Designing Robust Software Systems through Parametric Markov Chain Synthesis

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Abstract—We present a method for the synthesis of software system designs that satisfy strict quality requirements, are Pareto-optimal with respect to a set of quality optimisation criteria, and are robust to variations in the system parameters. To this end, we model the design space of the system under development as a parametric continuous-time Markov chain ($\mu$CTMC) with discrete and continuous parameters that correspond to alternative system architectures and to the ranges of possible values for configuration parameters, respectively. Given this $\mu$CTMC and required tolerance levels for the configuration parameters, our method produces a sensitivity-aware Pareto-optimal set of designs, which allows the modeller to inspect the ranges of quality attributes induced by these tolerances, thus enabling the effective selection of robust designs. Through application to two systems from different domains, we demonstrate the ability of our method to synthesise robust designs with a wide spectrum of useful trade-offs between quality attributes and sensitivity.

Keywords—software performance and reliability engineering; probabilistic model synthesis; multi-objective optimisation

I. INTRODUCTION

Evaluating the performance, reliability and other quality attributes of alternative designs is essential for the cost-effective engineering of software [1], [2]. Delaying this evaluation until integration or system testing can greatly increase engineering costs, as defects identified late in the development lifecycle require much more effort to fix [3]. A common method to avoid this delay uses model-based simulation [4] or formal verification [5] to predict the quality attributes of alternative designs. Models that meet the quality requirements of the system under development are then used as a basis for its implementation. Models based on queueing networks [7], probabilistic models [2], [5] and timed automata [8] have been used for this purpose, together with tools for their simulation (e.g. Palladio [9]) and verification (e.g. PRISM [10]). Furthermore, recently proposed approaches automate the search for suitable designs. Probabilistic model repair [11], [12] automatically modifies the transition probabilities of Markov models that violate a quality requirement, generating new models that meet the requirement. Precise parameter synthesis [13] identifies transition rates that enable continuous Markov models to satisfy a quality requirement or to optimise a quality attribute of the modelled system. Finally, probabilistic model synthesis [14] starts from a design template that captures alternative system designs, and uses multiobjective optimisation to generate the Pareto-optimal set of Markov models associated with the quality requirements of the system.

However, these promising approaches unrealistically assume that the parameters of the real system (e.g. service rates) will accurately match the parameters of the repaired or synthesised model. This assumption limits the usefulness of existing model repair and synthesis solutions, as Markov models are typically nonlinear, so slight differences between the actual and assumed parameters can lead to major differences between the real and modelled quality attributes of software systems.

Our paper addresses this major limitation for probabilistic model synthesis. To this end, introduce a method for the synthesis of sensitivity-aware Pareto-optimal sets of probabilistic models (i.e., designs) associated with: (a) the quality requirements of a system; and (b) designer-specified tolerances (i.e. permissible levels of variation) in the system parameters. The designs synthesised by our method are continuous-time Markov chains with transition rates constrained to bounded intervals that reflect the required tolerances. Accordingly, the Pareto-front element corresponding to each design is a bounded region of quality attribute values for the system. This region is a close over-approximation of all values that the quality attributes can attain for the considered design.

The shape and size of the quality-attribute regions, along with the parameter tolerances, provide key information for sensitivity analysis of the associated Pareto-optimal designs, and thus, for measuring their robustness. In particular, large-tolerance designs associated with small quality-attribute regions are robust. Robust designs [15] are of great interest because they can withstand changes in the system parameters, do not expose system users to large variations in quality attributes, and can be built with high-variability components that are often cheaper to develop or purchase, and may require less effort to maintain, than low-variability components. Conversely, large quality-attribute regions from the Pareto front correspond to designs that are highly sensitive to parameter variations, and should typically be avoided.

The main contributions of our paper are threefold. First, we adapt the concept of tolerance from other branches of engineering and apply it to software architectures by defining the parametric Markov chain synthesis problem and the sensitivity-aware Pareto dominance relation. Second, we introduce an efficient method that combines probabilistic model synthesis and precise parameter synthesis to automate the generation of sensitivity-aware Pareto fronts for quality engineering. Finally, we present a tool that implements our method
for designing robust software systems, which we evaluate on two case studies: a replicated file system used by Google’s search engine, and a cluster availability management system. To the best of our knowledge, our work is the first to integrate design synthesis and sensitivity analysis into a single end-to-end method — existing research efforts have tackled the challenges associated with design synthesis (e.g. [14], [16]) and sensitivity analysis (e.g. [17]–[21]) in isolation.

The paper is organised as follows. Sections II and III introduce the background for our work and define the parametric Markov chain synthesis problem, respectively. We then present our robust design synthesis method and tool implementation in Section IV. Finally, we describe the two case studies in Section V, compare our method to related work in Section VI, and conclude the paper with a brief summary in Section VII.

II. PRELIMINARIES

Design space modelling. We use a parametric continuous-time Markov chain (pCTMC) to define the design space of the software under development. To this end, we extend the original pCTMC definition [22], where only real-valued parameters determining the transition rates of the Markov chain are considered, and assume that a pCTMC also includes discrete parameters affecting its state space. Our definition captures the need for both discrete parameters encoding architectural structural information (e.g. by selecting between alternative implementations of a software function) and continuous parameters encoding configurable aspects of the system (e.g. network latency or throughput). As such, a candidate system design corresponds to a fixed discrete parameter valuation and to continuous parameter values from a (small) region.

Definition 1 (pCTMC). Let $K$ be a finite set of real-valued parameters such that the domain of each parameter $k \in K$ is a closed interval $[k^-, k^+] \subset \mathbb{R}$, and $D$ a finite set of discrete parameters such that the domain of each parameter $d \in D$ is a set $T^d \subset \mathbb{R}$. Let also $\mathcal{P} = \times_{k \in K} [k^-, k^+]$ and $\mathcal{Q} = \times_{d \in D} T^d$ be the continuous and the discrete parameter spaces induced by $K$ and $D$, respectively. A pCTMC over $K$ and $D$ is a tuple
\[
\mathcal{C}(\mathcal{P}, \mathcal{Q}) = (\mathcal{D}_S, \mathcal{D}_{init}, \mathcal{D}_R, L),
\]
where, for any discrete parameter $q \in \mathcal{Q}$,
- $\mathcal{D}_S(q) = S$ is a finite set of states, and $\mathcal{D}_{init}(q) \in S$ is the initial state;
- $\mathcal{D}_R(q) : S \times S \to \mathbb{R}[K]$ is a parametric rate matrix, where $\mathbb{R}[K]$ denotes the set of polynomials over the reals with variables $k \in K$;
- $L(q) : S \to 2^{AP}$ is a labelling function mapping each state $s \in S$ to the set $L(q)(s) \subseteq AP$ of atomic propositions that hold true in $s$.

A pCTMC $\mathcal{C}(\mathcal{P}, \mathcal{Q})$ describes the uncountable set of continuous-time Markov chains (CTMCs) $\{\mathcal{C}(p, q) \mid p \in \mathcal{P} \land q \in \mathcal{Q}\}$, where each $\mathcal{C}(p, q) = (\mathcal{D}_S(q), \mathcal{D}_{init}(q), \mathcal{R}(p, q), L(q))$ is the instantiated CTMC with transition matrix $\mathcal{R}(p, q)$ obtained by replacing the real-valued parameters in $\mathcal{D}_R(q)$ with their valuation in $p$.

Definition 2 (Candidate design) A candidate design of the pCTMC $\mathcal{C}(\mathcal{P}, \mathcal{Q})$ from (1) is a pCTMC
\[
\mathcal{C}(\mathcal{P}', \{q\}) = (\mathcal{D}_S, \mathcal{D}_{init}', \mathcal{D}_R', L')
\]
where $\mathcal{P}' = \times_{k \in K} [k^-, k^+] \subseteq \mathcal{P}$, $q \in \mathcal{Q}$, $\mathcal{D}_S(q) = \mathcal{D}_S(q)$, $\mathcal{D}_R(q) = \mathcal{D}_R(q)$, $\mathcal{D}_{init}(q) = \mathcal{D}_{init}(q)$ and $L'(q) = L(q)$. The tolerance of the candidate design with respect to the real-valued parameter $k \in K$ is defined as
\[
\gamma_k = \frac{k^+ - k^-}{2k^+},
\]
and sensitivity analysis (e.g. [17]–[21]) in isolation. The tolerance of the candidate design with respect to the real-valued parameter $k \in K$ is defined as
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\]
and sensitivity analysis (e.g. [17]–[21]) in isolation. The tolerance of the candidate design with respect to the real-valued parameter $k \in K$ is defined as
\[
\gamma_k = \frac{k^+ - k^-}{2k^+},
\]
of a set of CSL path formulas \( \{ \phi_i \}_{i \in I} \), such that for any \( i \in I \) and \((p, q) \in P \times Q\),

\[
f_i^*(C(p, q)) = \Lambda_{\phi_i}(p, q);
\]

(4)

2) A finite set of boolean constraints \( \{ c_j \}_{j \in J} \) corresponding to the set of CSL path formulas \( \{ \psi_j \}_{j \in J} \) and thresholds \( \{ \sim_j r_j \}_{j \in J} \) such that for any \( j \in J \) and \((p, q) \in P \times Q\),

\[
c_j(C(p, q)) \Leftrightarrow \Lambda_{\psi_j}(p, q) \sim_j r_j.
\]

(5)

Without loss of generality, we will assume that all objective functions \( \{ f_i \}_{i \in I} \) should be minimised.

### III. SYNTHESIS OF PARAMETRIC MARKOV CHAINS

Consider a system with design space \( C(P, Q) \), quality requirements given by objective functions \( \{ f_i \}_{i \in I} \) and constraints \( \{ c_j \}_{j \in J} \) and designer-specified tolerances \( \{ \gamma_k \}_{k \in K} \) for the continuous parameters of the system. Also, let \( F \) be the set of feasible designs for the system (i.e., of candidate designs that meet the tolerances \( \{ \gamma_k \}_{k \in K} \) and satisfy the constraints \( \{ c_j \}_{j \in J} \)):

\[
F = \{ C(P', q) \mid P' = X_{k \in K} [k^{\text{low}}, k^{\text{opt}}] \subseteq P \land q \in Q \land \forall k \in K. k^{\text{opt}} - k^{\text{low}} = 2\gamma_k (k^{\text{opt}} - k^{\text{low}}) \land \forall j \in J. c_j(C(p, q)) \}
\]

(6)

The parametric Markov chain synthesis problem consists of finding the Pareto-optimal set \( PS \) of candidate designs (2) (i.e. pCTMCs) with tolerances \( \{ \gamma_k \}_{k \in K} \) that satisfy the constraints \( \{ c_j \}_{j \in J} \) and are non-dominated with respect to the objective functions \( \{ f_i \}_{i \in I} \):

\[
PS = \{ C(P', q) \in F \mid \nexists C(P''', q') \in F \land C(P'', q') \prec C(P', q) \},
\]

(7)

where the sensitivity-aware dominance relation ‘\( \prec \)’ between two candidate designs is defined below.

**Definition 3.** A sensitivity-aware Pareto dominance relation over a feasible design set \( F \) and a set of minimisation objective functions \( \{ f_i \}_{i \in I} \) is a relation \( \prec \subseteq F \times F \) such that for any feasible designs \( d, d' \in F \)

\[
d \prec d' \iff (\forall i \in I. f_i(d) \leq f_i(d')) \land (\exists i \in I. f_i(d) < f_i(d')) \lor (\forall i \in I. f_i(d) \leq f_i(d')) \land (\exists i \in I. f_i(d) < f_i(d')) \land \text{sens}(d) \leq \text{sens}(d')
\]

(8)

where the objective functions \( \{ f_i \}_{i \in I} \) are now intended over designs \( C(P', q) \in F \), and are calculated using one of alternative definitions from Table I; \( \epsilon_i \geq 0 \) are sensitivity-aware parameters; and the sensitivity of a feasible design \( C(P', q) \) is defined as the volume of its quality-attributed region over the volume of \( P' \):

\[
\text{sens}(C(P', q)) = \frac{\prod_{i \in I} (f_i^+(C(P', q)) - f_i^-(C(P', q)))}{\prod_{k \in K} 2\gamma_k (k^{\text{opt}} - k^{\text{low}})}.
\]

Before discussing the rationale for this definition, we show that the sensitivity-aware Pareto dominance relation is a strict order like classical Pareto dominance.

**Theorem 1.** The sensitivity-aware Pareto dominance relation is a strict order.

### TABLE I: Alternative definitions for objective functions \( \{ f_i \}_{i \in I} \) over candidate designs.

<table>
<thead>
<tr>
<th>Type</th>
<th>Notation</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>lower bound</td>
<td>( f_i^-(C(P', q)) )</td>
<td>( \inf_{p \in P', q} \Lambda_{\phi_i}(p, q) )</td>
</tr>
<tr>
<td>upper bound</td>
<td>( f_i^+(C(P', q)) )</td>
<td>( \sup_{p \in P', q} \Lambda_{\phi_i}(p, q) )</td>
</tr>
<tr>
<td>mid-range</td>
<td>( f_i^*(C(P', q)) )</td>
<td>( \left( f_i^-(C(P', q)) + f_i^+(C(P', q)) \right)/2 )</td>
</tr>
</tbody>
</table>

**Proof.** We need to show that relation \( \prec \) from (8) is irreflexive and transitive. For any \( d \in F \), \( d \prec d' \) would require that \( f_i(d) < (1 + \epsilon_i) f_i(d') \) \( \lor f_i(d) < f_i(d') \) for some \( i \in I \), which is impossible. Thus, \( \prec \) is irreflexive. To show that \( \prec \) is transitive, consider three designs \( d, d', d'' \in F \) such that \( d \prec d' \) and \( d' \prec d'' \). According to (8), we have \( \forall i \in I. f_i(d) \leq f_i(d') \) \( \land \forall i \in I. f_i(d') \leq f_i(d'') \), so \( \forall i \in I. f_i(d) \leq f_i(d'') \) due to the transitivity of \( \leq \). Furthermore, at least one half of the disjunction from definition (8) must hold for each of \( d' \prec d'' \) and \( d'' \prec d' \). We have three cases. Assume first that the left half holds for \( d \prec d' \), i.e. \( (1 + \epsilon_i) f_i(d) < f_i(d') \) for some \( i_1 \in I \); as \( f_i(d') \leq f_i(d'') \), we also have \( (1 + \epsilon_i) f_i(d) < f_i(d'') \), so \( d \prec d'' \) in this case. Assume now that left half of disjunction (8) holds for \( d' \prec d'' \), i.e., \( (1 + \epsilon_i) f_i(d') < f_i(d'') \) for some \( i_1 \in I \); as \( f_i(d') \leq f_i(d'') \), we again have \( (1 + \epsilon_i) f_i(d) < f_i(d'') \) and \( d \prec d'' \). Finally, consider that only the right half of disjunction (8) holds for both \( d \prec d' \) and \( d' \prec d'' \). In this last case, \( \text{sens}(d) \leq \text{sens}(d') \leq \text{sens}(d'') \) and there is an \( i_1 \in I \) such that \( f_i(d) < f_i(d') \leq f_i(d'') \), so also \( d \prec d'' \), and therefore \( \prec \) is transitive.

The classical Pareto dominance definition can be obtained by setting \( \epsilon_i = 0 \) for all \( i \in I \) in definition (8). When \( \epsilon_i > 0 \) for some \( i \in I \), dominance with respect to quality attribute \( i \) holds in our generalised definition in two scenarios:

1) when the quality attribute has a much lower value for the dominating design, i.e. \( (1 + \epsilon_i) f_i(d) < f_i(d') \);
2) when in addition to a (slightly) lower quality attribute value, i.e. \( f_i(d) < f_i(d') \), the sensitivity of the dominating design is no worse than that of the dominated design, i.e. \( \text{sens}(d) \leq \text{sens}(d') \).

These scenarios are better aligned with the needs of designers than those obtained by using sensitivity as an additional optimisation criterion, which induces Pareto fronts comprising many designs with low sensitivity but unsuitably poor quality attributes. Similarly, each objective function definition from Table I captures specific needs of real-world systems. Thus, using the “upper bound” definition \( f_i^+ \) in (8) supports the synthesis of conservative designs by comparing competing designs based on the worst-case values of their quality attributes. This is suitable when the worst-case performance, reliability, etc. must be specified for a system, e.g. in its service-level agreement. In contrast, the “lower bound” definition from Table I \( f_i^- \) can be used when design selection must be based on the best expected quality values of a system. Finally, the “mid-range” definition \( f_i^* \) may be useful—in conjunction with the actual sensitivity (9)—to compare and select designs based on their reference midpoint quality values.
Importantly, for $\epsilon_i > 0$ our generalised definition induces Pareto fronts comprising designs with non-optimal (in the classical sense) objective function values, but with low sensitivity. We call such designs sub-optimal robust. Thus, $\epsilon_i$ can be finely tuned to sacrifice objective function optimality (slightly) for better robustness. This is illustrated in Fig. 1 for the quality-attribute regions induced by two potential pCTMC designs $d_1$, $d_2$ (which we assume associated with identical parameter tolerances and thus, same parameter space volume $V$) and two minimisation objectives $f_1$, $f_2$. In this scenario, using $f_i = f_i^\top$ in (8), we have $d_1 \prec d_2$ when $\epsilon_1 = \epsilon_2 = 0$ (classical dominance) because $f_1^\top(d_1) = 8 < 8.5 = f_1^\top(d_2)$ and $f_2^\top(d_1) = 4 < 4.2 = f_2^\top(d_2)$, but $d_1 \not\prec d_2$ when $\epsilon_1 = 0.1$ (so $d_1$ is retained in the sensitivity-aware Pareto-optimal set) because $1.1 \cdot f_1^\top(d_1) \not\leq f_1^\top(d_2)$, $1.1 \cdot f_2^\top(d_1) \not< f_2^\top(d_2)$ and $\text{sens}(d_1) \not\leq \text{sens}(d_2)$ because $\text{sens}(d_1) = ((8 - 1) \cdot (4 - 1))/V$ and $\text{sens}(d_2) = ((8.5 - 5) \cdot (4.2 - 2))/V$.

### IV. PARAMETRIC CTMC SYNTHESIS METHOD

Computing the Pareto-optimal design set (7) is typically unfeasible, as the design space $C(P, Q)$ is infinite due to its real-valued parameters. Also, every candidate design $C(P', q)$ consists of an infinite set of CTMCs that cannot all be analysed to establish its quality and sensitivity. To address these challenges, our pCTMC synthesis method combines search-based software engineering (SBSE) techniques [24] with techniques for effective pCTMCs analysis [13], [25], producing a close approximation of the Pareto-optimal design set.

Algorithm 1 presents the high-level steps of our pCTMC synthesis method. The approximate Pareto-optimal design set $\overline{PS}$ returned by this algorithm starts empty (line 2) and is assembled iteratively by the while loop in lines 3–12 until a termination criterion TERMINATE($C(P, Q), \overline{PS}$) is satisfied. Each iteration of this while loop uses an SBSE metaheuristic to get a new set of candidate designs (line 4) and then updates the approximate Pareto-optimal design set $\overline{PS}$ in the for loop from lines 5–12. This update involves analysing each candidate design $d = C(P', q)$, to establish its associated objective function and constraint values in line 6, where we use the shorthand notation $f_i^\top(d) \equiv f_i^\top(C(P', q))$, $f_i^\top(d) \equiv f_i^\top(C(P', q))$ and $c_{i,d} \equiv \forall p \in P', c_j(C(p, q))$ for all $i \in I, j \in J$. If the design satisfies all constraints (line 7), the for loop in lines 9-11 finds out if the new design $d$ is dominated by, or dominates, any designs already in $\overline{PS}$. Existing designs dominated by $d$ are removed from $\overline{PS}$ (line 11), and $d$ is added to the Pareto-optimal design set if it is not dominated by any existing designs (line 12).

The elements below must be concretised in the synthesis algorithm, and are described in the next two sections:

1. The ANALYSEDESIGN function for establishing the quality attributes and constraint compliance of a candidate design;
2. The CANDIDATES DESIGNS SBSE metaheuristic and the associated TERMINATE criterion.

#### A. Computing Safe Property Bounds for pCTMCs

To establish the quality attributes and sensitivity of candidate designs, ANALYSEDESIGN uses precise parameter synthesis techniques [13] to compute safe enclosures of the satisfaction probability of CSL formulae over pCTMCs. Given a pCTMC $C(P', q)$ and a CSL path formula $\phi$, these techniques provide a safe under-approximation $\Lambda^\phi_{\text{min}}$ and a safe over-approximation $\Lambda^\phi_{\text{max}}$ of the minimal and maximal probability that $C(P', q)$ satisfies $\phi$:

$$\Lambda^q_{\text{min}} \leq \inf_{p \in P', \phi(p, q)} \Lambda^\phi_{\text{min}} \quad \text{and} \quad \Lambda^q_{\text{max}} \geq \sup_{p \in P'} \Lambda^\phi_{\text{max}}$$

This allows us to safely approximate the bounds $\{f_i^\top, f_i^\top\}_{i \in I}$ of the objective functions, and the constraints $\{c_j\}_{j \in J}$. As shown in [13], the over-approximation quality improves as the size of $P'$ decreases, and thus can be effectively controlled.

The satisfaction function $\Lambda^\phi_{\text{max}}$ is typically non-monotonic (and, for nested properties, non-continuous), so safe bounds cannot be obtained by simply evaluating $\Lambda^\phi_{\text{max}}$ at the extrema of parameter region $P'$. Accordingly, our technique builds on a parametric backward transient analysis that computes safe bounds for the parametric transient probabilities in the discrete-time process derived from the pCTMC. This discretisation is obtained through standard uniformisation, and through using the Fox and Glynn algorithm [23] to derive the required number of discrete steps for a given time bound. Once the parametric discrete-time process is obtained, the computation of the bounds reduces to a local minimisation/maximisation of state probabilities in a time non-homogenous Markov process. Presenting the technique in detail is outside the scope of our paper, but the interested reader can find a complete description in [13].

Our approach can be easily extended to also support time-unbounded properties by using the method of [26] for parameter synthesis of discrete-time Markov models and properties expressed by time-unbounded formulae of probabilistic computation tree logic.
B. Metaheuristic for Parametric CTMC Synthesis

To ensure that CANDIDATEDESIGNS selects suitable candidate designs, Algorithm 1 is implemented as an established multiobjective optimisation genetic algorithm (MOGA) such as NSGA-II [27] or MOCell [28]. MOGAs are genetic algorithms specifically tailored for the synthesis of close Pareto-optimal set approximations that are spread uniformly across the search space. As with any genetic algorithm [29], possible solutions—candidate designs in our case—are encoded as tuples of genes, i.e. values for the problem variables. In particular, any candidate design \( \mathcal{C}(P', q) \) that satisfies a fixed set of tolerances \( \{\gamma_k\}_{k \in K} \) is uniquely encoded by the gene tuple \( (p, q) \), where \( p \in P \) is the centre point of the continuous parameter region \( P' \).

Given this encoding of candidate designs, the first execution of CANDIDATEDESIGNS from Algorithm 1 returns a randomly generated population (i.e. set) of feasible designs (6). This population is then iteratively evolved by subsequent CANDIDATEDESIGNS executions into populations of "fitter" designs through MOGA selection, crossover and mutation. Selection chooses the population for the next iteration and a mating pool of designs for the current iteration by using the objective functions \( \{f_i\}_{i \in I} \), the sensitivity-aware dominance relation (8) and the distance in the parameter space \( P \) between designs to evaluate each design. Crossover randomly selects two designs from the mating pool, and generates a new design by combining their genes, and mutation yields a new design by randomly modifying some of the genes of a design from the pool. The evolution of the design population terminates (i.e. predicate TERMINATE(\( \mathcal{C}(P, Q), \overrightarrow{P_S} \)) returns true) after a fixed number of design evaluations or when a predetermined number of successive iterations generate populations with no significantly fitter designs. The implementation of the selection, crossover and mutation operations is specific to each MOGA. Due to space constraints, we do not provide these details, which are available in [27] for the NSGA-II MOGA used in our experimental evaluation from Section V.

Complexity. The time complexity of the synthesis process is \( O(k \cdot N \cdot (|I| + |J|) \cdot t + k \cdot |I| \cdot N^2) \), where \( k \) is the number of iterations of the (MOGA) while loop in Algorithm 1; \( N = |CD| \) is the size of the candidate design population; \( |I| + |J| \) is the overall number of objective functions and constraints; and \( t \) is the time required to analyse a quality attribute of a candidate design. The term \( k \cdot N \cdot (|I| + |J|) \cdot t \) quantifies the complexity of evaluating candidate designs, while \( k \cdot |I| \cdot N^2 \) corresponds to comparing designs and building the front in lines 7–12 of Algorithm 1. Increasing the total number of design evaluations (i.e., \( k \cdot N \)) typically improves the Pareto optimality of the resulting design set, but also slows down the synthesis process.

The factor \( t \) depends on the size of the underlying state space and on the number of discrete-time steps required to evaluate the particular quality attributes. As shown in [13], \( t = O(t_{CSL} \cdot t_{pCSL}) \). The factor \( t_{CSL} = \phi|D| \cdot q \cdot t_{max} \) is the worst-case time complexity of time-bounded CSL model checking [23], where \( |\phi| \) is the length of the input CSL formula \( \phi \), \( t_{max} \) is the highest time bound occurring in it, \( M \) is the number of non-zero elements in the rate matrix and \( q \) is the highest rate in the matrix. The factor \( t_{pCSL} \) is due to the parametric analysis of the design and depends on the form of polynomials appearing in the parametric rate matrix \( D_R \). Models of software systems typically include only linear polynomials, for which \( t_{pCSL} = \mathcal{O}(n) \), where \( n \) is the number of continuous parameters.

C. Implementation

We developed a Java software tool that implements the pCTMC synthesis method from Algorithm 1. For its ANALYSEDESIGN function, we used PRISM-PSY [25], a verification engine that supports precise parameter synthesis by efficient parametric backward transient analysis. We realised the functionality of CANDIDATEDESIGNS using the jMetal [30] Java framework for multi-objective optimisation with metaheuristics. Our Robust DEsign Synthesis (RODES) tool operates with pCTMCs expressed in the high-level modelling language of PRISM [10] extended with the following constructs (adopted from [14]) for specifying the parameters \( k \in K \) and \( d \in D \) from Definition 1:

\[
\text{evolve double } k [\min..\max] \\
\text{evolve int } d [\min..\max] \\
\text{evolve module ComponentName}
\]

\( N > 1 \) instances of the last construct (with the same component name) define \( N \) alternative architectures for a component, introducing the index (between 1 and \( N \)) of the selected architecture as an implicit discrete parameter. The open-source code of RODES, supplementary material on the case studies and the full experimental results are available on our project website at http://www-users.cs.york.ac.uk/~simos/RODES.

V. CASE STUDIES

We evaluated our design synthesis method in two case studies from different domains, using the RODES tool with the following NSGA-II configuration: 10000 evaluations, initial population 20 individuals, and default values for single-point crossover probability \( p_c = 0.9 \) and single-point mutation probability \( p_m = 1/(|K| + |D|) \), with \( |K| + |D| \) the number of (continuous and discrete) design-space parameters.

Google File System (GFS). Our first case study considers the design of GFS, the replicated file system used by Google’s search engine [31]. GFS partitions files into chunks of equal size, and stores copies of each chunk on multiple chunk servers. A master server monitors the locations of these copies and the chunk servers, replicating the chunks as needed. During normal operation, GFS stores CMAX copies of each chunk. However, as servers fail and are repaired, the number \( c \) of copies for a chunk may vary from 0 to CMAX.

Previous work modelled GFS as a CTMC with fixed parameters and focused on the analysis of its ability to recover from disturbances (e.g. \( c < \text{CMAX} \)) or disasters (e.g. master server down) [32]. In our work, we adapt the CTMC of the lifecycle of a GFS chunk from [32] by considering several continuous and discrete parameters that a designer of the
holds in states where service level 1 (master up and at least one chunk copy available) is provided; 

\[ f_2: \phi_2 = C \leq 60 \]

where a reward of 1 is assigned to the states with a number of running chunk servers of at least 0.5M (i.e. half of the total number of chunk servers);

\[ c_1: \psi_1 = C \leq 60 \]

with threshold \( \sim 1 \) \( r_1 \equiv i \leq 5 \), where a transition reward of 1 is assigned to each chunk replication transition.

Objective \( f_1 \) maximises the probability that the system recovers service level 1 in the time interval \([10, 60]\) hours. Objective \( f_2 \) maximises the expected time the system stays in (optimal) states with at least 0.5M chunk servers up in the first 60 hours of operation. Finally, constraint \( c_1 \) restricts the number of expected chunk replications over 60 hours of operations.

Given these objective functions and constraint, and the GFS pCTMC, we used our RODES tool from Section IV-C to generate Pareto-optimal design sets for the GFS system, with tolerances \( \gamma \in \{0.01, 0.02, 0.05\} \) for both continuous parameters (\( c\text{HardFail} \) and \( c\text{HardRepair} \)) of our pCTMC. Fig. 3 shows the Pareto fronts obtained using the “lower bound” definition from Table I for the objective functions \( f_1 \) and \( f_2 \) over candidate designs, and parameters \( c_1 = c_2 = c \in \{0, 0.05, 0.1\} \) for the sensitivity-aware Pareto dominance relation (8). These Pareto fronts provide a wealth of information supporting the evaluation of the optimality and robustness of alternative GFS designs. In particular, the Pareto front for \( \epsilon = 0 \) and \( \gamma = 0.01 \) contains several large (red) boxes that correspond to highly sensitive designs. For \( \epsilon \in \{0.05, 0.1\} \) and \( \gamma = 0.01 \), these poor designs are “replaced” by robust designs – surrounded by (red) borders – with very similar quality attributes but slightly suboptimal. The same pattern occurs for \( \gamma = 0.02 \) and to a lesser extent because the sensitivity (9) decreases when the tolerance grows) for \( \gamma = 0.05 \). This ability to identify poor (i.e. highly sensitive) designs and then alternative robust designs with similar quality attributes is a key and unique benefit of our design synthesis method.

We also observe that favouring objective \( f_1 \) over \( f_2 \) generally yields more robust designs (i.e., smaller quality-attribute regions towards the right end of the Pareto fronts) for all combinations of \( \epsilon \) and \( \gamma \). For fixed \( \epsilon \), increasing the parameter tolerance \( \gamma \) leads, as expected, to larger (more uncertain) quality-attribute regions and, typically, to an improved robustness (as explained above).

The corresponding synthesised sensitivity-aware Pareto-optimal designs provide key insights into the GFS dynamics, as shown in Fig. 4 for several \( \epsilon, \gamma \) combinations and fully on our project website. While for \( \epsilon = 0 \) we obtain only optimal solutions when parameters \( c\text{HardFail} \) and \( c\text{HardRepair} \) assume their extreme values, adding sensitivity leads to additional designs that are close to the optimum and at the same time are significantly more robust. These designs appear along an “ideal diagonal” in the horizontal plane suggesting the presence of an optimal ratio between \( c\text{HardFail} \) and \( c\text{HardRepair} \): designs outside this diagonal yield excessively fast or slow recovery times, and thus are far from the optimal \( f_1 \) values. Further,
our method reveals that the maximum number of chunks per server, NC, has a major influence on the design robustness, with high NC values leading to highly sensitive designs. These designs should be avoided in favour of the alternative designs with low NC values depicted in Fig. 4 (for $\epsilon > 0$).

We analysed the goodness of the Pareto-optimal designs obtained with our NSGA-II-based RODES against a tool variant that uses random search (RS). For each tool variant and combination of $\epsilon \in \{0.005, 0.10\}$ and $\gamma \in \{0.01, 0.02\}$ we carried out 30 independent runs, in line with standard SBSE practice [33]. As building the actual Pareto front for large design spaces is unfeasible, we again followed the standard practice and combined the sensitivity-aware Pareto fronts from all 60 RODES and RS runs for each $\epsilon, \gamma$ combination into a reference Pareto front. We then compared the Pareto fronts achieved by each variant against this reference front by using the metrics $M_1 = wI_e, norm + (1 - w)\text{wI}GD_{norm}$ and $M_2 = wI_e, norm + (1 - w)\text{wI}GD_{norm}$, which use a weight $w \in [0, 1]$ to combine normalised versions of the established (but sensitivity-agnostic) Pareto-front quality metrics $I_e$ and $I_{GD}$ [33] with the normalised design sensitivity. Fig. 5 compares RODES and RS across our $\epsilon, \gamma$ combinations using metrics $M_1$ and $M_2$ with $w = 0.5$. The RODES median is consistently lower than that of RS for all $\epsilon, \gamma$ combinations with the exception of $\epsilon = 0, \gamma = 0.01$ (which ignores design sensitivity) for $M_2$. For a given $\gamma$, RODES results improve

\begin{itemize}
  \item $\epsilon = 0$
  \item $\gamma = 0.01$
  \item $\epsilon = 0.1$
  \item $\gamma = 0.01$
  \item $\epsilon = 0$
  \item $\gamma = 0.05$
  \item $\epsilon = 0.1$
  \item $\gamma = 0.05$
\end{itemize}

Fig. 3: Sensitivity-aware Pareto fronts for the GFS model over objectives $f_1$ (x-axis) and $f_2$ (y-axis). Boxes represent quality-attribute regions, coloured by sensitivity (red: sensitive, blue: robust). Red-bordered boxes and arrows indicate the sub-optimal robust designs. For each front, we report mean sensitivity ($\mu$) and mean volume ($\nu$).

Fig. 4: Synthesised Pareto-optimal designs for the GFS model and experiments from Fig. 3. Rectangles in x-y plane correspond to the continuous parameter regions ($cHWF$: hardware failure rate; $cHWR$: hardware repair rate) induced by the tolerance $\gamma$. The box heights show the value of the discrete parameter NC. Boxes are coloured by sensitivity.

The unary additive epsilon ($I_e$) gives the minimum additive term by which the objectives of a particular design from a Pareto front must be altered to dominate the respective objectives from the reference front. The inverted generational distance ($I_{GD}$) measures the shortest Euclidean distance from each design in the Pareto front to the closest design in the reference front. The indicators measure convergence to the reference front and design diversity.
Fig. 5: RODES vs. random search (RS) comparison for combinations of $\gamma \in \{0.01, 0.02\}$ and $\epsilon \in \{0, 0.05, 0.1\}$, over 30 independent GFS runs. For both metrics — $I_e$ indicator and sensitivity (left) and $I_{IGD}$ indicator and sensitivity (right) — smaller is better.

as $\epsilon$ increases, unlike the corresponding RS results. Thus, the difference between RODES and RS increases with larger $\epsilon$ for both metrics. This shows that RODES drives the search using sensitivity (9), and thus it can identify more robust designs. We confirmed these visual inspection findings using the non-parametric Mann-Whitney test with 95% confidence level ($\alpha = 0.05$). We obtained statistical significance ($p$-value $< 0.05$) for all $\epsilon, \gamma$ combinations except for $\epsilon = 0, \gamma = 0.01$, with $p$-value in the range $[1.71E-06, 0.0026]$ and $[1.086E-10, 0.00061]$ for $M_1$ and $M_2$, respectively.

Workstation Cluster (WC) For this case study we extend the CTMC of a cluster availability management system from [34]. This CTMC models a system comprising two sub-clusters, each with $N$ workstations and a switch that connects the workstations to a central backbone. For each component, we consider failure, inspection and repair rates (where repairs are initiated only after an inspection detects failures), and we assume that designers must decide these rates for workstations—i.e., the real-valued parameters $wsFail$, $wsFail$ and $wsRepair$ for our $p$CTMC, respectively. Additionally, we assume that designers must select the sub-cluster size $N$, and must choose between an expensive repair implementation (i.e., $p$CTMC module) with a 100% success probability and a cheaper repair module with 50% success probability—i.e., two discrete parameters for the $p$CTMC. This model is illustrated on our project website. For an initial system state with 5 workstations active in each sub-cluster and switches and backbone working, we formulate a $p$CTMC synthesis problem for quality requirements given by two maximising objective functions and one constraint:

\[ f_1: \phi_1 = \neg\text{premium } U[20, 100] \text{ premium where premium denotes a system service where at least } 1.25N \text{ workstations are connected and operating}; \]
\[ f_2: \phi_2 = C^\leq 100 \text{ where a reward of 1 is assigned to states with a number of operating clusters between } 1.2N \text{ and } 1.6N; \]
\[ c_1: \psi_1 = C^\leq 100 \text{ with threshold } \sim_1 r_1 \equiv ' \leq 80', \text{ where transition rewards are associated with repair actions of the workstations, switches and backbone.} \]

Objective $f_1$ maximises the probability that the system recovers the premium service in the time interval $[20, 100]$ hours, $f_2$ maximises the expected time the system spends in cost-optimal states during the first 100 hours of operation, and constraint $c_1$ restricts the cost of repair actions during this time (the definition of the cost is provided on our project website).

Due to space constraints, we include only the Pareto fronts obtained for a tolerance level $\gamma = 0.01$ for all real-valued system parameters, and for a sensitivity-awareness parameter $\epsilon \in \{0, 0.05, 0.1\}$ for both objective functions (Fig. 6, top). These Pareto fronts show again how increasing $\epsilon$ yields significant gains in design robustness, with mean sensitivity values for $\epsilon = 0.05$ and $\epsilon = 0.1$ that are 51% and 59% smaller than the mean sensitivity for $\epsilon = 0$, respectively. Visual inspection confirms that the large quality-attribute regions (corresponding to high-sensitivity designs) obtained for $\epsilon = 0$ are “replaced” by much smaller quality-attribute regions on the Pareto fronts obtained for both $\epsilon > 0$ values.

With respect to the system dynamics, our sensitivity-aware synthesis reveals that the most robust solutions correspond to the objective-function “extrema” from the Pareto front, i.e., to quality-attribute regions in which either $f_1$ is very high and $f_2$ is very low, or vice versa. We further observe and validate (Fig. 6, bottom and Table II) that the values of the parameter $N$ for the synthesised robust designs are 10 or 15. This shows an unexpected and interesting relationship between the size of the cluster and robustness, impossible to derive through existing analysis methods.

Performance. As the design synthesis is computationally demanding, the current RODES version analyses multiple candidate models in parallel using multi-core architectures. In this way, we are able to partially alleviate the burden related to the high number of evaluations. Table III shows the design synthesis run-times for $k = 500$ and $N = 20$ (i.e, for $kN = 10000$ design evaluations), for several variants of our case studies corresponding to different discrete parameter values (and thus to different $p$CTMC sizes). Run-time statistics are computed over 9 independent experiments each, given by all combinations of $\gamma \in \{0.01, 0.02, 0.05\}$ and $\epsilon \in \{0, 0.05, 0.1\}$. The synthesis time varies between 6262.22s for the smallest system instance (GFS, $N=5000$) and 12295.55s for the largest instance (WC, $N=15$). The average synthesis time over all scenarios is 7123.6s for the GFS case study and 11208.8s for WC, confirming that performance is affected by the size of the underlying $p$CTMC and the number of continuous parameters.

All the experiments of this section were run on a CentOS Linux 6.5 64bit server with two 2.6GHz Intel Xeon E5-2670 processors and 32GB memory, and reported run-times were obtained using multi-core parallelisation. In the oncoming version of the tool we plan to integrate the GPU-accelerated precise parameter synthesis methods of [25], which would significantly improve the scalability of the synthesis process with respect to the size of the candidate designs.

Threats to Validity. Construct validity threats may arise due to assumptions made when modelling the two systems. To mitigate these threats, we used models and quality requirements based on established case studies from the literature [31], [34]. Internal validity threats may correspond to bias in establishing cause-effect relationships in our experiments. We limit them by examining instantiations of the sensitivity-
In the established temporal logic CSL. PRISM parametric synthesis problem using objective functions (4) and constraints (5). We limit these threats by specifying pCTMCs in an extended variant of the widely used modelling language of PRISM [10], with objective functions and constraints specified in the established temporal logic CSL. PRISM parametric Markov models are increasingly used to model software architectures, e.g. in the emerging field of self-adaptive software [7], [8], [9]. Another threat might occur if our method generated a Pareto front that approached the actual Pareto front insufficiently, producing only low quality designs or designs that did not satisfy the required quality constraints. We mitigated this threat by using established Pareto-front performance indices to confirm the quality of the Pareto fronts from our case studies.

VI. RELATED WORK

In previous work [14], we proposed a purely search-based engineering approach that uses evolutionary algorithms to synthesise probabilistic models that satisfy multi-objective specifications. However, the designs generated by this approach are non-parameteric probabilistic models, and thus cannot support sensitivity analysis like our new method. Similarly, the research from [16] employs evolutionary algorithms to search the configuration space of Palladio Component Models, but does not consider the sensitivity of the obtained models.

Sensitivity analysis has long been used to assess the impact that changes in the parameters of the system under development have on the system performance, reliability and other quality attributes, e.g. in [17]–[19]. However, these approaches work by repeatedly sampling the parameter space of the system and evaluating the system behaviour for the sampled values. Accordingly, their results are not guaranteed to capture the entire range of quality-attribute values for the parameter region of interest. Our method overcomes this limitation by generating safe and close over-approximations of the quality-attribute regions associated with robust designs.

The sensitivity of software operational profiles has been analysed using the perturbation theory for Markov processes [20], to quantify the effect of variations in model transition probabilities. However, this approach does not synthesise...
the solutions, and does not work with the wide range of continuous and discrete parameters supported by our method.

Finally, research on parameter synthesis for probabilistic systems from temporal logic speciﬁcations focuses on deriving symbolic expressions for the satisfaction probability of the speciﬁcation as a function of the parameters [21], [35], [36] or on computing safe enclosures of the satisfaction probability for given intervals of parameter values [13], [26]. In contrast to this work, our robust design synthesis directly integrates sensitivity analysis into the automated design process.

VII. CONCLUSION

The analysis of model sensitivity is key for effective design automation, as it establishes how models are affected by parameter deviations, accounting for the unavoidable discrepancies between the real systems and their models. We presented a method for the automated synthesis of Pareto-optimal and robust software designs, which builds on search-based synthesis and parameter synthesis for parametric Markov chains. We developed a tool that implements the method and we used it in two case studies, showing that our synthesised sensitivity-aware Pareto-optimal design sets support the selection of robust designs with a wide range of quality-attribute values and provide insights into the system dynamics.

As future work, we plan to investigate Pareto-dominance relations deﬁned over intervals; alternative search techniques (e.g. particle swarm optimisation [38]); and extensions of the modelling language and the search method to support syntax-based synthesis [39] of robust designs from partial/incomplete pCTMC specifications.

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