# Optimization of polling systems with batch service 

Jan-Pieter Dorsman, Rob van der Mei, Erik Winands

## CWI

Centrum Wiskunde \& Informatica

11/27/2010

The polling model
A queueing system consisting of a number of queues and a single server, where there is a switch-over time when the server moves between queues.


[^0]annlications:

- Manufacturing systems
- Computer communication systems


## The polling model

A queueing system consisting of a number of queues and a single server, where there is a switch-over time when the server moves between queues.


The analysis of this kind of system is important in many real-life applications:

- Manufacturing systems
- Computer communication systems
- Traffic systems

We must decide
(1) The order in which to serve the queues;
(2) The number of customers to be served during a service period;
(0) The order in which customers within each queue are served.


We must decide
(1) The order in which to serve the queues;
(2) The number of customers to be served during a service period;
(3) The order in which customers within each queue are served.


We will limit
the analysis to the most common configuration:
(1) Cyclic service
(2) Exhaustive (server will switch iff queue is empty)
(3) First come first served

## Extended model

We consider an extended version of this model.

## Assumption

Processing time of a type-i batch is independent of its size!

## Examples:

- Oven with a fixed number of baking slots,
- Paint bath which paints several items at once.


## A trade-off arises...

The waiting time of a customer can be decomposed in two parts:

- $V_{i}$, the time a type- $i$ customer waits until its type- $i$ batch is fully accumulated,
- $W_{i}$, the time a type- $i$ customers waits in the inner system as part of a type-i batch.


We are confronted with a trade-off when choosing batch sizes. $D_{i}$ is the
size of type-i batches

- Mルーn taking $D$ small, Vi will below, but Wi will be high
- When taking $D_{i}$ large, $W_{i}$ will be low, but $V_{i}$ will be high!


## A trade-off arises...

The waiting time of a customer can be decomposed in two parts:

- $V_{i}$, the time a type- $i$ customer waits until its type- $i$ batch is fully accumulated,
- $W_{i}$, the time a type- $i$ customers waits in the inner system as part of a type-i batch.


We are confronted with a trade-off when choosing batch sizes. $D_{i}$ is the size of type-i batches:

- When taking $D_{i}$ small, $V_{i}$ will be low, but $W_{i}$ will be high!
- When taking $D_{i}$ large, $W_{i}$ will be low, but $V_{i}$ will be high!


## Problem description

## The problem at hand

How to take batch sizes $\vec{D}=\left(D_{1}, \ldots, D_{N}\right)$ such that the weighted sum of the mean total waiting times is minimized?

We need to define a cost function:

$$
C(\vec{D})=\sum_{i=1}^{N} c_{i}\left(\mathbb{E}\left[V_{i}\right]+\mathbb{E}\left[W_{i}\right]\right)
$$

Let $E_{i j}$ be the event that an arriving type- $i$ customer is the $j^{\text {th }}$ taking place in the currently accumulating type-i batch.
$\mathbb{E}\left[V_{i}\right]$ is then easily computed by using

$$
\mathbb{P}\left[E_{i j}\right]=\frac{1}{D_{i}} \text { and } \mathbb{E}\left[V_{i} \mid E_{i j}\right]=\frac{D_{i}-j}{\lambda_{i}}
$$

We end up with

$$
C(\vec{D})=\sum_{i=1}^{N} c_{i}\left(\frac{D_{i}-1}{2 \lambda_{i}}+\mathbb{E}\left[W_{i}\right]\right)
$$

## Problem description

The problem at hand

$$
\underset{\vec{D}}{\arg \min } \sum_{i=1}^{N} c_{i}\left(\frac{D_{i}-1}{2 \lambda_{i}}+\mathbb{E}\left[W_{i}\right]\right)
$$

No exact expression or even numerical method available to compute $\mathbb{E}\left[W_{i}\right]$. Two approaches possible:

- Approach 1: Use approximation by Boon et al., and approximate solution numerically,
- Approach 2: Use an even simpler approximation, $\mathbb{E}\left[W_{i, \text { app }}\right]$, and gain a closed-form approximation.


## Boon et al.

Boon, Winands, Adan and Van Wijk (2009) provide an approximation of the mean waiting time for general load:

$$
\mathbb{E}\left[W_{i, \text { Boon }}\right]=\frac{K_{0}+K_{1, i} \rho+K_{2, i} \rho^{2}}{1-\rho},
$$

where $K_{0}, K_{1, i}$ and $K_{2, i}$ are closed-form functions dependent on the polling system parameters and determined by three requirements:

Light traffic requirements:
(1) $\left.\mathbb{E}\left[W_{i, \text { Boon }}\right]\right|_{\rho=0}=\left.\mathbb{E}\left[W_{i}\right]\right|_{\rho=0}$
(2) $\left.\frac{d}{d \rho} \mathbb{E}\left[W_{i, \text { Boon }}\right]\right|_{\rho=0}=\left.\frac{d}{d \rho} \mathbb{E}\left[W_{i}\right]\right|_{\rho=0}$

Heavy traffic requirement:
(3) $\left.(1-\rho) \mathbb{E}\left[W_{i, \text { Boon }}\right]\right|_{\rho=1}=\left.(1-\rho) \mathbb{E}\left[W_{i}\right]\right|_{\rho=1}$

## Numerical Approach

Solve

$$
\underset{\vec{D}}{\arg \min } C_{\text {Boon }}(\vec{D})=\underset{\vec{D}}{\arg \min } \sum_{i=1}^{N} c_{i}\left(\frac{D_{i}-1}{2 \lambda_{i}}+\mathbb{E}\left[W_{i, \text { Boon }}\right]\right)
$$

numerically and round the obtained values.

Pro's:

- Very good performance.

Con's:

- Computation time may grow infeasibly long when the number of queues/dimensions increases.
- The numerical approach only gives limited insight in how the optimal batch sizes behave in the system's parameters.
- Implementation may be quite cumbersome.


## Closed-form approach

$\mathbb{E}\left[W_{i, \text { Boon }}\right]$ is too complex to gain a nice closed-form approximation of optimal batch sizes.
Therefore, we use a simpler approximation of $\mathbb{E}\left[W_{i}\right]$ with the form:

$$
\mathbb{E}\left[W_{i, \text { app }}\right]=\frac{a+b_{i} \rho}{1-\rho}
$$

Coefficients $a$ and $b_{i}$ are determined by two requirements:

- LT: $\left.\mathbb{E}\left[W_{i, \text { app }}\right]\right|_{\rho=0}=\left.\mathbb{E}\left[W_{i}\right]\right|_{\rho=0}$
- $\mathrm{HT}:\left.(1-\rho) \mathbb{E}\left[W_{i, \text { app }}\right]\right|_{\rho=1}=\left.(1-\rho) \mathbb{E}\left[W_{i, \text { simplification }}\right]\right|_{\rho=1}$

We end up with the following approximative cost function

$$
C_{a p p}(\vec{D})=\sum_{i=1}^{N} c_{i}\left(\frac{D_{i}-1}{2 \lambda_{i}}+\mathbb{E}\left[W_{i, a p p}\right]\right)
$$

## Closed-form approach

Solve

$$
\underset{\vec{D}}{\arg \min } C_{a p p}(\vec{D})=\underset{\vec{D}}{\arg \min } \sum_{i=1}^{N} c_{i}\left(\frac{D_{i}-1}{2 \lambda_{i}}+\mathbb{E}\left[W_{i, a p p}\right]\right)
$$

with ordinary calculus.

- The one-dimensional case is easily solved.
- For the multi-dimensional case, the system of equations $\frac{d}{d D_{i}} C_{a p p}(\vec{D})=0 \forall i$ does not result in nice expressions.


## Closed-form approach

Solve

$$
\underset{\vec{D}}{\arg \min } C_{a p p}(\vec{D})=\underset{\vec{D}}{\arg \min } \sum_{i=1}^{N} c_{i}\left(\frac{D_{i}-1}{2 \lambda_{i}}+\mathbb{E}\left[W_{i, a p p}\right]\right)
$$

with ordinary calculus.

- The one-dimensional case is easily solved.
- For the multi-dimensional case, the system of equations $\frac{d}{d D_{i}} C_{a p p}(\vec{D})=0 \forall i$ does not result in nice expressions.

Work-around: reduce multi-dimensional problem to a one-dimensional problem by a priori assuming ratios between optimal batch sizes.

## Closed-form approach

The problem at hand

$$
\underset{\vec{D}}{\arg \min } C_{\text {app }}(\vec{D})=\underset{\vec{D}}{\arg \min } \sum_{i=1}^{N} c_{i}\left(\frac{D_{i}-1}{2 \lambda_{i}}+\mathbb{E}\left[W_{i, \text { app }}\right]\right) .
$$

As batch sizes increase, the load of the inner system drops rapidly, hence $\mathbb{E}\left[W_{i, \text { app }}\right]$ will be near-insensitive to the batch sizes.

## Closed-form approach

The problem at hand

$$
\underset{\vec{D}}{\arg \min } C_{\text {app }}(\vec{D})=\underset{\vec{D}}{\arg \min } \sum_{i=1}^{N} c_{i}\left(\frac{D_{i}-1}{2 \lambda_{i}}+\mathbb{E}\left[W_{i, \text { app }}\right]\right) .
$$

As batch sizes increase, the load of the inner system drops rapidly, hence $\mathbb{E}\left[W_{i, \text { app }}\right]$ will be near-insensitive to the batch sizes.

The ratios of the optimal variables of the following problem can be determined:

$$
\underset{\vec{D}}{\arg \inf } C_{\text {app }}(\vec{D})=\underset{\vec{D}}{\arg \inf } \sum_{i=1}^{N} c_{i} \frac{D_{i}-1}{2 \lambda_{i}} .
$$

I.e., the numbers $d_{2}=\frac{D_{2}^{\text {opt }}}{D_{1}^{\text {ot }}}, \ldots, d_{N}=\frac{D_{N}^{\text {ott }}}{D_{1}^{\text {ott }}}$ are known here:

$$
d_{i}=\frac{\lambda_{i}}{\lambda_{1}} \sqrt{\frac{c_{1} \mathbb{E}\left[B_{i}\right]}{c_{i} \mathbb{E}\left[B_{1}\right]}}
$$

## Closed-form approach

The problem at hand

$$
\underset{\vec{D}}{\arg \min } C_{\text {app }}(\vec{D})=\underset{\vec{D}}{\arg \min } \sum_{i=1}^{N} c_{i}\left(\frac{D_{i}-1}{2 \lambda_{i}}+\mathbb{E}\left[W_{i, \text { app }}\right]\right) .
$$

As batch sizes increase, the load of the inner system drops rapidly, hence $\mathbb{E}\left[W_{i, \text { app }}\right]$ will be near-insensitive to the batch sizes.

The ratios of the optimal variables of the following problem can be determined:

$$
\underset{\vec{D}}{\arg \inf } C_{\text {app }}(\vec{D})=\underset{\vec{D}}{\arg \inf } \sum_{i=1}^{N} c_{i} \frac{D_{i}-1}{2 \lambda_{i}} .
$$

I.e., the numbers $d_{2}=\frac{D_{2}^{\text {opt }}}{D_{1}^{\text {ot }}}, \ldots, d_{N}=\frac{D_{N}^{\text {ott }}}{D_{1}^{\text {ott }}}$ are known here:

$$
d_{i}=\frac{\lambda_{i}}{\lambda_{1}} \sqrt{\frac{c_{1} \mathbb{E}\left[B_{i}\right]}{c_{i} \mathbb{E}\left[B_{1}\right]}}
$$

## Closed-form approach

Back to our problem, we write $D_{1}^{\text {opt }}=E, D_{2}^{\text {opt }}=d_{2} E, \ldots, D_{N}^{\text {opt }}=d_{N} E$ with the $d_{i}$ as found in the simple problem. Only optimization in $E$ is needed:

$$
E_{a p p}^{\text {opt }}=\sum_{i=1}^{N} \frac{\lambda_{i} \mathbb{E}\left[B_{i}\right]}{d_{i}}+\sqrt{2\left(\sum_{i=1}^{N} \frac{c_{i} d_{i}}{\lambda_{i}}\right)^{-1}\left(\sum_{i=1}^{N} c_{i} \omega_{i, a p p}\right)\left(\sum_{i=1}^{N} \frac{\lambda_{i} \mathbb{E}\left[B_{i}\right]}{d_{i}}\right)} .
$$

Going back to optimal batch sizes by multiplying with the $d_{i}$, we have:

$$
\begin{aligned}
\vec{D}_{\text {app }}^{\text {opt }} & =\left(D_{1, a p p}^{\text {opt }}, D_{2, a p p}^{\text {opt }}, \ldots, D_{N, a p p}^{\text {opt }}\right) \\
& =\left(E_{a p p}^{\text {opt }}, \frac{\lambda_{2}}{\lambda_{1}} \sqrt{\left.\frac{c_{1} \mathbb{E}\left[B_{2}\right]}{c_{2} \mathbb{E}\left[B_{1}\right]} E_{a p p}^{o p t}, \ldots, \frac{\lambda_{N}}{\lambda_{1}} \sqrt{\frac{c_{1} \mathbb{E}\left[B_{N}\right]}{c_{N} \mathbb{E}\left[B_{1}\right]}} E_{a p p}^{\text {opt }}\right) .} .\right.
\end{aligned}
$$

Proper rounding of these values gives a nicely defined and well-performing closed-form approximation.

## Closed-form approach

The obtained closed-form approximation...
Pro's:

- Performs increasingly well when the number of queues or switch-over times get larger,
- Is easily implemented and requires virtually no computation time,
- Gives insights in the dependency of the optimal batch sizes on the systems parameters.

Con's:

- Performs not as well as the numerical approach in case of small numbers of queues or small switch-over times. Complementary effect!

Validation by means of simulation, based on testbeds of symmetric and asymmetric systems, with a total of 1260 systems.

Differences expressed relatively in terms of costs in \%.
Overall:

| Test bed | Numerical | Closed-form |
| :---: | :---: | :---: |
| Symmetric | 0.303 | 1.624 |
| Asymmetric | 0.645 | 4.848 |

Categorized in the number of queues:

| Test bed | $N=2$ |  | $N=5$ |  |
| :---: | :---: | :---: | :---: | :---: |
|  | Numerical | Closed-form | Numerical | Closed-form |
| Symmetric | 0.428 | 2.776 | 0.178 | 0.471 |
| Asymmetric | 0.870 | 7.715 | 0.419 | 1.981 |

The current analysis may be extended in multiple directions:

- Optimization based on higher moments and tail probabilities,
- Model variations: non-cyclic routing, other service disciplines, size-dependent service requirements, introduction of the possibility to idle, etc.
- Rounding strategy of the fractional $D_{i}$-values.


[^0]:    The analysis of this kind of system is important in many real-life

