Modeling of Parametric Dependencies for Performance Prediction of Component-based Software Systems at Run-time

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Abstract—Model-based performance analysis can be leveraged to explore performance properties of software systems. To capture the behavior of varying workload mixes, configurations, and deployments of a software system requires formal modeling of the impact of configuration parameters and user input on the system behavior. Such influences are represented as parametric dependencies in software performance models. Existing modeling approaches focus on modeling parametric dependencies at design-time. This paper identifies run-time specific parametric dependency features, which are not supported by existing work. Therefore, this paper proposes a novel modeling methodology for parametric dependencies and a corresponding graph-based resolution algorithm. This algorithm enables the solution of models containing component instance-level dependencies, variables with multiple descriptions in parallel, and correlations modeled as parametric dependencies. We integrate our work into the Descartes Modeling Language (DML), allowing for accurate and efficient modeling and analysis of parametric dependencies. These performance predictions are valuable for various purposes such as capacity planning, bottleneck analysis, configuration optimization and proactive auto-scaling.

Keywords—Architecture, Component-based systems, Performance modeling, Parametric dependencies, Run-time, Descartes modeling language

I. INTRODUCTION

Architectural performance models provide a powerful tool enabling performance prediction for modern component-based software systems. These performance predictions can be used for multiple purposes, such as capacity planning [1] and automated resource management [2]. Providing accurate performance predictions using architectural performance models requires the modeling of several system properties. Specifically, it requires the explicit modeling of dependencies between different model parameters, for example the resource demand of a service might depend on the value of its input parameters. Modeling such parametric dependencies expands the range of system settings that can be accurately modeled [3]. Formal modeling of parametric dependencies allows predicting the impact of changing workloads, system reconfigurations, and deployment changes using a single performance model.

At run-time, variables and dependencies can be learned and continuously updated based on available monitoring data [7]. However, parts of the system may be inaccessible to monitoring as instrumentation might negatively impact the overall system performance [8]. At design-time, many details on component interactions remain open, limiting concrete specifications of parametric dependencies to aspects independent of component instantiation. In contrast, a run-time environment can supply sufficient information (e.g., using monitoring) to identify dependencies for specific component instances.

Existing architectural performance modeling formalisms [5] [9] [10] [11] [12] apply design-time assumptions when modeling parametric dependencies. In particular, we identified the following major limitations: (i) Existing parameter dependency models only support the modeling of dependencies per component type, not between specific component instances. However, in a run-time scenario, where dependencies between specific component instances can be obtained from monitoring data, modeling them becomes necessary. (ii) No support for parameterization based on multiple parametric dependencies, which would allow for selecting alternative input parameters based on what is measurable. (iii) Existing solutions [5] [10] [11] cannot incorporate and benefit from correlations if they are not based on previously executed parameters from the call path, such as backwards correlations.

This paper contributes a novel approach to solve parametric dependencies in architectural performance models of component-based software systems. The dependency resolution algorithm transforms its information to a directed graph and resolves this graph to derive a fully parameterized model. Compared to existing work, our approach enables the resolution of the following features: (i) parametric dependencies on a component instance level, (ii) multiple independent dependencies describing one variable and (iii) modeling of correlations as parametric dependencies.

Applying the presented approach, software architects benefit from an improved ability to reflect system behavior within architectural performance models based on a higher flexibility of inputs. This results in more accurate performance predictions valuable for various purposes such as capacity planning [13], bottleneck analysis [14], configuration
optimization [15] and proactive auto-scaling [16].

We implement our methodology and integrate it into the Descartes Modeling Language (DML) [2] [17], an architectural performance model with the goal of enabling run-time resource management.

We evaluate the practical applicability of our approach, based on two case studies in the context of an online video store application. The first case study shows that the CPU resource demand of a component can be described using two independent parameters. The second case study investigates the performance prediction accuracy for different parameter configurations. We show that DML can accurately predict the video store’s performance when varying language mixes. Predictions of video store utilization feature a mean absolute percentage error of below 5%, whereas response times can be predicted with an error of below 10%.

II. MOTIVATING EXAMPLE

We illustrate general deficiencies for modeling of parametric dependencies based on a video store application and then derive the general problem statement.

A. Video Store Example

The challenges of modeling parametric dependencies in run-time scenarios can be easily highlighted using an online video store application, similar to YouTube, Netflix or Amazon Video. The video store in our example provides its videos with subtitles in different languages. The subtitles are automatically generated and translated. We introduce two use cases which underlie common requirements for modeling parametric dependencies at run-time. The first use case covers the automatic generation of new subtitles by transcribing the audio using machine learning and subsequent translation to different languages. In the second use case, the video store retrieves subtitles from a subtitle repository with a cache.

Use case 1: This use case is inspired by YouTube’s ‘auto-caps’ feature. To automatically generate subtitles for newly uploaded videos, a transcription service uses machine learning techniques to transcribe the video’s audio track. Resulting subtitles are then automatically translated by a translation service, as shown in Figure 1. The resource demand of the transcription service can be derived from the size of the file it transcribes. Another way to characterize this resource demand is to reverse engineer it using the resulting number of subtitle lines.

This use case motivates two novel modeling features: First, when designing a performance model it might not be known for which parameters monitoring data will be available at run-time. Therefore, both dependencies have to be modeled and the decision which of these two dependencies should be used to characterize the resource demand of the transcription service should be made at run-time. Secondly, this use-case motivates the modeling of correlations as parametric dependencies. Variables can be described by correlations instead of relying on cause and effect. In general, the output of a method may encapsulate information about its internal execution process. In concrete, the correlation between the number of lines and the transcription resource demand opens an additional valid way to derive the resource demand.

Use case 2: This use case is inspired by video-on-demand providers, such as Netflix or Amazon Video. When a user requests a video, the subtitle repository provides subtitles in the corresponding language, as shown in Figure 2. The subtitle repository implements a cache, which contains the frequently requested subtitles. The retrieval of subtitles from the cache causes a lower resource demand than retrieving subtitles from the database. The cache probability depends on both the popularity and language of the requested video, as subtitles in a frequent language for popular videos are more likely to be in the cache. This interaction can not be generalized for all subtitle repository instances. Other subtitle repository instances might be used in a different context, where the access frequency does not depend on the subtitle language or video popularity. An example for this would be a component creating backups, which iterates over all subtitles, independent of language or popularity. This showcases the need to model dependencies on an instance level in addition to component-level dependencies. At run-time, correlations between parameters can be learned from monitoring data for the deployed system. These correlations are only applicable for specific component instances, not for all instances of a component.
B. Problem Statement

Illustrated by the video store example, we identified the following general requirements to model parametric dependencies for component-based systems in run-time scenarios:

**Instance-level dependencies** Instance-level dependencies describe interrelations between component instances. Modeling these dependencies for component types, as supported by existing approaches, would apply the dependency to all instances of the component.

**Multiple descriptions** The description of parameters using multiple independent parametric dependencies provides alternatives for run-time model parametrization. A typical use case can be, for instance, the specification of component-level dependencies and instance-level dependencies for the same variable.

**Correlations as dependencies** At a runnable system state, monitoring data may reveal correlations between parameters. Modeling these correlations as dependencies can be used to derive characterizations in case parameters cannot be measured. Existing parameter models can only capture strictly causal correlations as dependencies, since they enforce that a parameter may only depend on prior parameters from the same call path [5, 10, 11].

Existing performance modeling approaches [5, 9, 10, 11, 12] cannot model the parametric dependencies that occur in our video store example. In the following, we propose a modeling and resolution approach that provides native support for the above described modeling features.

III. PARAMETRIC DEPENDENCY MODELING

We integrate our work for modeling and resolution of parametric dependencies into a representative architectural performance modeling formalism, the Descartes Modeling Language (DML) [2, 3, 17, 18, 19]. Therefore, we briefly introduce its relevant parts. The DML meta-model is made of five sub-models: repository, assembly, resource environment, deployment, and usage profile. The repository model defines blueprints for the software components that get assembled and connected in the assembly model. The deployment model describes how these components are distributed across the hardware resources defined in the resource environment model. The usage profile model contains the workload definition. For a detailed introduction to the DML meta-model we refer to [3].

The integration of novel modeling features requires the identification of the affected meta-model parts. The resource landscape and the deployment do not affect parametric dependencies. Only the application architecture meta-model contains information about parameters and dependencies between them. In the application architecture, components are modeled, instantiated, and connected to other components using interface providing and requiring roles. Every interface signature provided by a component has a corresponding behavior description. It may contain control flow descriptions such as loops, branches, and forks. Additionally, behavior descriptions contain resource demands and external calls to other components. The specification of parametric dependencies builds upon three main concepts: (i) variables, (ii) parameters, and (iii) relationships.

Variables depict a core concept for parametric dependency modeling. Figure 3 shows the variable and parameter types to which dependency descriptions may refer to. Every variable inherits from RelationshipVariable. Each RelationshipVariable can either be an InfluencableVariable or a CallParameter, which are both contained in a BehaviorAbstraction. An InfluencableVariable can be a ResourceDemand, a BranchProbability, a CallFrequency, or a LoopIterationCount. Any RelationshipVariable contains a value attribute of type RandomVariable describing its distribution. The value attribute can be NULL if its distribution is to be derived based on parametric dependencies. The Characterization of a RelationshipVariable indicates whether the variable value is explicitly modeled or should be characterized using monitoring data.

Calls to components can contain parameters which influence the behavior of the called component. The value returned by a call to another component can also influence the calling component’s behavior. Common examples include file sizes and list lengths. In DML, such parameters are modeled as...
CallParameters, which are depicted in Figure 4. CallParameters include ExtCallParameters, ExtCallReturnParameters, ServiceInput-Parameters, and ServiceOutputParameters. ServiceInputParameters and ServiceOutputParameters model a component’s input and output parameters. Therefore they reference a ProvidedRole, which describes the interface and signature the parameter belongs to. The counterparts to these parameters are the ExtCallParameters and the ExtCallReturnParameters, which specify the input and output parameters for a call to another component. If two component instances are connected via an assembly, the ExtCallParameter and the respective ServiceInputParameter share the same distribution; the same applies to ServiceOutputParameters and ExtCallReturnParameters.

In order to model dependencies both on repository level and on component instance level, DML provides two types of Relationships, as shown in Figure 5. A DependencyRelationship represents a dependency on the repository level and is therefore modeled as part of the component blueprint in the Repository. CorrelationRelationships on the other hand are used to model dependencies on a component instance level. Therefore it is modeled as part of the System and refers to two or more AssemblyContexts, which represent specific component instances. Both types of Relationships contain an equation which can be used to derive the value of the dependent RelationshipVariable from the one or more independent RelationshipVariables.

IV. PARAMETRIC DEPENDENCY RESOLUTION

The second major objective of our approach is to automatically derive performance indices from models using our novel and existing dependency modeling features. The automated prediction requires a resolution of the declarative parametric dependency description to enable model analyses. Besides functional requirements, we formulate the following design goals for the realization of our dependency resolution approach: (i) modularity in order to improve maintainability the resolution and (ii) independence of concrete stochastic model solvers.

To achieve modular design, we decompose the resolution into the multi-step dependency resolution process depicted in Figure 6. It consists of the following steps:

- **Step 1** Extraction of possible call paths through the system from the architectural model into a CallpathModel.
- **Step 2** Transformation of the model parameters and the dependencies between them into a directed graph, denoted as DependencyGraph.
- **Step 3** Resolution of parametric dependencies within the DependencyGraph using our dependency resolution algorithm to generate the ResolvedDependencyGraph.
- **Step 4** Combination of the information contained in the CallpathModel and the Resolved-DependencyGraph in order to generate a StackframeModel. The StackframeModel represents a solution-ready model that can be solved using existing simulators and analytical solvers using a transformation to their respective analysis format.

The resolution of parametric dependencies should not rely on a specific prediction formalism in order to be reused in transformations to different stochastic models and respective analytical or simulation-based solvers. Through the transformation to the StackframeModel, our dependency resolution is independent of specific stochastic model solvers. In addition, this enables the reuse of all existing DML solvers. The description of employed intermediate models allows for their reuse in the context of further architectural performance modeling formalisms.

In the following, we detail the employed intermediate meta-models and our dependency resolution algorithm.

A. Intermediate Meta-Models

The dependency resolution algorithm applies a set of intermediate graph meta-models. In this section, we describe the CallpathModel, the DependencyGraph, and the StackframeModel.

**Callpath Model** The CallpathModel, depicted in Figure 7, captures all paths a request may take through the system. It contains a set of CallpathPoints representing entry points to the system. Each CallpathPoint specifies the Location where its Behavior is executed. A location does not refer to a physical node in the system, but to an assembled software component that contains the executed behavior. For every Call in the Behavior of a CallpathPoint, a CallMapEntry references another CallpathPoint representing the Call’s target Behavior and the assembly component it is executed
in. Every possible path that leads to the execution of a Behavior can be described by a single CallpathPoint as it contains a reference to its predecessor. Additionally, the CallpathModel contains Dependencies, which connect two or more CallpathPoints. The Behavior description of CallpathPoints contains the independent and dependent parameters. The nature of the dependency is abstracted in a DependencyCharacterization. The meta-model only contains the connections between CallpathPoints. Component level dependencies do not have to be modeled in the CallpathModel since the location of its dependent and independent components is captured within the model.

**Dependency Graph** The DependencyGraph, depicted in Figure 8 contains information about the model parameters and the dependencies between them. Every Node in the Graph represents a Parameter and a call path to it, which is represented by a CallpathPoint. This means that one Parameter can be contained in multiple Nodes if it lies on multiple call paths, allowing a Parameter to have different values depending on the call path. If the distribution of the Parameter in this call path is known the value is saved in its Distribution, otherwise it is NULL. The Nodes are connected by directed Edges which model the dependencies between them. Every Edge connects one dependent Node to one or more independent Nodes. The Edge’s StochasticExpression describes how the distribution of the dependent Node can be calculated if the values of the independent Nodes are known.

**StackFrame Model** We reuse the StackframeModel presented in [2] as output for our dependency resolution algorithm. The StackframeModel represents a solution ready form of an architectural performance model. In the StackframeModel the sophisticated aspects of architectural performance models are resolved, simplifying the transformation to solution models such as QPNs or LQNs, as described in [2]. Figure 9 shows the meta-model of the StackframeModel. It consists of a series of StackFrames which describe a ServiceBehaviorAbstraction and a ComponentInstanceReference, which describe the assembly instance on which the behavior is executed. For every ExternalCall in the StackFrame’s behavior a Successor annotates which StackFrame is called by the ExternalCall. Similarly, a ValueMapEntry annotates every ModelVariable in the StackFrame’s behavior with a RandomVariable describing its distribution.

**B. Resolution Process**

This section details how our dependency resolution algorithm uses the intermediate meta-models to transform a model containing parametric dependencies to an analysis-ready model without dependencies. The approach consists of the following four steps:

**Step 1** The CallpathModel can be extracted from an architectural performance model by creating CallpathPoints for all possible entry points. Next, iterating over all newly created CallpathPoints, a CallMapEntry and a target CallpathPoint has to be created for every Call inside the CallpathPoint’s Behavior. This needs to be recursively repeated for all CallpathPoints created by this step, until every call path ends in a CallpathPoint who’s Behavior does not contain any Calls.

**Step 2** The CallpathModel can be transformed to the DependencyGraph by iterating over all CallpathPoints in the CallpathModel and executing the following tasks on them:

- Create a Node for every parameter in the CallpathPoint Behavior.
- Create an Edge for every component level dependency described in the CallpathPoint’s Behavior.
- Create an Edge for every pair of input and output parameter in the CallpathPoint’s Behavior and its predecessor’s Behavior.
- Create an Edge for every instance level dependency modeled in the CallpathModel who’s dependent is contained in the CallpathPoint’s Behavior.

This generates a complete DependencyGraph, which can be used to derive values for all unknown parameters in the following step.

**Step 3** The DependencyGraph contains Nodes with known distributions and Nodes with unknown distributions. If all independent Nodes of an Edge have distributions the distribution of the dependent Node can be derived. To determine a resolution order which resolves distributions for all Nodes we use the dependency solver algorithm shown in Algorithm [1]. It iterates over all Edges in the dependency graph and evaluates if every independent Node of the Edge is already characterized. Should this be the case
the algorithm computes the distribution of the dependent Node of the Edge. The algorithm repeats these steps until no changes occur in the dependency graph after iterating over the Edges. This resolves distributions for all Nodes and therefore for every occurrence of every parameter in the system.

Step 4 We transform the CallpathModel and the ResolvedDependencyGraph to a Stackframe-Model. The CallpathPoints and CallMap-Entries connecting them can be directly mapped to StackFrames and Successor. For every parameter in a CallpathPoint Behavior, its distribution can be found in the corresponding Node of the Resolved-DependencyGraph. We transform it to a ValueMap-Entry of the StackframeModel. The result of the whole process is a fully parameterized Stackframe-Model, which can be analyzed using a variety of analytical approaches and simulations [2].

V. Evaluation

The evaluation goal is to show the suitability of the proposed run-time dependency modeling features and the capability of our approach to model and solve these parametric dependencies correctly. We refine our evaluation goal using the following research questions, to be evaluated on the previously introduced use cases:

RQ 1 Can model variables be accurately described by correlations when causal parameters cannot be measured?

RQ 2 Can we provide multiple characterizations of a parametric resource demand based on alternative to parameters that enable accurate performance predictions?

RQ 3 Does modeling parametric dependencies on component instance level improve the prediction accuracy?

To evaluate the research questions, we implemented parts of the motivating video store required for analysis. All of our experiments run on an HPE ProLiant DL160 server. It features an Intel Xeon E5-2650 v3 processor with 10 cores at 2.4 GHz and 32 GB RAM. After dependency resolution, we solve the resulting StackFrame model reusing a transformation to QPN and subsequent simulation using SimQPN, a discrete event simulation tool for QPNs [20].

A. Case Study 1 - Video Transcription

1) Setting: To provide an implementation of the video transcription service, we integrate the established open source speech recognition software CMUsphinx [2] into a Java EE servlet application. The processing time of the transcription service depends on the properties of the respective video. The length of a video, as well as the number of subtitles (counted as number of lines), impact the processing overhead. While the number of subtitle lines can be monitored from the Java interface, the monitoring of the file size requires a more intrusive monitoring. For the evaluation we collected a training data set and an evaluation data set, each consisting of 25 videos with 10 to 30 seconds of English spoken content from YouTube. Based on these videos, we investigate the response times of the transcription service for a mixture of videos.

2) Modeling: [Figure 10] models the video transcription use case. The CPU resource demand of the TranscriptionService is modeled as a Resource-Demand variable. Two ServiceInputParameters specify the file size and the number of lines parameters. Further, we model a DependencyRelationship describing the relationship between the file size and the resource demand on component-level. To describe the relationship between the number of lines and the resource demand of the TranscriptionService, we select a Correlation-Relationship to model the instance-level dependency.

3) Dependency characterization: To characterize the parametric dependencies, we measure the video file size, the amount of the generated subtitles in number of lines,
and corresponding resource demands for the training data set. Then, we fit polynomial functions up to fourth order that describe the resource demand from the file size and the number of lines. Our investigations show that increasing polynomial degrees does not significantly improve the prediction. Therefore, we conclude a linear correlation and model both aspects using first order functions. The CPU resource demand description of the transcription service based on the file size in KB is:

\[
\text{ResourceDemand} = 43.2 \times \text{FileSize} - 1662.5
\]

Additionally, we model the resource demand based on the number of lines parameter as:

\[
\text{ResourceDemand} = 2253.5 \times \text{NumberOfLines} + 3894.2
\]

In this use case, modeling the correlation between the number of lines parameter and the transcription service resource demand allows to accurately estimate the resource demand. This provides an additional description of the resource demand, which can be used as a fallback in case the size of the video files cannot be monitored.

4) Experiment results: Table I shows the residual standard error, multiple R-squared metric and p-value for estimations of four polynomial orders with either the file size or the number of subtitle lines as input. The low p-value indicates a significant relationship between the input parameter and the response time, which justifies modeling it. The residual standard error of the number of lines estimation exceeds the error of file size estimation by about 10%. Similarly, the file size estimation captures the variance within the sample slightly better, as described by the multiple R-squared metric. While the file size estimation produces more accurate predictions, the estimation using the number of lines is sufficient in case the file size cannot be monitored. Our experiments show that the correlation between the resource demand and the number of lines parameter provides an accurate description of the resource demand (RQ 1). Moreover, we demonstrate that we can provide two accurate description of the same variable based on different input (RQ 2).

To demonstrate that each of the two descriptions allows for accurate performance predictions, we analyze the accuracy of response time predictions for each description. We configure an exponentially distributed request inter-arrival rate with an average delay of 60 s which corresponds to a CPU utilization around 45%. The requests randomly select a video from the evaluation data set. The measured average response time was 44207 ms. The model predicts an average response time of 4518 ms when using the file size estimation and 46252 ms for the number of lines estimation. This corresponds to an accuracy of 97.03% and 95.38% respectively. While using the file size estimation achieves a better accuracy, the accuracy of both predictions is sufficient for capacity planning [19].

B. Case Study 2 - Subtitle Provider

1) Setting: The second case study monitors the impact of different parametrizations on the system performance for the subtitle retrieval. At the retrieval, subtitles have to be queried from a database if not cached within the subtitle repository component. Subtitles in frequent languages and for popular videos are more likely to be in the cache. Consequently, the likelihood of a subtitle being in the cache is influenced by the requested language as well as the popularity of the video. We assume two workload mixes depicted in Table II denoted as USA and EU. We assume American traffic to be predominated by English and Hispanic customers, whereas the European traffic consists of a wide variety of languages. The popularity of videos follows a long tail distribution [21]. As shown in Table III, the store provides 10,000 videos from which the 200 most frequently accessed videos make up for over half of the traffic. The next 800 most frequently accessed videos cause 30% of the traffic. For each video, subtitles can be requested in the seven languages. While the cache allows to store 250 subtitles at a time, the number of subtitles sums up to a total of 70,000. Next, we evaluate how caching behavior affects performance indices when moving applications from one region to another.

2) Modeling: Figure 11 shows modeling of the subtitle provider use case. The behavior of cache hits and misses is modeled as a BranchAction with an unknown BranchingProbability. The branch denoting a cache-hit is connected to a lower resource demand.
a cache probability of zero, since no subtitle is requested twice. However, the dependency from Section V-B3 would derive a cache probability > 0. This shows that modeling some dependencies on component instance level instead of repository component level is necessary (RQ 3).

4) Experiment results: Modeling this case study without parametric dependencies corresponds to using the average monitored value for the branching probability. Analysis results presented in Table V show this to be highly inappropriate to capture the system behavior due to an average utilization prediction error of 13%.

When modeling the dependency between the language and popularity distribution and the branching probability of the subtitle repository, the DML model is capable of accurately predicting the utilization for all eight scenarios, with a relative error below 5%, as shown in Table V. The response time prediction error is below 10%, except for a high load of EU traffic. Here, the model-based prediction underestimates the response time by 28.86%. This outlier is still within a 30% margin considered to be acceptable for capacity planning [13]. By modeling the cache probability as a parametric dependency, our model can accurately predict the performance impact of different language distributions on the performance of the system.

VI. LIMITATIONS AND THREATS TO VALIDITY

While our approach presents an improvement compared to the state of the art, there still are limitations and threats to the validity to be discussed.

Algorithm 1 for the resolution of parametric dependencies always terminates, since each iteration reduces the number of nodes without characterization. In case no new node was characterized, the algorithm also terminates.

Whenever a parametric performance model contains cyclic dependencies, one of the dependencies making up the cycle can be ignored since it describes an already known variable. Assuming that all dependencies describe the variable with the same accuracy, no information is lost.

In case the parameter model contains insufficient information to derive distributions for all variables, our algo-
algorithm still resolves as many distributions as possible and then returns the partially resolved DependencyGraph. This partially resolved DependencyGraph contains the information which variables could not be resolved and measurement values for which parameters would allow to resolve the missing distributions.

The distributions of two variables can be derived from the same parameter or share a common ancestor in the DependencyGraph. Then the resulting model wrongly assumes that the distributions of the two variables are statistically independent. This problem is also inherent to existing approaches [23]. In contrast to existing work, our approach allows to automatically detect this by checking whether two variables share a common ancestor in the DependencyGraph. This allows to proactively inform the user that the parameterization might be inaccurate.

VII. RELATED WORK

Related work discusses modeling parametric dependencies as well as the identification and characterization of parametric dependencies.

A. Meta-Models

Existing surveys on component-based performance modeling [29, 30] neglect a detailed discussion on capabilities to model parametric dependencies. We categorize existing performance modeling approaches according to their parametric dependency modeling capabilities into four categories:

a) Modeling formalisms having no parameter model lack modeling features to model parameters or their impact on the performance of individual components. Such models cannot capture changing workload mixes and system configurations within a single model. Examples include stochastic formalisms, like QN, QPN, LQN and process models, as well as some architectural models [31, 32, 33].

b) Meta-models with a static parameter model, as presented in [24, 25, 26, 27], allow for the parametrization of component instances to model the influence of instance-specific parameters on component performance. However, these approaches require each component instance to be parameterized individually. They lack features to model the impact of deployment changes on component performance. Instance-specific parameters can be hardware parameters, such as processing rate or number of cores, or software parameters, such as operating system, hypervisor, or number of virtual cores [26]. Parameters can also be used to model different component configurations, as for example, two instances of a compression component with different compression rates. Resource demands and external call frequencies can be described as a linear combination of the static parameters [25].

c) Dynamic parameter models are supported e.g., by PCM [5], RESOLVE [9], HAMLET [10], ROBOCOP [11]. While these models suit for design time analysis, they encounter deficiencies at run-time. This class of models allows the modeling of input [11] and output parameters for components and external calls [5]. The resolution of parameter values propagates from caller to callee which makes parameter values dependent on the deployment context. Correlations that do not propagate from caller to callee cannot be modeled.

d) Persistent parameter models allow to model internal state for subsystems and components based on parameters [28]. These parameters may change during the model simulation impacting the component behavior. Modeling the internal state increases the prediction accuracy, but cannot accurately model the case studies presented in this paper. Table VI compares the capabilities of existing modeling approaches with regard to modeling of parametric dependencies. Summarizing, none of the related approaches provides means to model correlations as dependencies, instance-level dependencies, or multiple descriptions of the same variable.

B. Model Learning

Parametric dependencies can be identified and characterized based on expert knowledge but also automatically based on static code analysis, correlation analysis, or machine learning. Automation reduces the overhead and required expertise to benefit from parametric dependencies. The following approaches can be transferred to the novel modeling features proposed in this work. Krogmann et al. [6] propose to combines static code analysis, micro benchmarks and a genetic search to automatically identify and characterize parametric dependencies. If static code analysis is not feasible, [19] proposes a technique to automatically characterize known dependencies based on monitoring data. Identifying the parameters influencing a target variable, is an established research topic in the area of machine learning called feature selection. Chandrashekar et al. [34] present a comprehensive survey on the state-of-the-art for feature selection.

To minimize the modeling effort for large scale systems, we propose to combine these approaches with fully automated model extraction approaches [35, 36] that are capable to derive non-parametric models.

VIII. CONCLUSION

This work provides novel modeling features for parametric dependencies and a corresponding solution algorithm, which extends state-of-the-art modeling with runtime specific features. In particular, it enables parametric dependencies on component instance level, multiple descriptions of a single variable, and modeling of correlations as dependencies. Applying the presented approach, software architects benefit from an improved ability to reflect system behavior within architectural performance models based on a higher flexibility of inputs. This results in more accurate performance predictions valuable for various purposes such as capacity planing or proactive auto-scaling.
our methodology based on two case studies. The first case study shows that multiple dependencies based on different input parameters can be used to describe the same variable. The second case study models parametric dependencies on a component instance level to characterize and accurately predict system behavior. Across both case studies, the mean prediction error for utilization and response time is mostly below 5% and 10% respectively.

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