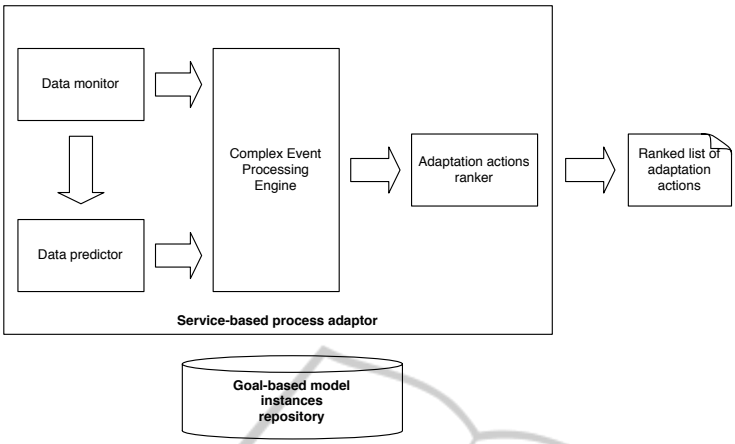


Figure 4: System architecture.

4 ARCHITECTURE

After having introduced the goal-based model and the data prediction in time series, as the cornerstones of our approach, the Figure 4 shows the architecture that combines them to support the service-based adaptation. Here, we assume that a monitoring infrastructure, composed by several probes, is properly deployed to gather information about the execution of the service-based process. As described in the following, the goal-based model instances repository contains information that is useful to understand all the modules composing our architecture. Indeed, it contains information regarding which are the constraints that must be satisfied (i.e., the goals) and the available adaptation actions (i.e., the treatments), along with information with which instrument the CEP engine to detect the violations (i.e., the events). Finally, the arrows reported in the figure reflects the data flow among the modules.

4.1 Data Monitor

Goal of the *Data Monitor* is to collect all the data made available by the probes and to compute the indicators used to define the goals to be fulfilled. For this reason, this module reads the goal-based model to obtain the list of the indicators that have to be calculated and the metrics to be used (see Table 1). In some cases, the computation directly reflects a monitored value (e.g., power consumption is equal to the value returned by a probe installed on a server). In some other cases, the computation is more complex and involve several probes (e.g., the MHz/Watt). Data collected by the *Data Monitor* are made available for the *CEP module* and the *Data Predictor*. In our testbed, a set of Nagios[2] plugins have been implemented to collect the required data.

Monitoring system usually has an impact on the overall performances. As a consequence, the setting of the monitoring frequency is a critical step. Having a high monitoring frequency means greater overhead and a lot of data to manage. On the contrary, low monitoring frequency means less impact on the performances but an higher probability to miss significant variations and also violations.

4.2 Data Predictor

For all the monitored indicators, the goal of this module is to identify the time series model and to predict future values starting from the data monitored up to a given time. The theoretical background of this module has been discussed in Section 3.2. Considering the monitoring frequency, the prediction can have a significant impact for the adaptation as it makes possible to anticipate the violation of several minutes. This module relies on GNU Octave Engine[3] and, in particular, on the following functions:

- *arburg* - it calculates the coefficients of an autoregressive (AR) model of complex data using the whitening lattice-filter method of Burg;
- *detrend* - it removes the trend from data, handles NaN's by assuming that these are missing values and unequally spaced data;
- *interp1* - it helps in replacing the outlier with values that do not alter the characteristics of the series, through the interpolation method.

[2]http://www.nagios.org/

[3]http://www.gnu.org/software/octave

In order to obtain an accurate prediction, the function initially performs a deep analysis of the series, calculating the mean and the variance first of all, just before moving to the elimination of outliers and possible trend components, cyclicity or seasonality. After that, the series is rendered with zero mean value, in order to decrease the prediction error. Now the series is ready for the calculation of the auto-covariance, a key element for the computation of the FPE, and then, finally, predictions for each model and possible criterion are estimated. At this point, among all the predictions calculated, the function will select the one that corresponds to the criterion passed as an input parameter and, at the same time, with the least value of FPE.

4.3 CEP Engine

Both the real monitored data and the predicted ones are inputs for the CEP engine[4], as the goal of this module is to monitor all the events related to changes in current, and also in future, values of the indicators. Each event is included in the initial goal-based model and might have positive or negative impact on the fulfillment of a given goal.

The adoption of a CEP engine is required as the information continuously flows from the *Data Monitor* and the *Data Predictor*. A query in a CEP, indeed, once it is issued it logically continuously runs over the incoming data, in contrast to traditional DBMS where the queries are run once over the current data set. Usually, queries for a CEP are based on Event Processing Language (EPL): an SQL-like language extended to handle event streams and patterns. Sample queries are reported in the following:

```
// Current Response time
SELECT * FROM RT(responseTime >5)

// Predicted CPU Usage
SELECT * FROM CPUUsagePrediction
(probability >60.0,CPUUsage <80) OR
CPUPrediction (probability >60.0,
CPUUsage >90)
```

Thus, the CEP has to verify if one of the events defined in the model is either occurring or, using the predicted data, will occur in the future. Since the occurrence of an event corresponds to a violation, the CEP will inform the *Adaptation actions ranker* about the critical situation to identify the most suitable adaptation strategy. Considering both the current and future data allows our system to support both reactive and pro-active adaptations.

[4]In our implementation we adopted Esper (http:// esper.codehaus.org/) as CEP engine

4.4 Adaptation Actions Ranker

Once a notification for a violation arrives, this module suggests to the user the best repairing action, among those implemented, to resolve the current or imminent violation. As a consequence, this module is also in charge of deciding if an adaptation should be enacted to solve the detected problem or not. Indeed, it depends on the severity of the violation and on the nature of the analyzed time series.

For time series with a significant stochastic component, any time-isolated violation is considered as an outlier, i.e., a value that is not logical to expect frequently. For this reason, only if several violations for a given indicator occur in a limited period of time, the module begins its adaptation selection procedure. In case of critical indicators, or time series with a limited stochastic component, the strategy selection will start as soon as the violation is detected.

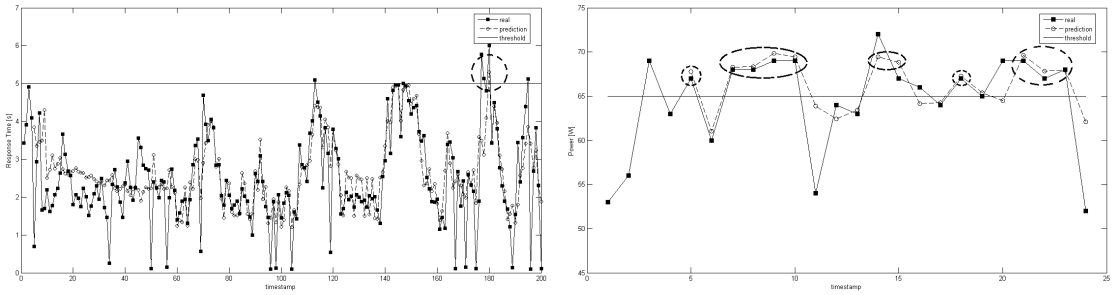
Starting from the goal-based model, the Adaptation actions ranker looks for the treatments that can have a positive impact on the goal under violation. As different degree of impact can be defined in the model, this module sorts the suggested actions according to a rating that is calculated by the difference between the number of positive and negative impacts a repairing action has on the system. These impacts are determined as relationships that each treatment has with the other elements of the goal-based model: the ones that introduce an alleviation of the effect an event has on the fulfillment of a goal is considered a positive impact, whilst the ones that promote a violation have negative impact.

The repairing actions suggested by the tool always have a score equal to zero if they do not modify the situation, or greater than zero if they improve the current condition of the system.

We assume that the final choice to activate or not a repairing action always depends on the user. Such a request for a human being interaction is intended to reduce false positives problem. According to the results of the simulations, false positives represent about 5% of a sample of 300 measurements. We believed that a human control, together with that of the machine, may further reduce this percentage.

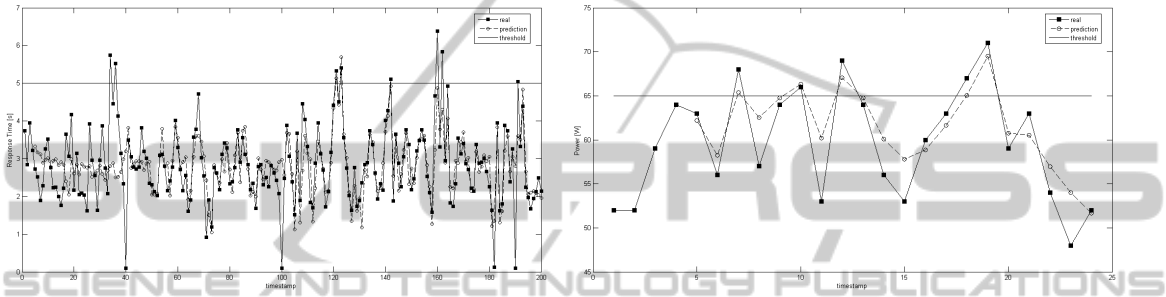
5 VALIDATION

With this validation we verify the ability of the system to detect a violation and to produce the list of available adaptation actions. This requires the correctness of the prediction offered by the *Data predictor* and the ability of the *CEP Engine* to capture the events of in-



(a) Response time (b) Process power consumption

Figure 5: Centralized deployment.



(a) Response time (b) Process power consumption

Figure 6: Distributed deployment.

terest. The adopted testbed is composed by 4 servers where Glassfish [5] is installed. The services composing the process introduced in Section 2 can run on any of these servers. A fifth server hosts the application that orchestrates the process: i.e., calling the services in the proper order (see Figure 1). A set of Nagios plugins are installed to be able to gather all the data that make possible the computation of the KPIs and GPIs, as defined in Table 1. In particular, we focused on: (i) the response time, as a typical KPI, calculated at the end of each invocation; and (ii) the process power consumption, representing GPIs class sampled every 180 sec.

As a first trial, we assume that the services composing the process are running only on *Server1* (i.e., *centralized deployment*). With such a configuration, the experiment lasts one hour, during which a new request to the process is sent every 1.0 sec in the average. Figure 5 shows the curves obtained for the response time and the process power consumption. The power consumption is computed summing the power consumption of all the five servers even if some of them are not used in that moment for the execution of the process. Indeed, we assume that these servers consume power as they remain in stand-by mode, ready to run applications. Given these curves, proving the correctness of a prediction means that we need to ensure that the distance between the predicted event at time $t-1$ and the real occurrence of the event at time t is minimum, in term of numerical value. Such a property is strongly linked to the goodness-of-fit of the model that describes the time series of the indicator. On these bases, we can notice how the prediction curves, after an initial set-up time, is able to follow the same trend of the actual ones. Especially in case of the power consumption this means that we are able to know the power consumption, in case of one-step prediction, three minutes before sensing the real value. This also means that we can anticipate the violation and having a proactive adaptation.

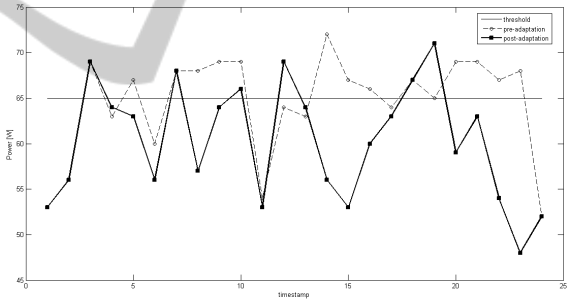


Figure 7: Process power saving.

Considering the process power consumption, the CEP module informs about the upcoming violation the *Adaptation actions ranker* every time the value is beyond the threshold (i.e., the horizontal line). As

[5] http://glassfish.java.net/

a consequence, after five to ten samples (i.e, fifteen to thirty minutes), the list of adaptation actions will be produced as the process power consumption systematically overcomes the limit value. This requires the goal-based model instance (see Figure 2), that is used by the *Adaptation actions ranker,* to realize that the violation of the constraint on this indicator can be solved in two ways: either redefining the deployment with a higher degree of distribution or reducing the CPU scaling frequency. These two actions compose the list that represents the result of our approach.

Figure 6 shows the effects of the process workload split among the various servers installed and running on the testbed. Despite a slight increase of the average response time, the benefits introduced with regard to the process power consumption are evident.

Figure 7 highlights the power saving that can be achieved applying one of the suggested adaptation strategies, such as a redistribution of the services composing the process among the servers. The dashed line represents the power consumption if no adaptation strategy was enabled after any detected violation; instead, the solid line depicts a situation in which an adaptation action was performed in order to solve the encountered problems and, at the same time, to reduce the energy consumption. An estimation of the value of such a power saving is around 0.085 kWh, equal to 6.75% of total energy consumption.

6 RELATED WORK

Focusing on the use of prediction in service-based systems, (Metzger et al., 2012) tries to work with online quality prediction. However, there are many challenging issues, as the limited control and visibility on the third-party services that call for concrete solutions. In our approach, instead, prediction is calculated based on KPIs and GPIs, that represent the quality of the system, both in terms of performance and for what concerns greenness. We defined these indicators and, with them, we are able to access every significant aspect of the system that we want to monitor. (Wetzstein et al., 2012) provides a detailed integrated monitoring, prediction and adaptation approach for preventing KPI violations of business process instances. Here, KPIs are used to map the process features and prediction is calculated starting from checkpoint, dislocated through the process itself, via a classification learning algorithm based on decision tree, called J48. This is the most closely related work to our approach. The differences stay in how to calculate the prediction and in the selection of the adaptation actions. We use an AR model to obtain a reliable prediction, while (Wetzstein et al., 2012) opts for decision trees, that means it needs a significant initialization step in order to built meaningful trees. Even the selection of the repairing action is computationally much more expensive of our: in (Wetzstein et al., 2012) there are no predefined actions, but only individual adaptation strategies that have to be combined to solve the ongoing or future violation. Instead, our tool relies on a goal-based model that contains all the possible actions that can solve the detected problem.

In (Zeng et al., 2008) the main concern is Quality of Service Management (QoSM), which is a new task in IT-enabled enterprises that supports monitoring, collecting and predicting QoS data. (Zeng et al., 2008) presents an event-driven QoS prediction system that contains a real-time metric and KPIs prediction mechanism. The differences with our work stand in the way of defining the KPIs and in the instruments they used to examine the events and to estimate the predictions. KPIs play a marginal role in (Zeng et al., 2008), as they are intended only as the result of the aggregation of some metrics, while they are on the basis of the whole architecture in this paper. We used Complex Event Processing and AR models to deal respectively with events and prediction; on the contrary, Event-Condiction-Action (ECA) rules and Exponential Smoothing are used by (Zeng et al., 2008) to process the events and to compute the predictions.

Artificial neural networks theory holds all the elements to be elected as the foremost prediction method. It resolves the problem of the identification of the model easily in respect of both ARMA structures and Box-Jenkins methodology. However, we preferred an autoregressive model because the accuracy of a neural network model may be seriously compromised when it is used recursively for multi-step prediction purposes. (Nguyen and Chan, 2004) and (Adya and Collopy, 1998) are both trying to investigate a hybrid methodology that combines artificial neural networks and ARMA models.

In the area of process monitoring and adaptation, using CEP techniques, several approaches have been proposed. CEVICHE (Hermosillo et al., 2010) is a framework that combines the strength of Complex Event Processing, a dynamic business process adaptation method via an AOP (Aspect-Oriented Programming) paradigm, which complements the more used object-oriented one, and an extension of the BPEL language for communication. It differs from our work just because is only able to activate a single adaptation action, that consists in skipping some optional services, and also it has only a reactive behavior. (Sen, 2008) discusses how the existing state-of-the-art BAM solutions, of which CEP is an essential compo-

nent, have not come up to the expectations of providing real-time information across business processes and supporting business users decision. Our work, on the contrary, is not limited to monitoring and visualization of events, but rather deals with analyzing and providing appropriate decision support for the users. (Leitner et al., 2010) proposes a framework, named PREvent, which is a system that integrates event-based monitoring via CEP, prediction of Service Level Agreement (SLA) violations, using machine learning techiniques, and automated runtime prevention of those violations by triggering adaptation actions. It differs from our work, first of all, in some aspects related to the prediction: in fact, it computes a prediction only when the esecution of the process reaches a checkpoint and the prediction targets are Service Level Objectives (SLOs), not indicators. Secondly, the predicted value is calculated by multilayer perceptrons, a variant of artificial neural network, while our approach relies on AR models.

7 CONCLUSIONS AND FUTURE WORK

This paper has introduced an approach for supporting the selection of adaptation actions in case of service-based processes to reduce the energy consumption. This approach combines the use of a conceptual model for defining the relationships between the system goals, in terms of KPIs and GPIs, and the adaptation actions, with a prediction system. The resulting architecture is able to support the reactive and proactive adaptation of a service-based process.

Future extensions of the proposed approach will involve the use of a n-step predictor to improve the proactiveness of the system. At the same time, to close the loop, an approach to automatically verifies the positive or negative effects of the selected adaptation actions is required.

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