Model-based performance self-adaptation

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Mumbai, India
Motivation

- Performance is a fundamental aspect of computing systems:
  
  “[…] in many practical deployment scenarios, particularly mobile, performance is the new correctness.”¹

- Reasoning about performance is hard:
  - Large input spaces, measurement and testing becomes difficult.
  - Behavior dependent on interplay between software and hardware, can be machine dependent.
  - Usage profiles may be uncertain, performance analysis done at design time may not be sufficient.

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¹Mark Harman and Peter O’Hearn. “From Start-ups to Scale-ups: Opportunities and Open Problems for Static and Dynamic Program Analysis”. In: SCAM. 2018.
Performance requirements at runtime

AWS Auto Scaling monitors your applications and automatically adjusts capacity to maintain steady, predictable performance at the lowest possible cost. Using AWS Auto Scaling, it’s easy to setup application scaling for multiple resources across multiple services in minutes. The service provides a simple, powerful user interface that lets you build scaling plans for resources including Amazon EC2 instances and Spot Fleets, Amazon ECS tasks, Amazon DynamoDB tables and indexes, and Amazon Aurora Replicas. AWS Auto Scaling makes scaling simple with recommendations that allow you to optimize performance, costs, or balance between them. If you’re already using Amazon EC2 Auto Scaling to dynamically scale your Amazon EC2 instances, you can now combine it with AWS Auto Scaling to scale additional resources for other AWS services. With AWS Auto Scaling, your applications always have the right resources at the right time.

It’s easy to get started with AWS Auto Scaling using the AWS Management Console, Command Line Interface (CLI), or SDK. AWS Auto Scaling is available at no additional charge. You pay only for the AWS resources needed to run your applications and Amazon CloudWatch monitoring fees.

Amazon Web Services

Introducing Predictive Scaling
Automatically scale your compute capacity in advance of traffic changes using ML technology.

Read the Blog>>

Amazon EC2 Auto Scaling has moved
You have several options for scaling with AWS.
Do you only need to manage Amazon EC2 instances?

Visit the Amazon EC2 Auto Scaling page »
**Objective:** Design systems that adapt themselves to changing environments while meeting desired performance-based service-level agreements (throughput, response time, utilization).

Three main activities:

1. monitor the system execution;
2. continuously update a model of the system;
3. trigger reconfigurations when required.
Objective: Design systems that adapt themselves to changing environments while meeting desired performance-based service-level agreements (throughput, response time, utilization)

Three main activities:

1. monitor the system execution;
2. continuously update a model of the system;
3. trigger reconfigurations when required.

Three main difficulties:

1. non-intrusive monitoring infrastructure;
2. efficient and accurate predictive models;
3. effective and robust planner.
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We build on queuing networks, an established class of performance models for computing systems.

Need to convince ICPE audience?
- Varsha Apte’s workshop was yesterday...
- Kishor Trivedi speaks tomorrow...
Queuing networks

A load balancing system

- Exponentially distributed service times—can be relaxed;\(^2\)
- single class of users—multiple classes later;
- multiple servers.

Queuing networks for self-adaptation?

Queueing networks enjoy efficient analysis techniques (e.g., BCMP theorem), but:

- In general, each parameterization requires a distinct analysis — large cost when exploring large parameter spaces.

**Our contribution:**
Efficient parametric analysis of queuing networks.

- Analytical results assume time-homogeneous networks, i.e., parameters do not vary with time — adaptation requires changing the system, hence the parameters of its model.

- Most analytical results available for the steady-state regime — adaptation might need to change parameters at all time points.

**Our contribution:**
Approximate queuing network analysis based on fluid models.
Parametric analysis of queuing networks

- Consider a queuing network with probability matrix $P$, vector of exogenous arrivals $\lambda$, and service rates $\mu$.
- Consider concrete as well as symbolic parameters.
- Solve for stationary average performance indices using a computer algebra system.$^3$

$$P = \begin{bmatrix} 0.0 & p_{1,2}^* & p_{1,3}^* & 0.0 \\ 0.0 & 0.0 & 0.0 & 1.0 \\ 0.0 & 0.0 & 0.0 & 1.0 \\ 0.5 & 0.0 & 0.0 & 0.0 \end{bmatrix} \quad \lambda = \begin{bmatrix} \lambda_1^* \\ 0.0 \\ 0.0 \\ 0.1 \end{bmatrix} \quad \mu = \begin{bmatrix} 1.5 \\ 2.0 \\ 3.0 \\ \mu_4^* \end{bmatrix}$$

---

Parametric analysis of queuing networks

- Consider a queuing network with probability matrix $P$, vector of exogenous arrivals $\lambda$, and service rates $\mu$.
- Consider concrete as well as symbolic parameters.
- Solve for stationary average performance indices using a computer algebra system.$^4$

$$AQL = -\frac{20\lambda_1^* + 1}{80\lambda_1^* + 60p_{1,2}^* + 60p_{1,3}^* - 116} - p_{1,2}^*(20\lambda_1^* + 1)$$

$$\quad \frac{4(21p_{1,2}^* + 20p_{1,3}^* + 20\lambda_1^*p_{1,2}^* - 40)}{10\lambda_1^*p_{1,2}^* + 10\lambda_1^*p_{1,3}^* + 1}$$

$$\quad - \frac{20\mu_4^*p_{1,2}^* - 40\mu_4^* + 20\mu_4^*p_{1,3}^* + 40\lambda_1^*p_{1,2}^* + 40\lambda_1^*p_{1,3}^* + 4}{p_{1,3}^*(20\lambda_1^* + 1)}$$

$$\quad - \frac{4(30p_{1,2}^* + 31p_{1,3}^* + 20\lambda_1^*p_{1,2}^* - 60)}{4(30p_{1,2}^* + 31p_{1,3}^* + 20\lambda_1^*p_{1,2}^* - 60)}$$

Numerical vs symbolic analysis

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## Numerical vs symbolic analysis

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Queuing networks for self-adaptation?

- Queuing networks enjoy efficient analysis techniques (e.g., BCMP theorem), **but:**
  - In general, each parameterization requires a distinct analysis — large cost when exploring large parameter spaces.

  **Our contribution:**
  Efficient parametric analysis of queuing networks.

- Analytical results assume **time-homogeneous** networks, i.e., parameters do not vary with time — adaptation requires changing the system, hence the parameters of its model.

  **Most analytical results available for the steady-state regime — adaptation might need to change parameters at all time points.**

  **Our contribution:**
  Approximate queuing network analysis based on fluid models.
Transient solutions for queuing networks?

Queuing network

Underlying continuous-time Markov chain

Forward (master) equations

\[
\dot{\pi}(2,0,0) = -2\mu_0 \pi(2,0,0) + \mu_1 \pi(1,1,0) + \mu_2 \pi(1,0,1)
\]

\[
\vdots
\]

\[
\dot{\pi}(0,0,2) = -\mu_2 \pi(0,0,2) + p_{0,2}\mu_0 \pi(1,0,1)
\]

State explosion

Number of states is exponential!
Transient solutions for queuing networks?

Queuing network

\[ \begin{array}{c}
M_0 \\
M_1 \\
M_2 \\
\end{array} \]

\[ \begin{array}{c}
<\mu_0, s_0 = \infty> \\
<p_{01}> \\
<p_{02}> \\
<\mu_1, s_1> \\
<\mu_2, s_2> \\
\end{array} \]

Underlying continuous-time Markov chain

State: \( <X_0, X_1, X_2> \)

\( s_1 = s_2 = 1 \)

Forward (master) equations

\[ \begin{align*}
\dot{\pi}(2,0,0) &= -2\mu_0 \pi(2,0,0) + \mu_1 \pi(1,1,0) + \mu_2 \pi(1,0,1) \\
\vdots \\
\dot{\pi}(0,0,2) &= -\mu_2 \pi(0,0,2) + p_{0,2} \mu_0 \pi(1,0,1)
\end{align*} \]

State:

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Incerto and Tribastone (IMT)

Model-based performance self-adaptation

ICPE'19 17/76
Markov population processes

\[ Q_0 \rightarrow Q_1, \quad p_{0,1} \mu_0 Q_0 \]
\[ Q_0 \rightarrow Q_2, \quad p_{0,2} \mu_0 Q_0 \]
\[ Q_1 \rightarrow Q_0, \quad \mu_1 \min\{ Q_1, s_1 \} \]
\[ Q_2 \rightarrow Q_0, \quad \mu_2 \min\{ Q_2, s_2 \} \]

\[ l_1 = (-1, +1, 0), \quad f_1(x) = p_{0,1} \mu_0 x_0 \]
\[ l_2 = (-1, 0, -1), \quad f_2(x) = p_{0,2} \mu_0 x_0 \]
\[ l_3 = (+1, -1, 0), \quad f_3(x) = \mu_1 \min\{ x_1, s_1 \} \]
\[ l_4 = (+1, 0, -1), \quad f_4(x) = \mu_2 \min\{ x_2, s_2 \} \]

Jumps and rate functions
Markov population processes

Master Equation

\[
\dot{\pi}_n(t) = -\sum_i f_i(n)\pi_n(t) + \sum_i f_i(n - l_i)\pi_{n-l_i}(t)
\]

for all states \( n = (n_0, n_1, n_2) \).

\[
\begin{align*}
Q_0 &\rightarrow Q_1, & p_{0,1}\mu_0 Q_0 \\
Q_0 &\rightarrow Q_2, & p_{0,2}\mu_0 Q_0 \\
Q_1 &\rightarrow Q_0, & \mu_1 \min\{Q_1, s_1\} \\
Q_2 &\rightarrow Q_0, & \mu_2 \min\{Q_2, s_2\} \\
\end{align*}
\]

\( \downarrow \)

\[
\begin{align*}
l_1 &= (-1, +1, 0), & f_1(x) &= p_{0,1}\mu_0 x_0 \\
l_2 &= (-1, 0, -1), & f_2(x) &= p_{0,2}\mu_0 x_0 \\
l_3 &= (+1, -1, 0), & f_3(x) &= \mu_1 \min\{x_1, s_1\} \\
l_4 &= (+1, 0, -1), & f_4(x) &= \mu_2 \min\{x_2, s_2\} \\
\end{align*}
\]

Jumps and rate functions
Equations for the average

Master equation

\[ \dot{\pi}_n(t) = - \sum_i f_i(n) \pi_n(t) + \sum_i f_i(n - l_i) \pi_{n-l_i}(t), \text{ for all states } n. \]

Call \( X(t) = (X_0(t), X_1(t), X_2(t)) \) the queue length process.

The true equations for the average queue lengths are:

\[ \mathbb{E}[X](t) = \sum_i l_i \mathbb{E} [f_i(X(t))] \]

Problem: equations are not closed!

\( l_1 = (-1, +1, 0) \), \( f_1(x) = p_{0,1} \mu_0 x_0 \)

\( l_2 = (-1, 0, -1) \), \( f_2(x) = p_{0,2} \mu_0 x_0 \)

\( l_3 = (+1, -1, 0) \), \( f_3(x) = \mu_1 \min\{x_1, s_1\} \)

\( l_4 = (+1, 0, -1) \), \( f_4(x) = \mu_2 \min\{x_2, s_2\} \)
Approximate equations for the average

True equations

\[ \mathbb{E}[\dot{X}](t) = \sum_i l_i \mathbb{E}[f_i(X(t))] \]

\[ l_1 = (-1, +1, 0), \quad f_1(x) = p_{0,1}\mu_0 x_0 \]
\[ l_2 = (-1, 0, -1), \quad f_2(x) = p_{0,2}\mu_0 x_0 \]
\[ l_3 = (+1, -1, 0), \quad f_3(x) = \mu_1 \min \{x_1, s_1\} \]
\[ l_4 = (+1, 0, -1), \quad f_4(x) = \mu_2 \min \{x_2, s_2\} \]

\[ \mathbb{E}[\dot{X}_0](t) = -p_{0,1}\mu_0 \mathbb{E}[X_0](t) - p_{0,2}\mu_0 \mathbb{E}[X_0](t) \]
\[ + \mathbb{E}[\mu_1 \min \{X_1(t), s_1\}] + \mathbb{E}[\mu_2 \min \{X_2(t), s_2\}] \]

How to close the equations?

\[ \mathbb{E}[\min \{X, Y\}] \approx \min \{\mathbb{E}[X], \mathbb{E}[Y]\} \]
Approximate equations for the average

True equations

\[ \mathbb{E} \dot{X}(t) = \sum l_i \mathbb{E} [ f_i(X(t))] \]

\[ l_1 = (-1, +1, 0), \quad f_1(x) = p_{0,1} \mu_0 x_0 \]
\[ l_2 = (-1, 0, -1), \quad f_2(x) = p_{0,2} \mu_0 x_0 \]
\[ l_3 = (+1, -1, 0), \quad f_3(x) = \mu_1 \min \{x_1, s_1\} \]
\[ l_4 = (+1, 0, -1), \quad f_4(x) = \mu_2 \min \{x_2, s_2\} \]

Fluid Approximation

\[ \dot{X}_0(t) = -p_{0,1} \mu_0 X_0(t) - p_{0,2} \mu_0 X_0(t) \]
\[ + \mu_1 \min \{X_1(t), s_1\} + \mu_2 \min \{X_2(t), s_2\} \]
\[ \dot{X}_1(t) = +p_{0,1} \mu_0 X_0(t) - \mu_1 \min \{X_1(t), s_1\} \]
\[ \dot{X}_2(t) = +p_{0,2} \mu_0 X_0(t) - \mu_2 \min \{X_2(t), s_2\} \]

How to close the equations?

\[ \mathbb{E}[\min \{X, Y\}] \approx \min \{\mathbb{E}[X], \mathbb{E}[Y]\} \]
Another interpretation: fluid limits

Markov population process

\[ l_1 = (-1, +1, 0), \quad f_1(x) = p_{0,1} \mu_0 x_0 \]
\[ l_2 = (-1, 0, -1), \quad f_2(x) = p_{0,2} \mu_0 x_0 \]
\[ l_3 = (+1, -1, 0), \quad f_3(x) = \mu_1 \min\{x_1, K s_1\} \]
\[ l_4 = (+1, 0, -1), \quad f_4(x) = \mu_2 \min\{x_2, K s_2\} \]

CTMC family

\[ X^1(0) = (Q_0, Q_1, Q_2) \]
\[ X^2(0) = 2(Q_0, Q_1, Q_2) \]
\[ \ldots \]
\[ X^K(0) = K(Q_0, Q_1, Q_2) \]

- Fix some initial condition \((Q_0, Q_1, Q_2)\)
- Consider Markov chains with increasing clients as well as servers
- In the limit as \(K\) goes to infinity one sample path of \(X^K(t)/K\) will converge to the fluid equations\(^5\)

---

Fluid approximation of queuing networks

- Let $1, \ldots, N$ be the queuing stations;
- let $P = (p_{i,j})_{1 \leq i,j \leq N}$ be the routing probability matrix;
- let $s_1, \ldots, s_N$ be the server multiplicities;
- let $\mu_1, \ldots, \mu_N$ be the service rates.

The fluid approximation is given by

$$\dot{X}_i(t) = -\mu_i \min\{X_i(t), s_i\} + \sum_j p_{j,i} \mu_j \min\{X_j(t), s_j\}, \quad i = 1, \ldots, N.$$ 

It can be also defined for time-varying parameters:

$$\dot{X}_i(t) = -\mu_i(t) \min\{X_i(t), s_i(t)\} + \sum_j p_{j,i}(t) \mu_j(t) \min\{X_j(t), s_j(t)\}$$

---

Mean approximation accuracy

$\mu_0 = 0.05$

$\mu_0 = 0.10$

$\mu_0 = 0.25$

$\mu_0 = 0.50$
Fluid limit accuracy

Comparison between a sample path of the CTMC and the fluid model
Interlude: ERODE session

https://sysma.imtlucca.it/tools/erode/

Running example: HAT architecture

- In house developed web application
- It resembles CPU intensive behaviour
- Dispatcher (i.e., LB) and Computation Node (i.e., C1, C2)
Model validation

(a) $N_1$ queue length

(b) $N_2$ queue length
Model validation

(a) System throughput

(b) System response time
Performance self-adaptation

**Objective:** Design systems that adapt themselves to changing environments while meeting desired performance-based service-level agreements (throughput, response time, utilization)

Three main activities:

1. monitor the system execution;
2. continuously update a model of the system;
3. trigger reconfigurations when required.

Three main difficulties:

1. non-intrusive monitoring infrastructure;
2. efficient and accurate predictive models;
3. **effective and robust planner.**
A Performance-driven MAPE-K control loop

An MAPE-K framework based on fluid QN
1 Efficient performance models

2 Symbolic performance adaptation

3 Model-predictive control for performance-driven self-adaptation

4 Moving horizon estimation of service demands
Symbolic performance adaptation

💡 **Idea:** Encode performance-driven adaptation as a satisfiability modulo theories (SMT) problem.\(^7\)

- **Goal:** Query an SMT solver for a feasible assignment of the system parameters needed to satisfy QoS requirements or getting a formal proof of its non-existence.

- We rely on a combination of:
  - **queuing networks:** quantitative model to represent QoS attributes of the system;
  - **symbolic analysis:** represent all possible system configuration as a set of nonlinear real constraints;
  - **SMT:** devise feasible system configurations.

---

Satisfiability Modulo Theory\(^8\) checks the satisfiability of logical formulas over one or more theory, i.e., if there exists an assignment or real number satisfying

\[3x + 2y - z \geq 4 \land x \geq 0 \land y \geq 0\]

We interpret the symbolic expressions as a set of constraints that the parametric values have to satisfy.

We augment them with further constraints representing the QoS requirements \(Q\).

\[\text{Exploiting the Non-Linear Real Arithmetic theory } \mathcal{NRA} \text{ we encode this problem as an SMT problem suitable to devise the set of feasible parameters satisfying } Q\]

---

The SMT adaptation problem

- $\mathcal{M}$ be the symbolic solution of the QN
- $\mathcal{Q}$ be a set of QoS requirements
- $\mathcal{D}$ be a set of domain assumptions
- $\mathcal{R}$ be a set of resource constraints

The QoS-based adaptation is turned into the satisfiability problem:

*Find an assignment of the variables for model $\mathcal{M}$ that ensures $\mathcal{Q}$ subjected to constraints $\mathcal{D} \land \mathcal{R}$.*

\[
\mathcal{Q} := \{ T_0 \geq C/2 \} \\
\mathcal{D} := \{ C = 350 \} \\
\mathcal{R} := \left\{ \forall i, j \in S. \sum_{k \in S} p_{i,k} = 1.0 \land \\
0 \leq p_{i,j} \leq 1.0 \land 1 \leq s_i \leq 40 \land 0.02 \leq \frac{1}{\mu_i} \leq 10 \right\}
\]
Case study

QN model for a three-tier system\(^9\)

Control objective

\[ R_S = \frac{C}{T_1} \leq 1 \quad C \in [1, 304], \quad Z = 0. \]

Case study: SMT problem formulation

\[ Q := (T_1 \geq C) \land \forall i \in S.((U_i \leq 1.0 \land U_i \geq 0.6) \lor U_i = 0.0) \]

\[ D \land R := (Z = 0) \land R_1 \land R_2 \]

\[ R_1 := \forall i, j \in S. (0.0 \leq p_{i,j} \leq 1.0) \land \forall i \in S. \sum_{j \in S} p_{i,j} = 1.0 \]

\[ R_2 := \forall i \in S. ((1.0 \leq s_i \leq 40.0) \land (0.06 \leq \frac{1}{\mu_i} \leq 10.0)) \]
Case study: numerical results

![Graph showing response time and utilization over number of clients]

Response Time (s)
- QoS Requirement

Utilization (%)
- Max U_i
- Min U_i
- QoS Requirement
Case study: numerical results

![Graph showing adaptation steps and fault conditions](image)

![Graph showing computation time vs number of clients](image)
Discussion

■ Advantages:
  ■ Computation pushed at design-time phase for the symbolic solution
  ■ Adaptation step is performed in a few ms even for realistic fully parametric three-tier models
  ■ The solver may return an unsatisfiability result, meaning that there is no configurations satisfying the requirements

■ Limitations:
  ■ Single class QNs model
  ■ Closed form QNs model for the symbolic solution
  ■ Steady state analysis
  ■ Scalability of the SMT solver
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2. Symbolic performance adaptation
3. Model-predictive control for performance-driven self-adaptation
4. Moving horizon estimation of service demands
Self-adaptation via model predictive control

💡 **Idea**: Encode performance-driven self-adaptation as a model predictive control (MPC) problem

- **Goals**: Get optimal assignments of the system parameters needed for steering an application toward a desired operating point (e.g., throughput)
  - fully automated
  - multiple adaptation knobs
  - considers actual run-time conditions
  - involves the solution of mixed integer nonlinear programs (MINLPs)

💡 As a main technical result we formally translate the naive MINLP MPC formulation in a mixed integer quadratic programming (MIQP) one

---

The main idea is to encode the discrete time version the ODE model as constraints of the optimization problem.
Naive MPC formulation

\[
\min_{\mu, s, p, x} \sum_{k=0}^{H-1} \sum_{i=1}^{M} w_{i,k}(m_i(k) - \hat{r}_i(k))^2 + w_{s_i,k} \Delta s_{i,k}^2
\]

s.t.

\[
x_i(k + 1) = (-\mu_i(k) \min\{x_i(k), s_i(k)\} + \sum_{j \in S} p_{j,i}(k) \mu_j(k) \min\{x_j(k), s_j(k)\}) \Delta t + x_i(k)
\]

\[
s_i(k) \in \{s_i, s_i + 1, \ldots, \bar{s}_i\}
\]

\[
0 \leq p_{i,j}(k) \leq 1, \sum_{j \in S} p_{i,j}(k) = 1
\]

for \(1 \leq i \leq M, 0 \leq k \leq H - 1, \hat{r}_i(k) \) set point
MIP formulation

💡 We reformulate the system relying on “virtual” adaptation knobs which are related to the original ones

- \( \min \{x_i(k), s_i(k)\} = \alpha_i(k) \) can be encoded through standard MIP techniques\(^{11}\)

- \( \mu_i(k)\alpha_i(k) \) can be encoded by adding slack variables \( \gamma_i(k) \) and proper bound constraints

\[
\mu_i(k)\alpha_i(k) = \hat{\mu}_i\alpha_i(k) + \gamma_i(k) \iff \mu_i(k) = \hat{\mu}_i + \frac{\gamma_i(k)}{\alpha_i(k)}
\]

\[
\begin{cases}
\mu_i(k) \leq \bar{\mu}_i \iff \gamma_i(k) \leq (\bar{\mu}_i - \hat{\mu}_i)\alpha_i(k) \\
\mu_i(k) \geq \underline{\mu}_i \iff \gamma_i(k) \geq (\underline{\mu}_i - \hat{\mu}_i)\alpha_i(k)
\end{cases}
\]

- The new linear time system is

\[
\dot{x}_i(t) = \gamma_i(t) + \sum_{j \in S}(-\gamma_j(t) + \zeta_{j,i}(t)), \quad i, j \in S
\]

\(^{11}\)www.gurobi.com/documentation/8.1/refman/constraints.html
Theorem

Denoting by \( S = \{\mu_i^*(k), p_{i,j}^*(k), s_i^*(k), x_i^*(k)\} \) an optimal solution of the non-linear adaptation problem, there exists an MPC problem based on the MIP formulation with linear dynamics such that its optimal solution \( S' = \{\gamma'_i(k), x'_i(k), \zeta'_{i,j}(k), s'_i(k)\} \) satisfies:

\[
\begin{align*}
\mu_i^*(k) &= \begin{cases} 
-\frac{\gamma'_i(k)}{x'_i(k)\Delta t} & \text{if } x'_i(k) \leq s'_i(k) \\
-\frac{\gamma'_i(k)}{s'_i(k)\Delta t} & \text{if } x'_i(k) > s'_i(k) 
\end{cases} \\
p_{i,j}^*(k) &= \frac{\gamma'_i(k) - \zeta'_{i,j}(k)}{\gamma'_i(k)}, \quad s_i^*(k) = s'_i(k),
\end{align*}
\]

for all \( k = 0, \ldots, H - 1 \).
Evaluation

- We evaluate the effectiveness and the scalability of the MPC approach on a real system
  - an in-house developed web application
- By studying two non-trivial adaptation scenarios
  - hardware degradation
  - workload fluctuation
- Scalability comparison with probabilistic model checking
HAT architecture

Incerto and Tribastone (IMT)

Model-based performance self-adaptation

ICPE’19 50 / 76
Numerical evaluation: hardware degradation

(a) System throughput

(b) Optimal control signals
Numerical evaluation: workload fluctuation

(a) $C_1$ queue length

(b) $C_2$ queue length
Numerical evaluation: workload fluctuation

Statistics of optimal control signals

Incerto and Tribastone (IMT)
Model-based performance self-adaptation
ICPE’19
MPC scalability evaluation

Comparison against MDP (TO: timeout after 120 s)$^{12}$

<table>
<thead>
<tr>
<th>W</th>
<th>MIP Runtime(s)</th>
<th>Markov Decision Processes</th>
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<td>120</td>
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<td>TO</td>
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<td>120</td>
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<td>744164883</td>
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</tbody>
</table>

$^{12}$Marta Kwiatkowska, Gethin Norman, and David Parker. “PRISM 4.0: Verification of Probabilistic Real-time Systems”. In: CAV. 2011.
Conclusion

- Contribution: a model predictive control based self-adaptive approach to continuously meet performance requirements

- Advantages:
  - fully automated
  - efficient
  - it works during the transient regime
  - the proposed linearization technique can be straightforwardly applied to more expressive models (e.g., Petri Nets)

- Limitations:
  - single-class model
  - QN parametrization
  - throughput and queue length QoS requirements only
Adaptation of co-located applications

- Meeting performance targets of co-located applications (e.g., virtualized cloud environments) is challenging

- Scaling techniques:
  - *Vertical scaling*: assigns resource shares on each individual machine
  - *Horizontal scaling*: chooses the number of virtual machines employed

- State-of-the-art approaches apply vertical and horizontal scaling in an isolated fashion (i.e., symmetric load balancing)

- Ineffective when machines have different hardware characteristics (e.g., software aging or hardware degradation)
Adaptation of co-located applications

- A model based approach:
  - Multi-class QN as the quantitative model
  - Analysed by means of QNs fluid approximation
  - Combined horizontal and vertical scaling formulated as an MPC quadratic programming problem

- Main technical results:\textsuperscript{13}
  - A multi-class model that enables an accurate representation of the \textit{capped allocation paradigm}
  - The specification of latency-based requirements
  - Extension of [ASE’17]

\textsuperscript{13}Emilio Incerto, Mirco Tribastone, and Catia Trubiani. “Combined Vertical and Horizontal Autoscaling Through Model Predictive Control”. In: \textit{EURO-PAR. 2018.}
The multi-class QN model

Multi class QN model of load balancer with two co-located applications
The multi-class fluid QN model

- For each station $i$ and each class $c$ we define the ODE:

$$
\dot{x}_{i,c}(t) = -\mu_{i,c} \min\{x_{i,c}(t), \alpha_{i,c}(t)s_i\} + \sum_{j \in S} p_{j,i,c}(t)\mu_{j,c} \min\{x_{j,c}(t), \alpha_{j,c}(t)s_j\}
$$

with $\alpha_{i,c}(t) \geq 0$, $\sum_{c \in C} \alpha_{i,c}(t) \leq 1$.

- We define the following metrics:
  - Class-$c$ throughput at station $i$
    $$
    T_{i,c}(t) = \mu_{i,c} \min\{x_{i,c}(t), \alpha_{i,c}(t)s_i\}
    $$
  - Instantaneous response time
    $$
    R_{i,c}(t) = \frac{x_{i,c}(t)}{T_{i,c}(t)}
    $$
In [ASE’17] we employed MPC for performance runtime adaptation for single class queuing networks.

We showed how it could be formulated as a series of mixed-integer quadratic program (MIQP).

Here we extend this formulation for controlling the multi-class QN under the cap allocation sharing.

- A positive side effect: quadratic programming (QP) formulation.
The QP formulation is possible due to the following:

\[
\min \{ x_{i,c}(t), \alpha_{i,c}(t)s_i \} = \gamma_{i,c}(t)
\]

\[
\uparrow
\]

\[
\begin{align*}
\gamma_{i,c}(t) & \geq 0, \\
\gamma_{i,c}(t) & \leq x_{i,c}(t) \\
\sum_{c \in C} \gamma_{i,c}(t) & \leq s_i
\end{align*}
\]

with \( i \in S, c \in C \)

then if \( \gamma_{i,c}^*(t) \neq x_{i,c}^*(t) \) the real actuator can be computed as

\[
\alpha_{i,c}^*(t) = \frac{\gamma_{i,c}^*(t)}{s_i}
\]
Numerical evaluation: system description

- We show that the combined vertical and horizontal adaptation can efficiently meet performance targets when either of the two techniques alone cannot.

- We used the OpenVz hypervisor while horizontal scaling has been enabled through a NodeJS-based load balancer.

- For emulating a multi class scenario, we ran two instances of the same load balanced HAT deployment consisting of two OpenVz virtual machines each.
Numerical evaluation: system description

Incerto and Tribastone (IMT)

Model-based performance self-adaptation

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CTRL

Monitor

Analyze & Plan

Execute

LP Solution

TCP Backlog Monitor: {1081, 1082, 1083, 1084}

share trigger

p_{i,c} trigger

W_1

W_2

LB_1

LB_2

C_{1,1}

C_{1,2}

C_{2,1}

C_{2,2}

VM

VM

VM

VM

\alpha_{1,1}

\alpha_{1,2}

\alpha_{2,1}

\alpha_{2,2}

CPULIMIT

Hypervisor: OpenVz

CPULIMIT

LM_1

6 CPUs: {0-5}

LM_2

6 CPUs: {6-10}

Operating System: Ubuntu 14.04 64bit openvz-2.6 kernel

32 CPUs VPS
Numerical evaluation: hardware degradation

From a symmetric set-up, inject a degradation event such that service rate at node LM1 becomes 3 times smaller.

- Objective: set points $R_1 = 2 \text{ s}$ and $T_2 = 50 \text{ r/s}$
- Workload of 200 users and think times with average 1 s
- Control approaches evaluated in two separate 20-minute-long sessions
Numerical evaluation: hardware degradation

(a) Vertical scaling only

(b) Vertical & horizontal scaling

(c) Vertical scaling only

(d) Vertical & horizontal scaling

Response time distribution without (a,b) and with (c,d) degradation
Numerical evaluation: hardware degradation

Class-2 average throughput with (a,b) and without (c,d) degradation
**Discussion**

- **Contribution**: an efficient approach for performance adaptation of distributed co-located applications.

- The main novelties lay:
  - The combined usage of vertical and horizontal scaling techniques
  - A multi-class fluid model for co-located applications under a capped resources allocation scheduler.

- Future works:
  - modeling response time distribution instead of its average only
  - include resource contention policies for network, memory, I/O
  - consider more expressive resource schedulers and system performance interactions
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Well calibrated model parameters are necessary for computing accurate predictions.

When dealing with queuing networks service demands are fundamental.

The estimation need to be performed:
- continuously
- non intrusively

💡 **MHE:** We formulate the estimation problem as a quadratic program solved according to the moving horizon paradigm.¹⁴

---

Estimator formulation

minimize \[ \sum_{k=1}^{H} \sum_{i=1}^{M} (\bar{x}_i(k) - \tilde{x}_i(k))^2, \]
subject to:

\[ \bar{x}_i(k + 1) = \bar{x}_i(k) - T_i(k) + \sum_{j=1}^{M} p_{j,i} T_j(k) \]
\[ \bar{x}_i(0) = \tilde{x}_i(0), \quad 1 \leq i \leq M, 0 \leq k \leq H - 1. \]

\[ \mu_i^* := \frac{\sum_{k=0}^{H-1} T_i^*(k)}{\sum_{k=0}^{H-1} \min \{ \bar{x}_i^*(k), s_i \}}, \quad 1 \leq i \leq M. \]
Numerical evaluation

Accuracy comparison between the queue length maximum likelihood estimation (QMLE)\(^{16}\) and our approach (MHE).

<table>
<thead>
<tr>
<th>K</th>
<th>QMLE MHE</th>
<th>QMLE MHE</th>
<th>QMLE MHE</th>
<th>QMLE MHE</th>
<th>QMLE MHE</th>
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<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.52 9.25 ± 1.03</td>
<td>1.37 9.63 ± 1.06</td>
<td>2.07 7.90 ± 1.01</td>
<td>3.40 6.58 ± 0.81</td>
<td>5.15 4.89 ± 0.69</td>
</tr>
<tr>
<td>2</td>
<td>448.30 4.13 ± 0.62</td>
<td>126.54 3.93 ± 0.58</td>
<td>67.18 4.20 ± 0.63</td>
<td>5.46 3.90 ± 0.56</td>
<td>2.33 3.59 ± 0.54</td>
</tr>
<tr>
<td>5</td>
<td>184.02 2.26 ± 0.33</td>
<td>60.41 3.02 ± 0.43</td>
<td>42.09 2.76 ± 0.38</td>
<td>8.78 2.07 ± 0.33</td>
<td>1.65 2.06 ± 0.34</td>
</tr>
<tr>
<td>10</td>
<td>92.29 1.65 ± 0.27</td>
<td>30.53 1.99 ± 0.31</td>
<td>23.18 1.82 ± 0.31</td>
<td>9.50 2.09 ± 0.30</td>
<td>3.89 1.50 ± 0.24</td>
</tr>
<tr>
<td>20</td>
<td>45.18 1.37 ± 0.21</td>
<td>15.01 1.13 ± 0.19</td>
<td>11.32 1.36 ± 0.18</td>
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<td>5.81 1.17 ± 0.18</td>
</tr>
<tr>
<td>50</td>
<td>18.67 0.74 ± 0.10</td>
<td>6.08 0.81 ± 0.14</td>
<td>4.57 0.78 ± 0.11</td>
<td>2.72 0.81 ± 0.12</td>
<td>5.17 0.73 ± 0.10</td>
</tr>
</tbody>
</table>

\(^{16}\)Weikun Wang et al. “Maximum likelihood estimation of closed queueing network demands from queue length data”. In: ICPE. 2016.
## Numerical evaluation

### MHE scalability analysis

<table>
<thead>
<tr>
<th>$M$</th>
<th>Errors</th>
<th>Runtimes (s)</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>min</td>
<td>avg</td>
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<tr>
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<tr>
<td>15</td>
<td>1.59</td>
<td>2.63</td>
</tr>
<tr>
<td>20</td>
<td>1.62</td>
<td>2.52</td>
</tr>
</tbody>
</table>
Conclusion

- We defined optimization methods based on fluid queuing networks enabling fast adaptation reactions under strict time constraints.

- Through an extensive numerical validation we have shown how complex multi-dimensional adaptation actions can be computed at a small computational cost in real-world scenarios.

- We developed the first transient estimation technique for service demands of QNs enabling effective and efficient parameter estimation in a minimally intrusive manner.
Future work

- The definition of model predictive control problem based on the fluid interpretation of layered queuing networks.

- The definition of performance-driven self-adaptation approaches considering higher-order statistics of the controlled quantities, e.g., variance

- The development of minimally intrusive estimation techniques for multi-class QNs with non-exponentially distributed service times
Further related work

- A number of results on self-adaptation by means of formal quantitative verification.\(^{17,18}\)
- Runtime use of discrete time Markov chains for reliability of self-adaptive systems.\(^{19}\)
- Control-theoretic approaches for learning and updating a linear model from measurements and controlling it via a single parameter.\(^{20}\)
- Control of software performance via service-rate adaption using a queuing model.\(^{21}\)

\(^{17}\) Carlo Ghezzi et al. “Managing non-functional uncertainty via model-driven adaptivity”. In: *ICSE’13*.


\(^{19}\) Antonio Filieri et al. “Self-adaptive software meets control theory: A preliminary approach supporting reliability requirements”. In: *ASE’11*.


\(^{21}\) Davide Arcelli et al. “Control theory for model-based performance-driven software adaptation”. In: *QoSA’15*.