



## Improving efficiency of analysis jobs in CMS

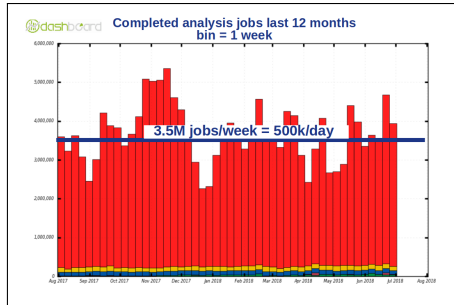
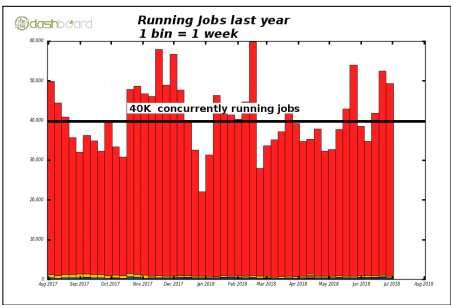
Todor Ivanov for the CMS collaboration

July 4, 2019



## Introduction

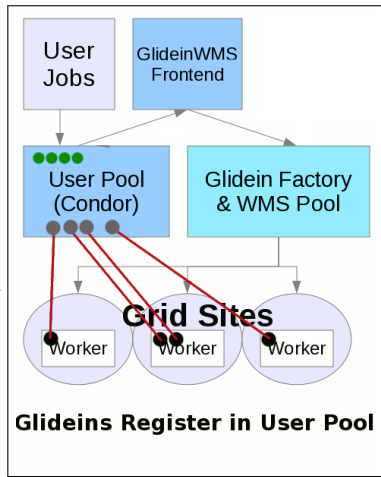
- CMS experiment has a workload management system that schedules and executes data processing, simulation and user Analysis tasks in a distributed Grid infrastructure.
- **Past focus** : make jobs run, offer users **painless and transparent** access to the Grid. We have been largely successful.
- **Recent focus:** on **efficiency and optimisation:** turnaround time, CPU efficiency, scalability of the system.
- **This contribution:**
  - improving the execution of analysis jobs. I.e. job submitted by users (few hundred different people using the system at any given time)
  - thus **w/o access** to the application itself





## Global Pool & glideinWMS

- Based on glideinWms:
  - Users:** Vanilla HTCondor jobs via **ad hoc tools** : **WMA** for production, **CRAB** for analysis
  - Glidein FrontEnd:** glideins (**PilotJobs**) → Grid Sites
  - PilotJobs:** **48 hours; 8 cores;**
  - 1 PilotJob** → **1 HTCondor startd** which joins the *GlobalPool*
  - 1 PilotJob** runs **many multi/single-core jobs** and keeps reallocating freed up cores until the end of its lifetime
- CMS takes ownership** of all issues of pool **fragmentation** due to running variable number of multi/single-core jobs of different length



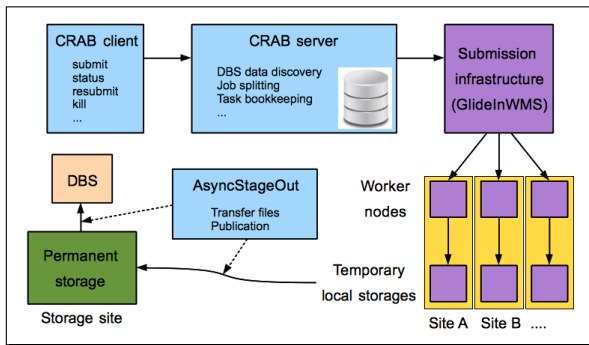


## Analysis jobs submission: CRAB

- **CMS Remote Analysis Builder (CRAB):**

- Turns a high level request (*run this executable on this set of files*) into a set of jobs whose execution is controlled by HTCondor DAGMAN
- Later an *Asynchronous StageOut* component moves job outputs from remote site storage to the user preferred site
  - Optionally record the files in CMS *Dataset Bookkeeping System*

- **Splitting:** 1 request (task) → many jobs





## Three lines of work

- **Automatic Splitting**
  - Optimise **job running time** (splitting a large task in many jobs)
    - *Too long*: High chance of killing by glitch → wasted resource
    - *Too short*: Too many jobs, unnecessary load on infrastructure, too much time in overheads
- **Time Tuning**
  - Optimise **job to pilot slot allocation** (tune the job time requirement)
    - Avoid killing/restarting pilots too soon, exploit the tail of each slot
    - Majority of jobs ask for 20h but only run 30min or less, how close to the pilot end of life is OK to start them ?
- **Overflow**
  - Optimise **scheduling of jobs across sites** (overflow from busy site queues)
    - We used to run where data are
    - We can now exploit **xrootd** to run also at other sites
    - But can't fully ignore where data are



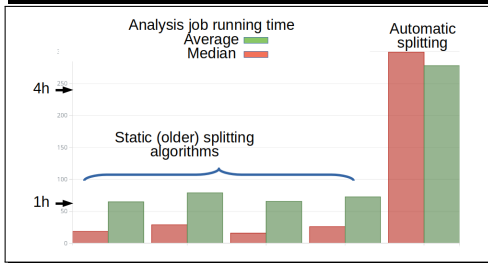
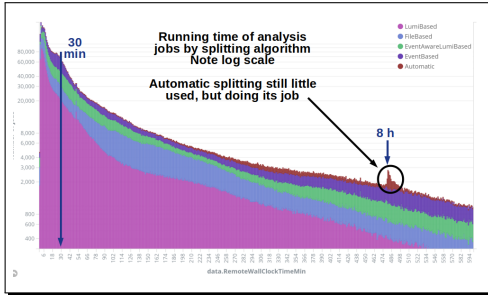


## Automating Splitting: Practice

- **Before:** 1 task  $\rightarrow$  1 DAG
  - **Good:** Splitting done in the TaskWorker (**one server**, centralized logs, **easy to debug**)
  - **Bad:** User finds best splitting by trial and error running same things **N times (invisible waste)**
  - **Overall:** Non optimal, but when things go wrong we blame the user and life goes on
- **After:** 1 task  $\rightarrow$  a few DAG's
  - **Good:** **It really works**
  - **Bad:** Splitting done on the schedd (**15 machines**, log scattered in user directories, hard to rerun in debug mode).
  - **Hard part:** **Not all use cases** can be addressed, e.g. for MonteCarlo generation there is no splitting.
  - **Overall:**
    - When things go wrong, it is on us to explain, solve and prevent
    - Large variation of WN CPU power and data serving performance at sites introduces large uncertainty in jobs run times. Leads directly to the need for Time Tuning (next slides).



## Automating Splitting: Results



- In production since February 2018.
- Users encouraged but not pushed.
- Few issues, generally high satisfaction.
- Extending usage requires education campaign: manpower issue.
  - Next step once all commissioning work is completed.
- **Current adoption is 2%**



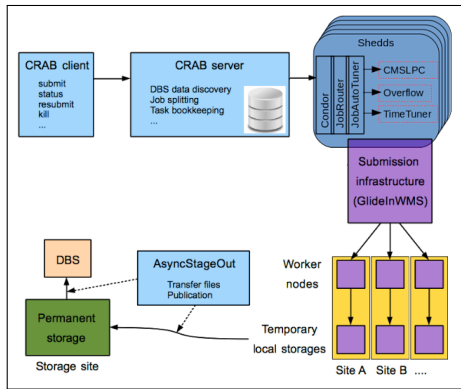


## Automating Tuning and CRAB3:

### Editing job requirements: HTCondor JobRouter

Both following lines of work (Time Tuning and Overflow) rely on modifying job requirements while jobs are idle in the HTCondor queue → different scheduling → freedom to optimise.

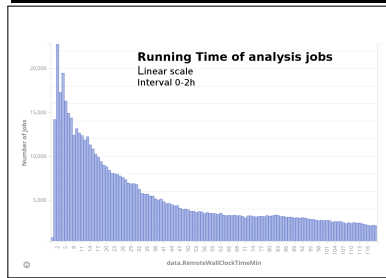
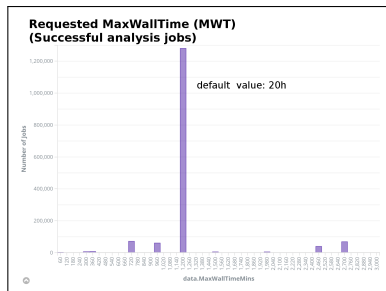
- **There's a tension:**
  - **Global overview** (best decisions) vs **Local action** in each schedd (efficient).
- **And there's a criticality:**
  - **Spiral of Death:**  
Massive condor\_qedit ⇒ schedd load ⇒ long negotiator time ⇒ starving pilots ⇒ job restarts ⇒ more load on the schedds
- **Our solution:**
  - A central process to collect information and make **stats based on a feed of HTC classAds to Elastic Search**.
  - HTCondor **JobRouter** to do the actual classAd remapping locally to each schedd
  - Strategy already in use for organized Production, but **larger workflows** and much more **top/down control**
- **Slow feedback** → care in turning knobs
  - $O(10min)$  in what we do -  $O(hours)$  in HTCondor reaction





## Time Tuning: Theory

- Jobs request a **MaxWallTime (MWT)** at submission. HTCondor kills jobs which hit it.
  - MWT is a common classAd attribute for all jobs in a task.
- Problem:** Majority of jobs ask for the **default 20h** MWT but most only run **30min** or less
  - This is not because users are nasty
    - Even if jobs are created equal, they run for different times
    - Even good willing users need to indicate a large, safe, value
  - Automatic splitting will help, but not all tasks will use it:
    - Set a realistic limit for PROCESSING DAG
    - Jobs which run longer are resplitted so that a safe maxTime can be set which still is  $O(hour)$
- Approach: Introduce EstimatedWallTime (EWT).**
  - Use EWT to schedule, MWT to kill
  - EWT : realistic, MWT: conservative.  
EWT  $\ll$  MWT





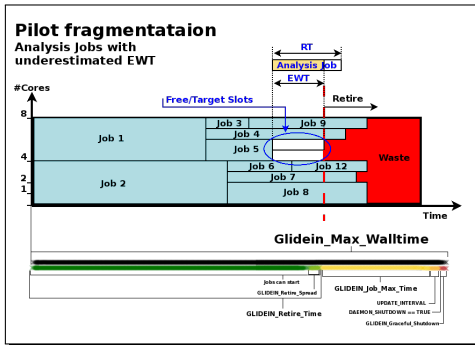
## Time Tuning: Practice

### ● Implemented solution:

- EWT computed **as soon as one job completes** and dynamically updated every 10 min
- EWT estimate algorithm tuned to contain most but not all jobs:
  - Pick **95th percentile** of collected RunTimes and apply **correction** dependent on **#jobs**
- EWT added and updated in each job via JobRouter.
- Jobs can **keep running** in the pilot's **tail** (the pilot's retire time) even after EWT expires, up to MWT
- If a job reach a pilot's **end of life-time** it is automatically and transparently **restarted** by HTCondor (but CPU is wasted)

### ● Issues to overcome:

- Limited statistics to work with, first jobs to complete may be **not representative**
  - This is a bullet that we have to bite
- Properly measure what we gain (**less fragmentation**) and what we lose (**wasted CPU**)





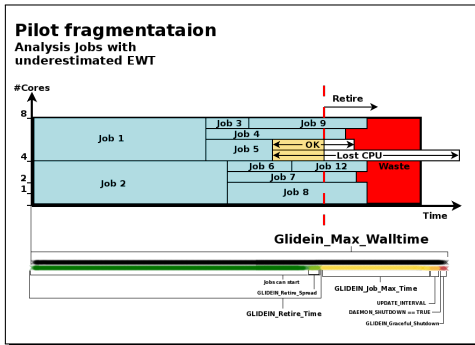
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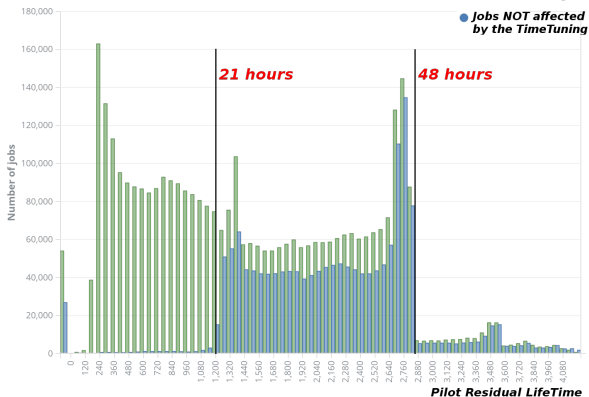


## Time Tuning: Results

### CONSERVATIVE SETUP:

JOBS running less than EWT:	95%
JOBS running longer but completed:	4%
JOBS restarted once and completed:	1%

**Pilot occupancy** - Number of jobs occupying a pilot aggregated per Pilot Residual Lifetime



### STILL VERY EFFECTIVE:

- Jobs which were TimeTuned filled mostly short living pilots
- Jobs which were not TimeTuned filled pilots longer than 21 hours



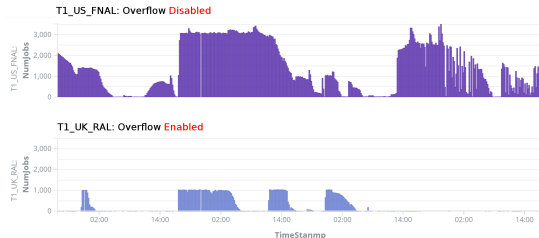
## Overflow: Why, What, How

- **Problem:** By default jobs are sent to sites which hosts the input data  $\implies$  **long waiting times** when target sites are overloaded.
- **Solution:** run some of those jobs elsewhere. CMS software exploits our **xrootd data federation** for remote reads
- **Old Way** *ad hoc* **glideinWms FrontEnd group** to define topology and running limits. Deployed for US sites since a few years. **Works, but can't extend it:**
  - US sites large and homogeneous. Dedicated pilots  $\rightarrow$  pool fragmentation. glideinWms suffers with many FrontEnd groups
- **New Way:** JobRouter **dynamically changes list of desired execution sites** for some jobs
  - Central overview opens to advanced **scheduling decisions** :e.g. add WAN information
- **Difficulties:**
  - will an overflow job complete earlier ? how much wait is too much wait ?
  - how much (more) remote reading a given site can handle ?
  - more remote reads = more, harder to debug, failures
  - if there are failures, are our remote reads the reason ?
  - large differences in site size and connectivity
  - need to go over country boundaries
- **Approach:** **Start slowly, watch carefully, push slowly, iterate.**
  - Users stand "wait but OK" better than "fail and need to retry"
  - Site admins do not like more problems and expect us to have extreme care



## Overflow: Results

### Idle analysis jobs per T1 Site



- **Current use limited to T1s:**
  - Facing the Tier1 problem is Critical for us. Analysis jobs get a small share in T1s. But there are datasets that are currently placed only at T1
- **Work in progress:**
  - Implementing a maximum overflow in a country and providing a way to substitute the old Overflow



## Summary

- We operate a complex setup with  $O(40k)$  analysis jobs running at any moment and where many things change constantly outside CMS Analysis Operation control.
- We have to be careful. It is NOT easy to push changes in production transparently to the user community nor to disentangle effect of the various changes.
- And that while our monitoring infrastructure is being migrated/rebuilt.

**But we managed to deploy** the needed knobs and dials and we look forward to learn how to better tune the system.





## Future lines of work

- Some of what we do requires guessing what users really need
  - Inferring the behaviour and needs of large tasks from small initial samples
  - Very tricky when we have many tasks with not many ( $< 100$ ) jobs each
- Some requires guessing the future
  - How sites and networks will react to load that we are about to place on them
- Will be a good arena for:
  - Central vs. Local control
  - Infer large sample behaviour from limited statistics
  - Machine Learning
  - Network scheduling
- **Future will be more fun than the past !**

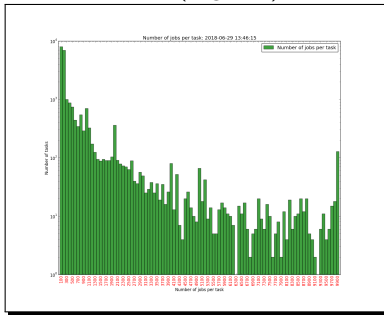
**Thank You!**

**Backup Slides:**



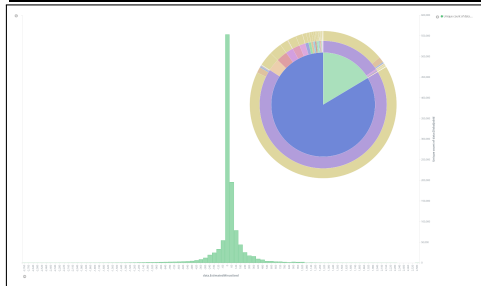
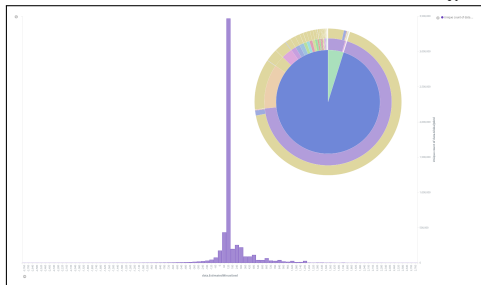
## Current implementation of Time tuning

### JobCountPerTask (LogScale):





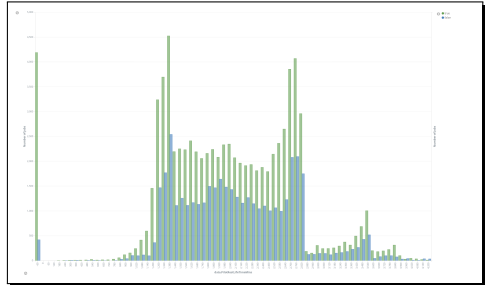
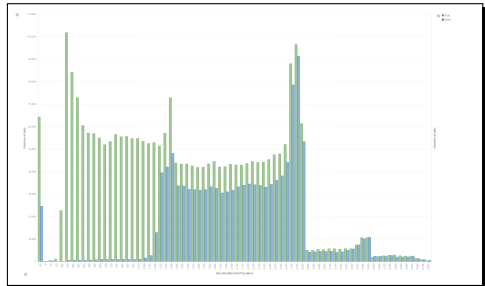
## Current results





## Current results

- Few more plots showing the results –





## Overflow - Problem:

- **The primary need:** to achieve a better resource utilisation
- **The secondary need:** to protect the sites from being flooded with jobs they cannot process || serve data for them.
- **The old Overflow mechanism** - what does it suffer from:
  - Statically defined overflow regions - can't be based on other criteria characterizing "proximity"
  - Overflow matching decision happens in the timescale of pilot lifetimes - not flexible enough to respond to faster changes in the status of the distributed CPU and storage resources
  - Requires additional FE groups to be set - a limitation in practice to the different number of settings that could be configured at once.
  - Based on a special type of pilots - fragmentation of the resources, increasing wastage



## Structure:

Three basic abstractions:

- **Information Lifetime:**

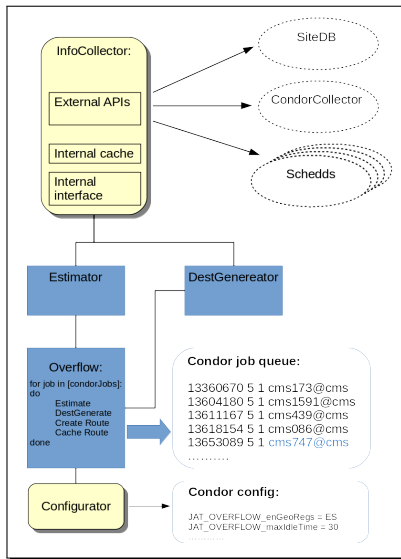
- static
- dynamic

- **The OverflowLevel:**

- PERTASK
- PERJOB
- PERBLOCK
- PERFILE
- PERDATASET

- **The OverflowType:**

- GEO
- TIER1
- TIER2
- DATALOCATION
- LOCALLOAD
- SRCLOAD
- DSTLOAD

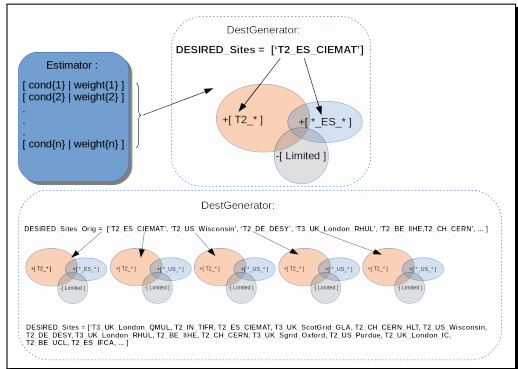






## Decision making & Subsets

- Weighted sum vs. Weighted single decision.
- Estimating the weights could be dynamic:  
In the future we can apply more elaborate mechanisms for estimating the optimal weights according to the prompt feedback about the reaction of the system.
- Subsets intersections.





## New Methods for improving the accuracy of Automatic Time Tuning

We estimate the Job Wallclock Time (EWT) based on the first completed jobs (`minTaskStat`) and continuously modify the Requested Wallclock Time of the idle jobs while gaining statistics. This is a method which has the intrinsic characteristics of a negative feedback amplifier. As expected, the error with respect to the Real Time (RT) follows a normal distribution':

$$err = EWT - RT \quad (1)$$

In order to minimise this error and avoid negative values we introduce a correction factor:

$$err = CorrFactor * EWT - RT$$

$$CorrFactor = f(n)$$

$$n : \text{number of completed jobs}$$

Different correction factors considered:

- static correction factor, a Heaviside function:

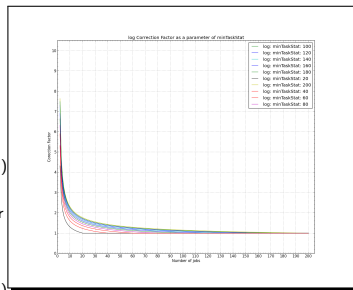
$$f(n) = \begin{cases} 1 & \text{if } n < \text{minTaskStat} \\ const & \text{if } n > \text{minTaskStat} \end{cases} \quad (2)$$

`minTaskStat` - here is a config parameter which acts as a trigger for the mechanism

- logarithmic correction factor:

$$f(n) = \log_n(\text{minTaskStat}) \quad (3)$$

- very steep
- `minTaskStat` - is now a parameter defining the slope of the function that the correction factor will follow while gaining more statistics
- a single parameter function
- the negative error is still at around 16% (shows dependency on more than a single parameter)





## New Methods for improving the accuracy of Automatic Time Tuning

- polylogarithmic:  
motivation - commonly used for estimating the order of time or memory consumption

$$f(n) = \sum_{k=1}^{\epsilon} a_k (\log_n(\text{minTaskStat}))^k \quad (4)$$

- more moderate slope
- high computational cost:  $O(n^\epsilon)$  for high values of  $\epsilon$
- now we can easily put more than a single parameter in the function and decide the order/degree up to which we want to calculate and  $\epsilon$  becomes the number of independent parameters. candidate parameters:

- job dependent:
  - number of jobs in the workflow with error code diff 0
  - dataset characteristics: like number of lumisections
  - distance between slot and dataset ... etc.
- infrastructure dependent:
  - network throughput of the slot
  - reliability of the (slot) ... etc

