WTTM 2015

7th Workshop on the Theory of Transactional Memory

On Exploring Markov Chains for Transaction Scheduling Optimization in Transactional Memory

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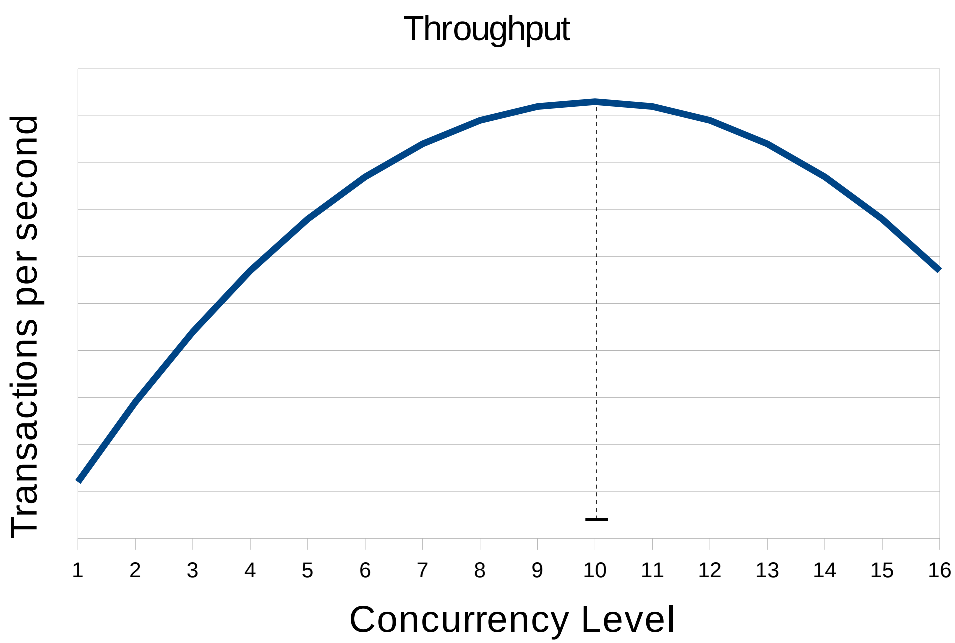
Effects of Concurrent Execution of Transactions



Transaction concurrency level too low:
performance is penalized due to limitation of parallelism and underutilization of hardware resources

Optimal transaction concurrency level

Transaction concurrency level too high:
loss of performance due to high **data contention** causing **abort and re-run of transactions**.

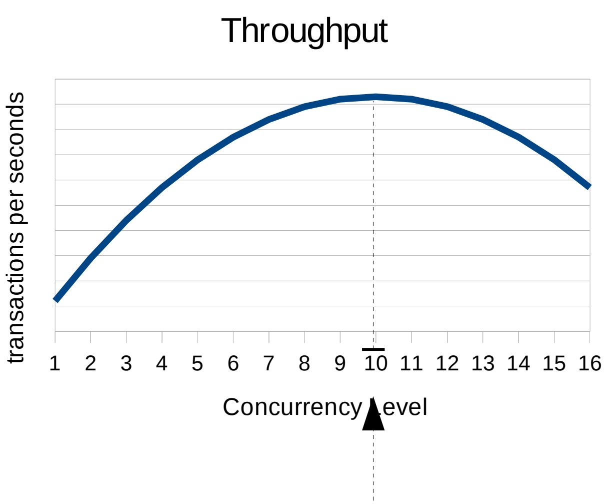
Identifying the optimal concurrency level ...

The **optimal concurrency level depends** on:

- transaction/workload profile (transaction length, data access distribution, read/write ratio, ...)
- hardware architecture

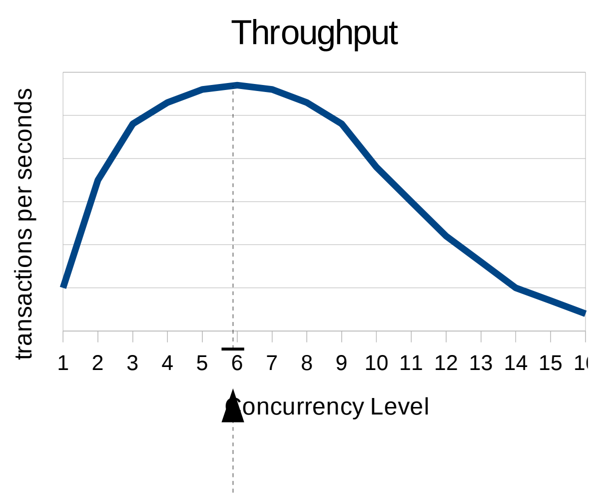
The workload profile may **change** during the execution of the application → the optimal concurrency level may **change** during the execution of the application

Application execution phase 1



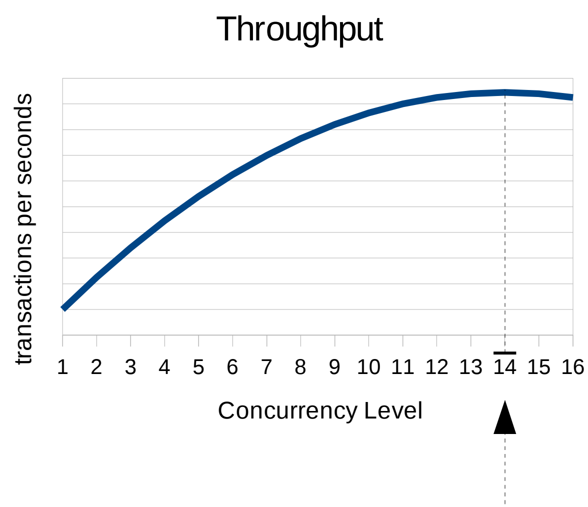
optimal concurrency level: 10

Application execution phase 2



optimal concurrency level: 6

Application execution phase 3



optimal concurrency level: 14

Transaction Scheduling

Transaction Scheduling: Transactions are blocked or allowed to run depending on some scheduling policy

The workload profile may **change** during the execution of the application

<u>Adaptive scheduling approach</u>: the scheduler takes decisions on basis of run-time observations

Transaction Scheduling in TM

Transaction Scheduling policies

Based on system performance prediction models

- Analytical model-based approaches [1]
- Parametric system performance models [2]
- Machine learning-based approaches [3]
- Interpolating functions [4]

Heuristic-based approaches

- Hill-climbing [5]
- Pro-active transaction scheduling: serializing transactions when the abort probability is (estimated to be) high [6,7,8]

Pros and Cons of Performance Prediction-based Approaches

Pros: the ability of predicting the system throughput for different system configurations allows at run-time to quickly “jump” to the best scheduler configuration

Cons: these approaches require ***a priori analysis phases*** *(e.g. training phases)*, during which various parameters have to be measured while running the application with different workload profiles and/or different scheduler configurations (in terms of, e.g., number of admitted transactions).

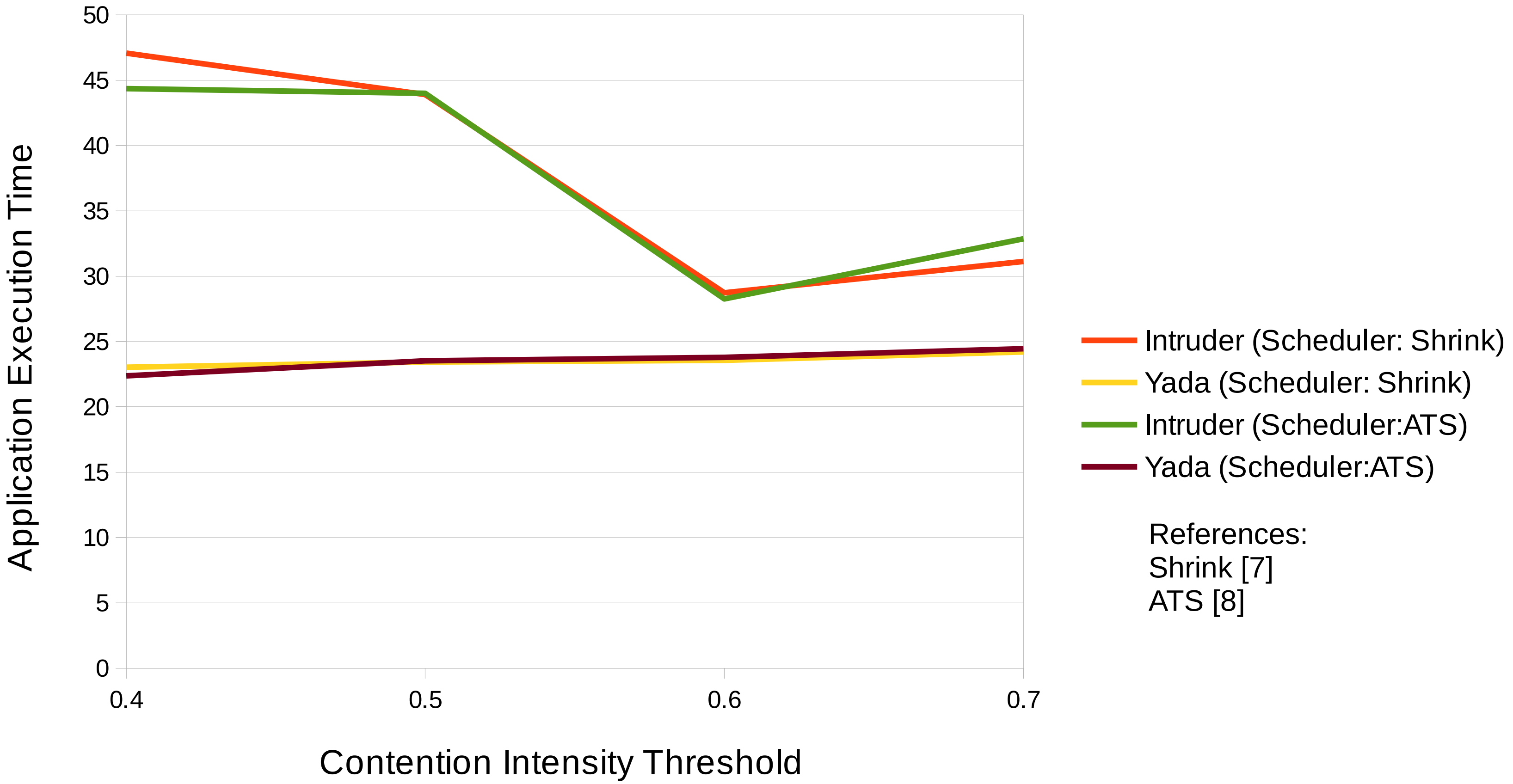
Pros and Cons of Heuristic-based Approaches

Pros: no a priori analysis phases of the application are required

Cons:

- the optimal solution is not guaranteed
- time to converge
- the user has to configure some parameters (e.g. conflict rate/abort probability thresholds) on the basis of which the scheduler takes decisions

Effects of Different Thresholds of Scheduling Algorithms



References:
Shrink [7]
ATS [8]

Hardware configuration:
16-cores HP ProLiant server, equipped with 2GHz AMD Opteron 6128 processors, 64 GB of RAM and the Linux operating system (kernel version 2.7.32-5-amd64).

Application configuration:
Intruder - input: -a10 -l128 -n262144
Yada - input: -a15 -i yada/inputs/ttimeu1000000.2

Getting the best of the two worlds ...

A system performance model ...

· for predicting the system throughput depending on the concurrency level, ...

· that can be instantiated on-the-fly (no a priori observation phases required), …

· easy to be re-configured when the workload profile changes, ...

and

· that does not require a “skilled” user for setting up the optimal scheduler configuration.

Target System Model

- ***N*** running threads

- each thread can execute both **transactions** or **non-transactional code (*ntc*) blocks.**

- a transaction is aborted and restarted upon conflict

- **Transaction scheduling policy:**

  - the scheduler accepts at most ***m*** (with $m \leq N$) concurrent transactions (other transactions are blocked)

  - a blocked transaction is allowed to run when another running transaction commits.

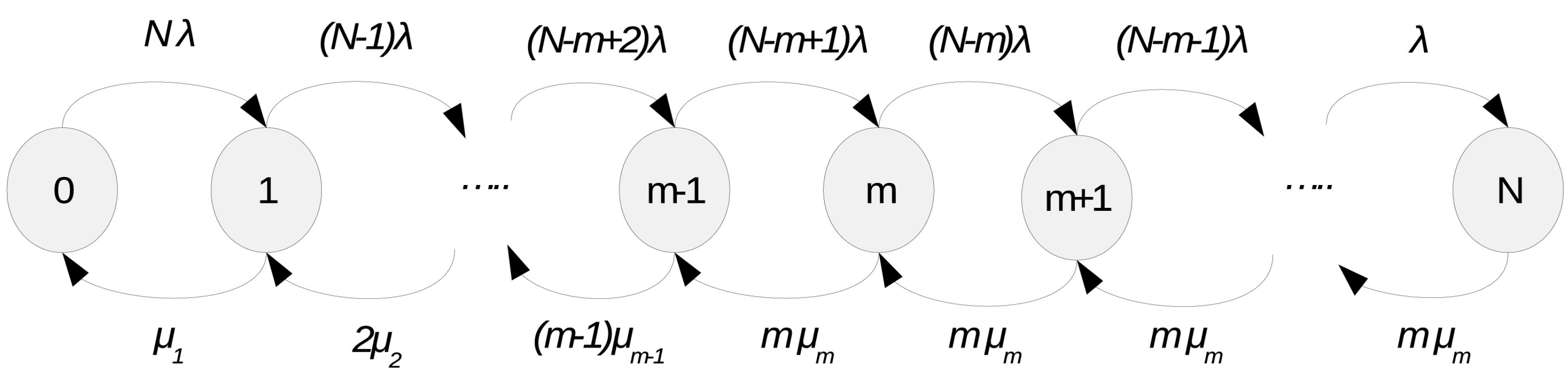
A lightweight Markov Chain-based Performance Prediction Model

Modelling the system behaviour through a set of *states* and *states transitions*

Continuous-time homogeneous Markov Chain (CTMC) with ***N*** states (finite state space)

· state ***k*** of the CTMC represents a state of the system when there are ***k*** threads executing transactions (both running or blocked transactions)

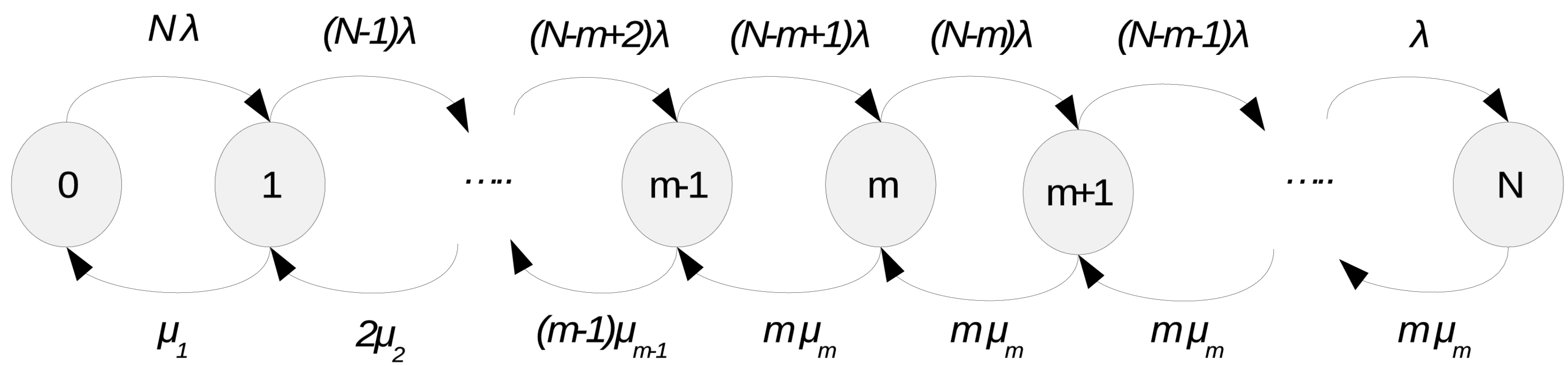
→when the system is in state ***k*** there are ***N-k*** threads executing *ntc* blocks.



A lightweight Markov Chain-based Performance Prediction Model

· A *transition* from state ***k*** to ***k+1*** occurs when a threads starts a new transaction

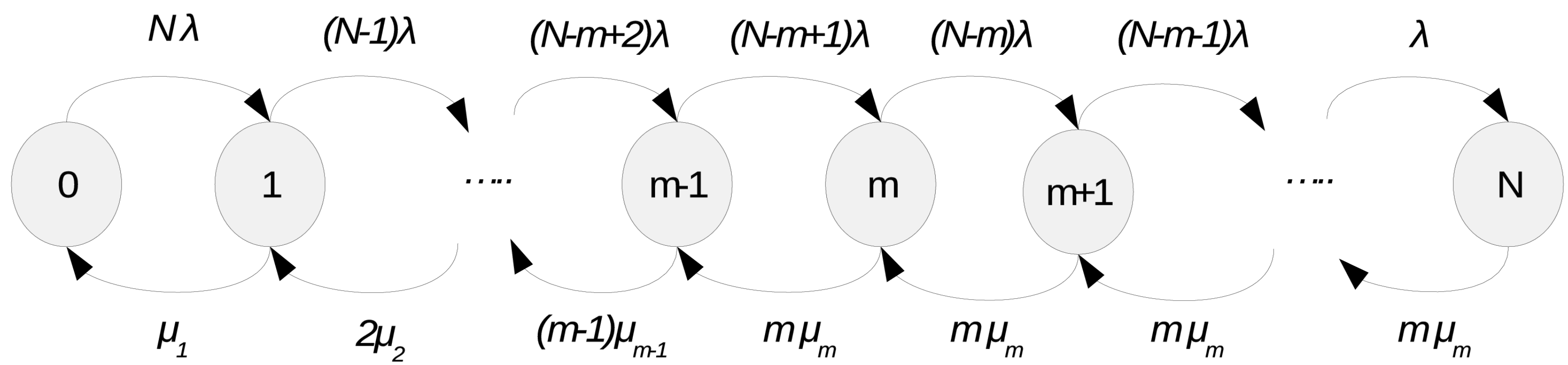
· A *transition* from state ***k*** to state ***k-1*** occurs upon the commit of whichever running transaction



A lightweight Markov Chain-based Performance Prediction Model

t$_{\textbf{ntc}}$: *average execution time* of *ntc blocks* →
inter-arrival rate of transactions along any thread $\lambda = \frac{1}{t_{ntc}}$

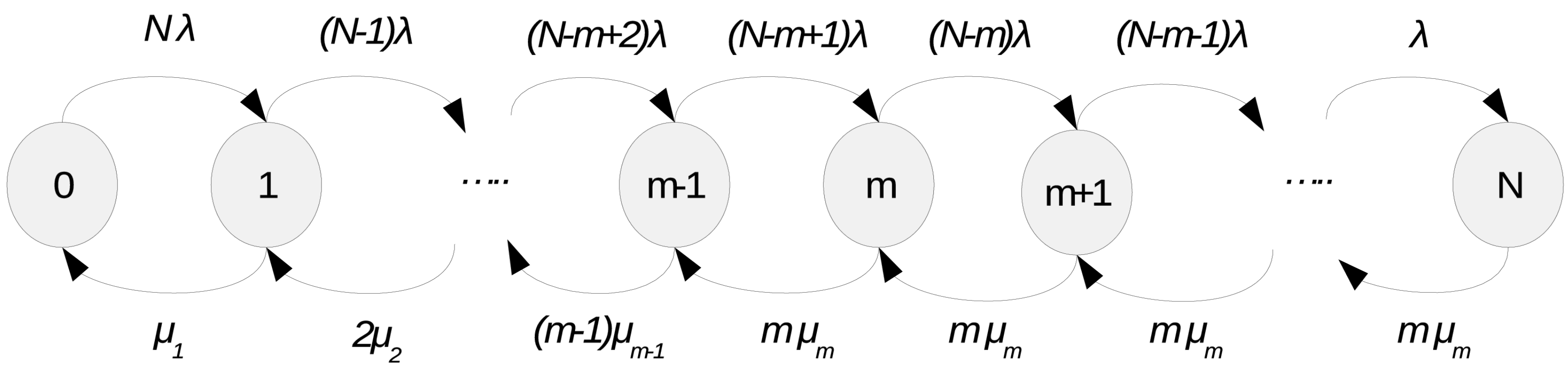
→ *transition rate* from state ***k*** to ***k+1***: $\lambda_k = (N - k) \cdot \lambda$



A lightweight Markov Chain-based Performance Prediction Model

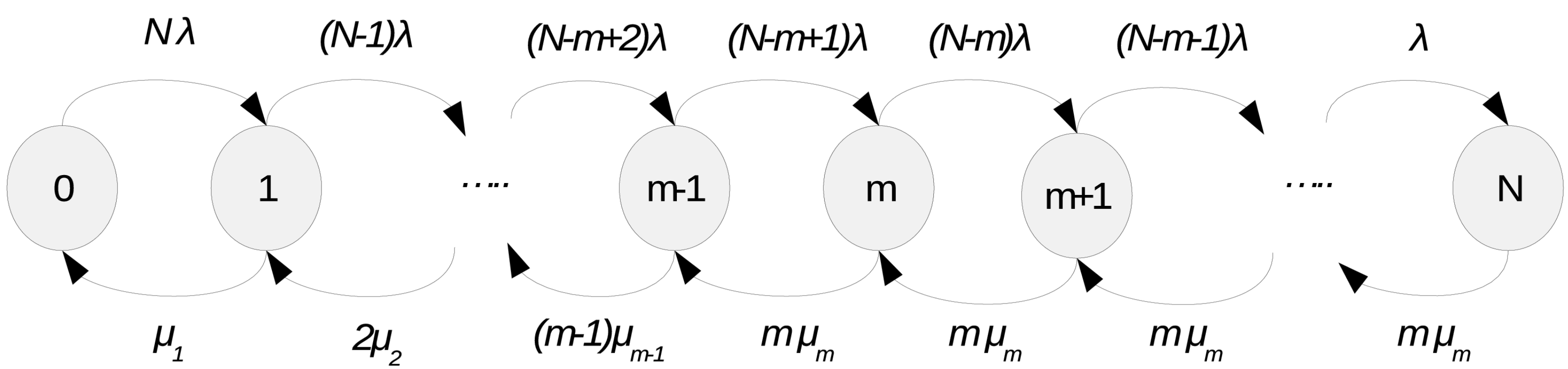
t_k: *average transaction execution time* when there are ***k*** executing transactions →

transaction execution rate of a thread for state ***k***: $\mu_k = \frac{1}{t_k}$



A lightweight Markov Chain-based Performance Prediction Model

· for any state ***k*** **≤** ***m***, since exactly ***k*** transactions are running (i.e. none is blocked), the t*ransition rate* from state ***k*** to state ***k* − *1*** is $\gamma_k = k \cdot \mu_k$



· for any state ***k*** **>** ***m***, the there are ***m*** running transactions (the other ***k* − *m*** transactions are blocked →

for all states such that ***k*** **>** ***m***, the *transition rate* from the state ***k*** to the state ***k* − *1*** is $\gamma_k = m \cdot \mu_k$

A lightweight Markov Chain-based Performance Prediction Model

Transaction execution time when the system is in state ***k***:

$$t_k = w_{t,k} + u_{t,k}.$$

Average time to execute all aborted runs (*wasted time*) of a transaction

Average time to execute the last run of a transaction (*useful time*), i.e. the run that successfully commits

$$w_{t,k} = w^r_{t,k} \cdot r_k$$

average time to execute an aborted transaction run

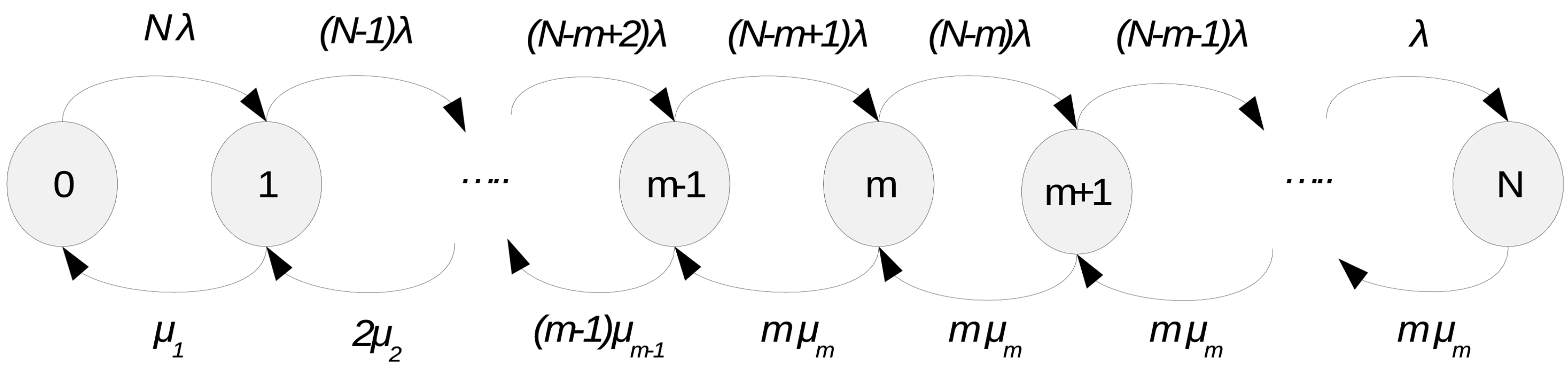
average number of aborts (or re-runs) of a transaction

$$r_k = \frac{p_k}{1 - p_k}$$

p_k : transaction abort probability for the state ***k***

A lightweight Markov Chain-based Performance Prediction Model

{q_k:0<=k<N} *stationary probability vector* of the CTMC



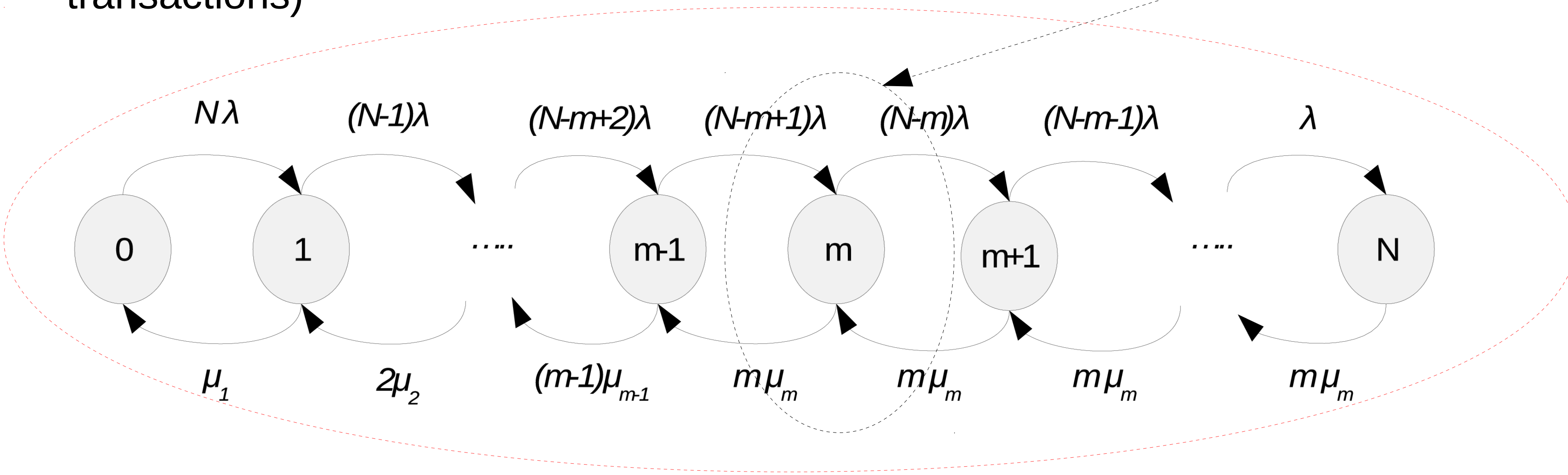
System throughput $\boldsymbol{thr_m}$ when the scheduler admits at most ***m*** running transactions:

$$thr_m = \sum_{i=1}^{N} q_k \cdot \gamma_k$$

Model Instantiation

To instantiate the model, values of parameters $u_{t,k}$, $w^r_{t,k}$, t_{ntc} and p_k have to be known.

They can be can be measured, for each ***k,*** by observing the system running with a **fixed scheduler configuration** (i.e., admitting at most ***m*** concurrent transactions)



What-if Analysis

Once above parameters have been measured, we can use the model for predicting the system throughput for **different scheduler configurations** (i.e. for different values of ***m****)*. This can be done by modifying the value of ***m*** of the CTMC and solving the model.

Experimental Evaluation: model validation with STAMP and TinySTM

Model validation

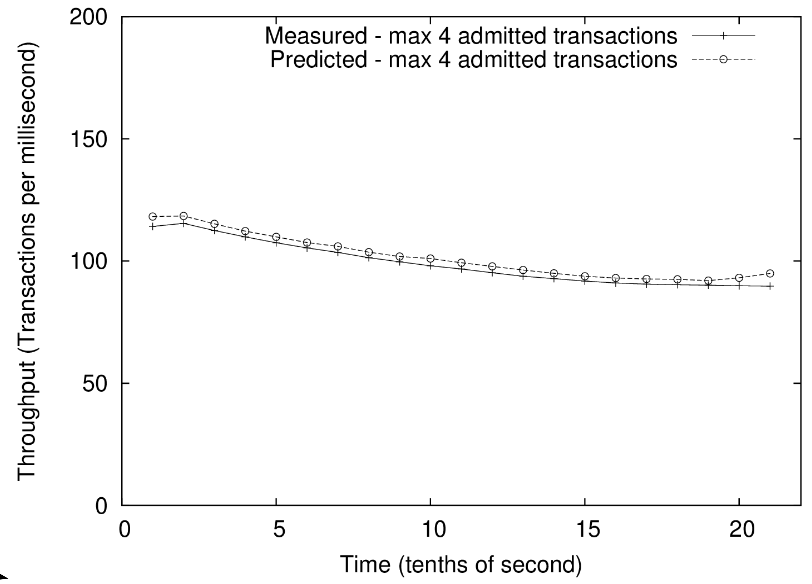
- 8 threads
- scheduler configuration: **m=4**
- observation period: 1000 executed transactions

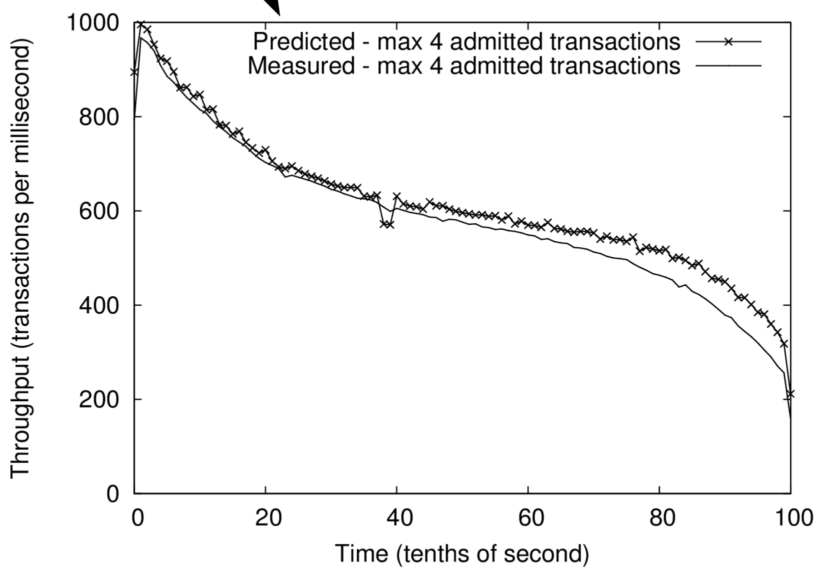
Average Relative Prediction Error:

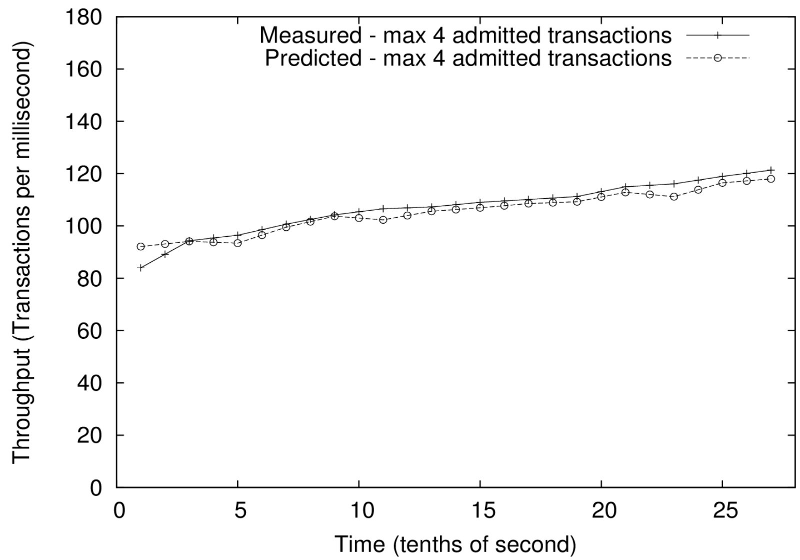
Vacation 2.7%

Yada 2.5%

Intruder: 8.9%







What-if Analysis with STAMP and TinySTM

What-if Analysis

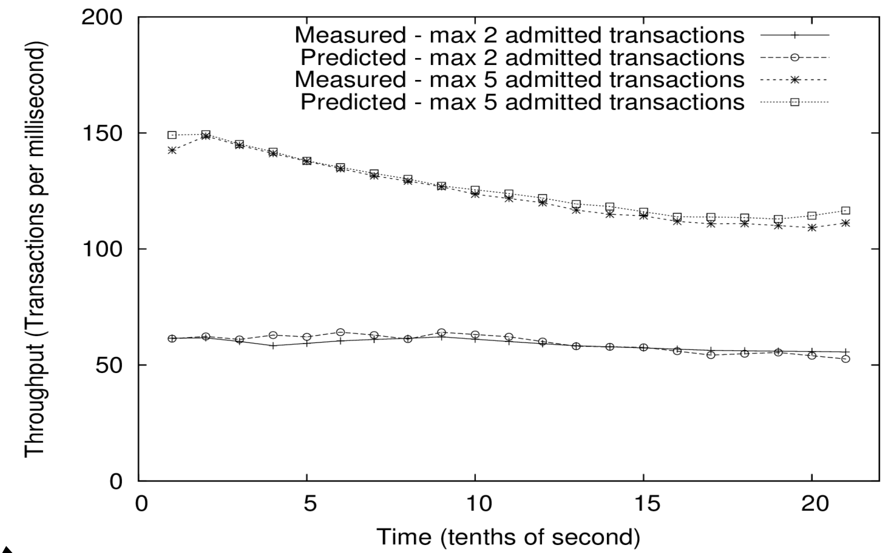
Throughput prediction for m=2 and m=5 based on system observation for m=4

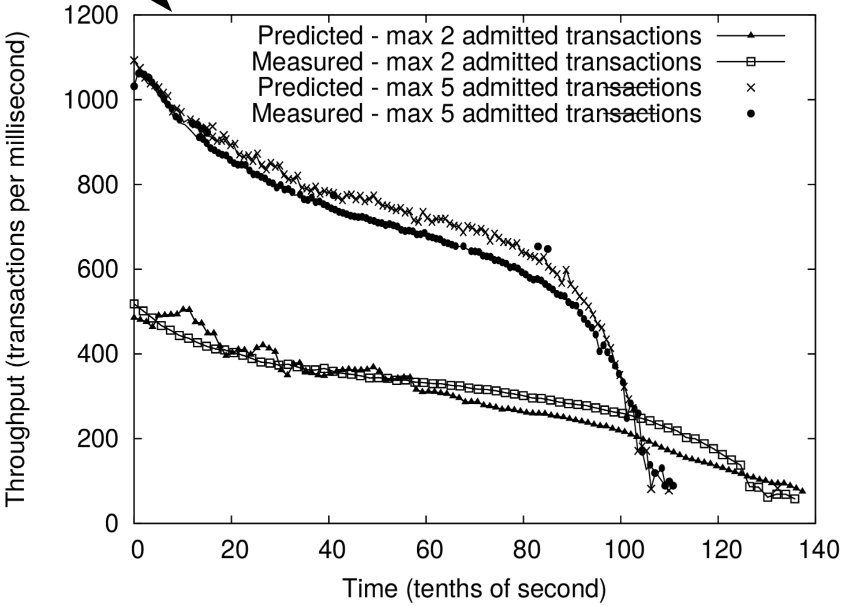
<u>Average Relative Prediction Error:</u>

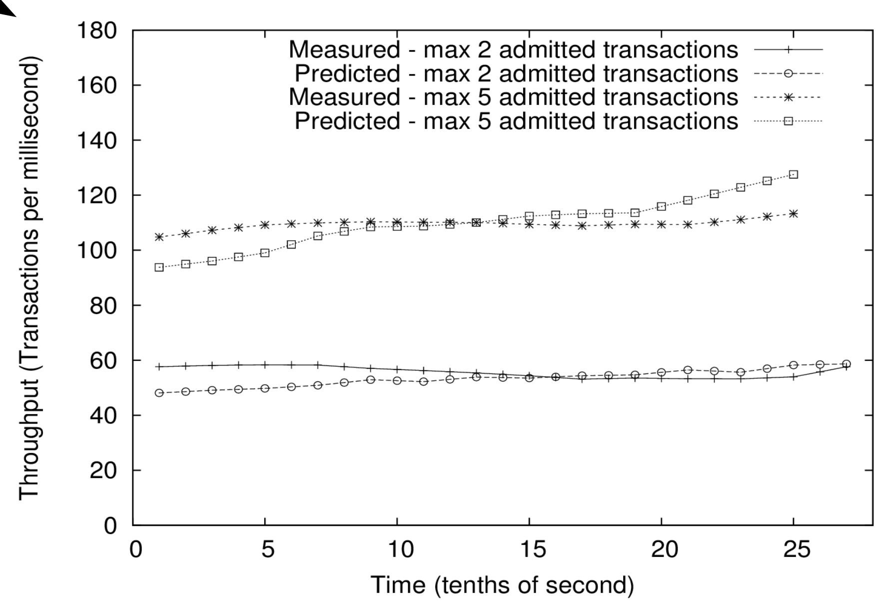
Vacation: 2.6% (m=2), 1.9% (m=5)

Yada: 7.2% (m=2), 5.9 % (m=5)

Intruder: 8.8% (m=2), 9.2% (m=5)







Thank you

References

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