Segmentation of EGEE Workload Measurements by Piecewise Autoregressive Model

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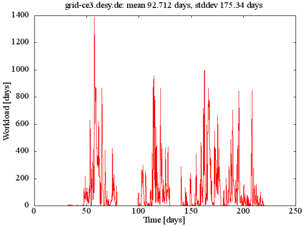
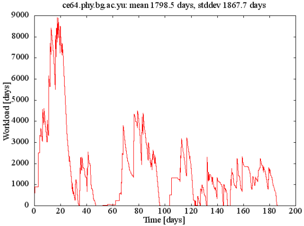
Why to segment?

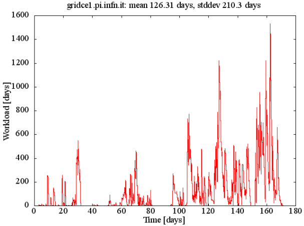
- In inductive inference, some kind of stationarity is often needed;
  - the “behaviour” of the system does not change over time.
- This is usually not true in practise: hourly/daily/weekly fluctuation, holidays, timing of projects, conferences, other events.
- Traditional methods of achieving stationarity
  - remove trends, seasonality,
  - possibly non-linear transformations (e.g. logarithm).
- Most of these methods are based on underlying expectations, earlier experiences.
- Our case: no expectations, no earlier experience.
  - Breaking the data into segments seems to be the best way to cope with possible non-stationarity.

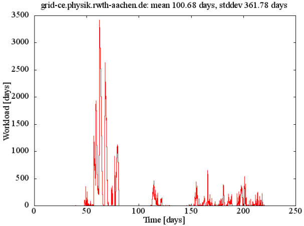
The workload series of a CE

- The workload of a CE is the total unfinished running time of jobs in its system.
- 4 examples with quite different behaviours: ratios of mean vs. scale of data; long term trends; “smoothness”.









A few details on the measurements

- The measurement data were collected from the Real Time Monitor published by the Grid Observatory.
- Time-period of the data collection: 2008 W34 – 2009 W13
- 6 fields were extracted from the raw text data
  - Name of CE; Userinterface_regjob_Epoch; logmonitor_accepted_Epoch; logmonitor_running_Epoch; logmonitor_done_Epoch; Worker Node Time
- Standard text parsing tools were used in the preliminary processing (e.g. grep, sed, gawk).
- The data was cleaned in the pre-processing
  - Those jobs were kept where all the important timestamps (e.g.: accept, start, done) were available.
  - The present analysis contains jobs whose total running time (done - start) was less than one day.

The MDL Principle

- MDL - Minimum Description Length
- Basic idea – find “regularity” in the data
  - ability to compress using some assumptions,
  - the assumptions are described as statistical models.
- Several competing assumptions (models): the one giving the best compression performance is selected.
- Use of the MDL principle
  - hypothesis selection, model selection,
  - prediction,
  - denoising,
  - similarity analysis and clustering,
  - etc.

The autoregressive model

- Popular modelling technique used for
  - prediction in statistics and signal processing,
  - capturing the correlation pattern of a time series.
- The autoregressive (AR) relation:

$$X_t = \gamma + \phi_1 X_{t-1} + \ldots + \phi_p X_{t-p} + \epsilon_t, \text{ where}$$

- X_t is the value of the random series at time t,
- γ represents the average level of the process,
- $\phi_k,\ k = 1, \ldots, p$ are the coefficients and
- ϵ_t is the noise term (e.g. Gaussian) at time t.

The Piecewise AR Model

- The statistical models assume constant environment, but in practise this is not at all the case.
- We don't know about the nature of the change in the workload of a CE (it can be the average, variation around the average or even subtle differences in the correlation structure).
- How to find these unknown changes?
  - Break the time series into segments with different autoregressive models – this is the piecewise autoregressive model.
- Flexible model selection: we can capture any of the changes mentioned above.
- Our main interests are the number and locations of the break points.

The Piecewise AR Model - Example

- Segment 1, $0 < t \leq 512$:

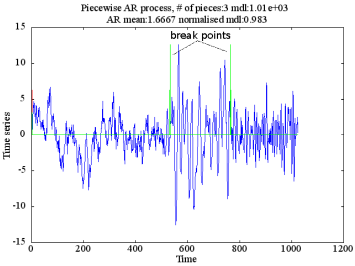
$$X_t = 0.9X_{t-1} + \epsilon_t$$

- Segment 2, $512 < t \leq 768$:

$$X_t = 1.69X_{t-1} - 0.81X_{t-2} + \epsilon_t$$

- Segment 3, $768 < t \leq 1024$:

$$X_t = 1.32X_{t-1} - 0.81X_{t-2} + \epsilon_t$$



- The error term ϵ_t, $0 < t \leq 1024$ is independent Gaussian with mean 0 and variance 1 ($\epsilon_t \sim N(0, 1)$ i.i.d.).

Fitting a piecewise AR model

- The work is based on the paper of Davis, R.A., Lee, T. and Rodriguez-Yam, G., *Structural Break Estimation for Nonstationary Time Series Models*, J. American Statist. Assoc. 101, 229-239, 2006.
- Given a workload series "W_t", a number of piecewise AR models F were used for the compression of "W_t"
- Two part code MDL:
  - code length for the model parameters "$CL_1(F)$",
  - code length for series using the model "$CL_2(W_t|F)$",
  - the code length estimation including the two parts is

$$CL = \log m + (m+1)\log n + \sum_{j=1}^{m+1} \log p_j + \frac{p_j+2}{2}\log n_j + \frac{n_j}{2}\log(2\pi\hat{\sigma}_j^2).$$

- The piecewise AR model F was selected that gives the shortest code length estimate.

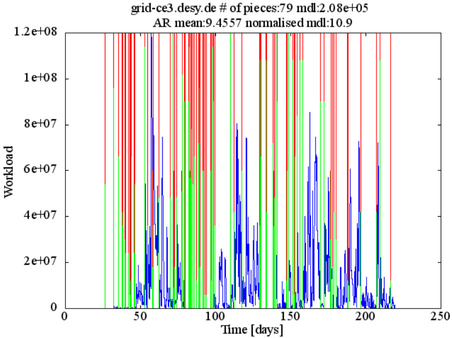
Segmentation example - workload

- The best fitting piecewise AR model was searched for by optimising the codelength function estimation.
- The optimisation was performed by a genetic algorithm proposed by Davis et al.
- The statistical quality of the best fitting model was analysed by several ways, for example:
    - whiteness of the residuals: Ljung-Box test and Dufour-Roy test,
    - stationarity of the AR model: Phillips-Perron test (unit root).
- Results for longer segments in the examples:

name of the CE	no. of segment	segment start [days]	segment end [days]	smallest root abs. value	unit-root test (p-value)	Ljung-Box test (p-value)
grid-ce3.desy.de	33	118.6	130.0	1.0421	0.25	0.03
ce64.phy.bg.ac.yu	13	13.2	22.0	1.0443	0.40	<0.01
gridce1.pi.infn.it	67	119.7	145.9	1.0083	0.32	<0.01
grid-ce.physik.rwth-aachen.de	26	56.9	64.3	1.0223	0.90	0.09

Conclusions on the piecewise AR fit

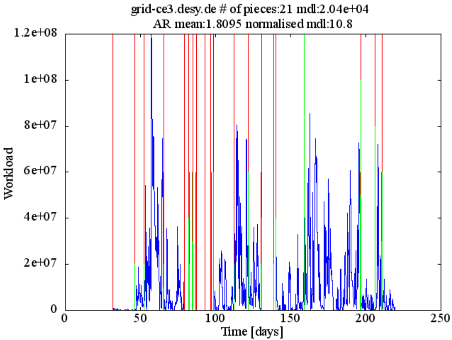
- 79 break points
- Average AR order above 9
- Only a few long segments
- The fitted AR models were “ill conditioned”.



- The piecewise AR model does not seem to explain the workload series well. Main reason is, that there are local trends in the workload.

Segmentation example – workload difference

- Smoothed workload difference
- 21 break points
- Average AR order below 2
- Longer segments
- "Nice" AR fit



name of the CE	no. of segment	segment start [days]	segment end [days]	smallest root abs. value	unit-root test (p-value)	Ljung-Box test on residuals (p-value)
grid-ce3.desy.de	18	158.91	196.53	1.5915	<0.01	0.05
ce64.phy.bg.ac.yu	19	109.61	160.65	2.1563	<0.01	0.04
gridce1.pi.infn.it	17	104.86	149.31	5.5711	<0.01	0.21
grid-ce.physik.rwth-aachen.de	27	151.39	190.16	1.1062	<0.01	0.05

Limitations of the method

- Two main limitations with the current implementation:
  - The objective function is not reliable for models where the segments are usually short – longer segments are preferred.
  - The optimisation is based on a genetic algorithm. The time of convergence is highly sensitive to the length of the data set.
- Possible improvements:
  - better objective function – in MDL theory, the Normalised Maximum-Likelihood codes have better properties (e.g. in consistency) than two part codes,
  - better optimisation method – more efficient chromosome representation; the optimisation problem can also be highly simplified.

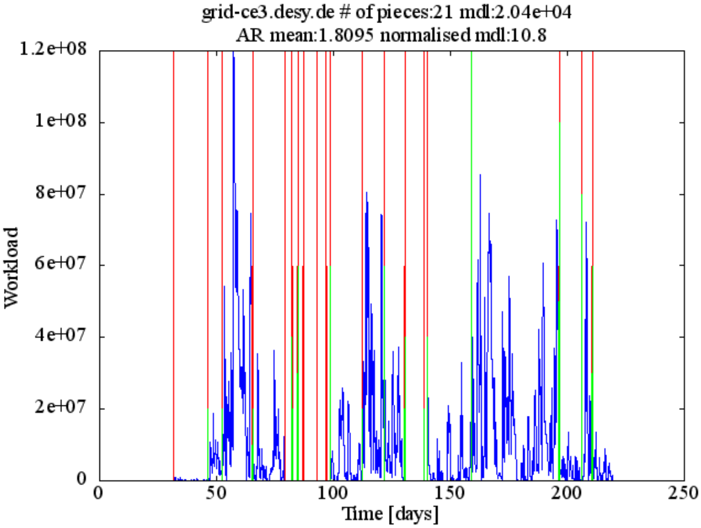
Conclusions and future work

- A flexible method based on the MDL principle and piecewise AR model was applied to detect break points in EGEE workload measurements made by the Grid Observatory.
- It was shown, that the workload process contains strong local trends. However, the workload difference can be used for segmentation.
- Besides the planned improvements regarding the reliability and computational complexity of the method, other time series models (e.g. ARMA or GARCH) will be added to the method.
- Using our results, an automated software tool detecting changes and/or predicting the CE activity can be designed for the EGEE system management.

Appendix: Some measurement details

Name of CEs	Total workload [years]	Number of jobs	10 percentile of workload process [days]	50 percentile of workload process [days]	100 percentile of workload process [days]
grid-ce3.desy.de	151.4	551K	0	10	303
ce64.phy.bg.ac.yu	103.8	87K	16	1331	3999
gridce1.pi.infn.it	81.9	205K	0	26	408
grid-ce.physik.rwth-aachen.de	58.4	336K	0	0.20	203
ce00.hep.ph.ic.ac.uk	51.6	184K	0	2.8	150
ce.cyf-kr.edu.pl	49.1	155K	0	0.6	87
ce05-lcg.cr.cnaf.infn.it	44.7	209K	0	0	73
ce06-lcg.cr.cnaf.infn.it	44.6	217K	0	0.1	78
ce04-lcg.cr.cnaf.infn.it	42.9	132K	0	3.6	83
gridce2.pi.infn.it	38.3	125K	0	0	0

Appendix: Workload segmentation



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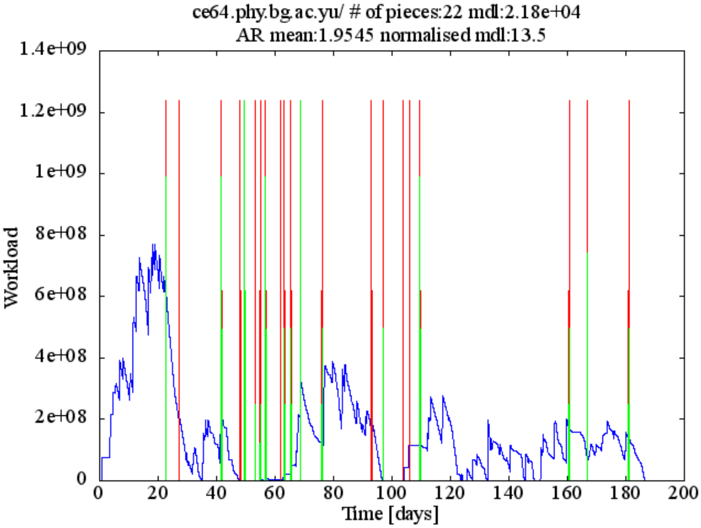

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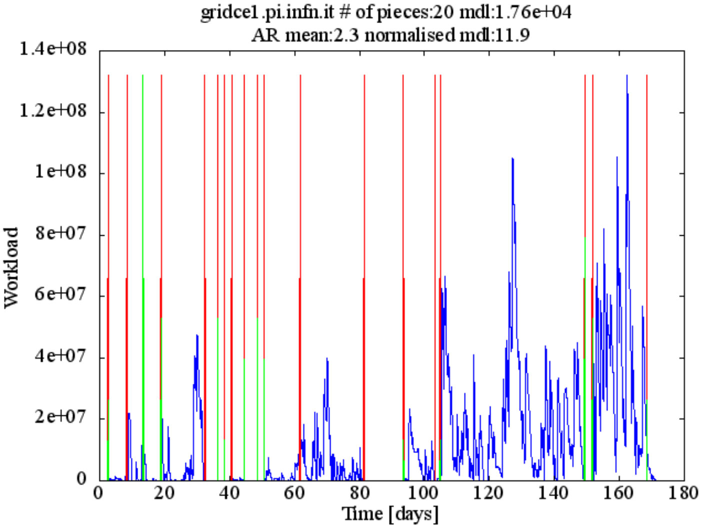

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